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A Novel Similarity Measure using a Normalized Hausdorff Distance for Trademarks Retrieval Based on Genetic Algorithm

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Abstract

In this paper we provide a novel measure based on direct Hausdorff distance (DHD). Most researchers have used the Euclidean distance (EUD) or DHD. We propose the use of normalized cosine distance (COSD) and EUD as finite set points instead of a set of image pixels. The proposed measure takes into account the integration of global and local features. For the performance assessment a genetic algorithm (GA) is applied to decide the best weight factors distribution. We have also used the retrieval efficiency equation in order to test the accuracy of the method. The obtained result showed that normalized Hausdorff distance (NHD) provides a significant improvement in retrieval accuracy and is robust against shape invariant transformations. Moreover, our shape retrieval algorithm proves to be efficient, promising and satisfies the human perception quite well.

1. Introduction

Trademark registration is an activity of considerable interest. In order to protect the rights of the registered trademarks, we need to confirm the uniqueness of trademarks by checking the similarities between the trademarks that are already registered and those that are due for registration. Currently, several researches conducted on trademarks retrieval adopted retrieval techniques based on combination of features or the use of a single feature. It is our first opinion that these techniques have insufficiencies in determining image similarities, as such, a process should also take into consideration the measurements associated with perceptual similarity and defining an appropriate similarity measure between shape features vector.

Nevertheless, measuring perceptual similarity and defining an appropriate similarity measure between trademark images remain largely unsolved. Several applications used EUD as dissimilarity function [1], [2]. Sometimes, the EUD is considered as key element in the similarity metric between two features vector, as in [3]-[5], where the Hausdorff distance is applied with Euclidean as the underlying metric. Our second vision is to ensure that a good method is chosen and a real-time system processing is used. From [6], [7], the drawbacks of using EUD and the DHD are enumerated. To tackle these shortcomings, we propose a new method that integrates several shape features and suggests a technique that uses NHD for trademark retrieval.

Our work focuses on accuracy, robustness and execution cost in distance dissimilarity/similarity computation between two trademark images. In order to search for trademarks in narrowed limit and reduce time computation trademark images database (DB) is indexed by their entropy value. In this system and as described also in [8]-[10] and detailed in section 3, four shape features comprising both global (invariant moments and eccentricity) and local features (entropy histogram and distance histogram) are used. As we are integrating four shape features, we have to avoid the influence of feature to another. Furthermore, the EUD dissimilarity function is the one chosen from the four kinds of measures that we are dealing with in our system.

We claim that one of EUD drawbacks is the tendency of the largest-scaled feature to dominate the others, in this case EUD takes into account the difference in magnitude which may be large between the features. However, if our system set features weight statically, we may not meet the efficiency of the search and retrieval, in that the output must include all the similar images. The list may have other images as well, but that is not very important. The important thing is that the similar ones should not be missed in the search process. If the image query (I_q) is not brought out, it would defeat the purpose of having an automated search.

The minimum of a derivation of DHD is used as similarity between two trademarks. We first normalize both COSD and EUD in order to get a new features vector that stands for points set of the NHD. The organization of the paper is as follows. We begin by reviewing literature on shape based retrieval. Section 2 deals with drawbacks of direct Hausdorff and Euclidean distances and also detailed the GA used in our system. In Section 3 we develop the similarity functions based on NHD and briefly deal with global and local features used in our retrieval system. In section 4 we describe our system and section 5 presents the experimental results of our system, conclusion and future work are in section 6.

2. Related work

Many technical achievements in the research area of image retrieval are provided by different research, especially content-based image retrieval (CBIR), an area that has been very active and beneficial in the past few years. CBIR uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In [6], shape based method is adopted, and both global and local features have been used.

From the related works mentioned above, it can be concluded that based on their evaluation, the shortcomings of Hausdorff distance are sensitivity to noise and occlusion. The drawbacks to the direct use of the Hausdorff distance in shape similarity can be divided into two parts. Firstly, if two images are composed with points set of pixels and the resemblance degree is determined by comparing each pixel from one image to another, this approach will not resist invariance transformations especially occlusion, noise or other outlier transformations, [18]. Secondly, the method possesses poor space and time complexities required by CBIR systems. To tackle these drawbacks, we propose a novel measure based on DHD, [16] and normalization of cosine and Euclidean distances as finite set points instead of set of image pixels. Furthermore, the incorporation of indexed DB based on entropy and the consideration of features vector as points set for the novel Hausdorff distance has lead to reduction in computation time, thus increasing the efficiency and overall robustness of our algorithm.

