Image Database Design Based on 9D-SPA Representation for Spatial Relations

Po-Whei Huang and Chu-Hui Lee

Abstract—Spatial relationships between objects are important features for designing a content-based image retrieval system. In this paper, we propose a new scheme, called 9D-SPA representation, for encoding the spatial relations in an image. With this representation, important functions of intelligent image database systems such as visualization, browsing, spatial reasoning, iconic indexing, and similarity retrieval can be easily achieved. The capability of discriminating images based on 9D-SPA representation is much more powerful than any spatial representation method based on Minimum Bounding Rectangles or centroids of objects. The similarity measures using 9D-SPA representation provide a wide range of fuzzy matching capability in similarity retrieval to meet different user's requirements. Experimental results showed that our system is very effective in terms of recall and precision. In addition, the 9D-SPA representation can be incorporated into a two-level index structure to help reduce the search space of each query processing. The experimental results also demonstrated that, on average, only 0.1254 percent $\sim$ 1.6829 percent of symbolic pictures (depending on various degrees of similarity) were accessed per query in an image database containing 50,000 symbolic pictures.

Index Terms—Image database, spatial relations, similarity retrieval, 9D-SPA, visualization.

1 INTRODUCTION

A pictorial database plays an important role in many applications including geographical information systems, computer aided design, office automation, medical image archiving, and trademark picture registration. The traditional approach to image database design is to use textual descriptions to annotate images and then store annotations in a text-based data base management system. Searching for desired images is equivalent to searching for the associated annotations. This approach is too tedious and labor-intensive. Moreover, the key words used in annotations or query descriptions are too subjective and may become inadequate, especially when the number of images in the database increase tremendously.

Content-based image retrieval (CBIR) is the current trend of designing image database systems as opposed to text-based image retrieval [7], [11], [14], [18], [23], [24], [25], [27]. The features used in content-based image retrieval can be roughly divided into two categories: the low-level visual features (such as color, texture, and shape) and the high-level features (such as pairwise spatial relationships between objects). Some examples of content-based image retrieval systems are QBIC [8], Virage [1], Retrieval Ware [29], VisualSEEK [26], WaveGuide [17], and Photobook [21]. They allow users to retrieve similar pictures from a large image database based on low-level visual features. On the other hand, there is also a large group of researchers

emphasizing image retrieval based on spatial relationships between objects [3], [4], [5], [10], [15], [16], [20], [22], [28]. In this paper, we only concentrate on iconic picture retrieval based on spatial relations where the number of icons in the database are fixed and each object in a picture must match an icon.

The method of representing images is one of the major concerns in designing an image database system. The representation method for an image should capture the knowledge about the image's content as much as possible. One way of representing an image is to construct a symbolic picture for that image which in turn is encoded into a 2D-string [5]. The 2D string representation method opened up a new approach to spatial reasoning, picture indexing, and similarity retrieval. There are many follow-up research works based on the concept of 2D string such as 2D C-string [15], [16], and 2D C⁺-string [9].

An ideal representation method for symbolic pictures should provide image database systems with many important functions such as similarity retrieval, visualization, browsing, spatial reasoning, and picture indexing. In this paper, we propose a new scheme for encoding spatial relations called 9-Direction SPanning Area (9D-SPA) representation method. Using the 9D-SPA representation, we can easily accomplish the following system design goals:

1. Iconic pictures can be easily reconstructed from 9D-SPA representations for visualization.
2. Flexibility and accuracy in similarity retrieval can be achieved at the same time through a set of coarse-to-fine similarity measures.
3. The 9D-SPA representation can be incorporated into an efficient index structure so that the search space will be restricted to a relatively small portion of the database for improving retrieval efficiency.

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The remainder of this paper is organized as follows: In Section 2, previous research works about knowledge representations for spatial relations are discussed. In Section 3, the 9D-SPA representation is introduced. In Section 4, we propose a visualization method for 9D-SPA representation. The algorithm of decoding the 9D-SPA representation for picture reconstruction is also presented in this section. Spatial reasoning and interpretation based on a 9D-SPA representation are presented in Section 5. In Section 6, we define a set of similarity measures for fuzzy matching. We also introduce an index structure based on 9D-SPA representation to facilitate image retrieval. The similarity retrieval algorithm is presented in this same section. The experimental results for demonstrating the efficiency and effectiveness of our approach are presented in Section 7. Finally, conclusions are given in the last section.

2 OVERVIEW OF SPATIAL KNOWLEDGE REPRESENTATION

Binary spatial relationships between objects have been identified as one of the most important features for describing the contents of images [6]. For example, a query such as “finding all the pictures containing a house to the east of a tree” relies on spatial relations to retrieve the desired pictures. Different kinds of spatial knowledge representations have been proposed so far. Chang et al. [5] proposed the 2D string as a spatial knowledge representation to capture the spatial information about the content of a picture. The fundamental ideal of 2D string is to project the objects of a picture along the x and y -directions to form two strings representing the relative positions of objects in the x and y -axis, respectively. Since a 2D string preserves the spatial relationships between any two objects in a picture, it has the advantage of facilitating spatial reasoning. Moreover, since a query picture [6] can also be represented as a 2D string, the problem of similarity retrieval becomes a problem of 2D string subsequence matching.

Jungert [12], Chang et al. [4], and Jungert and Chang [13] extended the idea of 2D strings to form 2D G-strings by introducing several new spatial operators to represent more relative positional relationships among objects of a picture. The 2D G-string representation embeds more information about spatial relationships between objects and, thus, facilitates spatial reasoning about sizes and relative positions of objects.

Following the same concept, Lee and Hsu [15] proposed the 2D C-string representation based on a special cutting mechanism. Since the number of subparts generated by this new cutting mechanism is reduced significantly, the lengths of the strings representing pictures are much shorter while still preserving the spatial relationships among objects. The 2D C-string representation is more economical in terms of storage space efficiency and navigation complexity in spatial reasoning. The 2D C⁺-string representation [9] extended the 2D C-string representation by adding relative metric information about the picture to the strings. As a consequence, reasoning about relative sizes and locations of

Fig. 1. Spatial reasoning is too sensitive in the 9DLT representation.

objects, as well as the relative distance between objects in a symbolic picture becomes possible.

