<u>15 September 2012. Vol. 43 No.1</u>

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645

<u>www.jatit.org</u>



USING GLOBAL FEATURES ON REFINED IMAGE PARTS FOR LOGO RECOGNITION

¹AHMED ZEGGARI, ²FELLA HACHOUF,

 ¹Asstt. Prof., Computer Science Department, University of Tebessa, Road of Constantine, 12000 Tebessa, Algeria.
 ²Assoc. Prof., Automatic & Robotic Lab, Electronic Department, Mentouri Constantine University, Road

of Ain El Bey, 25000 Constantine, Algeria.

ABSTRACT

In this paper we address the problem of what parts of an image can be used to well perform content-based image retrieval system. Local parts are selected and refined based on the clustering of interest points obtained by Harris corners and minimum bounding box detectors. Global features such as invariant moments and color histograms of the extracted local regions are combined to find similar logos on the database. Several inter-regions distances are compared to perform inter-images similarity based on the minimum average distance of the individual components. Our system is tested on logo and trademark databases; results demonstrate a good retrieval rate and tolerance to logo distortions such as rotation, occlusion and some amount of noise.

Keywords: Clustering, Logo Retrieval, Invariant Moments, Color Histogram, Region-Based Image Retrieval, Image Segmentation, Minimum-Bounding Region

1. INTRODUCTION

Content-Based Image Retrieval (CBIR) describes the task of searching images from a large data collection that match to a given query based on image features such as color, shape and texture. It has been an active research subject since several years, with an intensive literature and many applications in different fields. A detailed review of CBIR is given in [23].

The current advances in the field of image processing and applied mathematics have motivated researchers to adapt these techniques for treating low-level images. However, the major problem is the high level semantic interpretation of image contents called semantic gap [20]. To overcome this semantic gap, Manual annotations of image contents are used and they rely on text retrieval techniques for searching particular images. However, they has two main drawbacks [18]: subjective interpretation depends either on the person or on the context, and the time cost, so it is prohibitive to manually indexing images within a large database collection.

A logo is a symbol that distinguishes the origin of documents or products of a given company, it is conceived to be unique and highly representative of the company. Logo recognition is of great interest in document images recognition [4], in which a logo can be seen as an index for database documents retrieval. Another interesting application is the registration and search of conflicting marks [25]. Therefore, several relevant approaches dealing with logo detection and recognition problems have been proposed. These approaches use different image features and may combine various retrieval techniques. Phan and Androutsos employed Color Edge Co-occurrence Histogram (CECH) object detection scheme on compound color objects (objects that consist of a specific set of colors that are spatially arranged in a unique way), they introduced edge information to the CECH by virtue of incorporating color edge detection using vector order statistics [17]. Jain and Vailaya proposed a shape-based retrieval system in a trademark image database. Their system includes a two-stage hierarchy: a fast browsing stage using a histogram of the edge direction and invariant moment; and a detailed matching stage using deformable template matching [8]. Shape features are used as well by Kim and Kim in [11], where they employed Zernike moments as shape descriptors for retrieval in trademark database. Jiang et al. proposed a new approach by selecting visual features based on Gestalt principals like symmetry, continuity, and closure property of the trademark images [9]. Other researchers have investigated the problem of logo recognition; by applying positive and negative

Journal of Theoretical and Applied Information Technology <u>15 September 2012. Vol. 43 No.1</u>

© 2005 - 2012 JATIT & LLS. All rights reserved.

JATIT

ISSN: 1992-8645

www.jatit.org

E-ISSN: 1817-3195

shape feature [24], string-matching technique [3], and interactive feedback [2].

Global images characteristics are not suitable in the case of accidental distortions. like occlusion. rotation and noise, of the query image. In this paper we deal with the problem of retrieving logos based on integrated shape and color features of local image components. The proposed algorithm begins by segmenting the image in local parts based on the clustering of Harris interest points. Then, we use a minimum-bounding rectangle of the obtained clusters to get local regions. Invariant moment and color histogram are combined to obtain a logo feature vector. The local search algorithm has been tested on a database containing hundreds of collected logos; the obtained results showed some tolerance of our algorithm against considerable rate of images deformations. Note that the proposed method not deals with logo detection problem in which we assume that a logo is an entire image and not a part of an image in our database.