2.1 DHD background

Having a query image I_q and a similar image I_s from a DB, let $X = \{x_1, \ldots, x_n\}$ be the set of the image pixels of X and $Y = \{y_1, \ldots, y_n\}$ be the set of the image pixels of Y. X represents a set of I_q and Y as I_s. Hence, DHD between two images is expressed as:

$$\begin{aligned} &H(X,Y) = \max(h(X,Y), h(Y,X)) \\ &\text{where } h(X,Y) = \max_{x \in X} \min_{y \in Y} d(x,y) \\ &h(Y,X) = \max_{y \in Y} \min_{x \in X} d(y,x) \end{aligned} \tag{1}$$

Where d is given by the EUD.

Since this equation (1) works at the pixel level, only one pixel that is an outlier can dramatically modify the result of the Hausdorff Distance. If I_q and I_s are similar then the score takes on the value of zero. The similarity of I_q and I_s decreases as the score increases. Thus the equation is not suitable for direct use in shape based retrieval as image pixels may be distorted, also many transformations may occur on image pixels such as cropping, occlusions and noisy. Another drawback of the DHD is that it requires system to search for each pixel in the set X closest to the pixel of the set Y. This process may be very time-consuming.

For these reasons, we advocate the use of NHD based on four features enumerated and detailed in section 3 below. Hence, we generate a data matrix that leads to the creation of new features vector composed of a normalization of two distances as in equation (13) below. After that, a minimum of the summation between the normalization distances instead of set of pixels is obtained. In this case our method is robust against occlusion, noise and any other shape transformations.

2.2 GA background

The problem of dissimilarity function for trademark retrieval can be formalized as follows:

Statement 1: An image database DB is defined as

$$DB = \{I_i\}_{i=1}^{n} \tag{2}$$

Where I_i is an image in the DB.

Statement 2: Having I_q and I_s from a DB, their features *(X, Y)* can be represented in a 4×2- dimensional profile data matrix as given by:

$$\begin{bmatrix} X_1 & Y_1 \\ X_2 & Y_2 \\ X3 & Y3 \\ X4 & Y4 \end{bmatrix} \tag{3}$$

The i^{th} rows vector X_i, Y_i characterizes the i^{th} object from the sets X and Y. Each element in those sets corresponds to the i^{th} real-value feature $i = 1, 2, 3, 4$ of j^{th} the trademark image $j = 1, 2$ of n imaged from DB.

Let $I = \{I_1, I_2, \ldots, I_n\}$ be a set of n trademark images in DB, each having m features. Having I_q and I_s from a DB, their features *(X, Y)* can be represented in a 4×2 – dimensional profile data matrix as given by equation (3) above. The i^{th} rows vector X_i, Y_i characterizes the i^{th} object from the sets X and Y. Each element in those sets corresponds to the i^{th} real-value feature $i = x_1, x_2, x_3, x_4$ of j^{th} the trademark image $j = y_1, y_2$ and $y_j = y_{j_1}, y_{j_2}, \ldots, y_{j_n}$.

Statement 3: Given an image I and a set of feature parameters $\theta = \{\theta_i\}_{i=1}^{n}$, a feature extraction function f is defined as:

$$f : IX\theta \to R^d \tag{4}$$

Which extracts a real-valued d-dimensional feature vector.

Statement 4: Let x_f^I be the features vector of an image I on the basis of a feature extraction function f. Then, the integrated dissimilarity/similarity function, Dt between two images I_1 and I_2 is defined as

$$D_t(I_1, I_2) = \frac{\sum_{i=1}^{m} w_i D_{fi}}{\sum_{i=1}^{m} w_i} \tag{5}$$

where f_i is a feature extraction function, D_f is the distance measure between the feature vector $x_{f_i}^{I_1}$ and feature vector $x_{f_i}^{I_2}$, w_i is the weight assigned to feature vector set i determined by GA and m is the number of the feature vector sets.

