

ABSTRACT

Trademarks work as significant responsibility in industry and commerce. Trademarks are important component of its industrial property, and violation can have severe penalty. Therefore designing an efficient trademark retrieval system and its assessment for uniqueness is thus becoming very important task now a days. Trademark image retrieval system where a new candidate trademark is compared with already registered trademarks to check that there is no possibility of resemblance, has been identified as a major application area of Content Based Image Retrieval (CBIR). This paper proposes an automated system for rotation, translation and scale invariant color trademark recognition. Low level feature extraction techniques used in CBIR are proposed for trademark image retrieval. The performance of the trademark image retrieval system is evaluated using precision and recall.

KEYWORDS: CBIR, Trademark, Color feature Extraction, Texture feature Extraction, Shape feature Extraction

INTRODUCTION

CBIR or Content Based Image Retrieval is the retrieval of images based on visual features such as color, texture and shape. The features of the images in the database are extracted. These features are compared with the features of the query image for similarity computation. The main steps in CBIR are Feature Extraction, Indexing and Retrieval.

Feature Extraction – Features are extracted from the images. The description of features is predefined, such as color, texture and shape. These features are saved in the form of real-valued multi-dimensional vectors.

Indexing – The database of the extracted image features – is then arranged by using an indexing structure for retrieval.

Retrieval – The retrieval process comprise of the matching for similarity of the query image with the database images. Content-based retrieval can be done on the indexing structure effectively.

Number of applications of CBIR system exists such as trademark or logo image retrieval, Architectural and engineering design, Fashion and interior design and Medical diagnosis etc. Which leads to the big scope of research for improvements in the area of CBIR for the researchers.

This paper describes the method for retrieval of Trademark images by implementing feature extraction techniques for Color Feature extraction, Texture feature Extraction and Shape feature Extraction.

The rest of the paper is organized as follows:

Related work in the area of trademark image retrieval is discussed in section 2. The proposed methodology is described in section 3. Section 4 describes about classification. The experiments and performance evaluation are discussed in section 5. Section 6 concludes the paper.

RELATED WORK

Major relevant work in the area of trademark image retrieval includes the following.

J.P. Eakins *et al.* [1] have described the evaluation of ARTISAN, a system designed to provide automatic retrieval of abstract trademark images by shape feature. For evaluation of the system a pilot database of 268 images was built. This database contained 231 randomly selected trademark images, plus four series of test images provided by the Trade Mark Registry.

S. Alwis *et al.* [2] have discussed the first phase of an ongoing research project aimed at implementing a trademark retrieval system using an associative memory neural network. The preliminary experiments were conducted on the performance of the system using a smaller image database of 210 trademark images which was having nine groups of perceptually similar images.

Young sum kim *et al.* [3] have proposed a new trademark retrieval system based on the content or shape of the trademark. They designed an online graphical user interface for world wide web (WWW) which allowed a user to give a query in form of sketch or visual image to search for similar trademark in the database.

Marçal Rusiñol *et al.* [4] suggested an efficient queried-by-example retrieval system which was able to retrieve trademark images by similarity from patent and trademark offices' digital libraries. Logo images were described by both their semantic content, by means of the Vienna codes, and their visual contents, by using shape and color as visual cues. The trademark descriptors were indexed by a locality-sensitive hashing data structure aiming to perform approximate k-NN search in high dimensional spaces in sub-linear time. The resulting ranked lists were combined by using a weighted Condorcet method and a relevance feedback was used to iteratively revise the query and refine the obtained results. The database of 30000 trademark images structured in 1350 different categories was used for experimentation.

Zhenhai Wang *et al.* [5] have proposed a trademark retrieval algorithm combining the image global features and local features. They have extracted Zernike moments (ZMs) of the retrieved image and sort them according to similarity. Candidate images were formed. The scale invariant feature transform (SIFT) features were used for matching the query image accurately with candidate images. Experimental results shown that this method not only keeps high precision- recall of SIFT features and is superior than the method based on the single Zernike moments feature, but also improves effective retrieval speed compared to the single SIFT features. For evaluation, a standard image set "MPEG7 CE Shape-2 Part-B" was used as image database. This image database was containing 3621 shapes of mainly trademarks.

X. Hou and H. Shi [6] have proposed a Logo on Map (LoM) system which consists of three modules: picture extraction module (PEM), logo matching module (LMM) and web mapping module (WMM). Their experimental results have proven that visual search was more accurate than textual search.

