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Unsupervised Content Based Image Retrieval by Combining Visual Features of an Image With A Threshold

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Abstract--***Content-based image retrieval (CBIR) uses the visual features of an image such as color, shape and texture to represent and index the image. In a typical content based image retrieval system, a set of images that exhibit visual features similar to that of the query image are returned in response to a query. CLUE (CLUster based image rEtrieval) is a popular CBIR technique that retrieves images by clustering. In this paper, we propose a CBIR system that also retrieves images by clustering just like CLUE. But, the proposed system combines all the features (shape, color, and texture) with a threshold for the purpose. The combination of all the features provides a robust feature set for image retrieval. We evaluated the performance of the proposed system using images of varying size and resolution from image database and compared its performance with that of the other two existing CBIR systems namely UFM and CLUE. We have used four different resolutions of image. Experimentally, we find that the proposed system outperforms the other two existing systems in ecery resolution of image.***

***Keywords*: Content based image retrieval, image classification, unsupervised learning, and graph clustering algorithm.**

1. INTRODUCTION

Content-based image retrieval (CBIR, in short) uses the visual contents of an image such as color, shape and texture to represent and index the image. In a typical content-based image retrieval system (see Figure 1), the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. The similarities/distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search the image database for images similar to the query images in order to return the relevant images. Generally speaking, content-based image retrieval (CBIR) aims at developing techniques that support effective searching and browsing of large image digital libraries on the basis of automatically derived image features [3]. The objects that are similar to each other are put in one group (also called a cluster) and the objects that are dissimilar are put into different clusters. CLUE, cluster-based retrieval of images by unsupervised learning, proposed by Chen et al. [5, 6] is an example of CBIR technique based on unsupervised learning.

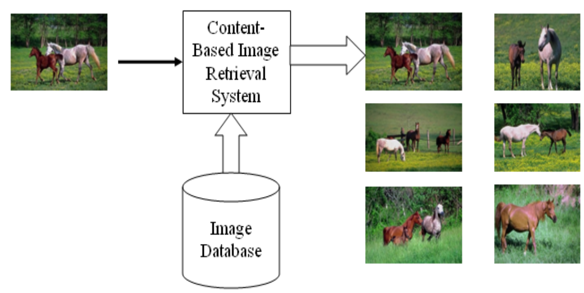

Figure 1: Content Based Image Retrieval System

In this paper, we propose a CBIR system that is also based on unsupervised learning and combines the visual features (shape-color features and texture-color features) with a threshold to compute the similarity of the query image with the images in image database.

This paper is organized as follows. In the next section, we discuss the background and related work. In Section 3, we discuss the details of unsupervised content based image retrieval and present the architecture of our proposed CBIR system. In section 4, we present our experimental results. Finally, we conclude in section 5.

2. BACKGROUND AND RELATED WORK

Existing CBIR systems can be grouped into two major categories: *full-image* retrieval system and *region-based* image retrieval system [1]. In a CBIR system, to search images by their content, two things have to be done [10].

1. The image has to be re-encoded into some mathematical form and stored in a database.
2. There should be a mechanism to compare these mathematical forms.

High-level features are features obtained from the combination of low-level features. Examples are edge and shape. But, the three of the most widely used features are (i) color (ii) texture and (iii) shape. Details of these features are discussed in [6].

A typical CBIR system views the query image and images in the database (target images) as a collection of features, and ranks the relevance between the query image and any target images in proportion to feature similarities [3]. Statistical classification methods group images into semantically meaningful categories using low level visual features so that semantically-adaptive searching methods applicable to each category can be applied [8, 9 and 11]. Color features are computed by color moment and color histogram [5, 7]. Shape features are calculated after images have been segmented into regions or objects [2, 12]. Shape information is captured in terms of edge images computed using Gradient Vector Flow fields [6]. Invariant moments are then used to record the shape features [6]. Texture features are computed by statistical Tamura feature and multi resolution filtering techniques such as Gabor and Wavelet Transform, characterize texture by the statistical distribution of the image intensity [2, 6]. UFM are explained in [2].

3. UNSUPERVISED CONTENT BASED IMAGE RETRIEVAL

The major difference between CBIR system based on unsupervised approach and the other CBIR systems lies in the two processing steps, selecting neighboring target images and image clustering, which are the major components of CLUE [5] shown in Figure 2.