Statement 5: Given an integrated dissimilarity/similarity function D_t, n training pairs for a given training database db a subset of DB, the total count TC(w) is defined as the number of correct hits given by D_t with the set of weights w for searching in db. From this algorithm, given a training pair $TP = (I_T; I_S)$, a correct hint will be I_S if it is selected by the integrated dissimilarity function D_t.

Statement 6: The set of weights w in a dissimilarity/similarity function D_t is defined as $w = \{w_i\}_{i=1}^{m}$, where w_i is the weight assigned to feature vector set i. The evaluation function is the total count $TC(w)$ defined as:

$$\arg\max_{w} TC(w) \tag{6}$$

2.3 Chromosome representation

A chromosome representation is used to describe an individual in the population of interest. A chromosome in our GA is defined as:

$$c = (w_1, w_2, \ldots, w_i, \ldots, w_m) \tag{7}$$

where w_i is the weight assigned to feature vector set i and m is the number of feature vector sets which is the same as the number of genes in the chromosome. Note that a population P is defined as:

$$P = c_1, c_2, \ldots, c_i, \ldots, c_{popsize} \tag{8}$$

Where $PopSize$ is the number of individuals in the population and c_i is a chromosome.

2.4 Selection function

A selection function plays a vital role in a GA because it selects individuals to reproduce successive generations. A probabilistic selection is performed based on the individuals' fitness such that the better individuals have an increased chance of being selected. The selection method used is Roulette wheel. The probability, P_i, for each individual is defined by

$$P[i] = \frac{F_i}{\sum_{j=1}^{PopSize} F_j} \tag{9}$$

Where F_i is equal to the fitness of individual i. A series of N random numbers is generated and compared against the cumulative probability, $C_i = \sum_j^i P_i$ of the population, if $C_{i-1} < \cup(0,1) \le C_i$, the individual is selected.

2.5 Analysis of EUD and its limitations

In majority of the literature, the most widely used underlying measure for Hausdorff distance is the standard EUD. As reported in [1], [6], [17], the EUD between any two p-dimensional patterns $\vec{X_i}$ and $\vec{Y_j}$ is defined as:

$$d(X,Y) = \left(\sum_{i=1}^{m} | xi - yi |^{\alpha} \right)^{1/\alpha} \tag{10}$$

Where α = 2 of the Minowsky metric. In this case, since the standard EUD does not take into account the spatial relationships between pixels, our similarity methods will not resist to small perturbation of images. Thus, the method pays no regard to other features that are relatively closer in distance. Systems adapting approaches based on the EUD method rank I_s as the most dissimilar to the I_q. Sequel to the aforementioned drawbacks of the Euclidean method, in accordance with equation (10), we propose the following suppositions:

1) The similar images should be close to the query image in all dimensions.

2) All similar images must be similar in all manners.

3. The proposed method

To improve the retrieval efficiency, trademark images should be pretreated using the methods described in [1]. For each image in the DB, we have chosen four features that dealt with scaled, rotational, shape transformation and translation invariant to represent a trademark. When a user runs a query, the features of the queried trademark are first extracted, and then are matched linearly with those in the DB, after which the minimum of the derivation of the DHD is used as similarity function between two trademarks. We first normalize both cosine and Euclidean distances in order to get a new features vector that represents for points set of the NHD. Based on the vector's dimension, the integration of features vector is obtained.

3.1 Implementation of GA

Step 1: The individuals of the initial population P are randomly initialized.

Step 2: Evaluate the fitness of each chromosomes in current population and then create a new population by repeating following steps until the new population is complete.

1) Select two parents $P{=}{>}C_h$; parents to produce children who will replace those who have died (the better fitness, the bigger chance to be selected).

2) Reproduce: $R{=}{>}G_1$; the best individuals according to their fitness.

3) With a crossover probability $C{=}{>}G_2$ cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

4) With a mutation probability $M{=}{>}RNd$ mutate new offspring at each locus (position in chromosome).

5) Evaluate new candidate and select individuals for next generation; Place new offspring in the new population.

Step 3: Use new generated population for a further run of the algorithm.