Chang [3] proposed a structure called 9DLT to encode the spatial relationships between objects in terms of nine directions. Since the 9DLT method uses centroid to represent the position of an object, such a representation is too sensitive in spatial reasoning. For example, the spatial relationships between the two objects shown in Figs. 1a, 1b, and 1c are all different in 9DLT representation; however, they seem not too much different in human visual perception.

The representation of spatial relations proposed by Zhou and Ang [28] combines the nine directional relations proposed in 9DLT with the five topological relations, namely, disjoint, meet, partly_overlap, contain, and inside. The topological relation can record the 2D relationship between any two nonzero-sized objects with irregular shapes and, therefore, makes spatial reasoning more accurate as compared to using MBR or centroid to represent an object. However, Zhou and Ang’s method still has the problem with being too sensitive when reasoning about directional relations.

Instead of combining the nine directional relations with the five topological relations, the 2D-PIR proposed by Nabil et al. [19], [20] combines the 13 projection interval relations with the topological relations. Although 2D-PIR seems particularly useful in similarity retrieval, it did not provide any picture reconstruction mechanism for visualization. Besides, incorporating 2D-PIR into any indexing structure is difficult. Thus, similarity retrieval based on 2D-PIR becomes inefficient if the volume of images in the database increases.

3 9D-SPA REPRESENTATION

To represent a picture using our method, the picture has to be preprocessed first. We assume that the objects in a picture can be identified by some image segmentation and object recognition procedures. Various techniques of image segmentation and object recognition can be found in [2].

Suppose that a picture P contains n objects ($O_1, O_2, \dots, O_n$). Then, the 9D-SPA representation of P can be encoded as a set of 4-tuples: $R = \{(O_{ij}, D_{ij}, D_{ji}, T_{ij}) \mid \forall O_i, O_j \in P, \text{ and } 1 \leq i < j \leq n\}$, where O_{ij} is the code for object-pair (O_i, O_j) , D_{ij} is the code for the direction-relation between objects O_i, O_j with O_j as the reference object, D_{ji} is the code for the direction-relation between O_i and O_j with O_i as the reference object, and T_{ij} is the code for the topological relation between O_i and O_j . It is obvious that the number of 4-tuples in R is $\frac{n(n-1)}{2}$.

TABLE 1
The Codes for Nine Neighborhood Areas of MBR of O_j

Area 4: (00001000) ₂ = 8	Area 3: (00000100) ₂ = 4	Area 2: (00000010) ₂ = 2
Area 5: (00010000) ₂ = 16	Area 0:(MBR of O_j) (00000000) ₂ = 0	Area 1: (00000001) ₂ = 1
Area 6: (00100000) ₂ = 32	Area 7: (01000000) ₂ = 64	Area 8: (10000000) ₂ = 128

Let O_i be the i th object in the image database ($1 \leq i \leq n$). We assign integer i to object O_i as its object number. Then, O_{ij} is called the *object-pair code* for object-pair (O_i, O_j) . Given two objects O_i and O_j , we can easily compute the object-pair code O_{ij} using the following formula:

$$O_{ij} = \frac{(j-1)(j-2)}{2} + i.$$

To obtain the two object numbers i and j from O_{ij} (or to decode O_{ij}), we use the formula $i = O_{ij} - \frac{a(a+1)}{2}$, where a is the largest integer such that $\frac{a(a+1)}{2} < O_{ij}$ and $j = a + 2$.

D_{ij} represents the value assigned to the directional relationship between objects O_i and O_j with O_j as the reference object. The value of D_{ij} is determined by the following procedure. First, we find the Minimal Bounding Rectangle (MBR) for reference object O_j . Then, we extend the four boundaries of this MBR horizontally and vertically until they cut the whole picture into nine neighborhood areas and then assign each area a binary code as shown in Table 1. The value of D_{ij} is determined by the formula $D_{ij} = \sum_{k=1}^8 b_k w_k$, where w_k is the binary code of neighborhood area k ; $b_k = 1$ if object O_i overlaps area k , otherwise, $b_k = 0$. The value of T_{ij} indicates the topological relationship between objects O_i and O_j . Possible values assigned to topological relations are: 0 (stands for "disjoint"), 1 (stands for "meet"), 2 (stands for "partly_overlap"), 3 (stands for "cover"), and 4 (stands for "contain" or "inside").

Let us look at the two pictures shown in Figs. 2a and 2b. Assume that object B is the reference object in both pictures. Then, in Fig. 2a, the code for D_{AB} is

$$(00001000 + 00010000 + 00100000 + 01000000 + 10000000)_2 = 248$$

and the code for T_{AB} is 0. In Fig. 2b, the code for D_{AB} is

$$(00000001 + 00000010 + 00100000 + 01000000 + 10000000)_2 = 227$$

and the code for T_{AB} is 0. In 2D*-string representations, the pictures in Figs. 2a and 2b are not distinguishable because they have the same spatial representation (i.e., $A\%B$ in both x and y -directions). However, we can easily tell the difference between them by using 9D-SPA representation because D_{AB} in Fig. 2a is 248, while D_{AB} in Fig. 2b is 227. Moreover, from $D_{AB} = 248 = (11111000)_2$, we can easily determine that object A spans five neighborhood areas of object B , namely, the northwest, the west, the southwest, the south, and the southeast neighborhood areas as shown in Fig. 2a. Similarly, from $D_{AB} = 227 = (11100011)_2$, we can easily determine that object A spans another different five neighborhood areas of object B , namely, the northeast, the east, the southeast, the south, and the southwest neighborhood areas as shown in Fig. 2b.

4 VISUALIZATION

In this section, we will describe how to construct a symbolic picture from a 9D-SPA representation. The capability of reconstructing pictures can support visualization and database browsing. Our goal is to construct a symbolic picture from a 9D-SPA representation so that each object in the picture is approximated by its MBR and the spatial relationships among all objects are also preserved. In other words, we need to determine the order of begin and end-positions of each object along the x and y -axis. Because the relative positions of objects in the x -axis are independent of their relative positions in the y -axis, the reconstruction procedure can be performed separately for each direction.

