Short Paper

Efficient Image Retrieval Based on Minimal Spatial Relationships*

SOO-CHEOL LEE, EENJUN HWANG+ AND JUNG-GEUN HAN++
Telematics Service Convergence Research Team
Telematics & USN Research Division
Electronics and Telecommunication Research Institute
Daejon, 305-700 Korea
+Department of Electronics and Computer Engineering
Korea University
Seoul, 136-701 Korea
E-mail: ehwang04@korea.ac.kr
++Department of Civil and Environmental Engineering
Chung-Ang University
Seoul, 156-756 Korea

Visual interfaces are known to be effective for retrieving images from databases based on spatial relationships between objects in the image. For efficient image indexing and visual querying, the images are represented using 2D strings, which are derived from symbolic projections of image objects. However, with this approach, it is sometimes difficult to describe the spatial relationships between objects in an image exactly. That is, ambiguities may arise in the representation of the image that inherently captures the 2D projection of the 3D real world, which leads to uncertainty during the retrieval of images. In order to remove these ambiguities, images can be referred to using the spatial location algebra reflecting their spatial relationships in the 3D space. In this paper, we present a unified representation of spatial objects for both topological and directional relationships based on Allen's temporal interval algebra. We also describe a set of reduction rules, which minimizes those relationships. Overall, this scheme can easily be integrated into any multimedia database system using a simple inference engine to provide better precision and flexibility in image retrieval.

Keywords: multimedia database, image retrieval, spatial relationship, content-based retrieval, reduction rules

1. INTRODUCTION

The emergence of multimedia technology and the possibility of sharing and distributing image data through large-bandwidth computer networks have accentuated the role

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+ Corresponding author.

of visual information [1, 2]. Due to the low cost of digital cameras, scanners, storage and transmission devices, digital images are now employed in a wide range of different applications such as entertainment, art galleries, advertising, medicine, and geographic information systems. Typical image database systems retrieve images either by high-level semantics, which define image contents at the conceptual level, or by visual contents, which are based on perceptual features such as color, texture, structure, and shape of the objects in the image and their spatial relationships [3-6].

The spatial relationship [7-9] is a fuzzy concept and usually depends on human interpretation. A spatial similarity function is used to assess the degree to which database images conform to the query image with respect to spatial relationships. Eventually, the database images are ranked and ordered by the spatial similarity. Here, qualitative spatial reasoning is used, because the reasoning of human beings in this domain is usually qualitative. For example, we are usually interested in whether object *A* is above object *B*, rather than whether object *A* has the same longitude as, but lower latitude than object *B*. High-precision quantitative measurements are of limited use in such cases. Once we have many objects in our database, it is very expensive, if not impossible, to store all the spatial relationships among them. Furthermore, some relationships may rarely be used due to lack of user interest. A straightforward approach to tackling this problem is to explicitly store the most frequently used spatial relationships and generate rarely used relationships on demand. This strategy requires a generalized spatial representation scheme [10], which handles stored spatial knowledge and computes additional spatial relationships easily by a spatial reasoning engine as well. This leads to saving in space for the relationships, which will be advantageous in a distributed environment, in which the meta-data is stored at user site with its limited storage capacity, while the actual images are stored at remote sites.

In this paper, we discuss the usage of minimal 3D relationships in the specification of query images in the content-based retrieval of 2D images. Also, we propose a unified representation of spatial relationships among image objects and a set of reduction rules to minimize these relationships. The unified representation is based on Allen's temporal interval algebra and defines both topological and directional relations.

The remainder of the paper is organized as follows. Section 2 describes the related works. Section 3 presents the concept of image indexing and symbolic coding of spatial relationship. Section 4 describes the reduction rules used to remove redundant spatial relationships among objects. Section 5 explains our prototype system. Section 6 describes the experimental results and finally, our conclusions are given in section 7.