Step 4: If the end condition is satisfied, ***stop***, and return the best solution C_i. If the maximum iterative step *GenerationNumber* is not reached, go to **Step** 2.

Initially, the fitness function $D_t()$, *LenghtOfGenome*, the probabilities *ProbaMut*, *ProbCross*, *GenerationNumber* are chosen, and *PopSize* is defined based on the problem to be solved. In our GA *Popsize* is 30, *ProbaMut* is *0.05*, and *ProbCross* is *0.6*. The individuals of the initial population *P* are randomly initialized. However, begins the first generation through the fitness calculation $D_t(C_i)$ with $i=1,\ldots,$ *PopSize* for each individual of the population. By applying selection to the individuals of population *P* a transition population C_h would result. From the application of crossover with the probability *ProbCross*, a further transition from *P* to population G_1 results. From the application of mutation operation, with the probability *ProbMut* to the individuals of population *P*, a new population results, which is designated G_2. If the maximum generation number, *GenerationNumber*, is not archived and the *TC* not fit, then the fitness is calculated, and the genetic operators are applied. If *GenerationNumber* achieved, then the optimization is terminated, and the fittest individual represents the solution of the optimization problem.

3.2 Hausdorff distance normalization

In this paper we propose a new similarity metric which is able to compute the distance between different matrixes, like the 4×2 -dimensional profile data matrix of shape feature vectors. From equation (3) the cosine similarity function is:

$$d(\overrightarrow{X}_i,\overrightarrow{X}_j)=\sum_{i=1}^{m}\cos(\overrightarrow{X_{j,i}};\overrightarrow{Y_{j,i}}) \tag{12}$$

From our experimental results, the drawbacks to the direct use of the Euclidean metrics are firstly, the tendency of the largest-scaled feature to dominate the others. Secondly, treating all features in the same way could affect the retrieval of results as images are transformed in different ways. To tackle these limitations, we resolve to normalizing the features vector by using COSD. Hence we get a new distance (13) that combines two distances together. Furthermore, as shown in the experimental results, the two distances measurements when normalized give better results as compared to the use of a single distance measurement separately.

Although, the cosine value is shown in interval of [0, 1] and the EUD is in interval of $[0,\sqrt{2}]$. After experimentation with different proportions of cosine and Euclidean distances, we finally arrive at optimal results after allocating 55% of the COSD and 45% of the EUD in the normalized method. The normalized distance is therefore expressed as follows:

$$NOMD\left(\vec{X}_i,\vec{Y}_j\right)=\sum_{i=1}^{m}a\left(1-\vec{X}_i\right),b\left(\sqrt{2}-\vec{Y}_j\right) \tag{13}$$

Where $\vec{X}_i$ the value of COSD method, $\vec{Y}_j$ is the value of EUD method, *a* and *b* are the proportions of each distance and *I* is an image from DB. To determine the range of the normalized method we consider the two extremes for both cosine and Euclidean distance methods. For the best matching results:

$I_{COSD}=1$ and $I_{EUD}=0\Rightarrow NOMD=0.45\times\sqrt{2}=0.6364$. For the least matching result $I_{COSD}=0$ and $I_{EUD}=\sqrt{2}\Rightarrow NOMD=0.55\times 1=0.55$. Therefore the new range for the normalized method is [0.55, 0.6364]. From the above normalized distance equation (13), the NHD similarity is therefore:

$$NHD(\overline{X},\overline{Y})=\min\left\{NOMD(\overrightarrow{X}_i,\overrightarrow{Y}_j),NOMD(\overrightarrow{Y}_i,\overrightarrow{X}_j)\right\} \tag{14}$$

3.3 Local features

Regarding our system, after dividing the object region into many blocks, the shape features of every block can be extracted. We have the two following features that represent the shape of the divided block:

1) The entropy histogram feature: In this research, to locate shape features in the trademark images, we have chosen entropy as local feature for two reasons. First reason, as we have used sub block subdivision based on polar coordinate system, for applying entropy is its robustness against image rotation, if it is computed in circular image regions (instead of rectangular regions). The second reason is that sometimes, our DB contains complex shape, and they are unpredictable complex regions, located in nearly uniform distributed areas and the beard regions. This fact leads us to use entropy as a measure for uncertainty and unpredictability.

