Logo Retrieval Using Morphological Pattern Spectrum

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Abstract

In this paper we propose a geometric approach to capture the shape and spatial relation attributes in binary images to build an efficient logo retrieval system. We extract the shape feature by computing the morphological pattern spectrum (MPS) for various structuring elements. The spatial relation among the disjoint components in the logo image is described by defining a simple and computationally inexpensive spatial relation graph (SRG). The SRG is obtained by joining the centroids of the two largest components with the centroids of the rest of the components. For retrieval purposes, the similarity measure is defined with respect to similarities in both shape and spatial relationship (MPS and SRG). The joint shape and spatial relation features enable us to obtain a very good precision rate. A relevance feedback mechanism is used to obtain the weights for various components in the similarity measure. The details of the method as well as results of experimentations are presented.

1 Introduction

Content based image retrieval (CBIR) systems retrieve the images based on visual features like color, texture, shape, spatial relation, etc. Most of the recent work in the image retrieval has concentrated on developing a single or a combination of such features.

Swain and Ballard [24] have developed a technique of identifying the objects in an image using the color histogram. This technique has been shown to be robust to the changes in the object's orientation, scale and viewing position. Since the color histogram lacks the spatial information, authors extended the approach to capture the spatial relation using the color correlogram as suggested in [12]. The color correlogram encodes the relationship between pixel intensities at two different locations, but it lacks the invariance to intensity variations. Jhanwar *et al.* presented in [15] a translation and illumination invariant image retrieval scheme using the motif cooccurence matrix. It makes use of the optimal Peano scan to encode an image.

Shape is also an important feature that describes the presence of specific types of objects in scene. Hence researchers have also explored the usefulness of shape features in CBIR applications. Shape representation falls into two categories, namely the boundary-based and the region-based. One of the boundary based shape representatives is a Fourier descriptor. The basic idea of Fourier descriptor is to use the Fourier transformed boundary as the shape feature. One such early work on this can be found in [25]. In order to incorporate digitization noise, Rui *et al.* proposed [30] a modified Fourier descriptor which is noise resilient and invariant to geometric changes. Similar work on boundary based shape representation has been proposed in [33]. The shape descriptor has been derived from the two dimensional Fourier transform on a polar-raster sampled shape image. One typical region based shape representative is moment invariants. Moment invariants are the spatial moments computed using the entire segmented region, which are invariant to shape transformations. Hu [11] identified seven moments to describe the shape completely. This work has been improved in [32] and moments have been evaluated based on the discrete version of Green's theorem. These techniques did not consider the influence of image digitization on invariants. A solution to this problem has been proposed in [7], which preserves the qualitative differential geometry of the object boundary. Mehtre *et al.* [23] compared the performance of boundary-based representations, region based representations, and combined representations. A scheme of obtaining a shape measure which requires only a minimal amount of segmentation has been proposed in [6]. Fariborz *et al.* in [20] extracted the shape feature from the orientation edge map. In [21, 22] authors have shown that the shape and the size of an object can be described effectively by the morphological pattern spectrum. Kosir and Talsic [18] have proved the translation and scale invariance properties of the pattern spectrum.

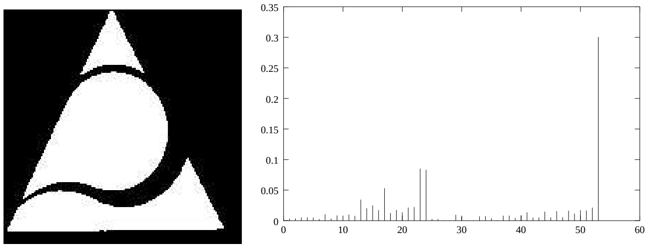
Spatial relation is another important image attribute that needs to be considered when an image contains multiple (disjoint) components. Many researchers have exploited the use of spatial relation feature to describe the spatial distribution of disjoint components. A string based approach to capture the spatial knowledge for representing symbolic pictures has been proposed in [4]. The proposed approach captures the spatial knowledge in terms of the orthogonal projections. Petraglia *et al.* [26] extended the approach to introduce the rotation invariance through a transformation in polar coordinate system. To take into account the binary spatial relationships, Gudivad *et al.* [9] further extended the approach and proposed an algorithm based on spatial orientation graph. The algorithm has a quadratic time complexity in terms of total number of objects in the image. A geometry based image representation to capture the spatial relation has been proposed in [8] to reduce the time complexity.

In this paper we present an approach to the retrieval of binary images of similar content from a database of logo images. This has applications at trademark registration offices while allocating logos to new companies during the registration process. Although we use it for logo retrieval purposes in this paper, the CBIR application is equally valid for query images having any type of binary pattern. Most of the recent logo retrieval systems are based on either the shape or the spatial relation attributes. Authors in [1] presented an affine model based shape matching and retrieval scheme. Kim *et al.* proposed [17] a trademark retrieval system which exploits a region based shape description technique. Zernike moments or pseudo Zernike moments have been used for representing the entire region. To explore the characteristics of both boundary-based and region-based representations, Aditya *et al.* proposed in [14] a trade mark retrieval system that uses the histogram of the edge directions and seven invariant moments to describe the global shape information. Recently Eakins *et al.* compared in [5] the comparative effectiveness of a number of different shape features and matching techniques in retrieving multicomponent trademark images.

Earlier research works on logo retrieval are mostly based on the shape features. Although moment based shape extraction method [14] provides good results, one finds it difficult to predict precisely the order of the moments by which shape of an object can be completely described. Also one finds that considerable computational complexity is involved in computing the moments. Further, one cannot handle partial matches of shapes. One common problem of the edge based shape recovery methods [34, 10] is sensitivity to noise, which is a main cause for inaccurate shape description. In other words, most of the edge extraction based methods have moderate success. One promising solution to the above problems is shape description using the morphological pattern spectrum (MPS). One key advantage of the MPS over moment based method lies in the extraction of precise shape information. It means, one can precisely terminate the computation of the spectrum as soon as the selected kernel completely inscribes the object. Morphological operations make MPS based method to outperform the edge based methods in the presence of noise. One may find the use of MPS in literature [19] for shape recognition. Our idea in this paper is to address the selection issue of structuring elements and efficient shape representation using the MPS due to several such kernels. One advantage of using multiple kernel based MPS over a single MPS lies in better capturing the global shape information by integrating the spectral characteristics due to multiple shape primitives. For an effective shape retrieval, the MPS feature vectors due to four different standard kernel shapes, such as square, circle, triangle, and rotated triangle are computed and integrated with the appropriate weights. Here the multiple kernel based MPS itself serves as the shape feature vector (SFV) of the logo. We also take into account the user's subjectivity by incorporating human interaction during the retrieval process. This is done by exploiting an appropriate relevance feedback mechanism to make the system more interactive.