There are two simple methods to select a collection of neighboring target images for query image [5].

- *Fixed-radius method* (FRM) takes all target images within some fixed radius ε with respect to *i*. For a given query image, the number of neighboring target images is determined by ε.
- *Nearest-neighboring method* (NNM) first chooses k NN of *i* as seeds. The *r* NN for each seed is then found. Finally, the neighboring target images are selected to be all the distinct *target* images among seeds and their *r* NN, i.e., distinct images in *k(r+1)* target images.

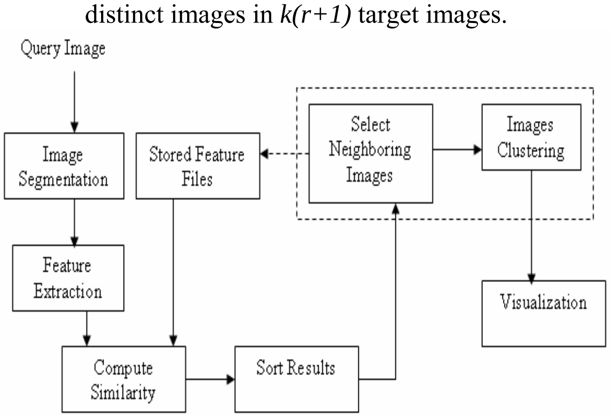

FIGURE 2: A CBIR SYSTEM BASED ON CLUE

A set of *n* images is represented by a weighted undirected graph G = (V, E).The nodes V = {1, 2, …., *n*} represent images, the edge E = {(*i*, *j*) : *i*, *j* ∈ V} are formed between every pair of nodes, and the nonnegative weight w_{ij} of an edge (*i, j*), indicating the similarity between two nodes, si a function of the distance(or similarity) between nodes(images) *i* and *j*. Given distance d*(i, j)* between images *i* and *j*, the nonnegative weight w_{ij} is given by

$$w_{ij} = e^{\frac{-d(i,j)^2}{s^2}} \tag{1}$$

where, *s* is a scaling parameter that needs to be tuned to get a suitable locality. The choice of exponential decay is based on support from psychological studies. The weight can be organized into a matrix W, named affinity *matrix* with *ijth* entry given by w_{ij}

Under a graph representation, clustering can be naturally formulated as a graph partitioning problem. The CLUE uses spectral graph partitioning methods called the normalized cut (N_{cut}) method for image clustering [3]. A graph partitioning method attempts to organize nodes into groups so that the within-group similarity is high, and/or the between-groups similarity is low.

Given a graph G = (V, E) with affinity matrix W, a simple way to quantify the cost for partitioning nodes into two disjoint sets A and B (A ∩ B = Φ and A ⋃ B = V) is the total weights of the edges that connecting the two sets. In graph theory, this cost is called a *cut*

$$cut(A, B) = \sum_{i \in A, j \in B} w_{ij} \tag{2}$$

which can also be viewed as a measure of the between-groups similarity.

Finding a bipartition of the graph that minimizes this cut value is known as the *minimum* cut problem. However, the minimum cut criterion favors grouping small sets of isolated nodes in the graph because the cut defined above, does not contain any within-group information. This motivates several modified graph partition criteria including the N_{cut}

$$N_{cut} = \frac{cut(A,B)}{cut(A,V)} + \frac{cut(A,B)}{cut(B,V)} \tag{3}$$

Given a graph representation of images G = (V, E) with affinity matrix W, let the collection of image clusters be $\{C_1, C_2, \ldots, C_m\}$, which is also partition of V, i.e.,

$$C_i \cap C_j = \Phi \text{ for } i \neq j \text{ and } \bigcup_{i=1}^{m} C_i = V. \tag{4}$$

Then the representative node (image) of C_i is

$$\arg\max \sum_{j \in C_i, t \in C_i} w_{jt} \tag{5}$$

this can also be viewed as a measure of the between-groups similarity.

Now, our propose architecture of a CBIR system based on unsupervised learning as shown in Figure 3. The major difference between the proposed CBIR system and the CBIR system based on CLUE lies in the stored features files. In the proposed CBIR system, we store the values of features in the stored features files after combining values of shape, texture and color features of an image with minimum 60% value of each feature in each image. In other words, we take 60% of the total value of texture features, 60 % of the value of color features and 60% of the value of the shape features for an image and combine these values and store that combined values into the stored features files as the feature values for the image.