The entropy histogram feature e_i denoted as the proportion of the object pixels in block which reflects the number of object pixels in No. i block, and the total pixels as B_i, then

$$e_i=\sum_{(x,y)\in B_i}f(x,y)\Big/\sum_{(x,y)\in B_i}1 \tag{15}$$

2) The distance histogram feature: As we were dealing in this research with CBIR especially shape based retrieval, edge histogram was needed. In the case of the absence of color information or in images with similar colors, this histogram is a significant tool in searching for similar images. As we combined local and global features, we have also exploited the edge histogram together with invariant moments, local entropy and eccentricity in trademark images similarity measurement. In our implementation, distance histogram, *di* denoted as the distance between center of mass of block and origin, and (x_{i0}, y_{i0}) as the center of mass of block *i*, then

$$d_i=|(x_0,y_0),(x_{i0},y_{i0})|/R \tag{16}$$

(x_{i0}, y_{i0}) is the center of mass of blocks i, and $x_{i0}=m_{10}/m_{00}$, $y_{i0}=m_{01}/m_{00}$ and R be a radius of the object. To keep invariance under scale, the distance should be normalized by the method of dividing R. To avoid the disturbance by noise, the distance d_i will be regarded as zero if the proportion is lower than a certain threshold value.

The proportion histogram of pixels and distance histogram are obtained by calculating the two shape features of every block and arranging these features according to their number. The histogram should be smoothed in order to avoid matching between two block areas with the same number and also to influence of the histogram value.

3.4 Hu invariant moments group and eccentricity

In addition, the global features of the image such as eccentricity (Ec) and Hu invariance moments group are extracted. Eccentricity is also called the elongation, and to some extent it describes the density inside the image region. According to experiment, the retrieval effect can be improved by using it.

1) Hu invariants moment are the one of region based features and they are a very popular shape measure. For a 2D image, *f(x; y)*, the central moment of order *(p + q)* is given by

$$m_{pq} = \iint x^p y^q f(x,y)dxdy \tag{17}$$

the first moment μ_{00} is denoted by m. If $\bar{x} = \mu_{10}/m$, $\bar{y} = \mu_{01}/m$ the central moments of order *(p, q)* are defined as:

$$\mu_{pq} = \iint (x - x^p)(y - y^q) f(x,y)dxdy \tag{18}$$

For a digital image, the integrals are replaced by summations as:

$$\mu_{pq} = \Sigma_x \Sigma_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) \tag{19}$$

$(\bar{x},\bar{y})$ is the center of mass of image. The normalized central moments denoted by η_{pq} , are defined as $\eta_{pq} = \mu_{pq} \int \left(\mu_{00}\right)^r$, where $0 \le r \le R$.

From the second-order moments and third-order moments a set of seven invariants moments, which is invariant to translation, scale change and rotation, has been derived and reported in [11]. The invariants moment group is made up of seven Hu invariant moments, which are educed from two or three step normalized center moments.

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\phi_4 = (\eta_{30} + 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\phi_5 = (\eta_{30} + 3\eta_{12})(3\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 + (3\eta_{21} - \eta_{30})(\eta_{21} - \eta_{30})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} - \eta_{30})^2]$$

$$\phi_6 = (\eta_{20} - 3\eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2][+4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})]$$

$$\phi_7 = (3\eta_{21} - \eta_{30})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{21}$$

where $\eta_{pq} = \mu_{pq}$ are normalized central moments defined above.

2) Eccentricity (Ec) is also a global feature used in features extraction proposed in this paper. The eccentricity of each Voronoi vertex V is in fact the ratio of a vertex v is the greatest distance between v and any other vertex.

Usually, moments of a shape are computed from the occupancy array representation of the shape. That is, all the shape's pixels are involved in the computation. In this paper we proposed a method which computes a convex hull CH(S) as referred in [12]. The points on convex hull locate on the image edge, and elimination of pixel points in the image can reduce set S and the computing burden will be reduced naturally. Therefore we may utilize 8-neighbour method to extract edge points of image as points set S, [1]. Eccentricity is defined as:

$$Ec = \frac{\mu_{20} + \mu_{02} - \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{\mu_{20} + \mu_{02} + \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}} \tag{20}$$

Where $\mu_{pq} = \Sigma_x \Sigma_y (x-\bar{x})^p (y-\bar{y})^q f(x,y)$, is the (p, q) order central moment of the shape ((x, y) is the center of the shape).