The shape based methods in [10, 14] become inappropriate retrieval schemes, when there are multiple (disjoint) components in the image, since they do not consider the spatial relationships among the components. Therefore shape based retrieval technique is suitable when the logo has only one component in the binary image. This motivates us to use an efficient shape as well as spatial relation feature based technique for logo retrieval. Despite having many methods [27, 8], where complexity involved in computing the spatial relationship is comparatively low, we propose a spatial relation graph (SRG) based matching technique to capture the (spatial) relational attribute. This is found to be very useful for retrieval purposes. We obtain a topological representation of the binary image comprising multiple disjoint components. We call this topological representation as SRG. We derive the spatial relation feature vector (SRFV) from the SRG. This SRFV is combined with the SFV in terms of similarity measures with suitable weights to describe the shape-spatial similarity measure. We incorporate translation, rotation, and scaling-invariance in the features to strengthen it further. In addition, a basic morphological prefiltering is used to make the system noise resilient. We demonstrate the performance of the method by providing experimental results by taking into account the shape and spatial relation attributes. We also show that our precision rates compare very favorably with those of other existing logo retrieval schemes. The basic problem addressed in this paper can thus be defined as follows: given a database of logo images we retrieve the logos of similar shape and spatial relationship by making use of multiple kernel based morphological pattern spectra and the spatial relation graph. The details of the method are discussed in this paper.

The remainder of the paper is organized as follows. section 2 presents the fundamentals of the pattern spectrum,



(a) (b)

Figure 1: (a) An example of a logo, and (b) its MPS due to a square shaped structuring element.

its use in the shape feature extraction, selection issue of various kernels shapes, shape similarity matching and relevance feedback mechanism. In Section 3 we describe the extraction of the spatial knowledge among the various components in the binary image and the spatial similarity measure. Experimental results based on the shape and the shape-spatial similarity measures are discussed in section 4. We also discuss the retrieval accuracy, stability and speed aspects in comparison with the three recent retrieval techniques. We conclude in section 5.

2 Retrieval using MPS

2.1 Morphological Pattern Spectrum

In signal processing the spectral contents of a signal $f(t)$ can be extracted from the Fourier transform. Here the pattern $e^{-i\omega t}$ probes into the signal $f(t)$ to get the spectral information. For geometric analysis of the two dimensional signals, a different kind of spectrum emphasizing the geometry is required. The morphological pattern spectrum (MPS) is one such feature used for geometric analysis of two dimensional signals. The pattern spectrum is the cardinality of the set comprising of the successive difference between the opening of a binary image X by the structuring element B of size n and $n+1$, respectively. Mathematically, the MPS of the j_{th} image in the image database due to the i_{th} structuring element is defined by the following equation

$$\begin{aligned} PS_{ij}(n) &= Area\{X_j \circ nB_i - X_j \circ (n+1)B_i\}, \\ for\ n &= 0, 1, \cdots N_{ij} - 1\ and \\ PS_{ij}(n) &= 0,\ for\ n \geq N_{ij} \end{aligned} \tag{1}$$

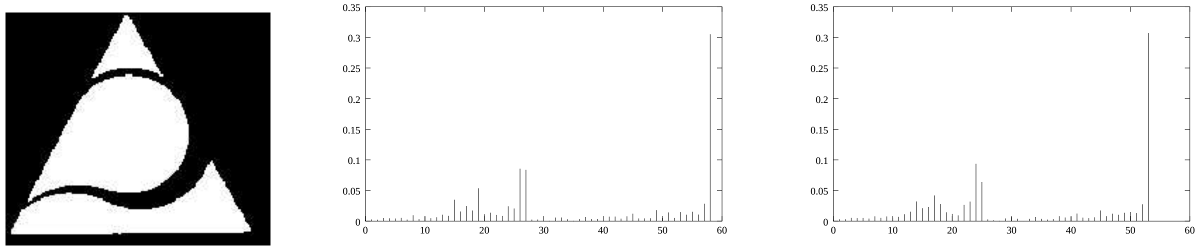
Where $\circ$ denotes the morphological opening operation and N_{ij} is the minimum size of the structuring element B_i, such that the erosion of an image X_j with N_{ij}B results in a null set. The MPS of an image due to a square shaped structuring element is shown in fig 1(b). The horizontal axis represents the size (n) of the structuring element B. The various entries in the plot tells us how much of the area in the image has been opened out for an incremental change in the size of the structuring element. Thus the sum of all the entries would be equal to the total area of the object. We use the total area to normalize the spectral components in fig 1. The example shows that the maximum inscribable square window inside the logo is of dimension 53×53 pixels. Fundamentals of the MPS and its other properties have been described in [22, 18, 19].

2.2 Shape feature

When we consider any logo, its shape usually resembles some of the standard geometrical structures like square, circle, triangle, rhombus, or any combination of these primitive shapes. This motivates us to use the shape as one of the possible features for logo retrieval. Since the MPS is known to capture the shape information well [18, 19], and since it is quite easy to compute the MPS for a given structuring element, we propose to use the MPS as a feature for the shape description of the logo. However, the MPS due to just a single kernel will be able to extract strong points of similar attributes only. This will be able to retrieve only a subset of the relevant images. This inspires us to explore the idea of integrating spectral characteristics due to different geometrical primitives in identifying the shape of the logo and trying to span the whole space of relevant shapes during retrieval.