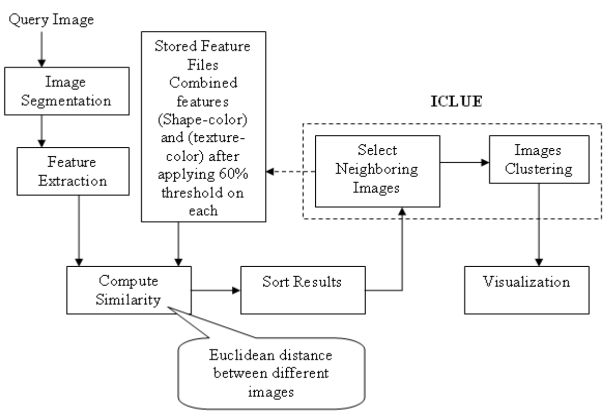

Figure 3: The Proposed CBIR system

The proposed system sums up the values of texture, color and shape features, of each image and stored that features in the feature database. We then compare the shape, texture and color features values of the target image with combined of two features shape-color and texture-color features values of each image. If the shape, texture and color features value of a target image is more than the 60% value for the shape, texture and color features respectively, we sum up the shape, texture and color values of the target images and store in the stored features files. Otherwise, we discard the target image as a relevant image. We assign the importance weights on the basis of combined feature values only to the target images, whose combined features values are stored in the stored feature files. On the basis of these importance weights, the relevant images are extracted from the image database.

We have used images of different size and of different resolution from four COREL databases.

(i) Database 1 : Image Resolution *185 X 84*
(ii) Database 2 : Image Resolution *185 X 96*
(iii) Database 3 : Image Resolution *185 X 85*
(iv) Database 4 : Image Resolution *256 X 384*

4. EXPERIMENTS AND RESULTS

We experimented with images of four COREL databases consisting of images of different size and of different resolution. We take the results for the both version namely (i) color-shape and (ii) color-texture of the improved CLUE algorithm on each database. We performed our experiments with a general purpose image database, which contained approximately 1,000 images. Our system used the same feature extraction technique as given in [4] and we used the Euclidean distance as the similarity measure for computing the similarity between the query and target images in the database. Our implementation provides a *Random* option that gives a user a random set of images from the image database to start with. Once a query image is received, the system displays a list of computed similarity measure values for the different images in the database. Then, it displays a list of images in decreasing order of their similarity with the query image. Now, we present the top 25 results due to space limitation from the proposed CBIR system and shown one result from each resolution of image database by randomly chosen query images as shown in Figures 4, Figure 5, Figure 6 and Figure 7.

To compare the performance of the proposed CBIR system with the other two CBIR systems based on CLUE and UFM, we test on every images and take each image as a query image from the 1000 image database. The database, we used, is a subset of the COREL database and it contains 100 images each from the 10 image categories and hence, a total of 1000 images.

In our experiments, we take each image as a query image from each of the image categories and hence, a total of 1000 query images. For each query, we select the top 100 results from the CBIR system to compute precision, i.e. precision at 100, but in this paper we show only top 25 results of some query image due to space limitation. Precision at 100 may be defined as the proportion of retrieved images that are relevant to the query in the top 100 retrieved images. We tested it with four different resolutions of images on COREL image database. Comparison shown in Figure 8 and Figure 9.

CBIR system Results of Database 1

Figure 4a. Proposed CBIR system Results (Color & shape) system: 9 matches out of 12

Figure 4b. Proposed CBIR system Results (Color & texture) system: 10 matches out of 12

Figure 4c. CLUE system Results: 8 matches out of 12

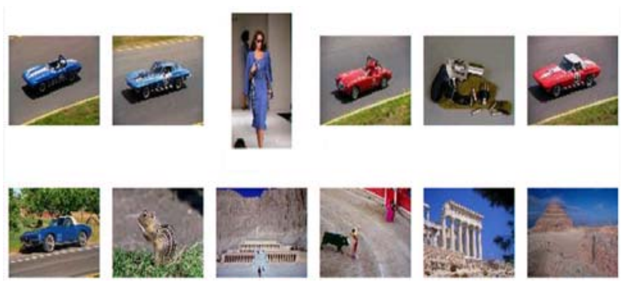

Figure 4d. CLUE system Results: 4 matches out of 12

Figure 4: Comparison of results of the Proposed CBIR, CLUE and UFM for car category on image database1.
The query image is the upper-left corner image of each block of images.