M. Bagheri *et al.* [7] have used the three shape description techniques, including Zernike moments, generic Fourier descriptors, and shape signature to extract informative features from logo images, and each set of features was fed into an individual classifier.

A. Alaei and M. Delalandre [8] have proposed a complete logo detection/ recognition system for document images. In the proposed system, first, a logo detection method was employed to detect a few regions of interest (logo-patches), which likely contain the logo(s), in a document image. The detection method was based on the piece-wise painting algorithm (PPA) and some probability features along with a decision tree.

S. Ghosh and R. Parekh [9] have designed an automated system for rotation and scale invariant logo recognition based on black and white logo images. Logo images were recognized using two shape features namely Moment Invariants and Hough Transform. The data set used was 1700 black and white logo images containing 100 different classes in which each class was having rotation, scaling and composite variations of each image, which were classified using Manhattan and Euclidian Distances.

S. Ghosh and R. Parekh [10] have proposed an automated system for rotation and scale invariant color logo recognition. Shape of the logo was modeled using the first two central normalized Hu's invariant moments while color was modeled using the mean, standard deviation. Classification was done using Manhattan and Euclidean distances.

In the proposed work rotation, scale and translation invariant trademark image retrieval system is designed by taking Color, texture and shape features of trademark images into consideration for retrieval.

PROPOSED METHODOLOGY

The experiments were conducted on the performance of the CBIR system using an image database of 2000 trademark images. This dataset used in the experimentation is collected from different websites saved in JPG format and each resized to the size 256 x 256. Some sample trademark images from the database are shown in figure 3.1.

The block diagram of the proposed work is shown in figure 3.2. The visual content of an image is analyzed in terms of low-level features extracted from the image. These primarily constitute color, Shape and texture features [11]. In the proposed system for trademark image retrieval, for Color Feature extraction, Color Histogram, Color Moments and Color Correlogram are used. For Texture feature Extraction Gabor wavelet and Haar Wavelet are implemented. And for Shape feature Extraction, Fourier Descriptor, Circularity features are used. The dimensions of the extracted features are then reduced by using co occurrence matrix. These features are finally classified with similarity computation so as to retrieve the relevant trademark images from the database. Performance of the system is evaluated using precision and recall.



figure 3.1: Typical Trademark images in the database

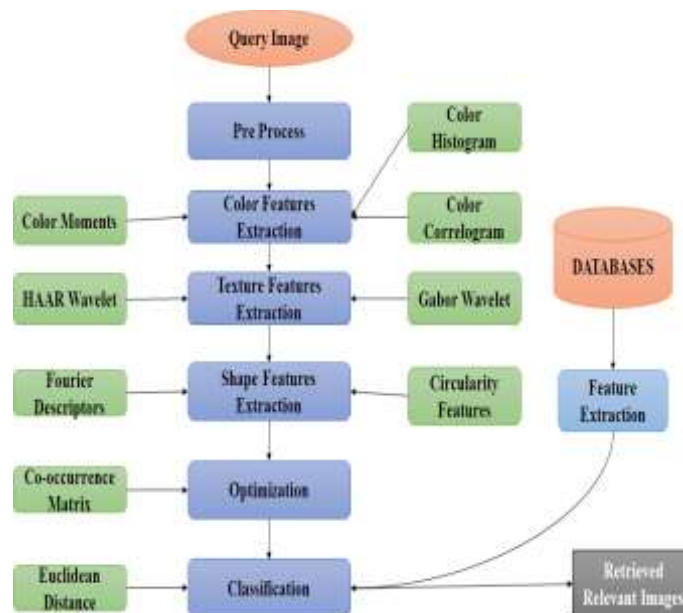


Figure 3.2: Block Diagram of the proposed work

COLOR FEATURE EXTRACTION

Color feature extraction involves analyzing the absolute color value of each pixel. Color distribution is a statistical feature and techniques such as color histogram, color moments and color correlogram are implemented. [11]

Color Histogram

A color histogram is a vector, where each element represents the number of pixels falling in a bin, of an image. The color histogram has been used as one of the feature extraction attributes with the advantage like robustness with respect to geometric changes of the objects in the image.

Color Moments

The first order (mean), the second (variance) and the third order (skewness) color moments are used for effective representing color distribution of images[11].