The remainder of this paper is organized as follows. In section 2 we overview the general architecture of our system. In section 3 we describe the local regions extraction scheme. The image features extraction is given in section 4. In section 5 we present the similarity measure used to perform image comparisons. Experimental results are given and discussed in section 6. Section 7 concludes this paper and gives some directions for new improvements of this work.

2. SYSTEM OVERVIEW

2.1. Retrieval System Architecture

Our retrieval system operates in two distinct steps: features database creation and logo retrieval. For all images in the database, our algorithm starts with the offline detection and storage of local features. When a query image is presented to the retrieval system, their local features are computed and then we measure a similarity distance between the query image and the other images on the database. The resulting images are presented to the user based on their ranked similarity. The whole scheme of our retrieval system is reported in Figure 1.

2.2. Logo Database

A logo is a symbol that distinguishes the origin of documents, products or services of a given institution or company. A logo is conceived to be unique and highly representative of the company. A good logo should be easy to memorize and recognize.



Figure 1: General architecture of our CBIR system.

To enhance diversity, we manually constructed our logo database with hundreds of colored logos collected from several worldwide sources. Our dataset contains logos of different sizes and categories: 30 % of textual logos (Figure 2.a), 35% of graphical logos (Figure 2.b) and 35 % mixture of text and graphic logos (Figure 2.c).



(a) Textual logo (b) Graphical logo (c) Mixed logo Figure 2: Some examples of trademarks in the dataset.

2.2. Logo Distortions

The input logos are subject to different corruptions caused by several phenomena such as fax machines, photocopiers, segmentation processes and illumination conditions. We artificially reproduce such degradations by adding noise and synthetically occluding the original logos. To simulate logos distortions the following transformations were applied to 50% of our database logos (half of each category):

- Twirl: a twirl is the geometric transformation by which each image pixel is rotated by an angle proportional to the pixel radial distance to the image center.
- Rotation: images are rotated by different angles (between 30° and 270°), in most cases the rotated image are occluded.
- Occlusion: during the automatic detection, logos are over or sub segmented, we reproduce this by manually adding or removing logo parts, generally in the

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645

www.jatit.org



boundaries. The amount of occlusion varies within 10% and 30%.

- Illumination changes: logos are edited by manually changing theirs illumination values.
- Noise: a synthetic noise is added to the input logos by changing the value of each pixel with a certain probability. Noise is applied either to the whole image or to a restricted zone.

Figure 3 summarizes the different deformations

used in our study to reproduce possible distortions. (a) Original Images (b) Twirl Transform (c) Illumination (c) Illumination (c) Rotation (c) Occlusion (c) Occlusion

Figure 3: A potential logos distortions used in our study.

3. LOCALIZATION OF INTEREST REGIONS

3.1. Interest Points

Interest points in an image are defined as twodirection discontinuity of intensity function or their derivatives, or as one direction discontinuity in the case of an edge (see Figure 4).

Interest points are points that provide valuable information about the scene, they have some characteristics: they are present on all images; also they are robust under local and global perturbations like occlusion and illumination variation. Furthermore an interest point is a consistent source of information. In fact, using a small set of image points reduces the amount of the data to be processed and the required computation time.



(a) Corner point

(b) Edge point

Figure 4: Signal intensity variation in the case of corner and edge: a) significant variations on each direction; b) few variations on edge direction.

Algorithms proposed by Harris [5], Lowe [13]; and Mikolajczyk and Schmid [14] are among the most popular detectors of interest points. Harris detector uses the auto-correlation function to determine point's locations [5]. The SIFT key-point detector and descriptor [13] proposed by Lowe uses the difference-of-Gaussian (DoG) on the scalespace theory proposed by Lindeberg [12]. Mikolajczyk and Schmid [14] used Laplacian-of-Gaussian (LoG) and Harris detectors in their scale and affine invariant interest point detector.

An overview of different interest points detectors is presented in [21], the authors compared the stability of several detectors using repeatability, a quantitative evaluation measure which is the percentage of detected interest points repeated between two images: they concluded that the Harris detector provides the best repeatability, and it is invariant to rotation, illumination, scale and some amount of noise.

The choice of using Harris corner detector is justified by the fact that logo images are not complex pictures, they have less intensity levels and colors. In addition, logo and trademarks exhibit a lower spatial distribution of intensities and colors than complex images. Furthermore, Harris detector is computationally faster than other detectors.