CBIR system Results of Database 2

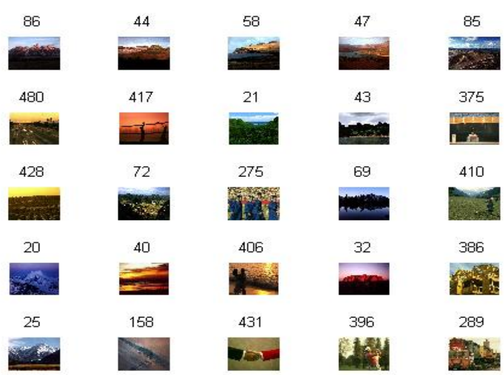

Figure 5a. Proposed CBIR system Results (Color & shape) system: 11 matches out of 25

Figure 5b. Proposed CBIR system Results (Color & texture) system: 14 matches out of 25

Figure 5: Results of the Proposed CBIR system on image database2. CLUE and UFM not shown,
The query image is the upper-left corner image of each block of images

CBIR system Results of Database 3

Figure 6a. Proposed CBIR system Results (Color & shape) system: 10 matches out of 25

Figure 6b. Proposed CBIR system Results (Color & Texture) system: 16 matches out of 25

Figure 6: Results of the Proposed CBIR system on image database3. CLUE and UFM not shown,
The query image is the upper-left corner image of each block of images

Table 1: Semantic Descriptor of the images of COREL Database resolution 256 X 384

Category No.	Category Name
1	African people and village
2	Beach
3	Buildings
4	Buses
5	Dinosaurs
6	Elephants
7	Flowers
8	Horses
9	Mountains and glaciers
10	Food

This table shows that database of different categories and each category have 100 images, hence the total images it contains 1000.

CBIR system Results of Database 4

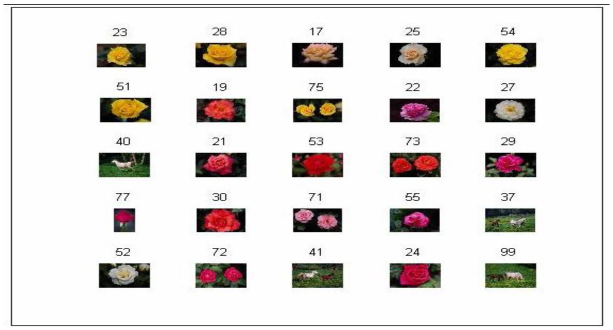

Figure 7a. Proposed CBIR (shape-color) system Results: 21 matches out of 25

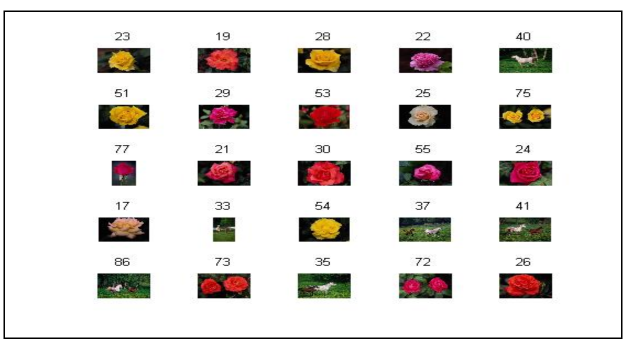

Figure 7b. Proposed CBIR (texture & color) system Results: 19 matches out of 25

Figure 7: Comparison of results of the Proposed CBIR and CLUE for flower category. UFM not shown
The query image is the upper-left corner image of each block of images.