The first three moments are defined as shown in the following equations number 1, 2 and 3.

$$\mu_i = \frac{1}{N} \sum_{j=1}^N f_{ij} \quad \dots\dots\dots(1)$$

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j=1}^N (f_{ij} - \mu_i)^2} \quad \dots\dots\dots(2)$$

$$S_i = \sqrt[3]{\frac{1}{N} \sum_{j=1}^N (f_{ij} - \mu_i)^3} \quad \dots\dots\dots(3)$$

Where f_{ij} is the value of the i^{th} color component of the image pixel j , and N is the number of pixels in the image.

Color Correlogram

A color correlogram expresses how the spatial correlation of pairs of colors changes with distance.

Let I be an $n \times n$ image. (For simplicity, we assume that the image is square.) The colors in I are quantized into m colors c_1, \dots, c_m .

For a pixel $p = (x, y) \in I$, let $I(p)$ denote its color. Let $I_c = \{ p \mid I(p) = c \}$. Thus the notation $p \in I_c$ is synonymous with $p \in I, I(p) = c$. For pixels $p_1 = (x_1, y_1), p_2 = (x_2, y_2)$ the distance between p_1 and p_2 is given by $|p_1 - p_2| = \max \{ |x_1 - x_2|, |y_1 - y_2| \}$. The set $\{ 1, 2, 3, \dots, n \}$ is denoted by $[n]$.

Let a distance $d \in [n]$ be fixed a priori. Then the correlogram of I is defined for $i, j \in [m], k \in [d]$ as

$$r_{ci,cj}^{(k)}(I) = \frac{pr}{p_1 \in I_c, p_2 \in I} [p_2 \in I_{cj}, |p_1 - p_2| = k] \quad \dots\dots\dots(4)$$

Given any pixel of color c_i in the image, $r_{ci,cj}^{(k)}$ gives the probability that a pixel at distance k away from the given pixel is of color c_j . [11]

TEXTURE FEATURES EXTRACTION

The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. For Texture feature extraction Gabor wavelet transform and Haar wavelet transform are implemented.

Gabor Wavelet:

Gabor wavelet transform represents efficient technique for image texture retrieval in content - based image retrieval applications. Offering the capacity for edge and straight line detection with variable orientations and scales not being sensitive to lighting conditions of the image.

A two dimensional Gabor function $g(x, y)$ is defined as:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left\{ -\frac{1}{2} \left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi j W x \right\} \quad \dots\dots\dots(5)$$

where, σ_x and σ_y are the standard deviations of the Gaussian envelopes along the x and y direction. Then a set of Gabor filters can be obtained by appropriate dilations and rotations of $g(x, y)$:

$$g_{mn}(x, y) = a^{-m} g(x', y') \text{ where}$$

$$x' = a^{-m} (x \cos \theta + y \sin \theta)$$

$$y' = a^{-m} (-x \sin \theta + y \cos \theta)$$

$$\theta = n\pi/L, n = 1, 2, \dots, L \text{ and } m = 0, 1, \dots, S-1$$

where $a > 1$, $\theta = n\pi/k, n = 0, 1, \dots, K-1$, and $m = 0, 1, \dots, S-1$. K and S are the number of orientations and scales. The scale factor a^{-m} is to ensure that energy is independent of m .

Given an image $I(x, y)$, its Gabor transform is defined as :

$$W_{mn}(x, y) = \int I(x, y) g_{mn}^*(x - x_1, y - y_1) dx_1 dy_1$$

where * indicates the complex conjugate. Then the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of

$W_{mn}(x, y)$, i.e. $f = [\mu_{00}, \sigma_{00}, \dots, \mu_{mn}, \sigma_{mn}, \dots, \mu_{s-1k-1}, \sigma_{s-1k-1}]$ can be used to represent the texture feature of a homogenous texture region. [11]

Haar Wavelet: Haar wavelets, are fastest to compute and simplest to implement. User queries tend to have large constant-colored regions, which are well represented by this basis. Haar wavelet can be represented as:

$$\left. \begin{array}{l} \Psi(t) = 1 \quad 0 \leq t \leq 1/2 \\ \Psi(t) = -1 \quad 1/2 \leq t \leq 1 \\ \Psi(t) = 0 \quad \text{otherwise} \end{array} \right\} \dots \dots \dots (6)$$