The projection positions of objects in a picture along the x and y -directions can be represented by two directed acyclic graphs $G_x = (V_x, E_x)$ and $G_y = (V_y, E_y)$, called the *Spatial Relation Graphs*. A node in V_x contains one or more variables whose values indicating either the begin or end-positions of objects in the x -direction. Similarly, a node in V_y contains one or more variables whose values indicating either the begin or end-positions of objects in the y -direction. All variables in the same node will be assigned the same position value. For example, if $uv \in E_x$, b_i and e_j are two variables in node u while b_k is a variable in node v , then $b_i = e_j < b_k$.

Given a 9D-SPA representation, we can construct two spatial relation graphs G_x and G_y , which in turn will be used

Fig. 2. Pictures (a) and (b) are not distinguishable in all 2D*-string representations. However, the difference can be easily determined by the 9D-SPA representation.

to construct a corresponding symbolic picture. The algorithm shown below allows us to create spatial relation graphs from a 9D-SPA representation. For convenience of explanation, we use the notations below to describe the algorithm.

- G_x (or G_y): the spatial relation graph for the x -direction (or y -direction).
- b_i^x (or e_i^x): the begin-position (or end-position) of object O_i in the x -direction.
- b_j^y (or e_j^y): the begin-position (or end-position) of object O_j in the y -direction.

Algorithm: Generating spatial relation graphs.

Input: A 9D-SPA representation R .

Output: G_x and G_y .

1. $V_x \leftarrow \emptyset$; $E_x \leftarrow \emptyset$; $V_y \leftarrow \emptyset$; $E_y \leftarrow \emptyset$.
2. $\forall (O_{ij}, D_{ij}, D_{ji}, T_{ij}) \in R$,
 - a. Decode O_{ij} to obtain two object numbers i and j as described in Section 3.
 - b. Create four nodes $B_i^x, E_i^x, B_j^x, E_j^x$ containing variables $b_i^x, e_i^x, b_j^x, e_j^x$, respectively. Create another four nodes $B_i^y, E_i^y, B_j^y, E_j^y$ containing variables $b_i^y, e_i^y, b_j^y, e_j^y$, respectively.
 - c. Compare D_{ij} with the binary codes of the 8 neighborhood areas of O_j to find the projection relations among the begin-positions and end-positions of O_i and O_j along the x -direction. Then, create the edges corresponding to these projection relations among the nodes $B_i^x, B_j^x, E_i^x, E_j^x$ and add them to G_x .
 - d. Similarly, find the projection relations among the begin-positions and end-positions of O_i and O_j along the y -direction. Then, create the edges corresponding to these projection relations among the nodes $B_i^y, B_j^y, E_i^y, E_j^y$ and add them to G_y .
 - e. Exchange indices i and j , then repeat Steps c-d to process D_{ji} .
3. For each cycle C in G_x , use node d to replace all the nodes in C such that
 - a. d has all the variables originally contained in each node in C .
 - b. If there is an in-edge from a node not in C to any node in C , then this edge is redirected to d .
 - c. If there is an out-edge from a node in C to any node not in C , then this edge is modified to originate from d .
4. Remove all cycles from G_y by a similar procedure as described in Step 3.
5. Return G_x and G_y .

Once two spatial relation graphs G_x and G_y have been created from a 9D-SPA representation, we can easily construct a symbolic picture from G_x and G_y as follows:

Algorithm: Picture reconstruction.

Input: G_x and G_y .

Output: A symbolic picture.

1. Find the set of nodes $S_1 \subseteq V_x$ from G_x such that $\forall u \in S_1, u$ has no in-edges.

Fig. 3. A picture containing four objects.

2. $i \leftarrow 1$.
3. $\forall u \in S_1$, assign value i to all the position variables contained in node u and mark u as "inspected."
4. Find the immediate successors of the nodes in S_1 such that they have not been inspected. Let this set be S_2 . If $S_2 = \emptyset$, then go to Step 6.
5. $i \leftarrow i + 1$; $S_1 \leftarrow S_2$. Go to Step 3.
6. Assign values to all position variables contained in G_y by a similar procedure as described in Steps 1-5.
7. For each object O_i , draw the rectangle with (b_i^x, b_i^y) and (e_i^x, e_i^y) as the coordinates of the bottom-left and the top-right corners, respectively.

We use the picture shown in Fig. 3 to illustrate our reconstruction algorithm. The 9D-SPA representation for this image is shown in the first column of Table 2. From each tuple of this 9D-SPA representation, we can determine the nodes and the edges to be added into spatial relation graphs G_x and G_y . For example, if a tuple $(1, 12, 64, 0)$ in the first row of Table 2 is given, the two involved objects are O_1 and O_2 . Thus, the nodes to be added into G_x are B_1^x, E_1^x, B_2^x , and E_2^x . The nodes to be added into G_y are B_1^y, E_1^y, B_2^y , and E_2^y . For $D_{12} = 12$, the edges to be added into G_x are $\overrightarrow{B_1^x B_2^x}, \overrightarrow{B_2^x E_1^x}, \overrightarrow{E_1^x E_2^x}$. The edges to be added into G_y are $\overrightarrow{B_2^y E_2^y}, \overrightarrow{E_2^y B_1^y}, \overrightarrow{B_1^y E_1^y}$. Similarly, for $D_{21} = 64$, the edges to be added into G_x are $\overrightarrow{B_1^x B_2^x}, \overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x E_1^x}$, and the edges to be added into G_y are $\overrightarrow{B_2^y E_2^y}, \overrightarrow{E_2^y B_1^y}, \overrightarrow{B_1^y E_1^y}$. As a consequence, the spatial relation graphs G_x and G_y constructed are shown in Figs. 4a and 4c, respectively. Notice that there exists a cycle in G_x . After removing this cycle from G_x , a new graph is formed as shown in Fig. 4b. From Figs. 4b and 4c, we assign a number to each node of the graphs according to their precedence order. By assigning the node number to all variables contained in that node, we have $b_1^x = 1, b_3^x = 2, b_2^x = 3, e_1^x = e_2^x = 4, b_4^x = 5, e_4^x = 6, e_3^x = 7$, and $b_3^y = 1, b_4^y = 2, e_4^y = 3, e_3^y = 4, b_2^y = 5, e_2^y = 6, b_1^y = 7, e_1^y = 8$. Based on the above information, we can easily reconstruct a picture shown in Fig. 5. Notice that the original picture (Fig. 3) and the symbolic picture reconstructed from the 9D-SPA representation (Fig. 5) are the same in terms of the spatial