Table 2: Comparison of performance of Proposed CBIR, CLUE, and UFM using precision for each category of Database 4

ID	Category Name	Precision at 100 (UFM)	Precision at 100 (CLUE)	Precision at 100 (Shape-Color)	Precision at 100(Texture-Color)
1	People	0.38	0.49	0.53	0.53
2	Beach	0.29	0.34	0.42	0.43
3	Buildings	0.34	0.35	0.37	0.40
4	Buses	0.61	0.63	0.62	0.65
5	Dinosaurs	0.93	0.96	0.95	0.92
6	Elephants	0.23	0.28	0.30	0.32
7	Flowers	0.63	0.75	0.74	0.77
8	Horses	0.62	0.70	0.77	0.78
9	Mountains	0.25	0.28	0.30	0.30
10	Food	0.45	0.60	0.64	0.65
Average		**0.473**	**0.538**	**0.564**	**0.575**

This table shows that precision at 100 in both proposed approaches in almost all categories are better than CLUE and UFM approaches that described in [6].

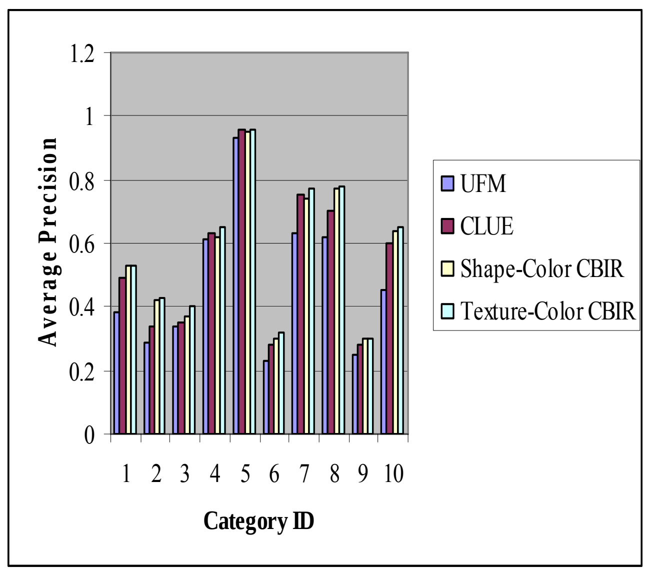

Figure 8: Results of Comparison of proposed (Shape-Color && Texture-Color) CBIR with CLUE and UFM on the Average Precision for each category

Table 3: Average Precision on each resolution of image database

Image Database	UFM	CLUE	ICLUE(C&S)	ICLUE(T&C)
Database 1 (185 X 84)	0.28	0.55	0.69	0.76
Database 2 (185 X 96)	0.36	0.37	0.42	0.44
Database 3 (185 X 85)	0.39	0.41	0.49	0.52
Database 4 (384 X 256)	0.473	0.538	0.564	0.575

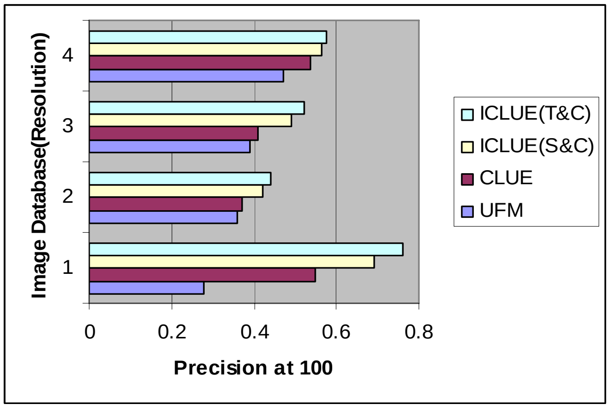

Figure 9: Pictorial representation of Table 2 comparison shown on each resolution of image database

This figure shows that on each resolution of image database proposed approach outperform.

5. CONCLUSION

In this paper, we proposed a content based image retrieval system based on unsupervised learning, where in, we combine all the features values namely shape, color and texture of an image for assigning a weight on different images (as a target images) in the image database with threshold of 60%. We can take any value as a threshold means minimum value of matching individual feature as well as combined of both features value. We tested it on threshold value 60 and we got the better results in comparison to given precision value by UFM and CLUE on [6]. We experimented with a standard image database of four different resolution of image each database consisting of approximately 1000 images to compare the performance of the proposed systems by combining both shape-color features and color-texture features with two other existing CBIR systems. In our experiments, we used Euclidean distance as the similarity measure for computing the similarity of images in the database with a query image. Experimentally, we found that the proposed CBIR systems gives better results than the CLUE and UFM based CBIR systems in almost all categories of an image databases.

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