3.1.1. Harris corner detector

Based on Moravec operator [15], Harris uses the local auto-correlation matrix C of intensity (called second moment matrix), which describes the gradient distribution in a local neighborhood of a point:

$$C = G(\sigma) \otimes \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Where $G(\sigma)$ is a gaussian function with standard deviation σ and \otimes is the convolution

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645

www.jatit.org



E-ISSN: 1817-3195

operator. I_x and I_y denote the partial derivatives in x and y, respectively.

Interest points are detected corresponding to the large eigenvalues of C, Harris propose to use the following computationally less expensive metric:

$$Cornerness = \det(C) - K \times trace^{2}(C)$$

Where K = 0.04 is a constant parameter.

3.2. Interest Regions

The choice of significant parts of an image is very important to well perform images comparison. Regions of interest are logo parts that contain an important presence of interest points. Logos are first segmented based on the clustering of interest points using K-means algorithm.

Figure 5 shows the resulted clusters and their intuitive surrounding rectangles where the angle θ between the major axis and the horizontal axis is 0. The white points on the image (b) are similar to their corresponding area in the oriented image (e) however; the other regions are not similar. Figures (c) and (f) show these anomalies.

To refine our results and give better corresponding regions, we investigated the computation of the minimum bounding rectangles. We exploited the algorithm proposed in [1] as follows:

- To determine the boundary points *B* of cluster C, we explore that cluster in eight directions. The maximum of eight boundary points are detected.
- Computing the centroid (\bar{x}, \bar{y}) of C: $1 \sum_{n=1}^{n} 1 \sum_{j=1}^{n}$

$$\overline{x} = \frac{1}{n} \sum_{i=1}^{n} x_i, \quad \overline{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$$

Where (x_i, y_i) are the *n* points of *C*. Notice that the centroids are computed during the last iteration of K-means.

• Computing the orientation angle θ of the major axis with the horizontal axis:

$$\tan(2\theta) = \frac{2\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} \left[(x_i - \bar{x})^2 - (y_i - \bar{y})^2 \right]}$$

The minor axis passes through the centroid and is perpendicular to the major axis.

 Computing the upper and lower furthest edge points from major and minor axis: Let a(x_i, y_i) ∈ B, $V_{maj}(a) = (y_i - \overline{y}) - \tan \theta(x_i - \overline{x})$ $V_{maj}(a) = (y_i - \overline{y}) - \cot \theta(x_i - \overline{x})$ Let $a_1(x_1, y_1), a_2(x_2, y_2)$ be respectively the

upper and lower points from the major axis, and let $a_3(x_3, y_3)$, $a_4(x_4, y_4)$ be respectively the upper and lower points from the minor axis, and let θ be the orientation angle, so pixel P(x, y) belongs to the region R limited by a_1 , a_2 , a_3 and a_4 and θ if all the following inequalities are satisfied:

$$(y - y_1) - \tan \theta(x - x_1) \le 0$$

$$(y - y_2) - \tan \theta(x - x_2) \ge 0$$

$$(y - y_3) - \cot \theta(x - x_3) \le 0$$

$$(y - y_4) - \cot \theta(x - x_4) \ge 0$$



Figure 5: Regions selection based on the intuitive surrounding rectangles.

4. FEATURES EXTRACTION

Features are important information extracted from an image and used to make logos comparison. Using color only as feature is not enough, for example conflicting marks in trademarks registration where a new designed company logo has the same shape as, but different colors than, another company logo.

Color and shape are integrated and used as characteristic features, for each image in the database, features are computed offline. We use color histogram and moments for each selected region, thus the logo l having n regions can be represented as a feature vector F_l :

$$F_l = (H_1, H_2, ..., H_n, M_1, M_2, ..., M_n)$$

Where H_i and M_i represents color and shape features of region *i*.

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645

www.jatit.org

E-ISSN: 1817-3195

4.1. Color Histogram

In order to characterize the color content of an image the RGB color space is used. Color representation is easy to compute and essentially invariant under translation and rotation of the query image, so color histogram is an effective tool for color image representation and characterization.

A normalization of the histogram is suitable to provide scale invariant. Let H be a histogram of region R, the normalized histogram H_N is defined

as:
$$H_N(i) = \frac{H(i)}{\sum_i H(i)}$$
 where *i* represents the

histogram bin.