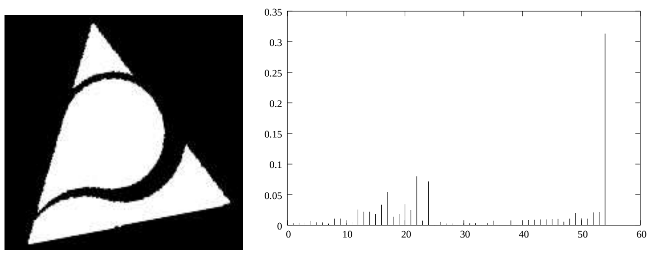
In our approach we consider four different geometrical structures to describe effectively the shape of the logo. The geometrical structures define the structuring elements while computing the MPS. The reason behind using four structuring elements lies in the fact that one single primitive shape may not be able to capture effectively the shape of the logo. We obtain the shape features by computing the MPS of each logo in the database due to above mentioned structuring elements according to the equation 1.

When the size of the database logo is different from that of the query logo, we make it scale invariant by performing a linear scale interpolation on the shape feature vector. Thus the length of the morphological pattern spectra can be normalized with respect to a scale such that they all have the same size of the maximum inscribable structuring element. In other words, all the images should have the same N_i for a given structuring element. The MATLAB function INTERP1 is used to rescale the MPS. This is illustrated in fig 2. In this study, morphological pattern spectra of all the database images due to a structuring element are normalized with respect to the median size of all spectra (N_i in equation 1) in the database. The advantage of normalizing with respect to the median is that the MPS of the database images need not be normalized for a new query. Only the query image needs to be normalized with respect to the median size of the MPS. This drastically reduces the computational complexity of our scheme. The median is preferred over the mean to avoid any outlier data in the database. Fig-



(a) (b) (c)

Figure 2: (a) Scaled logo of fig 1(a), and (b) its MPS due to the same structuring element. (c) The MPS after scale normalization through linear interpolation.



(a) (b)

Figure 3: (a) Logo rotated by 10^o(CCW) of fig 1(a) and (b) its MPS due to the same structuring element.

ure 2 illustrates how to make our approach scale invariant. Figure 2(a) is a magnified version of the figure given in fig 1(a). This is evident from the fact that the highest spectral component is N_i=53 in fig 1(b), but N_i=58 in fig 2(b). The spectrum is resized in fig 2(c) to make N_i=53 even for figure 2(a). One can see that both the spectra of fig 1(b) and 2(c) are very similar.

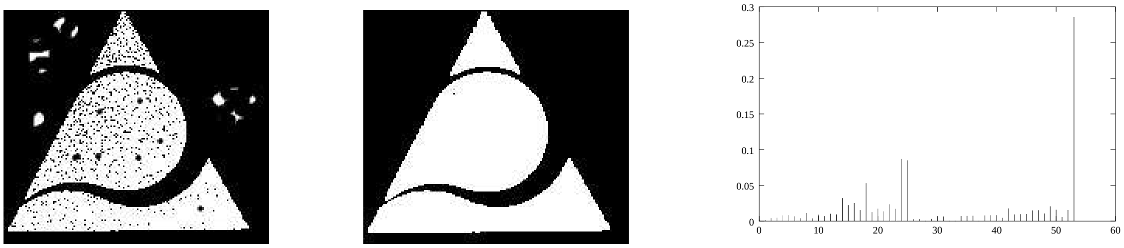
Morphological operations are not rotation invariant unless either the structuring element or the object is. Use of the circle as the primitive satisfies the rotational invariance requirement. However, the MPS due to a circular structuring element is not good enough to capture all the details of the shape and the corresponding retrieval is not very good. Hence we also use other structuring elements, albeit they are not rotation invariant. The logo shown in fig 1(a) is rotated counter clockwise by 10^o and is shown in fig 3 (a). One can observe that the spectra in fig 3(b) and 1(b) for a rectangular structuring element are quite similar and such a similarity suffices for retrieval purposes. The translation invariance is easy to prove. Since the computation of MPS involves only the opening operations, and opening is proven to be translation invariant, the MPS is translation invariant. We also consider the robustness property of the MPS against noise. The shape feature vectors of such images are computed after a preprocessing step. During the preprocessing we appropriately apply morphological filtering operations before computing the MPS. There are two kinds of noise that can exist in the logo. One is inside the background region and the other is within the foreground region, inside the logo. Initially we apply morphological CLOSE operation using a small structuring element of size 3×3 to minimize the noise in the background region. Followed by CLOSE operation we use the OPEN operation to eliminate the noise within the logo. This successive CLOSE-OPEN operation eliminates most of the noise in the logo image. When the noise extends to multiple pixels a structuring element of larger size is required. However, it disturbs the precision of detecting the object boundary. Therefore one should appropriately choose the size of the structuring element. One such noisy logo image is shown in fig 4(a). The logo image with noise removed and its MPS due to the square structuring element are shown in fig 4(b,c), respectively. This shows that the MPS broadly remains unchanged even in the presence of noise. Hence we use the MPS as the shape feature to retrieve logo images similar to the query image from the database. However, as mentioned earlier, instead of using the MPS for a single structuring element, we use the pattern spectra for several structuring elements.

2.3 Similarity measure

One may measure the distance between the feature vectors of the query image and the database image using the Euclidean distance norm as discussed in [31]. The distance of the j_{th} image X_j for the i_{th} structuring element can be computed using the following equation

$$d_{ij} \quad = \quad \sqrt{\sum_{n=1}^{n=N_i} (PS_{ij}(n) - PS_i'(n))^2},$$

where N_i denotes the length of the MPS after scale normalization for the i_{th} structuring element and $PS_i^{'}$ is the corresponding MPS of the query image Q. However, since the higher spectral components in the the MPS characterizes the shape of the logo more closely, the higher components are emphasized and the smaller ones are deemphasized. This is



(a) (b) (c)

Figure 4: (a) A noisy logo, (b) Logo with noise removed and its (c) MPS due to the square shaped structuring element.

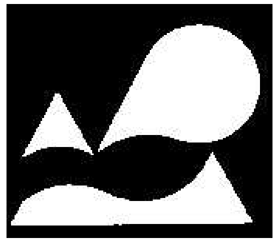


Figure 5: A new logo created by spatially shifting the components of the logo given in fig 1 (a).

achieved by modifying the distance function as

$$d_{ij} \;=\; \sqrt{\sum_{n=1}^{n=N_i} w_i(n) * (PS_{ij}(n) - PS'_i(n))^2},$$

where $w_i(n) = e^{-S(1-\frac{n}{N_i})}$ and S is a non-negative control variable called the slope factor which emphasizes or deemphasizes various spectral components appropriately.