TABLE 2
Constructing the Spatial Relation Graphs G_x and G_y

4-tuple	object-pair	D_{ij}	Edges added to G_x and G_y .
(1,12,64,0)	(1,2)	$D_{12}=00001100$	$\overrightarrow{B_1^x B_2^x}, \overrightarrow{B_2^x E_1^x}, \overrightarrow{E_1^x E_2^x}, \overrightarrow{B_2^y E_2^y}, \overrightarrow{E_2^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
		$D_{21}=01000000$	$\overrightarrow{B_1^x B_2^x}, \overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x E_1^x}, \overrightarrow{B_2^y E_2^y}, \overrightarrow{E_2^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
(2,12,192,0)	(1,3)	$D_{13}=00001100$	$\overrightarrow{B_1^x B_3^x}, \overrightarrow{B_3^x E_1^x}, \overrightarrow{E_1^x E_3^x}, \overrightarrow{B_3^y E_3^y}, \overrightarrow{E_3^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
		$D_{31}=11000000$	$\overrightarrow{B_1^x B_3^x}, \overrightarrow{B_3^x E_1^x}, \overrightarrow{E_1^x E_3^x}, \overrightarrow{B_3^y E_3^y}, \overrightarrow{E_3^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
(3,4,224,0)	(2,3)	$D_{23}=00000100$	$\overrightarrow{B_3^x B_2^x}, \overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x E_3^x}, \overrightarrow{B_3^y E_3^y}, \overrightarrow{E_3^y B_2^y}, \overrightarrow{B_2^y E_2^y}$
		$D_{32}=11100000$	$\overrightarrow{B_3^x B_2^x}, \overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x E_3^x}, \overrightarrow{B_3^y E_3^y}, \overrightarrow{E_3^y B_2^y}, \overrightarrow{B_2^y E_2^y}$
(4,8,128,0)	(1,4)	$D_{14}=00001000$	$\overrightarrow{B_1^x E_1^x}, \overrightarrow{E_1^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x B_1^x}, \overrightarrow{E_4^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
		$D_{41}=10000000$	$\overrightarrow{B_1^x E_1^x}, \overrightarrow{E_1^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x B_1^x}, \overrightarrow{E_4^y B_1^y}, \overrightarrow{B_1^y E_1^y}$
(5,8,128,0)	(2,4)	$D_{24}=00001000$	$\overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x B_2^x}, \overrightarrow{E_4^y B_2^y}, \overrightarrow{B_2^y E_2^y}$
		$D_{42}=10000000$	$\overrightarrow{B_2^x E_2^x}, \overrightarrow{E_2^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x B_2^x}, \overrightarrow{E_4^y B_2^y}, \overrightarrow{B_2^y E_2^y}$
(6,255,0,4)	(3,4)	$D_{34}=11111111$	$\overrightarrow{B_3^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x E_3^x}, \overrightarrow{B_3^y B_4^y}, \overrightarrow{B_4^y E_4^y}, \overrightarrow{E_4^y E_3^y}$
		$D_{43}=00000000$	$\overrightarrow{B_3^x B_4^x}, \overrightarrow{B_4^x E_4^x}, \overrightarrow{E_4^x E_3^x}, \overrightarrow{B_3^y B_4^y}, \overrightarrow{B_4^y E_4^y}, \overrightarrow{E_4^y E_3^y}$

relationships (both directional and topological) between any two objects.

5 SPATIAL REASONING AND INTERPRETATION

Since a 9D-SPA representation already contains all pairwise spatial relations between objects of a picture, the spatial reasoning and interpretation process based on 9D-SPA representation becomes very simple and efficient. Given a 4-tuple $(O_{ij}, D_{ij}, D_{ji}, T_{ij})$ of a 9D-SPA representation, the topological relationship such as "dis-joint," "meet," "partly_overlap" between objects O_i and O_j is clearly indicated by the value of T_{ij} . To decide whether a topological relation is either "contain" or "inside," we use the following rules: If $D_{ij} = "11111111"$

and $T_{ij} = 4$, then O_i contains O_j ; if $D_{ji} = "11111111"$ and $T_{ij} = 4$, then O_i is inside of O_j . Furthermore, if $D_{ij} = D_{ji} = "00000000,"$ then O_i coincides with O_j .

The 9D-SPA representation can also decide another three topological relationships which are rarely discussed, but occur quite often in the real world as shown in Fig. 6:

1. Object O_j is surrounded by object O_i if $T_{ij} = 0$ and $D_{ij} = "11111111."$
2. Object O_j is tightly enclosed by object O_i if $T_{ij} = 1$ and $D_{ij} = "11111111."$
3. Object O_j is overlapped with object O_i at the inside boundary of O_i if $T_{ij} = 2$ and $D_{ij} = "11111111."$

To determine the directional spatial relationship between object O_i and O_j from (O_{ij}, D_{ij}, D_{ji}) is quite obvious. Notice

Fig. 4. Spatial relation graphs G_x and G_y for the picture shown in Fig. 3. (a) G_x with a cycle, (b) G_x , and (c) G_y .

Fig. 5. The symbolic picture reconstructed from G_x and G_y shown in Fig. 4.

that D_{ij} indicates the spatial location of object O_i viewed from object O_j , and D_{ji} indicates the spatial location of O_j viewed from object O_i . Without loss of generality, we use O_j as the reference object to interpret D_{ij} .

1. O_i is to the east of O_j if $D_{ij} = "00000001."$
2. O_i is to the northeast of O_j if $D_{ij} = "00000010."$
3. O_i is to the north of O_j if $D_{ij} = "00000100."$
4. O_i is to the northwest of O_j if $D_{ij} = "00001000."$
5. O_i is to the west of O_j if $D_{ij} = "00010000."$
6. O_i is to the southwest of O_j if $D_{ij} = "00100000."$
7. O_i is to the south of O_j if $D_{ij} = "01000000."$
8. O_i is to the southeast of O_j if $D_{ij} = "10000000."$

For more complicated cases, it is not so easy to precisely describe the directional relationship between O_i and O_j if D_{ij} has more than one nonzero bit. Since D_{ij} implies the spanning neighborhood areas of object O_i viewed from object O_j , we simply enumerate all the neighborhood areas spanned by O_i to indicate the directional relationship between O_i and O_j . For example, if $D_{ij} = "00111100,"$ then we say that O_i spans the north, the northwest, the west, and the southwest neighborhood areas of object O_j . If $D_{ij} = "00000011,"$ then object O_i spans the east and the northeast neighborhood areas of object O_j . As we can see, this kind of description and interpretation is general as well as precise for directional spatial relationship between nonzero-sized objects.