We use and compare 3 different histogram distances to measure colors regions similarity. let R_1 and R_2 two regions from two distinct logos, and D_{Hist} is a distance between their normalized histograms H_{N1} and H_{N2} . Bhattacharyya, Intersection and a normalized version of Correlation distances are given by:

• *Bhattacharyya* distance:

$$D_{Hist}(H_{N1}, H_{N2}) = \sqrt{1 - \sum_{i} \frac{\sqrt{H_{N1}(i) \cdot H_{N2}(i)}}{\sqrt{\sum_{i} H_{N1}(i) \cdot \sum_{i} H_{N2}(i)}}}$$

- Intersection distance: $D_{Hist}(H_{N1}, H_{N2}) = 1 - \sum_{i} \min(H_{N1}(i), H_{N2}(i))$
- Correlation distance:

$$D_{Hist}(H_{N1}, H_{N2}) = \frac{\sqrt{\sum_{i} H_{N1}(i)^2 \cdot H_{N2}(i)^2} - \sum_{i} H_{N1}(i) \cdot H_{N2}(i)}{2 \cdot \sqrt{\sum_{i} H_{N1}(i)^2 \cdot H_{N2}(i)^2}}$$

where $H_{N}(i) = H_{N}(i) - (\frac{1}{I})(\sum_{j} H_{N}(j))$

and I is the number of histogram bins.

Note that the value of D_{Hist} lies in the interval [0,1], where 0 implies a perfect match and 1 implies a total mismatch.

4.2. Invariant Moment

Invariant moments are shape features widely used in the literature; they demonstrate satisfactory results in practical applications [6]. For η_{pq} the

normalized center moment, defined as: $\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{'}}$

Where:

$$\gamma = \frac{1}{2}(p+q) + 1$$
 for $p+q \ge 2$

And μ_{pq} , the center moment of order (p, q) and centroid $(\overline{x}, \overline{y})$ defined as:

$$\mu_{pq} = \sum_{x} \sum_{y} (x - \overline{x})^p (y - \overline{y})^q f(x, y)$$

The seven invariant moments $\phi_1, ..., \phi_7$ can be computed as follows:

$$\begin{split} \phi_{1} &= \eta_{20} + \eta_{02} \\ \phi_{2} &= (\eta_{20} - \eta_{02})^{2} + 4\eta_{11}^{2} \\ \phi_{3} &= (\eta_{30} - \eta_{02})^{2} + (3\eta_{21} - \eta_{03})^{2} \\ \phi_{4} &= (\eta_{30} + \eta_{12})^{2} + (3\eta_{21} + \eta_{03})^{2} \\ \phi_{5} &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \Big[(\eta_{30} + \eta_{12})^{2} - 3(\eta_{22} + \eta_{03})^{2} \Big] \\ &+ \eta_{03})^{2} \Big] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \Big[3(\eta_{30} + \eta_{12})^{2} \\ &- (\eta_{21} + \eta_{03})^{2} \Big] \end{split}$$

$$\phi_{6} = (\eta_{20} - \eta_{02}) \Big[(\eta_{30} + \eta_{12})^{2} - (\eta_{21} + \eta_{03})^{2} \Big] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\ \phi_{7} = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \Big[(\eta_{30} + \eta_{12})^{2} - 3(\eta_{21} - \eta_{30})^{2} \Big] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{30}) \Big[3(\eta_{30} + \eta_{12})^{2} - (\eta_{21} + \eta_{03})^{2} \Big]$$

The shape distance between two local regions R_1 and R_2 represented by their respective moments $M^{(1)}$ and $M^{(2)}$ is given by: $D'_{Moment}(R_1, R_2) = \sqrt{\sum_{i=1}^{7} (M_i^{(1)} - M_i^{(2)})^2}$

Hu moments are invariants to geometric transformations such as translation and rotation. We compute the moments of each detected region and add this shape feature to the color histogram in the logo feature vector.

5. SIMILARITY MEASURE

A choice of correct similarity measure remains an open discussion and domain dependent problem [22]. Given an input image, to find their similar images we must compute the similarity between

<u>15 September 2012. Vol. 43 No.1</u>

© 2005 - 2012 JATIT & LLS. All rights reserved

ISSN: 1992-8645	www.jatit.org	E-ISSN: 1817-3195

their feature vector and all feature vectors of a given database.