2. RELATED WORKS

To date, many CBIR (Content-based Image Retrieval) systems [11-14] and techniques have been reported. The QBIC system developed by IBM allows an operator to specify various properties of an image, including its shape, color, texture and location. The system returns a selection of potential matches to these criteria, sorted by a score indicating the appropriateness of the match. Pentland *et al*. presented another CBIR system which incorporates a more sophisticated representation of texture and limited degree of automatic segmentation. Virage [15] and Chabot also retrieved images using low-level image properties. However, none of these systems considers spatial properties in a way that supports object querying.

Jagadish [16] proposed the shape similarity retrieval method based on a two-dimensional rectilinear shape representation. In this work, two shapes are considered to be similar if the error area is small when one shape is placed on the top of the other.

In our previous work [17], we proposed a new domain-independent spatial similarity and annotation-based image retrieval system. In this system, images are decomposed into multiple regions of interest containing objects and their spatial relationships are analyzed and annotated.

Tanimoto [18] suggested the use of picture icons as indices, thus introducing the concept of the iconic index. This concept has since been given a theoretical framework, in which the abstraction operations are formalized so as to obtain various picture indices, and to construct icons which can be used to facilitate the accessing of pictorial data.

Chang *et al*. [19] further developed the concept of iconic indexing by introducing the 2D string representation of an image, and this 2D string approach has since been extended. For example, the 2D-H string [20] is an extension of the 2D string. The 2D-PIR graph can consider both the directional and topological relationships between all possible spatial object pairs in an image. However, the 2D and 2D-H strings can only represent directional relationships, since they use only one symbol to represent relationships such as overlap, contain, inside, cover, covered by and equal. The 2D-PIR graph [21] manages interval relationships for the x and y-axis and topological relationships between all spatial object pairs in an image, but it is too expensive in terms of storage space.

3. ANALYSIS OF SPATIAL INFORMATION

In this section, we describe how to represent the spatial information of the objects contained in an image.

3.1 Representation of Spatial Information

Each image in a database contains a set of unique and characterizing image objects that are scattered in arbitrary locations, among which various spatial relationships could exist. Each object's spatial location can be represented either by the relative coordinate or by the absolute coordinate. In a 3D space, the spatial location of an object O in an image is represented as a point P_o where $P_o = (X_o, Y_o, Z_o)$, and an image itself is represented as a set of points $P = \{P_1, P_2, \ldots, P_n\}$, where n is the number of objects of interest in the image. Each point can be tagged or annotated with label, in order to capture any necessary semantic information of the object. We call each individual point representing the spatial location of an image object a *spatial location point* [17]. For the sake of simplicity, we assume that the spatial location of an image object is represented by a single spatial location point and, hence, that the entire image is represented by a set of spatial location points. Especially, we used 3D spatial relationships among spatial location points to capture the spatial information of an image. Based on this scheme, we can define the image relation algebra for image objects X, Y and Z, as shown in Table 1.

Table 1. Image relation algebra.

Relation	Meaning	Definition
A BL *B*	Below	$A_x\{d, di, s, si, f, fi, e\}B_x \wedge A_y\{b, m\}B_y$
A UP *B*	Upper	$A_x\{d, di, s, si, f, fi, e\}B_x \wedge A_y\{bi, mi\}B_y$
A LT *B*	Left	$A_x\{b, m\}B_x \wedge A_y\{d, di, s, si, f, fi, e\}B_y$
A RT *B*	Right	$A_x\{bi, \mathrm{mi}\}B_x \wedge A_y\{d, di, s, si, f, fi, e\}B_y$
A LU *B*	Leftupper	$(A_x\{b, m\}B_x \wedge A_y\{bi, mi, oi\}B_y) \vee (A_x\{o\}B_x \wedge A_y\{bi, mi\}B_y)$
A LL *B*	Leftlower	$(A_x\{b, m\}B_x \wedge A_y\{b, m, o\}B_y) \vee (A_x\{o\}B_x \wedge A_y\{b, m\}B_y)$
A RU *B*	Rightupper	$(A_x\{bi, mi\}B_x \wedge A_y\{bi, mi, oi\}B_y) \vee (A_x\{oi\}B_x \wedge A_y\{bi, mi\}B_y)$
A RL *B*	Rightlower	$(A_x\{b, m\}B_x \wedge A_y\{b, m, o\}B_y) \vee (A_x\{oi\}B_x \wedge A_y\{b, m\}B_y)$
A OL *B*	Overlaps	$A_x\{d, di, s, si, f, fi, o, oi, e\}B_x \wedge A_y\{d, di, s, si, f, fi, o, oi, e\}B_y$
A IS *B*	Inside	$A_x\{d\}B_x \wedge A_y\{d\}B_y$
A OS *B*	Outside	$A_x\{di\}B_x \wedge A_y\{di\}B_y$
A IN *B*	In front of	$A_z(b, m)B_z \Leftrightarrow A_z\{bi, mi\}B_z$