Ec and Hu invariant moments group show invariance towards translation, rotation, mirroring, and scale alteration of image object. Therefore, composition of the two global features with the above mentioned histograms can adequately describe the features of trademark images.

In order to check the accuracy of our experiment, an important criterion for testing the efficiency of the search and retrieval is that the output must include all the similar images. The important thing is that the similar ones should not be missed in the search process. The process is such that the system retrieves the short list of the best-first images first and then final decision can be taken by a human perception expert in the loop.

To evaluate the performance of retrieval as given, we have used retrieval efficiency. The efficiency of retrieval for a given short list of the best-first images retrieved of size *K* is given by:

$$\eta_K = \begin{cases} n/N & \text{if } N \le K \\ n/K & \text{if } N > K \end{cases} \quad (22)$$

Where *n* is the number of similar images retrieved, *K* is the size of a short list of the best-first images retrieved and *N* is the total number of similar images in the DB. Note that if $N \le K$, then η_K reduces to the traditional *recall* information retrieval. And if $N > K$, then η_K computes the *precision* measure of information retrieval, [13].

4. System model

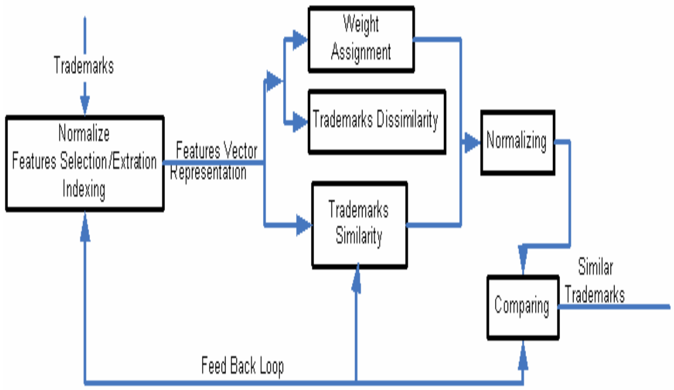

Figure 1. The proposed shape-based trademark retrieval system

From figure 1 above: Trademarks representation refers to the number of images in DB. Feature selection is the process of identifying the most effective subset of the original features to use in shape retrieval. Weight assignment block refers to the training of weight using GA. Trademark dissimilarity/similarity is usually measured by a distance function defined on vector of features. The normalizing and comparing steps can be performed. The outputs of similar trademarks are the results analyzed using retrieval efficiency function.

To test the validity of algorithms in this paper, we use the greyscale trademarks images our DB contains 500 images with binary value. Only trademarks images with size 200×200 are tested. The aim is to inspect the achieved translation, rotation, scale alteration, and image invariance of the GA algorithm proposed in this paper, and to see whether the retrieval effect satisfies visual requirement, especially human perception. In summary two steps are adopted:

We randomly choose 100 trademark images belonging to different types from DB. Perform any combination of the following transformations to one of the selected image samples and we accordingly get four similar images of the original image. In order to test the recall rate for cropped, rotated and scaled trademark images, we conducted the following experiment:

1) Cropped Query: Every image in DB was cropped by using some tools such as Matlab 6.0 and Paint. We added Gaussian noise and made some holes or shadows into trademarks images.

2) Rotated Query: Every image in DB was rotated arbitrarily with the range of $\pm 10\%$ and then presented as the query image.

3) Scaled Query: Every image in DB was scaled arbitrarily and then presented as the query image. The scaling factors were bounded by 0.5 and 50.

4) Shape transformation: Distort or extend image in some degree.