As mentioned earlier, one particular structuring element may not be able to capture the shape variation very well. Hence we suggest the use of four different structuring elements to compute the corresponding MPSs. When we consider all these four MPSs, the distance between the query image Q and the j_{th} image X_j in the database is given by

$$SIM\_Shape(X_j, Q) \;=\; \sum_{i=1}^{i=4} \alpha_i d_{ij}, \qquad (2)$$

where α_i is an appropriate weight for the i_{th} structuring element.

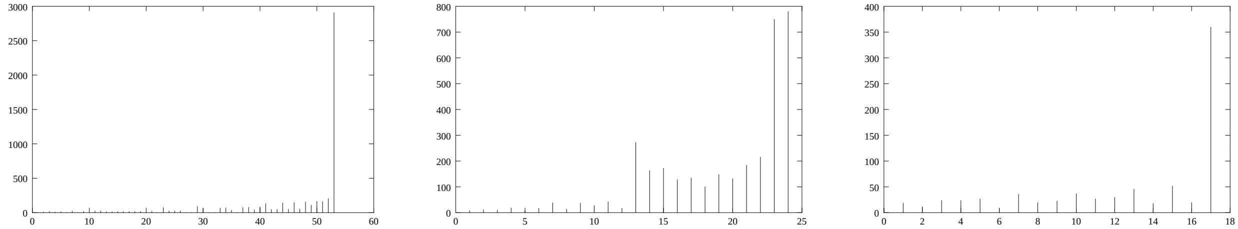
Now we discuss the choice of structuring elements. Typically, the circle is a preferred choice of structuring element as this is rotation invariant. Hence we select circle as one of the structuring elements. Next we observe the typical shapes that occur in various logo images and we find that there is a preponderance of square and triangular shapes. The advantage of selecting a square shaped structuring element is that it is invariant with respect to horizontal and vertical positioning. The square, thus, becomes our second choice of the structuring element. We also select the triangle as another structuring element, due to its prevalence in logo shapes. However we note that the triangle (defined as a Pascal's triangle on the discrete grid) is not rotation invariant and hence we select a rotated triangle (rotated by 90^o) as the fourth structuring element. One can use more number of such primitive shapes to compute the respective MPS. However a choice of four such structuring elements was experimentally found to suffice for logo retrieval purposes.

2.4 Relevance feedback

Most of the CBIR systems use one-shot approach in retrieval where query is specified in the form of a feature vector and retrieval is done based on the similarity of feature vectors. However, usually in these systems the subjectivity of human perception is not considered. In order to capture the user's perceptual subjectivity and allow the user to have more control over the search criteria we incorporate an interactive mechanism that involves human as a part of retrieval process. We now ask the question how one can select the weights ρ_i in equation 2 using an appropriate relevance feedback mechanism. Initially we experimented with the optimization technique proposed in [28] to compute the explicit optimal solutions for the query vector and inter weights ρ_i. The optimal update formula for inter weights ρ_i has been shown to be

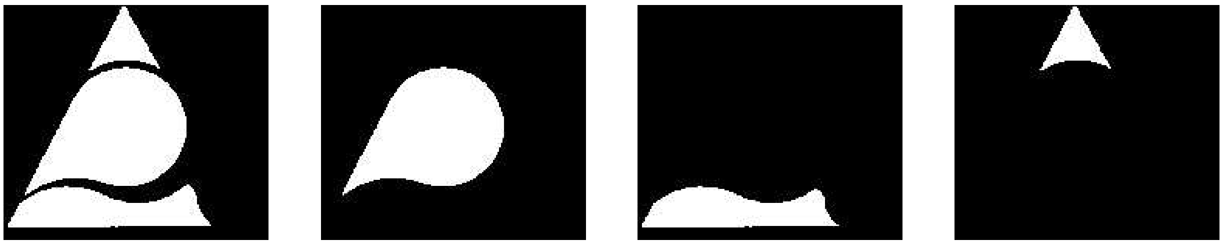
$$\rho_i \;=\; \sum_{m=1}^{m=4} \sqrt{\frac{g_m}{g_i}},$$

where $g_i = \sum_{j=1}^{M} \sigma_j d_{ij}$, and $\vec{\sigma} = [\sigma_1, \cdots, \sigma_M]$ is the degree of relevance vector of M training images provided by



(a) (b) (c)

Figure 6: Pattern spectrum for corresponding components in fig 1 (a) for a square shaped structuring element, (a) circular shaped component, (b) the bottom component, and (c) the triangular shaped component.



(a) (b) (c) (d)

Figure 7: (a) A database logo similar to the query logo in fig 1(a) and (b), (c), (d) are its components in the descending order of their areas.

the user. However this inter weight update formula does not fully utilize the information of all the retrieved images and the performance was not found to be satisfactory. Hence, we use the scoring method proposed in [29]. The scoring approach makes use of all the retrieved images, and an efficient use of these retrieved images has been made in [16]. Therefore we use the relevance feedback method proposed in [16]. In this method both the retrieved relevant and retrieved irrelevant images are considered for updating the weights α_i.

In this section we have used the shape as the predominant and the distinguishing visual feature to describe the shape of a logo. The proposed shape descriptor extracts the shape of the logo effectively by appropriately integrating the MPSs for four different kernels. Another important characteristic of the proposed shape descriptor is its translation, and scale invariance. Indeed, it is very easy to compute the above features. Experimental results does strongly support the above analyses. These results are further improved using a relevance feedback mechanism, which makes a greater use of information of all the retrieved images. However, we notice that there is scope of improvement for the cases when the logo consists of several disjoint components. It is easy to prove that the pattern spectrum remains the same even when one randomly displaces each component of the logo, thus destroying the overall shape of the logo. For a proper retrieval, it is imperative that one considers the spatial relationships among various components in the logo image.