Let
$$R$$
 a set of returned images, D database

and
$$q$$
 a query image, similarity measure S must satisfies the following Propriety:

$$l \in R \Longrightarrow S(q, l) \le S(q, p), \forall p \in (D - R)$$

5.1. Regions Similarity

One of the difficulties encountered when integrating different distance measures is the difference in the range of associated dissimilarity values [8]. Histogram distance D_{Hist} between regions lies in the interval [0,1], we normalize moments distance D'_{Moment} to be within the same range as follows:

$$D_{Moment}(R_1, R_2) = \frac{(D'_{Moment}(R_1, R_2) - D_{\min})}{(D_{\max} - D_{\min})}.$$

Where D_{\min} and D_{\max} are the minimum and maximum moment dissimilarity values between two logos.

To obtain regions similarity measure D_{Reg}

between two regions R_1 and R_2 , we integrate the color and moment distances D_{Hist} and D_{Moment} as follows:

$$D_{Reg}(R_1, R_2) = w_H \cdot D_{Hist}(R_1, R_2) +$$

 $W_M \cdot D_{Moment} (R_1, R_2)$

 w_H and w_M are the histogram and moment weight factors. A frequent method used to determine the weight coefficients is link them to the accuracy of the individual features, for example systems based on relevance feedback using reweighting features. In the present implementation we have used the unit values $w_H = w_M = 1$, which means that color and shap have the same contribution to compute distance.

5.2. Logos Similarity

In our study, region-based logo similarity measure is used based on the independent best match as follows: For each region R_1 , find the distance to the regions of logo L_2 that is closest to it in term of feature space. The similarity between two logos is the average of these distances for all régions of the input logo. Thus, we can formulate the similarity between two logos L_1 , L_2 as follows:

$$S(L_1, L_2) = \frac{1}{n} \sum_{i=1}^{n} \min \{ D_{reg}(R_i, D_j), j = 1, ..., m \},$$

Where *n*, and *m* represent the number of local regions of L_1 and L_2 respectively. Notice that in our implementation we used (n = m) so the score is commutative. But, in general $S(L_1, L_2) \neq S(L_2, L_1)$ since the number of components is not the same.

6. EXPERIMENTAL RESULTS

We carried out a set of experiments in order to reveal the advantages and performances of the proposed algorithm over a set of assorted database. The evaluation was based on database containing 850 original logos added to 50 % of damaged logos from the overall database.

6.1. Validation Criterion

We need a consistent way of evaluating the retrieval performance. A set of quantitative measures for comparing CBIR systems was proposed in [16]. The evaluation measures frequently used for Information Retrieval (IR), and recently for CBIR, are precision P and recall R measures [19] [26]:

$$P = \frac{Relevent in Scope}{Scope} R = \frac{Relevent in Scope}{Relevent in Database}$$

Where Scope is the top N ranked trademarks presented to the user.

Precision and recall are combined on so-called PR-graph, which is a standard evaluation measure used to evaluate performances on current CBIR systems; PR-graph shows the precision rate under standards recall points. In our work, we use a precision-scope [7] and recall-scope curves to evaluate performances, in which the recall rate spotlights the recall at a specific value of scope.

6.2. Database Organization

Our database is transformed to a collection of feature vectors. So all the database features computations are done offline in order to reduce the amount of computations.

We tested our algorithm in the case when the database contains damaged images of the original logo, and when it contains only original one as more relevant to the query logo. For an objective performance evaluation we use a destroyed logo as a query and their original logo remains on the

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645	www.jatit.org	E-ISSN: 1817-319
ISSN: 1992-8645	<u>www.jatit.org</u>	E-ISSN: 181'

database. Moreover, the query logo is out of the image database.

6.3. Test 1: Database Contains Damaged Versions of the Input Image

For a given original logo i, we construct its relevant logos by artificially rotating, damaging and adding noise to i. Sample returned results are shown in Figure 6, images are ranked based on their respective similarity to the input one.



Figure 6: A query on the top and the highest ranged sixretrieved logos when a database contains original and damaged version of logos.

In order to quantify the effect of different distortions, Table 1 gives the average precisions when the number of returned images (scope = 6). As can be seen, the retrieval precision varies with different distortions. We can easily observe a good retrieval rate in the case of local distortions and geometric transformations (rotation and twirl), this is justified by the local structure of similarity, the components that are not damaged conserve all their feature values. On the other hand, we can see a poor performance in the case of global noise and illumination degradations. The reason is that we have not used any method to reduce noise or illumination effects.

