TRADEMARKS RECOGNITION BASED ON LOCAL REGIONS SIMILARITIES

Ahmed Zeggari[1,3], *Fella Hachouf*[3], *and Sebti Foufou*[1,2]

[1] Le2i Lab, Université de Bourgogne, B.P. 47870, 21078 Dijon, France.
[2] CSE, CENG, Qatar University, P.O. Box 2713, Doha, Qatar.
[3] Automatic & Robotic Lab, Electronic Department, University of Mentouri, Road of Ain El Bey, 25000 Constantine, Algeria.

ABSTRACT

This paper deals with content based image retrieval. We propose a logo recognition algorithm based on local regions, where the trademark (or logo) image is segmented by the clustering of points of interest obtained by Harris corners detector. The minimum rectangle surrounding each cluster is detected forming the regions of interest. Global features such as Hu moments and histograms of each local region are combined to find similar logos in the database. Similarity is measured based on the integrated minimum average distance of the individual components. The results obtained demonstrate tolerance to logos distortions such as rotation, occlusion and noise.
*Index Terms_* Clustering, Information retrieval, moments, Image color analysis, pattern recognition, Image segmentation.

1. INTRODUCTION

Content Based Image Retrieval (CBIR) is an image search technique based on image features such as color, 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 [1].

Logo recognition is of great interest in document images recognition [2], in which a logo can be seen as a search index for database documents. Another interesting application is the registration and search of conflicting marks [3]. Therefore, several relevant approaches dealing with logo detection and recognition problems have been proposed. Phan and Androutsos employed Color Edge Co-occurrence Histogram (CECH) object detection scheme on compound color objects [4]. Jain and Vailaya proposed a shape-based retrieval system in a trademark image database using edge direction histogram, moments and deformable template matching [5].

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 locale regions. Invariant moment and color histogram are combined to find the logo features vector. Note that the proposed method does not deal with logo detection problem, we assume that a logo is an entire image and not a part of an image in our database.

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 and similarity is presented in section 4. Experimental results are given and discussed in section 5. Section 6 concludes this paper.

2. SYSTEM OVERVIEW

2.1. Retrieval system architecture

Our retrieval system operates in two distinct steps: creation of features database, and logo retrieval. For all images in the database, our algorithm starts with the offline detection and storage of locales features. The new database is then disposed into k clusters represented by theirs minimum and maximum feature values (we used $k=5$). The offline clustering is justified by the use of the same distance. When a query image is presented to our system, their local features are computed and then the system selects close clusters. Afterward, we measure the similarity between the query image and the images of the selected clusters. The obtained images are presented to the user in the order of their similarity to the query image.

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.

To enhance diversity, we have manually constructed our logo database with hundreds of colored logos collected from several worldwide sources. Our dataset contains logos of different sizes and categories with resolution of 96 PPI (Figure 1). The input logos are subject to different corruptions caused by several phenomena such as fax

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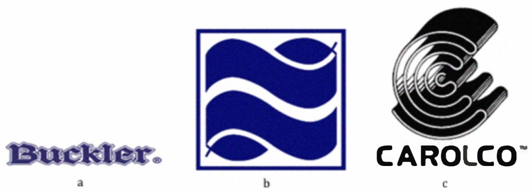

Fig. 1. Some examples of trademarks in the dataset: (a) textual logo, (b) graphical logo and (c) mixed logo

machines, segmentation processes and illumination conditions. We artificially reproduce such degradations over 50% of our logos, which serve as queries and also as database contents.

3. LOCALIZATION OF INTEREST REGIONS

3.1. Interest points

Interest points in an image are defined as two-direction discontinuity of intensity function or their derivatives, or as one direction discontinuity in the case of an edge.

Algorithms proposed by Harris [6], Lowe [7]; and Mikolajczyk and Schmid [8] are among the most popular detectors of interest points. The choice of using Harris corner detector in our implementation is justified by the fact that logo images are not complex pictures, they have less intensity levels and colors. In addition, logos and trademarks exhibit a lower spatial distribution of intensities and colors than complex images. Furthermore, Harris detector is computationally faster than others detectors.

3.1.1. Harris corner detector

Harris corner detector uses, C, the local auto-correlation matrix 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 operator.

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.

