ABSTRACT
In this paper we propose a scale invariant approach to capture the shape and spatial relation attributes in binary images (logos) to build an efficient logo retrieval system. We extract the shape feature using the morphological pattern spectrum for various structuring elements. The spatial relation feature is represented by computing the difference of angles made by the two largest components of an image with the rest of the objects. The joint shape and spatial relation features enable us to get good precision and recall rates.

I. INTRODUCTION

Content based image retrieval systems retrieve the images based on visual features like color, texture, shape, etc. Most of the recent work in the image retrieval has concentrated on developing a single or a combination of the features like color, shape, texture, etc. In [1] authors extracted the color feature using the color histogram technique. Shape is also an important feature that describes the presence of specific types of objects in scene. Hence researchers have explored the usefulness of shape feature in CBIR applications. Authors in [2] have shown that the shape and the size of an object can be described by morphological pattern spectrum (MPS). Kosir and Talsic in [3] proved the translation, scale, rotation invariance properties of the pattern spectrum. A shape based trade mark retrieval technique has been proposed in [4]. The histogram of the edge directions and invariant moments have been used to describe the global shape information.

Earlier research works on logo retrieval are mostly based on the shape features [4]. Although the morphological pattern spectrum (MPS) has been used in literature [3] for shape detection, we find a moderate success and notice that there is enough scope for improving the shape detection performance. We also find that no one has looked into efficient shape representation technique by studying the morphological pattern spectral characteristics due to different standard kernel shapes (structuring element). In this paper we address the selection issue of standard kernel shapes and the MPS of a logo due to these kernels. One advantage of multiple kernels based MPS over moment based methods is in the extraction of precise shape information as soon as the selected kernel completely inscribes the object. For an effective shape recognition, the MPS feature vectors due to four structuring elements (SE) such as square, circle, triangle, and rotated triangle are computed and integrated with appropriate weights. The shape based methods fail to yield good results when there are multiple (disjoint) components in the image. Therefore we incorporate spatial similarity also to achieve an effective retrieval. Spatial feature is an angle vector, elements of which are angles measured with respect to the largest two components in an image. This spatial relation descriptor is combined with shape descriptor in terms of similarity measures with suitable weights. Proper weights are chosen using a relevance feedback mechanism to improve the precision rate. The proposed technique is scale invariant and performs well even in presence of noise. We show that our precision and recall rates compare very favorably with those of other logo retrieval schemes.

II. RETRIEVAL USING MPS

II-A. Pattern spectrum

In signal processing spectral content of a signal \( f(t) \) can be extracted from the Fourier transform. Here the pattern \( e^{-j\omega t} \) probes into the signal \( f(t) \) to get the spec-
Fig. 1. Pattern spectrum of a logo image due to a square shaped structuring element.

Fig. 2. Scaled logo of fig 1 and its PS due to the same structuring element.

Fig. 3. A Noisy logo, the dilated noisy logo and its PS due to the square structuring element.

Thus the pattern spectra are normalized with respect to scale such that they all have the same size of the maximum inscribable structuring element. This is illustrated in fig 2. These results show that our approach is scale invariant.

When an image contains multiple components, we decompose the image using connected component labeling algorithm. Now we extract the disjoint feature of each decomposed image object by computing its pattern spectrum. When the image components are varying in size, pattern spectra are normalized with respect to scale of the largest component in the query image.

We also considered some noisy logo images in the database. The shape feature vectors of such images are computed after preprocessing. During preprocessing we dilate these images appropriately before computing the PS. One such noisy logo image is shown in fig 3. The dilated image and its PS due square structuring element is shown in fig 3. This shows that the PS broadly remains unchanged even in the presence of noise.

II-C. Similarity measure

We measure the distance between the query feature vectors of the image and database image using $L_2$ norm. The distance of $j_{th}$ image for $i_{th}$ structuring element can be computed using the following equation

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

Where $N_i$ denotes the length of pattern spectrum after scale normalization and $PS_i$ is the pattern spectrum of
the query image due to \( i_{th} \) structuring element. However, since the largest value in the pattern spectrum characterizes the shape of the logo, the largest value is emphasized and smaller values are deemphasized. This is achieved by modifying the distance function as

\[
d_{ij} = \sqrt{\sum_{n=1}^{n=N} w_i(n) \ast (PS_{ij}(n) - PS_i(n))^2}
\]

where \( w_i(n) = \exp^{-S(1-\frac{n}{n})} \) and \( S \) is a non-negative control variable called the slope factor which emphasizes the shape feature appropriately.

We now need to consider the distance metric for four different structuring elements \( i \). Hence the similarity feature is given by

\[
SIM(X_j, Q) = \sum_{i=1}^{i=4} \alpha_i d_{ij}
\]

(2)

Where \( \alpha \) is an appropriate weight for \( i_{th} \) PS and \( Q \) is the query image.

**II-D. Relevance feedback**

We used the relevance feedback [5] mechanism to minimize the number of irrelevant images in the ranklist. Here we consider top N number of images from the ranklist due to \( SIM(X_j, Q) \). We update the weights \( \alpha_i \) in equation 2 for each structuring element by adding score of +1 if an image in ranklist due to \( d_{ij} \) exists in the ranklist due to \( SIM(X_j, Q) \). Otherwise a score of -1 is assigned.

