An efficient Descriptor for Image Retrieval: Application to COIL-100 Database

EL ASNAOUI Khalid, CHAWKI Youness, AKSASSE Brahim, OUANAN Mohammed
Moulay Ismail University
Faculty of Sciences and Techniques
Department of Computer Science, ASIA Team, M2I laboratory
BP 509 Boutalamine 52000, Errachidia, Morocco
khalid.elasnaoui@gmail.com,youness.chawki@gmail.com,baksasse@yahoo.com,
ouanan_mohammed@yahoo.fr

Abstract: - In this study, a new technique for image retrieval based on color feature is presented. This new algorithm is based on two defined equations, the standard deviation and the mean of the image. The performance of the proposed approach is tested on a large image collection of the COIL-100 database. Experimental results show that the proposed approach can achieve significant precision (up to 95% better) and, at the same time, the system is fast.

Key-Words: - Image retrieval, COIL database, Query Image, Color features, Indexing.

1 Introduction
Recently, the development of image archives has grown rapidly due to the advancement and popularization of internet technologies and data storage devices. Content-Based Image Retrieval (CBIR) was an active research domain for decades. In addition, image retrieval has an important role, because this sort of system can help efficiently users to find specific images in a database. One of the fundamental problems for image retrieval is how to represent the image. In general, to represent an image, the image features (texture, color, shape) are extracted from it and stored within an descriptor.

When handling an image database, the image characteristics are extracted and stored in another database for future uses. Given a query image, the system extracts the visual content (in the form of a feature vector), and checks similarity between the query image and the images stored in the database. If the distance between feature vectors of the query image and images in the database is small enough, according to a threshold, the corresponding image in the database is considered as a match for the query. The search is usually based on similarity rather than on correctness, and the retrieved results are then ranked accordingly to a similarity index.

We outline the main application domains of content-based image retrieval such as biometrics fingerprint or eye color recognition, handwriting recognition, pattern recognition, and medical imaging. The CBIR system diagram is shown in (Fig. 1).

The remainder of this paper is organized as follows. We first present overview of related work in section 2. The similarity measure is discussed in section 3. Section 4 deals with the result and evaluation. We provide the conclusions and future works in section 5.

2 Related works
Recently, there are many CBIR approaches e.g., [1,2,3,4,5,6,7,8,9,10,11]. In this section, we will...
briefly outline some of the already developed methods as described in the literature.

Alaoui et al. [12], introduced the local histograms to describe the spatial information of colors, even though, a single local histogram is not enough for efficient and robust image retrieval system. He proposed the use of color local histograms on multi-resolution. The multi-resolution color local histograms give much better retrieval efficiency. The multi-resolution images are generated using the median filter.

The technique presented in Kundua et al. [13], introduces a new CBIR scheme that abstracts each image in the database in terms of statistical features computed using the Multi-scale Geometric Analysis (MGA) of Non-subsampled Contourlet Transform (NSCT).

The method proposed by Talib et al. [14], uses a semantic feature extracted from dominant colors (DC). This technique helps reduce the effect of image background on the image matching decision where an object’s colors receive much more focus. In addition, a modification to DC-based similarity measure is also proposed.

The technique given by Ren et al. [15], proposes to use a local mode histogram as the texture feature to match images and applying the residual coefficients to filter non-confident modes. The geometrical correspondence between two images is also considered.

In Fazal et al. [16], the quantized histogram statistical texture features are extracted from the DCT (Discrete Cosine Transformation) blocks of the image using the significant energy of the DC and the first three AC coefficients of the blocks.

ElAlami [17] proposed a model composed of four major phases, namely: features extraction, dimensionality reduction, artificial neural network classifier and matching strategy. As for the feature extraction phase, it extracts a color and texture features, respectively, called color co-occurrence matrix (CCM) and the difference between pixels of scan pattern (DBPSP). However, integrating multiple features can overcome the problems of single feature, but the system works slowly, mainly because of the high dimensionality of the feature space. Therefore, the dimensionality reduction technique selects the effective features that jointly have the largest dependency on the target class and minimal redundancy among themselves. These features reduce the calculation work and the computation time in the retrieval process. The artificial neural network (ANN) serves as a classifier so that the selected features of query image are the input and its output is one of the multi classes that have the largest similarity to the query image. In addition, the matching strategy depends on the idea of the minimum area between two vectors to compute the similarity value between a query image and the images in the determined class.

The color information of the image is also used in Elasnaoui et al. [18]. The proposed approach is based on the intersection of 2-D histograms in HSV space. The used histogram is based not only on the intensity of pixels but also on a 3x3 window. This approach overcomes the drawback of the classical histogram which ignores the spatial distribution of pixels in the image.

To escape the effects of the discretisation of the color space, which is intrinsic to the use of histograms [18], another approach has been successfully used by Elasnaoui et al. [19]. This approach combines 2-D histogram and statistical moments in the HSV color space. The method was applied to different real images to demonstrate the performance of the algorithm of color image retrieval. The results obtained were compared to other methods and show that that the new method is more efficient than other methods.

Image indexing has grown in recent years and rapidly became color-oriented, since most of the images are colors.

The method proposed in this paper is based on color feature and provides an effective solution to the problems identified in existing studies.