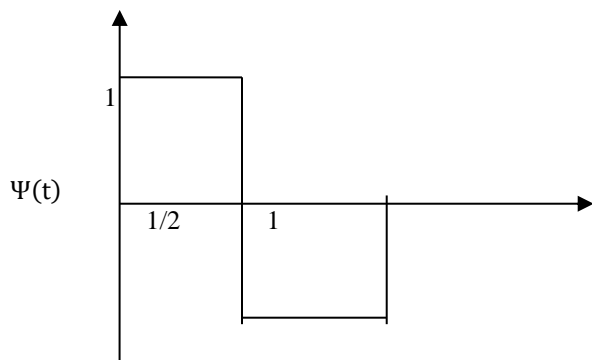


Fig 3.3 Haar wavelet Representation

As is required, $\psi(t)$ integrates to zero. One-level decomposition is performed on image I, which yields approximation image (A1) and horizontal, vertical and diagonal detail images (D11, D12, D13) as shown in Fig. 3.3.

SHAPE FEATURES EXTRACTION

The methods for shape description can be categorized into either boundary-based (rectilinear shapes, polygonal approximation, finite element models, and Fourier-based shape descriptors) or region-based methods (statistical moments). For retrieval of shape feature Fourier Descriptor and circularity features are implemented.

Fourier Descriptors

Fourier descriptors describe the shape of an object with the Fourier transform of its boundary. Again, consider the contour of a 2D object as a closed sequence of successive boundary pixels (xs, ys), where 0 ≤ s ≤ N-1 and N is the total number of pixels on the boundary. Then three types of contour representations, i.e., curvature, centroid distance, and complex coordinate function, can be defined.

The curvature K(s) at a point s along the contour is defined as the rate of change in tangent direction of the contour, i.e.

$$K(s) = \frac{d}{ds} \theta(s) \dots\dots\dots(7)$$

Where θ(s) is the turning function of the contour.

The centroid distance is defined as the distance function between boundary pixels and the centroid (xc, yc) of the object:

$$R(s) = \sqrt{(X_s - X_c)^2 + (Y_s - Y_c)^2} \dots\dots\dots(8)$$

The complex coordinate is obtained by simply representing the coordinates of the boundary pixels as complex numbers:

$$Z(s) = (X_s - X_c) + j(Y_s - Y_c) \dots\dots\dots(9)$$

The Fourier descriptor of the curvature is:

$$f_k = [|F_1|, |F_2|, \dots, |F_{M/2}|] \dots\dots\dots(10)$$

The Fourier descriptor of the centroid distance is:

$$f_R = \left[\frac{|F_1|}{|F_0|}, \frac{|F_2|}{|F_0|}, \dots, \frac{|F_{M/2}|}{|F_0|} \right] \dots\dots\dots(11)$$

Where Fi in (10) and (11) denotes the ith component of Fourier transform coefficients. Here only the positive frequency axes are considered because the curvature and centroid distance functions are real and, therefore, their Fourier transforms exhibit symmetry, i.e., |F-i| = |Fi|.

The Fourier descriptor of the complex coordinate is:

$$f_Z = \left[\frac{|F_{-(M/2-1)}|}{|F_1|}, \dots, \frac{|F_{-1}|}{|F_1|}, \frac{|F_2|}{|F_1|}, \dots, \frac{|F_{M/2}|}{|F_1|} \right] \dots\dots\dots(12)$$

where F1 is the first non-zero frequency component used for normalizing the transform coefficients. Here both negative and positive frequency components are considered. The DC coefficient is dependent on the position of a shape, and therefore, is discarded.

To ensure the resulting shape features of all objects in a database have the same length, the boundary ((xs, ys), 0 ≤ s ≤ N-1) of each object is re-sampled to M samples before performing the Fourier transform. For example, M can be set to 2^m = 64 so that the transformation can be conducted efficiently using the fast Fourier transform. [11]

Circularity, Eccentricity, and Major Axis Orientation

Circularity is computed as:

$$\alpha = \frac{4\pi S}{p^2} \dots\dots\dots(13)$$

Where S is the size and P is the perimeter of an object. This value ranges between 0 (corresponding to a perfect line segment) and 1 (corresponding to a perfect circle).

The major axis orientation can be defined as the direction of the largest eigenvector of the second order covariance matrix of a region or an object. The eccentricity can be defined as the ratio of the smallest eigen value to the largest Eigen value. [11]

CLASSIFICATION

The dimension of the extracted features of the images in the database is reduced by using Co-occurrence matrix and for classification Euclidian distance is used in the proposed work.