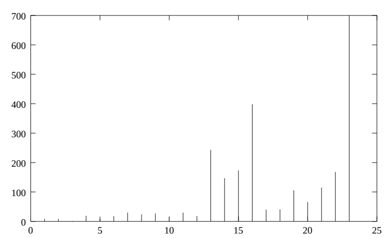


Figure 8: The MPS of the component in fig 7 (c).

Now we discuss how this can be achieved in the next section.

3 Inclusion of spatial similarity

Some of the recent works [14, 10] mainly focus on different shape representation strategies in CBIR. Identifying the shapes of the logos using the shape based approach discussed in section 2 can only provide at best a partial solution. This is evident from fig 1(a) and fig 5 where the shape based retrieval scheme considers both the logos to be similar. Although they are similar in terms of shape of the individual components of the logo, spatially they look very different. They should be classified as different logos. However, they both have identical MPS. This motivates us to use the spatial relation attribute in addition to the shape attribute to capture logos similar to the query logo. To tackle this problem several authors have proposed in [4, 9, 8] various models to describe the spatial similarity. In this section we focus on a simple and computationally inexpensive spatial relation representation.

When an image contains multiple isolated segments, to extract the shape feature, we decompose the image using the connected component labeling algorithm. For example a query logo in fig 1(a) or fig 5 has three independent components. We extract the feature vector (MPS) for each connected component by computing its individual pattern spectrum. These are shown in figures 6 (a-c) for the rectangular structuring element. The MPS shown in fig 1(b) is indeed the sum of all the three pattern spectra of the components (see fig 6 (a-c)). In order to account for the scale invariance, the pattern spectra are normalized with respect to the scale of the largest inscribed structuring element. For illustration, a database logo which is slightly distorted version of the logo given in fig 1 (a) and its components are shown in fig 7. Since the second component in fig 7(c) is partly different from that of the given logo image, there is some difference in the corresponding pattern spectrum (see fig 8) and compare it to the MPS given in fig 6 (b). The other two components have the identical pattern spectra.

To capture the spatial relation, we obtain a topological representation of the binary image containing multiple disjoint components. We name this topological representation as a spatial relation graph (SRG). To obtain the SRG, we label the components in descending order of their area. The position of a connected component is specified by its center of mass (centroid). Now we compute the centroid of each component. Each component is represented by a node with its location at its center of mass. We consider the top two largest nodes as the reference. The SRG is obtained by joining the centroids of the two largest nodes with the centroids of the rest of the nodes. Thereby we obtain the topological representation in terms of nodes (vertices) and their connectivities (arcs). Note that the SRG representation is invariant to translation, rotation and scaling of the image. An example of the SRG representation among the components of an arbitrary binary image is shown in fig 9(a), where the components 1, 2, 3, 4, and 5 correspond to the nodes and the lines connecting centers of mass correspond to the arcs. Each node of SRG is associated with certain geometrical and physical attributes. Physical attributes associated with each node are area, center of mass, and the MPS for four structuring elements. As discussed in section 2 we perform matching of the individual physical attributes to define the shape similarity. The geometrical attribute associated with each node is its reference angle subtended by the two largest components 1 and 2 at a given node (see fig 9(b)). The spatial similarity is defined by matching the SRG of the query logo with the SRG of the database logo.

To perform graph matching we extract the geometrical attributes defined as the spatial relation feature vector (SRFV) from the SRG by computing the angles with respect to the centers of mass of the largest two components as the consideration of spatial similarity is meaningful only when there are at least three components in the image. In order to match the two logos shown in images 1 and 2 in fig 9, we expect that $\theta_3^{'} \approx \theta_3$, $\theta_4^{'} \approx \theta_4$, and the area of node 5 to be very small compared to the other nodes, besides matching the MPS for each individual components. The SRFV is given by the following quantities

$$\theta = \{\theta_3, \theta_4, \cdots \theta_L\},$$

where L is the number of disjoint nodes in the image. We now define spatial similarity measure for the j_{th} image X_j to the given query image Q by (see fig 9)

$$\begin{aligned} SIM\_Graph &= \sum_{m=3}^{m=\min(L,L^{'})} w_m \mid \sin(\theta_m - \theta_m^{'}) \mid + \\ & \sum_{m=\min(L,L^{'})+1}^{\max(L,L^{'})} w_m, \end{aligned} \quad (3)$$

where L and $L^{'}$ are the number of nodes for the two images to be matched, and w_m is the weight based on the areas of the nodes. The weight w_m is chosen as

$$w_m = \frac{A_m + A_m^{'}}{\sum_{l=1}^{\max(L,L^{'})} A_l + A_l^{'}},$$

where A_m and $A_m^{'}$ are the areas of the m_{th} nodes for the database and query images, respectively. When the two images do not have the same number of nodes, we append a number of zero mass nodes to the SRG with lower number of nodes so that both the SRGs have the same number of nodes and the weights w_m can be calculated. The use of area of each component to define the weights in equation 3 helps us in assigning more weights to the larger components as these larger components play a bigger role in defining the similarity between the images.

We use the sine function for the similarity measure to handle the modulo 2π nature of θ. We define the overall similarity measure by integrating the shape and the spatial relation similarities with appropriate weights. The total similarity $TSIM(X_j, Q)$ measure for the j_{th} image X_j to a given query image Q is given by

$$\begin{aligned} TSIM(X_j, Q) &= SIM\_Shape(X_j, Q) + \\ & \beta SIM\_Graph(X_j, Q), \end{aligned} \quad (4)$$

where β is the relative weight assigned to the spatial similarity.