Then, we get a DB including 550 trademark images that possesses 100 categories with each one containing five images. After pretreating the DB images, we used GA for better weighting assignment to the four features. The population size, *PopSize*, was 30 and the maximum number of iterations was set to 400. In addition, there were 40 *TP* and the size of the db that was 200. The values of the weights (genes) were bounded by 0 and 1. The probability of application of crossover was 0.6 and the probability of application of mutation was 0.05. The experiments were repeated 15 times with different random seeds. We gave an evaluation of our GA, like, if the target is ranked in the first position, *TC(w)* is increased by one. If it is ranked in the second position, *TC(w)* is increased by 0.95. If it is ranked in the third position, *TC(w)* is increased by 0.9 and so on. This method helps the GA to search for a better solution in a smaller number of iterations.

By taking any single image from DB as sample, the retrieval result returns the first 100 images arranged according to similarity based on four functions. The similarity between sample image and itself is 1 for COSD distance similarity, 0 for EUD distance dissimilarity and 0 for NHD dissimilarity, also the same as DHD. Hence the returned first image will be the sample image itself.

Before computation of four distance dissimilarity/similarity metrics and the return of the images most similar to the I_q, a subset of DB is obtained. According to the entropy of the querying image and the entropies for the image in DB, we can limit the searching range to reduce the searching time. Using the entropy of the I_q, the system will find the subset of images in DB whose entropy is closest to the entropy of querying image. Our experimental results show that image indexing is done in two ways. The selected images must have entropy value ranked in [0, 0.5] or [0.5, 1]. After that, the dissimilarity/similarity functions are computed between images from DB subset and the queried image. Without having any exclusion mechanisms like the narrowed searching window and entropy difference, the time will be 6.25% longer as compared to that of both direct and normalized Hausdorff methods.

5. Experimental results

The system is implemented in VC++, on a Window workstation. The user runs a query and selects an image to be retrieved. Four features detailed in section 3 above are computed for I_q (Sample) and for also all trademark images in DB. Hence each image in the DB is indexed on those four shape features.

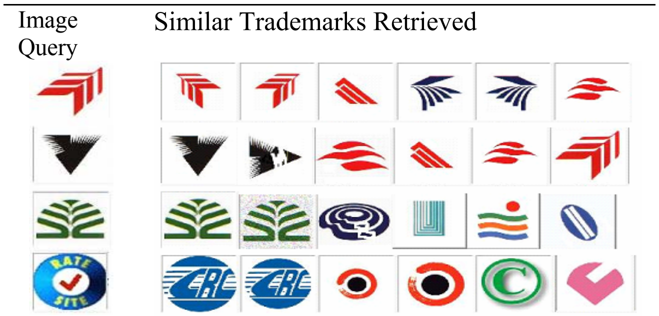

Figure 2. Results of similarity retrieval for DHD method

In our system, to get NHD, we first normalize the Euclidean and cosine methods results from different shape features combined together and then the resulting minimum of the summation is obtained. Moreover, this made the system invariant against shape transformations thereby improving the accuracy of the new similarity measure. To evaluate the retrieval effectiveness of different shape measures, a test was designed as follows: 100 query images representing the population were selected.

Figure 3. Results of similarity retrieval for NHD method

For each I_q, a list of similar images present in the 500-images DB was first manually found. The above described shape features of the I_q were then compared to the corresponding shape features of the images in the DB to obtain a short list of similar images. Then base on equation (22), the retrieval efficiency η_K was calculated. This was computed over several sizes of the best-first retrieved images query for $K = 5$, $K = 10$, $K = 15$ and $K = 20$. Table 1 shows the average retrieval efficiency; η_K computed over 56 queries.

A query shape similarity retrieval output for an I_q is shown in figure 2 and figure 3. Here the I_q having a curved or star shapes have been used. Those two figures show the similarity retrieval output using the combination of global and local features. It can be seen from the experimental result that the output retrieved via the combined features is better than that of the individual features. And typical human perception is more in agreement with the NHD than the DHD, as displayed in figure 2 and figure 3. For other experiments, as shown in table 1, results obtain by NHD method are more accurate than those of the DHD. For the first 5 images returned by the system, the two methods agree, they succeeded in returning all best images in the DB when the images with different component are queried.

However, as the list of returned images increases, the DHD method misses some images that should have appear in the list, especially, the ones transformed based on noise and cropping. For cropped $K = 10$, it looses 4%, when $K = 15$ it looses 8%. Finally when $K = 20$, the DHD looses a significant percentage. In order to overcome these shortcomings and display the relevant similar images to the query image, we normalized the Hausdorff distance by taking the minimum of normalized of Euclidean and cosine distances. Hence decreasing the percentage of missing images (DHD method: from 20% down to 1%). As shown in table 1, O represents: original query, R: rotated query S: scaled query, N: noisy query: cropped query.