**III. INCLUSION OF SPATIAL SIMILARITY**

Spatial relation is also another important image attribute, that need 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. The use of the PS for individual components, as discussed in section II, does not consider the spatial similarity of relative position of components during retrieval. This inspired us to use the spatial relation feature in addition to using the shape feature vector. In our scheme we implemented a new measure for spatial similarity. An example of spatial relation among the objects is shown in fig 4. Our new spatial representation is just an angle vector given by the following elements (see fig 4) \( \Theta = \{\Theta_3, \Theta_1, \cdots, \Theta_L\} \), where \( L \) is the number of disjoint nodes in the image and \( \Theta \) is geometrical attribute of the binary image. The angles are

![Image 1 and Image 2 with angles labeled](attachment:image.png)

**Fig. 4. Illustration of spatial relations among the image components.**

defined with respect to the centroids of the largest two components as the consideration for spatial similarity is useful only when there are at least three components in the image. We now need to define spatial similarity measure for the \( j_{th} \) image \( X_j \) to given query by

\[
s_j = \sum_{m=3}^{m=L} \sin(\theta_m - \theta'_m) \mid w_m
\]

where \( w_m \) is the weight based on the areas of the nodes. \( \theta_m \) is the angles introduced by the \( m_{th} \) node of the database logo and \( \theta'_m \) is that of the query logo. The weight \( w_m \) is given by

\[
\frac{A_m}{\sum A_m}
\]

for example, where \( A_m \) is the area of \( m_{th} \) node. \( \sum A_m \) is sum of the areas of the nodes 3, \cdots, \( L \).

We define the over all similarity measure by integrating the shape and the spatial relation similarities with appropriate weights. The total similarity measure for \( j_{th} \) image \( X_j \) to a given query image \( Q \) is given by

\[
T.SIM(X_j, Q) = SIM(X_j, Q) + \beta s_j.
\]

where \( \beta \) is the weight assigned to the spatial similarity.

As discussed in II we apply relevance feedback mechanism to update the weights to minimize false positives.

**IV. EXPERIMENTAL RESULTS**

Our benchmark for retrieval evaluation is from MSU USA. In order to evaluate the performance of the proposed method, we conducted extensive experiments for various queries on a binary logo image database of size 2000. To assess the retrieval effectiveness, we
computed the precision recall rates. The precision rate is defined as the fraction of the retrieved images which are relevant and recall rate is the fraction of the relevant images which have been retrieved. In all experimental results image displayed first is the query itself and ranking begins after the query and it goes from left to right and top to bottom.

**IV-A. Use of shape similarity**

We performed experiments on each test group to extract the shape feature due to each SE. Using equation 2 we integrated contributions of all SEs. We choose the appropriate weights using a relevance feedback mechanism. The results obtained after applying relevance feedback mechanism are found to be satisfactory as shown in fig 5. Even then images which are not spatially similar are predominating with higher rank. Therefore we prefer to combine spatial relation to obtain promising results. Experimental results for second test group are shown in fig 7. Therefore experimental results show that when the logo has no disjoint components shape based retrieval scheme is more suitable.

**IV-B. Use of shape and spatial similarity**

Although some logos with ranking 5,9,14,15,16,19 (see fig 5) look similar to the query, they do not have spatial similarity in terms of number of components or appear with the higher rank in the rank list. Therefore experimental results for the query image of fig 1 using both the shape and spatial neighborhood similarities are shown in fig 6. Results show that images with three components and having a similar shape have higher ranking compared to the images having more than three components. For example logos with rank 5, 9, 14, and 15 in fig 5 now appear with rank 20, 19, 18, and 17, respectively in fig 6. The logo with rank 17 appears with rank 12 and logo with rank 16 is expelled from the rank list. Although the logos are not completely relevant to query, they preserve approximate spatial and shape similarity. Shape based retrieval results due to second query in fig 7 indicate that images with rank 9-15, 17, 19, and 20 lack spatial similarity. We notice from the results in fig 8 that by incorporating spatial relation one can obtain favourably good results.

**IV-C. Retrieval accuracy**

The precision-recall curves for different structuring elements are shown in fig 9. The search performance in each case is not as significant as when the all SEs are integrated. However the peak search performance is achieved when we consider the spatial relation attribute with the shape attribute as be seen in fig 9. It performs significantly better than the existing methods.

We now compare the performance of the proposed scheme with other existing binary image retrieval methods. Although the curvature scale space representation of contour in [6] 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 [7] relies on several special edges in the images, which may not furnish the appropriate shape description of an object. Despite the shape-based retrieval scheme in [8] comes out with promising results, it may not be an appropriate approach when the logo has disjoint multiple components. It is evident from (see fig 10) shape-spatial relation experimental results that the proposed approach has favourably good retrieval accuracy. Retrieval scheme of [7] has the lowest accuracy.

V. CONCLUSION

In this work, we presented an efficient logo retrieval scheme using shape and spatial relation attributes. Here we showed how morphological pattern spectrum can be used as an effective shape feature descriptor by considering four different structuring elements. When an image contains disjoint components, we incorporated spatial relation attribute using a simple computationally inexpensive technique. Proper selection of weights using relevance feedback mechanism has also been shown. Scale invariance property of our scheme has also been demonstrated as well. The detailed search performance in comparison with the three recent retrieval schemes is provided.

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REFERENCES