In general, the spatial relationship between any two objects is not symmetric. The spatial relationship between objects O_i and O_j viewed from O_j (i.e., D_{ij}) may be different from the spatial relationship between the same two objects

viewed from O_i (i.e., D_{ji}). For example, object O_i spans the east neighborhood area of object O_j ; however, object O_j may span the northwest, the west, and the southwest neighborhood areas of object O_i . In other words, both D_{ij} and D_{ji} are needed in order to determine the spatial relationship between objects O_i and O_j correctly.

6 SIMILARITY RETRIEVAL

In similarity retrieval, the user must present a query picture to match with the database images. One convenient way of presenting a query is to draw a sketch diagram called query picture [6] in which all objects must match some icons in the database. The task of image retrieval is to measure the similarity between the query picture and the database picture, then retrieve relevant pictures from the database. Usually, the user may not remember the exact spatial relationships among the objects in a desired picture. To accommodate this flexibility, the system should provide the user with a set of coarse-to-fine similarity measures to measure the difference between the query picture and the database picture. With a coarse measure, we allow the retrieved images to be slightly different from the query picture. However, the retrieved images still meet the user's requirements in term of user's visual perception.

6.1 Similarity Measures

Before giving detailed definitions for similarity measures, we introduce the following notations first:

- R_p (or R_q): the 9D-SPA representation for picture p (or q).
- t^p (or t^q): a tuple in R_p (or R_q).
- $t.O$: the object-pair code of tuple t .
- $t.D_1$: the directional relation-code, with O_j as the reference object, of tuple t .
- $t.D_2$: the directional relation-code, with O_i as the reference object, of tuple t .
- $t.T$: the topological relation-code of tuple t .
- $t.D_1(j)$ (or $t.D_2(j)$): the j th bit of the binary code of $t.D_1$ (or $t.D_2$).
- $x(k)$: the k th bit of the binary code x (or y).

Let $R_q = \{t_1^q, t_2^q, \dots, t_m^q\}$ and $R_p = \{t_1^p, t_2^p, \dots, t_n^p\}$ be the 9D-SPA representations for query picture q and database picture p , respectively. Let ε be a relation from R_q to R_p . Without loss of generality, we assume that $\varepsilon(t_i^q).O = t_i^p.O$ for $1 \leq i \leq k$ with $k \leq \min\{m, n\}$.

The basic idea of defining a directional similarity measure is explained as follows: Assume that A and B are

Fig. 6. Three special topological relationships.

Fig. 7. A similarity measurement example.

two target objects represented by the same icon and C is a reference object. Let x and y be the directional relation-codes associated with object-pair (A, C) and (B, C) , respectively. Then, the similarity between x and y is measured by the number of neighborhood areas spanned by $A \cap B$ divided by the number of neighborhood areas spanned by $A \cup B$. As a consequence, the directional similarity between two pictures p and q is first measured by summing up the directional similarity between r_1 and r_2 for all r_1 and r_2 (where r_1 is a directional relation in p ; r_2 is a directional relation in q ; r_1 and r_2 have the same target and reference objects, but are in two separate pictures) and then normalizing the measure by the total number of directional relations in both pictures. Thus, the directional similarity measure between R_p and R_q is defined as

$$S_D(R_p, R_q) = \frac{\sum_{i=1}^k s_D(\varepsilon(t_i^q).D_1, t_i^q.D_1) + \sum_{i=1}^k s_D(\varepsilon(t_i^q).D_2, t_i^q.D_2)}{m+n}, \quad (1)$$

where

$$s_D(x, y) = \begin{cases} 1, & \text{if } \sum_{k=1}^8 x(k) \vee y(k) = 0 \\ \frac{\sum_{k=1}^8 x(k) \wedge y(k)}{\sum_{k=1}^8 x(k) \vee y(k)}, & \text{otherwise.} \end{cases} \quad (2)$$

In the above formula, symbol “ $\wedge$ ” (“ $\vee$ ”) represents the logical “AND” (“OR”) operation. Similarly, we define the topological similarity measure between R_p and R_q as follows:

$$S_T(R_p, R_q) = \frac{2 * (\sum_{i=1}^k s_T(\varepsilon(t_i^q).T, t_i^q.T))}{m+n}, \quad (3)$$

where

$$s_T(r_1, r_2) = 1 - \frac{|r_1 - r_2|}{4}. \quad (4)$$

In (4), r_1 and r_2 are the codes for two topological relations. Thus, $|r_1 - r_2|$ represents the distance between them. Our numbering scheme for topological relations reflects the degree of difference among all topological relations. For example, the distance between “disjoint” and “meet” is 1, while the distance between “disjoint” and “partly_overlap” is 2. In a similar way of calculating directional similarity measure, (3) computes the topological similarity between two pictures p and q by considering all corresponding topological relations in both pictures and then normalizing the measure.

Notice that $S_D(R_p, R_q)$ and $S_T(R_p, R_q)$ are undefined if relation ε does not exist (i.e., there is no object pair in query picture q such that the same pair also appears in database picture p). Based on the above two similarity measuring

equations, we provide the following definitions for directional-similarity and topological-similarity.

Definition 1. A database picture p is directionally similar to a query picture q with a degree of similarity s_1 iff $S_D(R_p, R_q) = s_1$.

Definition 2. A database picture p is topological-similar to a query picture q with a degree of similarity s_2 iff $S_T(R_p, R_q) = s_2$.