Notice that the recall rate is near to the precision rate in the case when scope = 6, because relevant logos in the database (damaged versions) close to the scope.

All the experiments tests are performed using Bhattacharyya distance; Figure7a shows the retrieval rates using different histograms distances integrated with invariant moments distance. Bhattacharyya distance well exceeds intersection and correlation distances in terms of accuracy in different scopes.

Table 1: Precision(%) ± *standard deviation at the top of*

6 returns from different distortions.

Distortions	Precision ±std-dev(%)
Occlusion	94 ±1,7
Illumination	61 ±3,2
Rotation	95 ±2,2
Local noise	$94 \pm 1,2$
Twirl	92 ±2,5
Global noise	42 ±5,5

We test our method over a set of top returned results. Figure 7b plots the scope-precision (recall) graph, the average precision = 62% and the average recall = 74%. Precision and recall rates are better when scope is less than 6 and greater than 5 respectively. The average recall is better than the average precision because in most cases the scope exceeds the database relevant images.



Figure 7: Accuracy versus scope graph in terms of color histograms distances (a) and precision/ recall measures (b).

Finaly, we compared the performance of our method with other methods that uses symbolic images as database. The first methode was

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

ISSN: 1992-8645 www.jatit.org	E-ISSN: 1817-3195
-------------------------------	-------------------

proposed by Kim and Kim [10] which is based on Zernike moments (ZMs), the second approach use a hit statistic on a dartboard of the color trademark [27]. We increase the number of relevant images by adding rotated logos on different directions and different parts of occlusion to get 19 relevant images for each tested logo. Figure 8 plots the performance curve of the compared methods; we can see that our approach outperforms the other methods in terms of precision stability, noting that illumination changes are not used in this comparison.



Figure 8: The performance comparison of three different methods.

6.4. Test 2: Database Contains Only Original Logos (Target Search)

In this test, a database contains only original logos as the more relevant and the user provides a deformed version as a query. Unlike the previous test, the list of relevant images is not known in advance and it is subjective. Figure 9 displays the top returned logos in the case of rotated query.

Table 2: Retrieval rates (%) of the original image ranks.

Distortions	1st	2nd	3rd	4th	5th
Occlusion	85	6	2	1,6	1,5
Illumination	24	28	8	8	4
Rotation	88	5	0,7	0,3	0,2
Local noise	83	6	0,4	0,2	0,1
Twirl	76	10	5	0,1	0,1
Global noise	2,5	4,5	9,2	12	13,6

In this test, the rank of the returned original logos is most important to evaluate the returned results. Table 2 shows the accuracy rate when the relevant image is within the rank [1,5]. We observe

also that the system tends to retrieve more accurately a graphical and mixture logos than the textual one. The raison for this is that compact logos approve more tolerance to the tested deformations than do textual logos.



Figure 9: A query on the top and the highest ranged sixretrieved logos when a database contains original logos only.

7. CONCLUSIONS

This paper addresses color logos retrieval in image database, we used Harris interest points as input of a standard clustering algorithm to construct local regions. An adapted clustering algorithm to well perform interest points classification is to be enhanced in a future works. Shape and color features are integrated to perform image similarity assessment. In retrieval scenarios, our approach seems to be more stable under local distortions, which leads to a higher and more precise retrieval rate. Finally, our algorithm needs to be adapted and improved to support global noise and affine transformations on real applications.

REFRENCES:

- D. Chaudhuri and A. Samal. "A simple method for fitting of bounding rectangle to closed regions", *Pattern Recognition*, 40(7):1981– 1989, July. 2007.
- [2] G. Ciocca and R. Schettini. "Content-based similarity retrieval of trademarks using relevance feedback", *Pattern Recognition*, 34:1639–1655, 2001.
- [3] G. Cortelazzo, G. Vezzi, G A. Mian, and P. Zamperoni. "Trademark shapes description by

15 September 2012. Vol. 43 No.1

© 2005 - 2012 JATIT & LLS. All rights reserved.

						2/(111
ISSN: 1992-8645		<u>www.jati</u>	<u>t.org</u>		E	-ISSN: 1817-3195
string-matching	techniques"	Pattern	[17] R.	Phan and I	D. Androutsos.	"Content-based

Recognition, 27(8):1005–1018, 1994.