Allen [22] proposed temporal interval algebra for representing and reasoning about temporal relations between events represented as intervals. The elements of the algebra are sets of seven basic relations and their inverses that can hold between two intervals.

In our system, we consider 8 directional and 4 topological relations, which are classified into the following two categories:

- Directional relations: upper, below, left, right
- Mixed directional relations: leftupper, leftlower, rightupper, rightlower

We use *A*, *B*, etc. to represent the arbitrary spatial objects and *Ax* and *Ay* to represent their projected intervals on the *x*- and *y*-axes, respectively. $\wedge$ and $\vee$ are the standard logical AND and OR operators, respectively. The notation {} is used to group together multiple instances of the $\vee$ operator involving different interval operators. For example, $A_x\{b, m, o\}B_x$ is equivalent to $A_x\ b\ B_x \vee A_x\ m\ B_x \vee A_x\ o\ B_x$.

Suppose we are given an image with *n* objects of interest. We can describe their spatial information using a unidirectional graph, in which each object corresponds to a vertex, and the spatial relationship between any two objects are labeled along their edges. We refer to this graph as a *spatial graph*. Fig. 1 shows a sample image and its spatial graph for the image objects.

4. SPATIAL REDUCTION RULES

The number of spatial relationships increases exponentially as the number of image objects increases. However, some of the spatial relationships are redundant in that they can be inferred from the other relationships [23].

To remove such redundant spatial relationships, we propose a set of reduction rules. In this way, we can obtain a simpler and more compact set of spatial relationships.

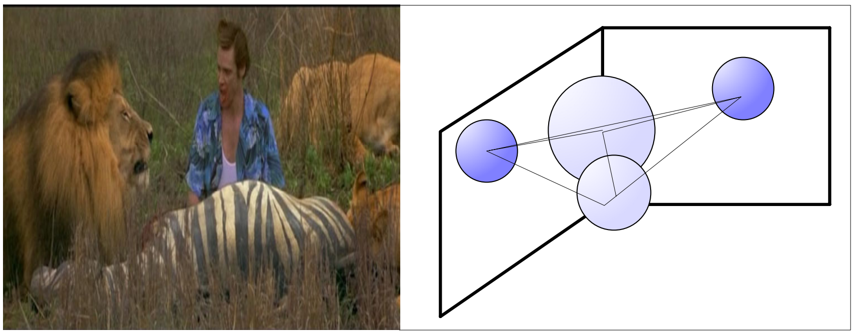

Fig. 1. Sample image and its spatial graph.

Rule 1 $A\ e\ A$, $A\ o\ A$; reflexive

Rule 2 $A\ e\ B \Leftrightarrow B\ e\ A$, $A\ o\ B \Leftrightarrow B\ o\ A$; symmetric

Rule 3 $A\ _{\mathrm{UP}}\ B \Leftrightarrow B\ _{\mathrm{BL}}\ A$, $A\ _{\mathrm{RU}}\ B \Leftrightarrow B\ _{\mathrm{LL}}\ A$
$A\ _{\mathrm{LU}}\ B \Leftrightarrow B\ _{\mathrm{RL}}\ A$, $A\ _{\mathrm{RT}}\ B \Leftrightarrow B\ _{\mathrm{LT}}\ A$; inverse