Now, we use the pictures shown in Fig. 7 to illustrate our similarity measures. The 9D-SPA representations for pictures p_1 , p_2 , p_3 , and p_4 are listed below:

$$R_{p_1} = \{(1, 255, 0, 4), (4, 24, 129, 0), (5, 24, 129, 0)\}.$$

$$R_{p_2} = \{(1, 255, 0, 4), (4, 8, 128, 0), (5, 8, 128, 0)\}.$$

$$R_{p_3} = \{(1, 255, 0, 4), (4, 8, 128, 0), (7, 12, 64, 0), (5, 8, 128, 0), (8, 4, 224, 0), (10, 2, 32, 0)\}.$$

$$R_{p_4} = \{(1, 241, 0, 3), (4, 14, 64, 1), (7, 8, 128, 0), (5, 4, 224, 0), (8, 8, 128, 0), (10, 8, 128, 0)\}.$$

We arbitrarily pick up R_{p_3} and R_{p_1} to illustrate the process of calculating $S_D(R_{p_3}, R_{p_1})$ and $S_T(R_{p_3}, R_{p_1})$. After applying (2) to each tuple in R_{p_1} and the corresponding tuple in R_{p_3} , we obtain the following results:

$$\begin{aligned} s_D(t_1^{p_3}.D_1, t_1^{p_1}.D_1) &= 1, & s_D(t_2^{p_3}.D_1, t_2^{p_1}.D_1) &= 1/2, & s_D(t_4^{p_3}.D_1, t_3^{p_1}.D_1) &= 1/2, \\ s_D(t_1^{p_3}.D_2, t_1^{p_1}.D_2) &= 1, & s_D(t_2^{p_3}.D_2, t_2^{p_1}.D_2) &= 1/2, & s_D(t_4^{p_3}.D_2, t_3^{p_1}.D_2) &= 1/2. \end{aligned}$$

Thus, the similarity measure $S_D(R_{p_3}, R_{p_1})$ is

$$\begin{aligned} & \frac{\sum_{i=1}^3 s_D(\varepsilon(t_i^{p_1}).D_1, t_i^{p_1}.D_1) + \sum_{i=1}^3 s_D(\varepsilon(t_i^{p_1}).D_2, t_i^{p_1}.D_2)}{3+6} \\ &= \frac{4}{9} = 0.44. \end{aligned}$$

By applying (4) to each tuple in R_{p_1} and the corresponding tuple in R_{p_3} , we obtain the following results:

$$s_T(t_1^{p_3}.T, t_1^{p_1}.T) = 1, \quad s_T(t_2^{p_3}.T, t_2^{p_1}.T) = 1, \quad s_T(t_3^{p_3}.T, t_3^{p_1}.T) = 1.$$

Thus, the similarity measure $S_T(R_{p_3}, R_{p_1})$ is

$$\frac{2 * (\sum_{i=1}^3 s_T(\varepsilon(t_i^{p_1}).T, t_i^{p_1}.T))}{3+6} = \frac{2 * 3}{9} = 0.67.$$

Similarly, we calculate the similarity measures between picture p_1 and pictures p_2 and p_4 :

$$\begin{aligned} S_D(R_{p_2}, R_{p_1}) &= 0.67, & S_T(R_{p_2}, R_{p_1}) &= 1, \\ S_D(R_{p_4}, R_{p_1}) &= 0.24 & S_T(R_{p_4}, R_{p_1}) &= 0.56. \end{aligned}$$

Fig. 8. An example of index structure for a pictorial database.

As a result, we can say that picture p_2 is directionally similar to picture p_1 with a degree of similarity 0.67. Picture p_3 is directionally similar to picture p_1 with a degree of similarity 0.44. Picture p_4 is directionally similar to picture p_1 with a degree of similarity 0.24. Picture p_2 is topological-similar to picture p_1 with a degree of similarity 1. Picture p_3 is topological-similar to picture p_1 with a degree of similarity 0.67. Picture p_4 is topological-similar to picture p_1 with a degree of similarity 0.56. As compared to the pictures shown in Fig. 7, the similarity measures calculated by the system are consistent with what we expected.

6.2 Index Structure

The 9D-SPA representations of database pictures can be incorporated into a two-level index structure to facilitate image retrieval. An example of such an index structure is shown in Fig. 8. There are two levels of indices in this index structure based on 9D-SPA representation. The first-level index, called the *level-1 index array*, is an array of size $\frac{n(n-1)}{2}$, where n is the number of distinct objects in the database. Each entry in this array may contain two pointers. One points to a list of directional relation-codes, called “direction-code list.” The other points to an array of size 5, called “topological relation array.” Each item in a direction-code list is an array of four elements: the first element is the directional relation-code D_{ij} ; the second one is the directional relation-code D_{ji} ; the third one is a pointer to a list of database images having directional relation-codes D_{ij} and D_{ji} ; the fourth one is a pointer to the next item in the current direction-code list. Each entry in a topological relation array corresponds to one type of topological relations and may contain a pointer to a list of database images. For example, in Fig. 8, the tuple (4, 14, 64, 1) will be mapped to image p_4 according to our indexing scheme. In other words, image p_4 must contain objects O_1 and O_4 because object-pair code 4 is decoded into object codes 1 and 4; Object O_1 is to the northeast or north or northwest of object O_4 because directional relation-code 14 is decoded into “0000010” $\vee$ “00000100” $\vee$ “00001000;” Object O_4 is to south of object O_1 because directional relation-code 64 is decoded

into “01000000;” and the topological relationship between objects O_1 and O_4 is “meet” because $T_{1,4} = 1$.

6.3 Image Retrieval Algorithm

The index structure helps reducing the search space of query processing. The algorithm of retrieving similar images based on 9D-SPA representation and the two-level index structure is presented as follows:

Algorithm: Similarity retrieval.

Input: A 9D-SPA representation R_q for query picture q and two thresholds h_D and h_T .

Output: $\{p | p \text{ is a database picture such that } S_D(R_p, R_q) \geq h_D \text{ and } S_T(R_p, R_q) \geq h_T\}$.