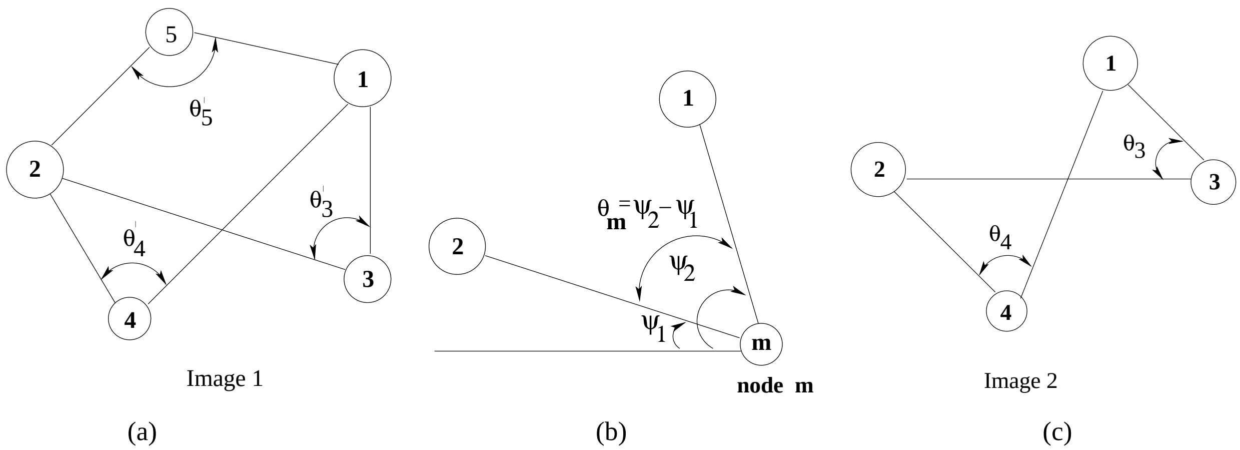


Figure 9: Illustration of SRG representation. (a) An SRG for an image with five disjoint components, (b) Illustration of how the angles are defined. (c) SRG of another image to illustrate how the matching is performed (see text).

In summary, the spatial relation has the following characteristic features. It can be computed very easily and follows the linear time complexity and compares favorably with existing methods. It may be noted from equation 3 that we are actually not doing any graph matching. The nodes of the SRGs of two images are matched based on their labels and the labels are assigned based on the relative size of the components in the image. Ideally one may want to perform an exhaustive search for all possible pairs of nodes in the SRGs for matching the MPSs. Although it is computationally more expensive, an exhaustive search would be expected to yield a better retrieval. However, experimental results show that the gain in retrieval precision is quite marginal when one uses an exhaustive search. On evaluating the retrieved results, we realize that the area of a component is probably as important as its shape (captured by the MPS) to claim that two images are quite similar. Hence we refrain from doing an exhaustive search in this paper.

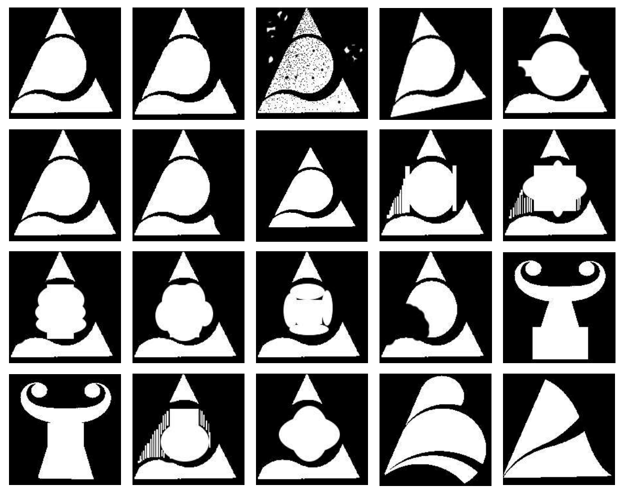


Figure 10: Retrieved images due to all four structuring elements.

4 Experimental Results

Our ground-truthed test image database consists of 200 different binary image datasets. Each image in the dataset contains 25 similar images. This database is downloaded from secured ftp site ftp.cse.msu.edu/pub/prip/database/trademark.tar.gz". We ran extensive experiments for various queries on this binary logo test image database. We conducted experiments considering initially only the shape similarity and then combining it with the spatial similarity. The first image in each result is the query itself. Ranking begins in all the cases after the query image and it follows from left to right and top to bottom.

4.1 Use of shape similarity alone

We initially performed experiments considering an individual structuring element (SE) to extract the shape feature due to a single SE.

Although morphological operations are not rotation invariant, in all the experimental results we also find the rotated images as the relevant retrievals. Since the logo in the database is rotated by a small amount (about 10^o), its MPS does not differ significantly from the MPS of the query logo.

The experimental results for retrieval using a single SE indicate a low retrieval efficiency of our scheme. Therefore we integrated the contributions of all these SEs and the corresponding results are shown in fig 10. Despite integrating the contributions we find a few irrelevant retrievals having rank 14 and 15 (see fig 10). We

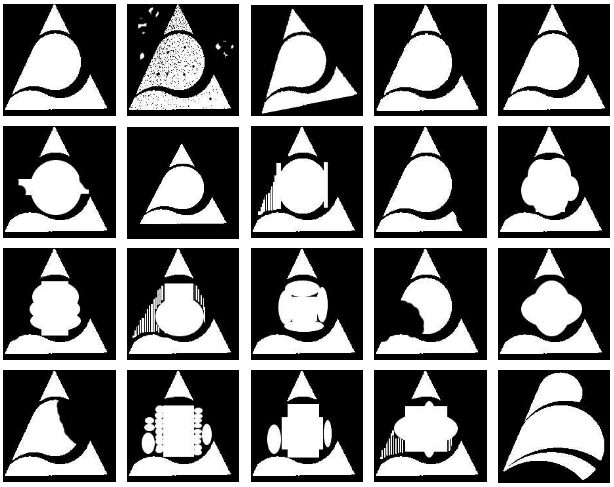


Figure 11: Retrieved images using relevance feedback based on only shape similarity.

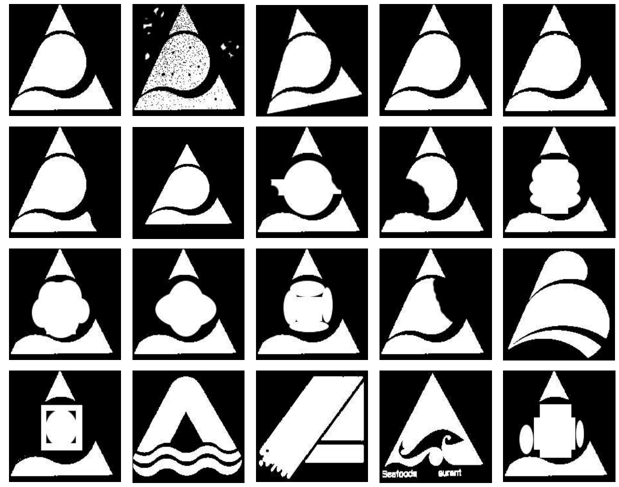


Figure 12: Retrieved images using both shape and spatial neighborhood similarity.

then adopted a relevance feedback mechanism to obtain optimum weights (α_1=0.13(square), α_2=0.10(circle), α_3=0.44(triangle), α_4=0.33(rotated triangle)). The results of retrieval after the relevance feedback is given in fig 11. We observe that most of the retrievals, barring the 11th, 16th and 17th retrievals are quite relevant. Hence, we use the spatial similarity also to improve on our retrieval results.