3 Similarity measure

In order to quantify the similarity degree, we suggest the following calculation method:

Let \( V_Q \) and \( V_I \) be the descriptors -created from our new algorithm- of query image and image I in a database respectively. We associate to \( V_Q \) and \( V_I \) the following values:

\[
V_Q = \{ M_{R_0}, M_{G_0}, M_{B_0}, \sigma_{R_0}, \sigma_{G_0}, \sigma_{B_0}, \lambda_{R_0}, \lambda_{G_0}, \lambda_{B_0} \}
\]

\[
V_I = \{ M_{R_1}, M_{G_1}, M_{B_1}, \sigma_{R_1}, \sigma_{G_1}, \sigma_{B_1}, \lambda_{R_1}, \lambda_{G_1}, \lambda_{B_1} \}
\]

After calculating the descriptor \( V_Q \) of query image, we will compare it with the \( V_I \) of database images, which already are processed and stored in descriptors database. Having had the final image descriptor, the distance between two images is the...
distance between two descriptors. This distance can be calculated by the following formula [20]:

\[
D(Q,I) = \frac{\sum_{i=1}^{9} |V_0 - V_i|}{\sum_{i=1}^{9} V_0} \tag{1}
\]

Where \(Q\) is the query image, \(I\) an image in database, \(V_0\) descriptor of \(Q\), \(V_i\) descriptor of \(I\) and \(D(Q,I)\) the distance between the images \(Q\) and \(I\).

4 Experiments and discussion

4.1 Applied database

We use in our work Columbia Object Image Library (COIL-100) database which is well known for object recognition. The Columbia Object Image Library (COIL-100) is the dataset used for the experimental purpose. COIL-100 contains 7200 color images of 100 objects, which corresponds to 72 different orientations of each object (Fig 2).

![Fig. 2: The COIL-100 database contains images of 100 objects.](image)

4.2 Performed tests

To evaluate the retrieval effectiveness, we used the precision and recall as statistical comparison parameters for the proposed CBIR method. The definitions of these two measures are given by following equations.

\[
\text{Precision} = \frac{R_A}{A} \times 100 \tag{2}
\]

\[
\text{Recall} = \frac{R_A}{B} \times 100 \tag{3}
\]

For example, a CBIR method for a query image retrieves totally 14 images with 8 relevant images out of totally 72 relevant images in database. Then the precision is \(8/14 = 57\%\) and recall is \(8/72 = 11.1\%\).

4.3 Image retrieval

To check the retrieval performance and robustness of the proposed method, 24 experiments are conducted on COIL-100 database. On the basis on the distance (equation (1)), each image below the threshold 0.08 will be taken into consideration. We display the best 14 similar images found to prove the performances of our proposed algorithm. The results are presented separately.

![Image of 24 different objects from COIL-100 database.](image)
Other experiments are tabulated below.

TABLE I: THE AVERAGE PRECISION AND RECALL

<table>
<thead>
<tr>
<th>Image</th>
<th>Returned Images</th>
<th>Recall (%)</th>
<th>Precision (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>obj1_0</td>
<td>14</td>
<td>18,05</td>
<td>92</td>
</tr>
<tr>
<td>obj2_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj3_0</td>
<td>14</td>
<td>18,05</td>
<td>92</td>
</tr>
<tr>
<td>obj4_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj5_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj6_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj7_0</td>
<td>14</td>
<td>18,05</td>
<td>92</td>
</tr>
<tr>
<td>obj8_0</td>
<td>2</td>
<td>2,77</td>
<td>100</td>
</tr>
<tr>
<td>obj9_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj10_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj11_0</td>
<td>14</td>
<td>16,66</td>
<td>85</td>
</tr>
<tr>
<td>obj12_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj13_0</td>
<td>11</td>
<td>15,27</td>
<td>100</td>
</tr>
<tr>
<td>obj14_0</td>
<td>14</td>
<td>18,05</td>
<td>92</td>
</tr>
<tr>
<td>obj15_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj16_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj17_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj18_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj19_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj20_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj21_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj22_0</td>
<td>14</td>
<td>19,44</td>
<td>100</td>
</tr>
<tr>
<td>obj23_0</td>
<td>14</td>
<td>18,05</td>
<td>92</td>
</tr>
</tbody>
</table>

We recall that the same tests were performed using HSV, HSL space, etc, with following distance measures: Euclidean, Manhattan, Chebyshev and Minkowski with $p = 3$ and we find that the choice that achieves the best results is to use RGB space with Swain distance (equation 1).

5 Conclusion

We suggest in this work a novel method for color image retrieval. This approach is simple, and it can be used to overcome limitations of existing algorithms which use the color feature. The evaluation of the proposed approach shows that the ability of the CBIR system to retrieve relevant information from all images collection is better. It is possible to achieve up to 95% of efficiency in retrieval of images. Satisfactory retrieval of expected images is provided faster due to the lower number of iterations in the searching process. The results obtained indicate that the proposed approach might be considered as a solution for the development of visual information retrieval. In future, the performance may be improved using more databases, more sophisticated feature extraction techniques and other distance metrics.
References:


[21] Flores-Pulido, L., Starostenko,O., Flores-Quéchol, D., Rodrigues-Flores,J. I., Ingrid,