- [4] D. Doermann, E. Rivlin, and I. Weiss. "Applying algebraic and differential invariants for logo recognition", *Machine Vision and Applications*, 9(2):73–86, 1996.
- [5] C. Harris and M. Stephens. "A combined corner and edge detector", *Alvey Vision Conference*, pages 147–151, 1988.
- [6] M K. Hu. "Visual pattern recognition by moment invariants", *IT*, 8(2):179–187, February. 1962.
- [7] D P. Huijsmans and N. Sebe. "How to complete performance graphs in content-based image retrieval: Add generality and normalize scope", *IEEE Trans. Pattern Analysis and Machine Intelligence*, 27(2): 245–251, Feb. 2005.
- [8] A K. Jain and A. Vailaya. "Shape-based retrieval: A case-study with trademark image databases" *PR*, 31(9): 1369–1390, September.1998.
- [9] H. Jiang, C W. Ngo, and H K. Tan. "Gestaltbased feature similarity measure in trademark database", *Pattern Recognition*, 39(5): 988– 1001, 2006.
- [10] W Y. Kim and Y S. Kim. "A region-based shape descriptor using zernike moments", 16(1-2): 95–102, September 2000.
- [11] Y S. Kim and W Y. Kim. "Content-based trademark retrieval system using visually salient features", *in: Proceedings of IEEE CVPR*, pages 307–312, 1997.
- [12] T. Lindeberg. "Scale-space theory: A basic tool for analysing structures at different scales", J. of Applied Statistics, 21(2): 224–270, 1994.
- [13] D. Lowe. "Distinctive image features from scale-invariant keypoints", *International Journal of Computer Vision*, 60(2): 91–110, 2004.
- [14] K. Mikolajczyk and C. Schmid. "Scale and affine invariant interest point detectors", *International Journal of Computer Vision*, 60(1): 63–86, 2004.
- [15] H. Moravec. "Obstacle avoidance and navigation in the real world by a seing robot rover", *Technical report, CMU-RI-TR-3*, Carnegie-Mellon University, Robotics Institute, 1980.
- [16] H. Müller, W. Müller, D M. Squire, S. Marchand-Maillet, and T. Pun. "Performance evaluation in content-based image retrieval: Overview and proposals", *Pattern Recognition Letters*, 22(5):593–601, 2001.

- [17] R. Phan and D. Androutsos. "Content-based retrieval of logo and trademarks in unconstrained color image databases using color edge gradient co-occurrence histograms", *computer vision and image understanding*, 2009.
- [18] E. Riloff and L. Hollaar. "Text databases and information retrieval", ACM Computing Surveys, 28(1):133–135, 1996.
- [19] G. Salton. "Evaluation parameters. in the SMART Retrieval System", *Experiments in Automatic Document Processing*, pages 55–112, 1971b.
- [20] S. Santini, A. Gupta, and R. Jain. "Emergent semantics through interaction in images databases", *IEEE Transactions on knowledge and data engineering*, 13(3):337–351, 2001.
- [21] C. Schmid, R. Mohr, and C. Bauckhage. "Evaluation of interest point detectors", *International Journal of Computer Vision*, 37(2):151–172, 2000.
- [22] N. Sebe, M. Lew, and N. Huijsmans. "Towards optimal ranking metrics", *IEEE Trans. On Pattern Analysis and Machine Intel.(PAMI)*, pages 1132–1143, 2000.
- [23] A W M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain. "Content-based image retrieval: The end of the early years", *IEEE Trans, PAMI*, 22(12):1349–1380, Dec. 2000.
- [24] A. Soffer and H. Samet. "Using negative shape features for logo similarity matching", *Proceedings of the Fourth International Conference on Pattern Recognition*. Brisbane, Australia, pages 571–573, 1998.
- [25] USPTO. "The united states patent and trademark office", www.uspto.gov.
- [26] C J. van Rijsbergen. "Evaluation, Information Retrieval", chapter 7, pages 112–123. Prentice Hall, Englewood Cliffs, New Jersey, USA, 1979.
- [27] C C.Wang and L H. Chen. "Content-based color trademark retrieval system using hit statistic", *International Journal of Pattern and Artificial Intelligence*, 16:603–619, 2002.