To refine our results and give better corresponding regions, we investigated the computation of the minimum bounding rectangles. We exploited the algorithm proposed in [9] 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:

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

  Where (x_i, y_i) are the n points of C.
- Computing the orientation angle θ of the major axis with the horizontal axis:

  $$\tan(2\theta) = \frac{2\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}[(x_i - \bar{x})^2 - (y_i - \bar{y})^2]}$$
- Computing the upper and lower furthest edge points from major and minor axis: Let $a(x_i, y_i) \in B$

  $$V_{maj}(a) = (y_i - \bar{y}) - \tan\theta(x_i - \bar{x})$$
  $$V_{min}(a) = (y_i - \bar{y}) + \cot\theta(x_i - \bar{x})$$

  if a is an upper point from major axis then:
  $V_{maj}(a) \geq V_{maj}(b), \forall b \in B$
  if a is a lower point from major axis then:
  $V_{maj}(a) \leq V_{maj}(b), \forall b \in B.$
  if a is an upper point from minor axis then:
  $V_{min}(a) \geq V_{min}(b), \forall b \in B.$
  if a is a lower point from minor axis then:
  $V_{min}(a) \leq V_{min}(b), \forall b \in B.$

Having the upper and lower points, we can easily affect each pixel to their corresponding region.

4. FEATURES EXTRACTION AND SIMILARITY

Color and shape are integrated and used as characteristic features. The features of each image in the database are computed offline. We use color histogram and moments for each selected region.

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.

We use *Bhattacharyya* distance to measure histograms similarity, let R_1 and R_2 two regions from two distinct logos. A distance D_{Hist} between their normalized histograms H_{N1} and H_{N2} is given by:

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

Where $H_N(i)$ is the normalized histogram defined as: $H_N(i) = \frac{H(i)}{\sum_i H(i)}$ and i represents the histogram bin.

4.2. Invariant moment

Invariant moments are shape features widely used in literature as they demonstrate a satisfactory results in many practical applications [10].

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.

4.3. Similarity measure

The choice of the correct similarity measure stays an open discussion and domain dependent. Given an input image, to get their correspondent images we must compute the similarity between their feature vector and all feature vectors of a given database. Let $\mathcal{R}$ a set of returned images, $\mathcal{D}$ the database, and q a query image:

$$l \in \mathcal{R} \Rightarrow \mathcal{S}(q, l) \leq \mathcal{S}(q, p), \forall p \in (D - \mathcal{R})$$

Where $\mathcal{S}$ is a similarity measure.

4.4. Regions similarity

One of the difficulties encountered when integrating various distance measures is the difference in the range of associated dissimilarity values [5]. 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 fellow:

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

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 fellows:

$$D_{Reg}(R_1, R_2) = w_H.D_{Hist}(R_1, R_2) + w_M.D_{Moment}(R_1, R_2)$$

w_H and w_M are the histogram and moment weight factors in our case ($w_H = w_M = 1$).

4.5. Logos similarity

In this 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. Hens, we can formulate the similarity between two logos L_1, L_2 as follows:

$$\mathcal{S}(L_1, L_2) = \frac{1}{n}\sum_{i=1}^{n} Min_j(Dis_{Reg}(R_i - R_j), j = 1, ..., m),$$

Where n, and m represent the number of local regions of L_1 and L_2 respectively.

5. 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 uses a database containing 850 original logos completed by about 50% of damaged logos from the overall database.

We need a consistent way of evaluating the retrieval performance. A set of quantitative measures for comparing CBIR systems was proposed in [11]. The evaluation measures frequently used are *precision (P)* and *recall (R)* measures:

$$P = \frac{Relevant\ in\ Scope}{Scope}, \quad R = \frac{Relevant\ in\ Scope}{Relevant\ in\ Database}$$

Where *Scope* is the top *N* ranked trademarks presented to the user. In our work, we used a precision (recall)-scope curves to evaluate performances.

We tested our algorithm in the case when the database contains damaged images of the original logo.

Fig. 2. Example of image retrieval results when the database contains the original and damaged versions of logos: A query image (top) and six retrieved logos ordered according to their similarity to the query logo.

For a given original logo *i*, we construct its relevant logos by artificially rotating, damaging and adding noise to *i*.

Samples of returned results are shown in Figure 2, images are ranked based on their respective similarity to the input one.

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 from one distortion to another. 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 raison is that we haven't used any method to reduce noise or illumination effects.

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

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

Table 1. Precision (%) $\pm$ standard deviation at the top of 6 returns from different distortions.

Finally, we test our method over a set of top returned results. Figure 3 plots the scope-precision (recall) graph, the average precision is 62% and the average recall is 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.

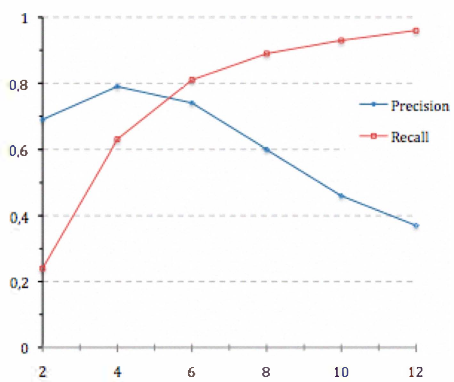

Fig. 3. Accuracy versus scope graph in terms of precision and recall

6. 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.

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