Co-occurrence matrix:

Cooccurrence Matrix is used to perform correlation process for an image, i.e. to reduce or optimize the dimensions of extracted features. This is done using Gray Level Co-Occurrence matrix. The extracted features values of the database image's are converted into image format, and are passed to the graycomatrix function which returns the gray-level co-occurrence matrix (GLCMS).The mean of this GLCMS is taken to get the features values in the form of row vectors(rounded values as shown in table 4.1). The offset used for the computation of the co-occurrence matrix is default i.e. [0,1] hence the value of angle (θ) is 0(zero).

Classification:

Euclidean distance:

The Euclidean distance or Euclidean metric is the "ordinary" distance between two points in Euclidean space. With this distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. In Cartesian coordinates, if $p = (p_1, p_2, \dots, p_n)$ and $q = (q_1, q_2, \dots, q_n)$ are two points in Euclidean n-space, then the distance (d) from p to q, or from q to p is given by the Pythagorean formula:

$$d(p, q) = d(q, p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \dots + (q_n - p_n)^2} \dots\dots\dots(14)$$

$$= \sqrt{\sum_{i=1}^n (q_i - p_i)^2}$$

The position of a point in a Euclidean n-space is a Euclidean vector. So, p and q are Euclidean vectors, starting from the origin of the space, and their tips indicate two points.

EXPERIMENTS AND PERFORMANCE EVALUATION

For experimentation an image database of 500 images was used. Feature vector's database was formed by extracting color, texture and shape features of all 500 images. The value of each feature vector for a sample of 10 trademark images is as shown in table 4.1. Euclidian distance was used to measure the similarity between query image and images in the database.

To introduce variations between the training and test images, transformation are applied to each of the query image viz. rotation factor of 35°, scaling factor of 0.5 and translation of the image by shifting the image by 15 pixels in the X direction and 25 pixels in the Y direction.

The experiment includes giving a query image, applying transformation and retrieving relevant trademark images from the database. Which is as shown in figure 5.1, figure 5.2 and figure 5.3 respectively.



Figure 5.1 Giving a query Image



Figure 5.2 Transformed query Image (with rotation, scaling and translation)



Figure 5.3 Output retrieved relevant images from the database

PERFORMANCE EVALUATION

The performance of the proposed system was evaluated in terms of standard evaluation parameters precision and recall, which can be defined as follows:

$$\text{Precision} = \frac{\text{Number of retrieved relevant images}}{\text{Total number of retrieved images}}$$

$$\text{Recall} = \frac{\text{Number of retrieved relevant image}}{\text{Total number of relevant images in the database}}$$

The results in terms of precision and recall are tabulated in table 5.1 for a sample of 20 trademark query images.

SNO	QUERY IMAGE	PRECISION	RECALL
1		0.726721	0.59652
2		0.759605	0.565654
3		0.686901	0.651506
4		0.75866	0.540568
5		0.444007	0.627193
6		0.703384	0.578308
7		0.651059	0.647401
8	 	0.66951	0.584238
9		0.601653	0.612346
10	 Microsoft	0.742336	0.567123
11		0.675703	0.623942
12		0.702171	0.630039
13		0.733361	0.598058
14		0.873462	0.814962
15		0.693416	0.62327
16		0.530257	0.690272

17		0.85401	0.495814
18		0.854117	0.50044
19		0.559247	0.695281
20		0.87084	0.552961

Table 5.1: Precision and Recall values for sample 20 query images

The average values of precision and recall were found as following:

$$\text{AVERAGE PRECISION} = 0.704521$$

$$\text{AVERAGE RECALL} = 0.609795$$

CONCLUSION

The need of development of effective and efficient CBIR systems for Trademark images has emerged due to the increase in the size of image databases. In the proposed work an automated system for rotation, translation and scale invariant color trademark recognition is designed by implementing color, texture and shape feature extraction techniques. The performance of the trademark image retrieval system is evaluated using precision and recall the average values of precision and recall are found to be 0.704521 and 0.609795 respectively. In the future scope of work the data mining concept with Relevance Feedback technique can be incorporated in CBIR system for trademark images to achieve the high retrieval quality of the system and to overcome the problems like redundant browsing and exploration convergence.

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