1. $\forall$ tuple $t = (O_{ij}, D_{ij}, D_{ji}, T_{ij}) \in R_q$
 - a. Find the direction-code list L and topological relation array M associated with O_{ij} from the level-1 index array.
 - b. If $h_D = 1$, then traverse the list L to find the set Γ'_t of images associated with items I in L such that the two directional relation-codes in I are D_{ij} and D_{ji} .
 - c. If $h_T = 1$, then obtain the set Γ''_t of images associated with $M[T_{ij}]$.
 - d. If $h_D \neq 1$ and $h_T \neq 1$, then collect all the images pointed by $M[u]$ with $0 \leq u \leq 4$ and store them in Γ''_t .
2. Case of
 - a. $h_D = 1$ and $h_T = 1$: $\Gamma \leftarrow (\cap_{t \in R_q} \Gamma'_t) \cap (\cap_{t \in R_q} \Gamma''_t)$.
 - b. $h_D = 1$ and $h_T \neq 1$: $\Gamma \leftarrow \cap_{t \in R_q} \Gamma'_t$.
 - c. $h_D \neq 1$ and $h_T = 1$: $\Gamma \leftarrow \cap_{t \in R_q} \Gamma''_t$.
 - d. Otherwise: $\Gamma \leftarrow \cup_{t \in R_q} \Gamma''_t$.
3. If $h_D \neq 0$, then

$\forall p \in \Gamma$, if $(S_D(R_p, R_q) < h_D)$, then remove p from Γ .

4. If $h_T \neq 0$, then

$\forall p \in \Gamma$, if $(S_T(R_p, R_q) < h_T)$, then remove p from Γ .

5. Sort Γ by using $S_D(R_p, R_q)$ as the primary key and $S_T(R_p, R_q)$ as the secondary key in descending order.

6. Return Γ .

We use the index structure in Fig. 8 to illustrate our similarity retrieval algorithm. The index structure contains the pictures shown in Fig. 7. Assume that the 9D-SPA representation for query picture q is $R_q = \{t_1, t_2, t_3\} = \{(1, 255, 0, 4), (4, 24, 129, 0), (5, 24, 129, 0)\}$ and the similarity requirement is $(h_D, h_T) = (1, 1)$. Therefore, we obtain $\Gamma'_{t_1} = \{p_1, p_2, p_3\}$, $\Gamma'_{t_2} = \{p_1\}$, $\Gamma'_{t_3} = \{p_1\}$, $\Gamma''_{t_1} = \{p_1, p_2, p_3\}$, $\Gamma''_{t_2} = \{p_1, p_2, p_3\}$, and $\Gamma''_{t_3} = \{p_1, p_2, p_3, p_4\}$, respectively. So, $\Gamma = (\cap_{t \in R_q} \Gamma'_t) \cap (\cap_{t \in R_q} \Gamma''_t) = \{p_1\}$. Since $S_D(R_{p_1}, R_q) = 1$ and $S_T(R_{p_1}, R_q) = 1$, therefore, p_1 is the only qualified picture.

Now, we set the similarity requirement (h_D, h_T) to $(0.6, 0.5)$. Then, we obtain $\Gamma'_{t_1} = \Gamma'_{t_2} = \Gamma'_{t_3} = \{p_1, p_2, p_3, p_4\}$. Therefore, $\Gamma = \cup_{t \in R_q} \Gamma'_t = \{p_1, p_2, p_3, p_4\}$. The similarity measures (S_D, S_T) for p_1, p_2, p_3 , and p_4 with respect to q are $(1, 1)$, $(0.67, 1)$, $(0.44, 0.67)$, and $(0.24, 0.56)$, respectively. According to the current similarity requirement $(h_D, h_T) = (0.6, 0.5)$, only pictures p_1 and p_2 are qualified and retrieved.

7 EXPERIMENTAL RESULTS

In this section, we present the simulation results to demonstrate the efficiency and effectiveness of our similarity retrieval system based on 9D-SPA representation and the two-level index structure. Without using an index structure, we need to inspect all 9D-SPA representations associated with the database images and compare them with the 9D-SPA representation of the query picture during image retrieval. By using the two-level indexing structure, the search space can be restricted to a small set of images. In the first part of our experiment, we would like to estimate the percentage of the average number of pictures to be accessed per query. We expect that this percentage will be very small if the index structure is used. In the second part of our experiment, we would like to demonstrate the performance of our image retrieval system in terms of recall and precision based on the knowledge structure of 9D-SPA representation.

7.1 Efficiency of Image Retrieval

In this part of the experiment, a database containing 50,000 pictures and 26 different iconic objects were created. There are three versions of databases. A picture in version-1 database contains four to six objects. A picture in version-2 database contains six to eight objects and a picture in version-3 database contains eight to 10 objects. There are also three types of query pictures used for experiment. Type-1 picture contains two to three objects. Type-2 picture contains three to four objects and type-3 picture contains four to five objects. The pictures were randomly generated by considering all possible directional and topological relations between objects.

We use the notation $[Q_l, Q_u]$ to represent the case that the number of objects contained in a query picture is between Q_l and Q_u . Similarly, $[P_l, P_u]$ denotes that the number of objects contained in a database picture is between P_l and P_u . There are nine test cases in this experiment:

TABLE 3
The Values of p for Nine Test Cases against Four Similarity Requirements where
 $p = \frac{\text{Average Number of Pictures Accessed per Query}}{\text{Total Number of Pictures in the Database}} \times 100$ Percent

$[Q_l, Q_u]$	$[P_l, P_u]$	(h_D, h_T)			
		(0,0)	(1,0)	(0,1)	(1,1)
[2,3]	[4,6]	1.5569	0.1861	1.4210	0.1743
	[6,8]	3.1692	0.3971	2.9252	0.3745
	[8,10]	5.8012	0.5974	5.3409	0.5593
[3,4]	[4,6]	0.2494	0.0017	0.1860	0.0013
	[6,8]	0.9182	0.0078	0.8175	0.0070
	[8,10]	2.0102	0.0131	1.7330	0.0119
[4,5]	[4,6]	0.0849	0.0000	0.0678	0.0000
	[6,8]	0.3000	0.0000	0.2183	0.0000
	[8,10]	1.0564	0.0004	0.7138	0.0002
Average		1.6829	0.1337	1.4915	0.1254

1. $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [4, 6]$.
2. $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [6, 8]$.
3. $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [8, 10]$.
4. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [4, 6]$.
5. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [6, 8]$.
6. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [8, 10]$.
7. $[Q_l, Q_u] = [4, 5]$ and $[P_l, P_u] = [4, 6]$.
8. $[Q_l, Q_u] = [4, 5]$ and $[P_l, P_u] = [6, 8]$.
9. $[Q_l, Q_u] = [4, 5]$ and $[P_l, P_u] = [8, 10]$.