4.2 Use of both shape and spatial similarity

We conducted experiments incorporating the spatial neighborhood similarity along with shape similarity to retrieve more number of relevant logos which are similar in both the shape and the spatial relation. Experimental results (see fig 12) indicate that the top 18 retrieved logos match perfectly with the query logo. A few irrelevant images do exist but they have much poorer rank. Figure 13 shows the shape similarity results for a second query image. We notice that the retrieved list not only contains relevant images but also some irrelevant images. After incorporating spatial similarity, we obtain more relevant retrievals (see fig 14). This has improved the overall retrieval efficiency of our scheme. These results indicate the need for both the shape and spatial features to obtain a favorably good retrieval accuracy.

Figure 15 describe these experimental results for another query image. Since both these query images have a single component, there is no need for spatial similarity. The obtained results are quite good in terms of retrieval accuracy.

4.3 Retrieval accuracy

In [13] Jain *et al.* address some of the features of an efficient CBIR system such as accuracy, stability and speed. The retrieval evaluation in all these cases is performed using standard evaluation benchmarks such as precision and recall rates [2]. Let x_1 be the number of images retrieved in top 20 positions that are close to the query. Let x_2 represent the number of images in the database similar to the query. Evaluation standards $recall$ and $precision$ are defined as follows:

$$\text{Recall} = \frac{x_1}{x_2} \times 100\%$$

$$\text{Precision} = \frac{x_1}{20} \times 100\%$$

The precision-recall curves for different structuring elements are shown in fig 16(a). The search performance in each case is not as significant as the case when the contributions of all the SEs are considered. We notice a peak search performance when both the spatial relation and shape attributes are considered. It does perform significantly better than the other methods.

We also compared the performance of two different relevance feedback mechanisms. As discussed in section 2.4, we found two different relevance feedback methods, namely Rui-Huang's method [28], and Jin-King-Li method [16], suitable for the current application. The corresponding precision-recall rates are shown in fig 16(b). Although both the methods offer a similar nature of the curves, the Jin-King-Li method [16] yielded better results and hence this method of relevance feedback is adopted in this study for all further analysis.

We now compare the performance of the proposed method with three recently proposed retrieval schemes [10, 34, 3]. The recall rates for all these methods are given in fig 17(a) and this shows that the proposed method offers

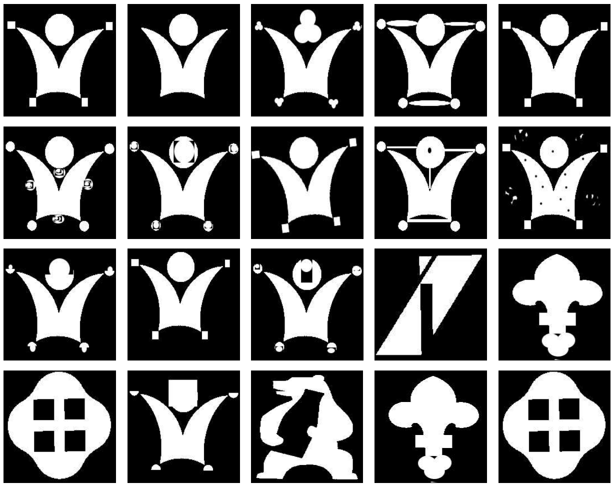


Figure 13: Retrieved images for a second query using the shape similarity alone.

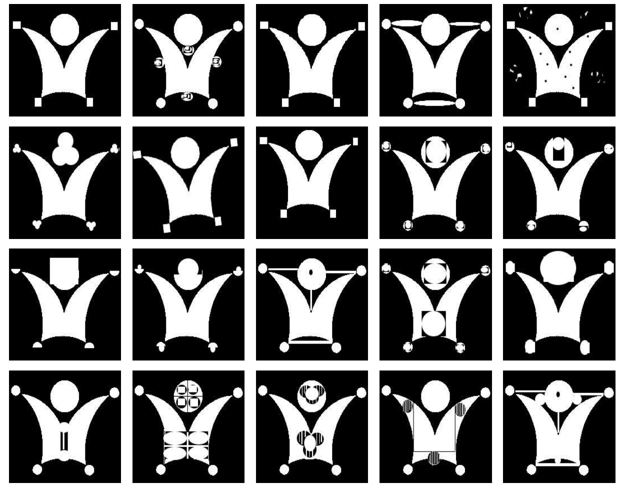


Figure 14: Retrieved images using the shape and the spatial neighborhood similarity for the second query image.

a better accuracy. We argue that these schemes [10, 34, 3] lack some distinguishability features which reduce the retrieval accuracy. Although the curvature scale space representation of contour in [3] extracts the shape features at multiple scales, it lacks the description of structural information of edges and global features of the edge curve. The shape descriptor in [34] relies on several special edges in the images, which may not furnish the appropriate shape description of an object. Both the retrieval schemes in [3, 34] follow an one-to-one matching strategy while computing the similarity measure, which is usually harmful to retrieval process. Although one obtains quite promising results with the shape based retrieval scheme [10], it may not be an appropriate approach when the logo has multiple disjoint components. To overcome the disadvantage of [10] we combine the spatial relation attribute with the shape attribute to obtain the highest retrieval accuracy.