Table 1. Average retrieval effective values for NHD and DHD methods

Query nature	K=5		K=10		K=15		K=20	
	DHD	HDN	DHD	HDN	DHD	HDN	DHD	HDN
O	100	100	100	100	100	100	100	100
R	100	100	100	100	100	100	100	100
S	100	100	99	100	98	100	97	100
N	98	100	97	100	97	100	96	100
C	98	100	96	100	92	100	80	99

To verify the performance of the proposed method, a set of trademarks were used as queries to the trademark DB. From the results obtained, the trademarks retrieved agreed well with human perception. In addition, the average time of 10 trials for feature extraction and DB querying were 2.96s and 0.08s respectively. Furthermore, the retrieval results in table 1 and plotted in figure 4 were showing NHD with the weights found by the GA: K list refers to the position of the correct retrieval. Our aim of retrieving all best trademarks images is achieved because the percentage of non-retrieved images in the top 20 matches is null for NHD. Hence, this is the key of the outperformance of NHD technique to DHD technique.

Since shape similarity is a subjective issue, in order to further evaluate the proposed method of human in loop is adopted in this paper, 10 volunteers were asked to perform similarity retrieval based on shape on the DB of 500 trademarks images. Given a query, they were asked to choose the best match from the DB. Figure 4 presents the results of retrieval of our system and agreed with the volunteers. As observed from the results, our simple shape measure was effective in retrieving cropped, rotated and scaled images. This is because the four shape features that we chose are all invariant on any shape transformation.

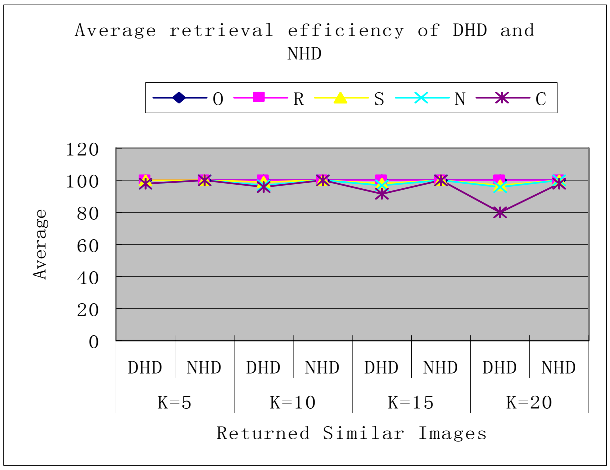

Figure 4. Average Values of DHD and NHD

Moreover, all the target images were ranked in the top twenty positions. This reveals that the novel similarity function models the human perception quite well.

6. Conclusion and future work

In this paper, we suggested to integrate different trademark images features by using the dissimilarity/similarity function for retrieving similar trademarks. A method for finding the weighting factors of the difference function using a GA has been proposed. Furthermore, this technique has been applied on EUD and COSD distances, especially on novel dissimilarity function which is NHD. The results show that the weighting factors found by the GA improves the accuracy of trademark retrieval. We have applied GA in optimization of other general dissimilarity measures (other than a sum of weight EUD).

According to our experiment results conducted, we noticed that with trademark images, retrieval accuracy and effectiveness on the basis of dissimilarity measure between trademark images, the NHD is better than DHD. The normalization of cosine and Euclidean distances in derivation of Hausdorff distance made the proposed measure to outperform other measures. Hence the combination of global and local features formulated a finite set of points instead of a set of image pixels usually used in DHD, this increases retrieval accuracy and efficiency. In particular, the normalized method has decreased the percentage of missing similar images in the results returned by the system.

Future research will combine texture and shape contents. Our system will consider using more shape features like Zernike moments or edge angles to further improve the accuracy of retrieval. Moreover, the wavelet transform will be applied to the images that are difficult to retrieve using shape content like images with sea or sky background and so on. The features weights will be trained using Neural Network algorithm, [14], [15].

7. References

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