The similarity requirement of a query process is denoted by (h_D, h_T) , where h_D is the threshold for directional-similarity and h_T is the threshold for topological-similarity. The similarity requirement $(h_D, h_T) = (0, 0)$ means that a database picture p is similar to the query picture q if some object-pair in q can also be found in p without considering the spatial relationships among objects in both pictures. The similarity requirement $(h_D, h_T) = (0, 1)$ means that q and p have the same objects and all topological relationships between objects in the query picture must be fully matched with those in a relevant database picture. The similarity requirement $(h_D, h_T) = (1, 0)$ means that q and p have the same objects and all directional relationships between objects in the query picture are matched with those in a relevant database picture. For $(h_D, h_T) = (1, 1)$, two pictures are considered as similar only if they have the same objects and all the spatial relationships (both directional and topological) between objects in the query picture are fully matched with those in the database picture.

In our experiment, we tested nine cases against four similarity requirements as shown in Table 3. For each case and each similarity requirement, we randomly generated 100 query pictures and calculated the average number of database pictures accessed per query. Each data entry shown in Table 3 is the average number of database pictures accessed per query divided by the total number of database pictures. It can be seen that the percentages are very low for all test cases and similarity requirements. For example, in

TABLE 4
The System's Performance in Terms of Recall and Precision by Considering Directional-Similarity ($h_T = 0$)

$[Q_l, Q_u]$	$[P_l, P_u]$	$h_D=0.2$		$h_D=0.4$		$h_D=0.6$		$h_D=0.8$	
		Rec.	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.	Pre.
[2-3]	[2-4]	100.0	43.0	77.4	54.5	65.1	94.7	64.0	99.2
[3-4]	[3-7]	100.0	10.5	83.1	77.8	80.2	96.0	80.0	100.0
[3-4]	[3-10]	81.2	15.9	77.1	87.5	70.7	96.5	68.5	100.0
average		93.7	23.1	79.2	73.3	72.0	95.7	70.8	99.7

the case of $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [8, 10]$, the percentage of the average number of database pictures accessed per query with similarity requirement $(h_D, h_T) = (0, 0)$ is 5.8012 percent. Moreover, similarity requirement $(h_D, h_T) = (0, 0)$ represents the fuzziest measure while similarity requirement $(h_D, h_T) = (1, 1)$ represents the most precise measure. The average percentages of images accessed per query for all nine cases from $(h_D, h_T) = (0, 0)$ to $(h_D, h_T) = (1, 1)$ are 1.6829 percent, 0.1337 percent, 1.4915 percent, and 0.1254 percent, respectively. As we can see, only a very small portion of database images are accessed per query based on our two level index structure, thus the efficiency of similarity retrieval is well demonstrated.

7.2 Effectiveness of Image Retrieval

In this part of the experiment, we measured the effectiveness of our image retrieval system in terms of recall and precision. For a given query picture, let a be the number of all relevant pictures, b be the number of pictures that are relevant and retrieved, and c be the number of pictures retrieved. Then, recall = $\frac{b}{a} \times 100$ percent and precision = $\frac{b}{c} \times 100$ percent. First, we consider directional-similarity retrieval (i.e., $h_T = 0$). The three test cases are:

1. $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [2, 4]$.
2. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [3, 7]$.
3. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [3, 10]$.

As we can see from Table 4, recall is decreasing while precision is increasing as h_D increases from 0.2 to 0.4, to 0.6,

then to 0.8 for all three test cases. When $h_D = 0.2$, the recall reaches 93.7 percent with 23.1 percent precision rate on an average. This is because the similarity requirement was set to a very low value. However, as h_D increases to 0.8, the precision rate reaches 99.7 percent, while the recall rate still maintains at 70.8 percent on average.

Next, we evaluate the recall and precision by considering topological-similarity retrieval (i.e., $h_D = 0$). There are also three test cases:

1. $[Q_l, Q_u] = [2, 3]$ and $[P_l, P_u] = [2, 4]$.
2. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [2, 4]$.
3. $[Q_l, Q_u] = [3, 4]$ and $[P_l, P_u] = [3, 7]$.

Table 5 shows that recall is decreasing while precision is increasing as h_T is increased from 0.5 to 0.6, to 0.8, then to 0.9 for all three test cases. As h_T increases to 0.9, the precision rate increases to 94.4 percent and the recall rate drops from 82.6 percent to 51.0 percent on an average.

8 CONCLUSIONS

Content-based image retrieval (CBIR) based on visual features of images is the trend of designing a modern image database system. In the past, symbolic pictures are used to approximate segmented images containing recognized objects. Searching for desired images based on symbolic pictures is called "iconic indexing." The most important feature of a symbolic picture is probably the binary spatial relationships between objects. Thus, an

TABLE 5
The System's Performance in Terms of Recall and Precision by Considering Topological-Similarity ($h_D = 0$)

$[Q_l, Q_u]$	$[P_l, P_u]$	$h_T=0.5$		$h_T=0.6$		$h_T=0.8$		$h_T=0.9$	
		Rec.	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.	Pre.
[2-3]	[2-4]	73.6	50.7	55.8	77.7	38.1	85.9	38.1	95.8
[3-4]	[2-4]	100.0	12.5	100.0	45.2	77.8	75.0	77.8	90.5
[3-4]	[3-7]	74.3	39.9	61.7	59.5	49.1	92.3	37.2	97.0
average		82.6	34.4	72.5	60.8	55.0	84.4	51.0	94.4

appropriate knowledge representation for spatial relations plays an important role in designing a CBIR system.

A novel image representation called 9D-SPA has been presented in this paper to capture the information about the spatial relationships between objects in a segmented picture. The capability of representing a picture using 9D-SPA representation is more powerful than any other representation schemes based on MBR or centroids of objects. The 9D-SPA representation well supports visualization and browsing, spatial reasoning, as well as similarity retrieval. The flexibility of similarity measures are provided to support fuzzy matching that is highly desired to meet user's different requirements. By exercising a database containing 50,000 pictures, we successfully demonstrated the efficiency and effectiveness of our image retrieval system based on 9D-SPA representation and a two-level index structure.

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