4.4 Computational efficiency

The retrieval time primarily depends on the size of the image database, the software and the hardware versions that system runs on, size of the feature vector, and the similarity measure used. We implemented our scheme under a Linux-9.0 platform. We used a Pentium-4 2.0GHz PC with 512MB DRAM as the main memory. Implementation software includes both C and MATLAB codes. We computed the retrieval time for every image in the database as a query. In the proposed approach maximum size of the shape feature vector is N_i and maximum spatial feature vector size is $(r-2)$ where r is the number of logo components. The value of N_i depends on the median size of the logo in the database. Therefore the length of the feature vector is $(r\sum_i^4 N_i + r - 2)$. The summation refers to the use of four different structuring elements. The proposed approach was found to require an average time of 0.3s for retrieval. We compare the computational time requirement of the proposed method with those of [10, 34, 3]. Fig 17(b) shows the average retrieval time for all the four approaches. This figure clearly shows the usefulness of the proposed method.

In summary, we conducted extensive experiments on the ground-truthed test database. To test the robustness of our approach we have used every image in the dataset to serve as a query image. We obtained favorably good results in all the cases. The retrieval time of our approach is considerably less in comparison to the two approaches [10, 3] and is marginally better than that of the approach in [34]. These observations provide appropriate validation to the usefulness of our scheme.

5 Conclusions

In this paper, we presented a robust and efficient logo retrieval scheme using shape and spatial relation attributes. Here we showed how multiple kernel based morphological pattern spectrum can be used as an effective shape feature descriptor by considering four different standard kernel shapes. When an image contains multiple disjoint components, we exploited the spatial relation among the components with a simple computationally inexpensive representation technique. We also demonstrated an effective retrieval of the logos by combining the shape attribute with the spatial relation attribute. Proper selection of weights using an appropriate relevance feedback mechanism has been suggested. The performance of the proposed technique has been shown to be better than those of different recent retrieval schemes. Translation , and scaling invariance properties of our scheme have been demonstrated. The working

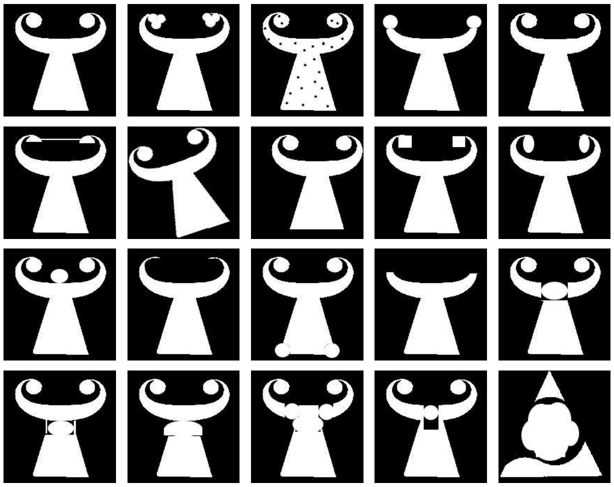


Figure 15: Retrieved images for yet another query based on shape similarity.

of the technique in presence of noise has also been demonstrated. We also show that the proposed technique is computationally very efficient compared to some of the recent CBIR methods. In future we would like to study the usefulness of other types of similarity measures for the retrieval purposes. Currently we are investigating the logo retrieval problem in gray scale and colored logo databases.

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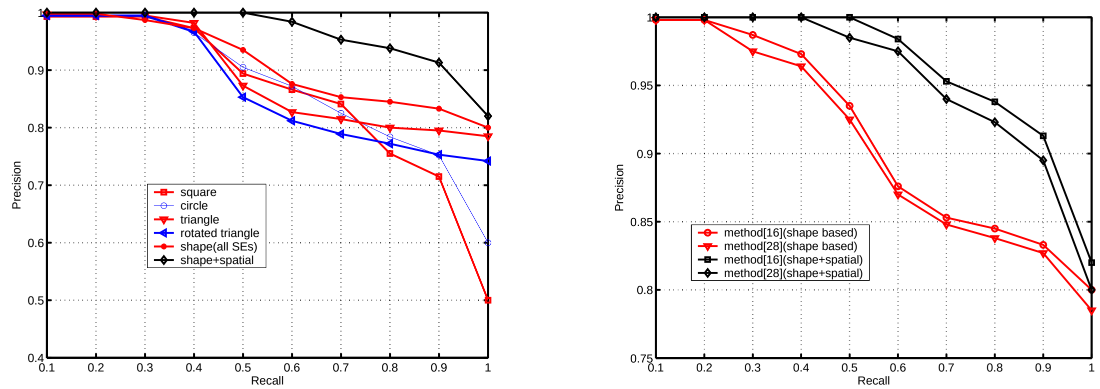
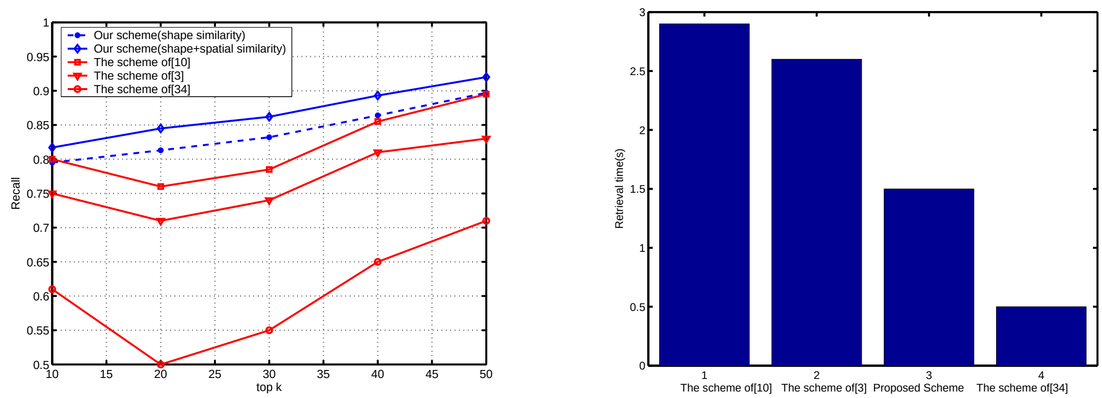


(a) (b)

Figure 16: (a) Precision/recall diagram for logo retrieval using various shape primitives, (b) Precision/recall diagram for two different relevance feedback methods.



(a) (b)

Figure 17: (a) Comparison of retrieval accuracy of the proposed scheme with three other methods, (b) Retrieval time comparison of the four approaches.

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