Rule 4 Let $\theta \in$ {LU, RU, LL, RL, LT, RT, IS, E} then
$A\ \theta B \wedge B\ \theta C \Rightarrow A\ \theta C$; transitive

Rule 5 $A\ _{\mathrm{IS}}\ B \Rightarrow A\ _{\mathrm{OL}}\ B$, $A\ e\ B \Rightarrow A\ _{\mathrm{OL}}\ B$; implicative

Rule 6 $A\ _{\mathrm{IS}}\ B \wedge A\ _{\mathrm{OL}}\ C \Rightarrow B\ _{\mathrm{OL}}\ C$
$A\ _{\mathrm{IS}}\ B \wedge A\ _{\mathrm{OS}}\ C \Rightarrow B\ _{\mathrm{OS}}\ C$

Rule 7 Let $\theta \in$ {LT, RT, UP, BL} then $A\ _{\mathrm{IS}}\ B \wedge B\ \theta C \Rightarrow A\ \theta C$

Rule 8 Let $\theta \in$ {LT, RT, UP, BL} then $A\ \theta B \wedge B\ _{\mathrm{OL}}\ C \wedge C\ \theta D \Rightarrow A\ \theta D$

Rule 9 $A\ _{\mathrm{UP}}\ B \wedge B\ _{\mathrm{LU(RU)}}\ C \Rightarrow A\ _{\mathrm{LU(RU)}}\ C$, $A\ _{\mathrm{BL}}\ B \wedge B\ _{\mathrm{LL(RL)}}\ C \Rightarrow A\ _{\mathrm{LL(RL)}}\ C$
$A\ _{\mathrm{LT}}\ B \wedge B\ _{\mathrm{LU(RU)}}\ C \Rightarrow A\ _{\mathrm{LU(RU \vee UP)}}\ C$, $A\ _{\mathrm{RT}}\ B \wedge B\ _{\mathrm{RU(RL)}}\ C \Rightarrow A\ _{\mathrm{RU(RL)}}\ C$

Rule 10 $A\ _{\mathrm{LT}}\ B \wedge \mathrm{B}\{_{\mathrm{LU,\ LL}}\}C \Rightarrow A\ _{\mathrm{LT}}\ C$, $A\ _{\mathrm{RT}}\ B \wedge B\{_{\mathrm{RU,\ RL}}\}C \Rightarrow A\ _{\mathrm{RT}}\ C$
$A\ _{\mathrm{UP}}\ B \wedge B\{_{\mathrm{RU,\ LU}}\}C \Rightarrow A\ _{\mathrm{UP}}\ C$, $A\ _{\mathrm{BL}}\ B \wedge B\{_{\mathrm{RL,\ LL}}\}C \Rightarrow A\ _{\mathrm{BL}}\ C$

5. IMPLEMENTATION

Based on the spatial information described above, we implemented a prototype image retrieval system under the following three basic principles: (i) Real world images are described in the database in terms of the 3D space of the scene that they represent. (ii) Querying is done through a virtual scene that is defined by the direct manipulation of the 3D symbols. (iii) All the spatial relationships among objects are represented using XML.

The images and their descriptions are stored in an XML database. XML is a simple and flexible text format derived from SGML. Originally designed to meet the challenges of large-scale electronic publishing, XML is also playing an increasingly important role in the exchange of a wide variety of data, both on the Web and elsewhere. XML permits document authors to create markup for virtually any type of information. This extensibility enables document authors to create entirely new markup languages to describe specific types of data, including mathematical formula, chemical molecular structures, music, recipes, etc. Fig. 2 shows a snapshot of the image analysis process in the prototype system. During this step, each object of interest in the image is manually marked by a rectangle called an ROI (Region of Interest). The edges of each marked object are extracted and any necessary semantic information is coded into an XML document. The window at the bottom left of Fig. 2 shows the spatial graph of the marked image objects. The 3D location of an image object in the spatial graph can be changed using the forward and back buttons. Therefore, each rectangle in the image represents both the object itself and its location. The query interface of the system is used to define and visualize a query image on the 3D or 2D canvases. For example, Fig. 3 shows a query image specification on the 3D canvas.

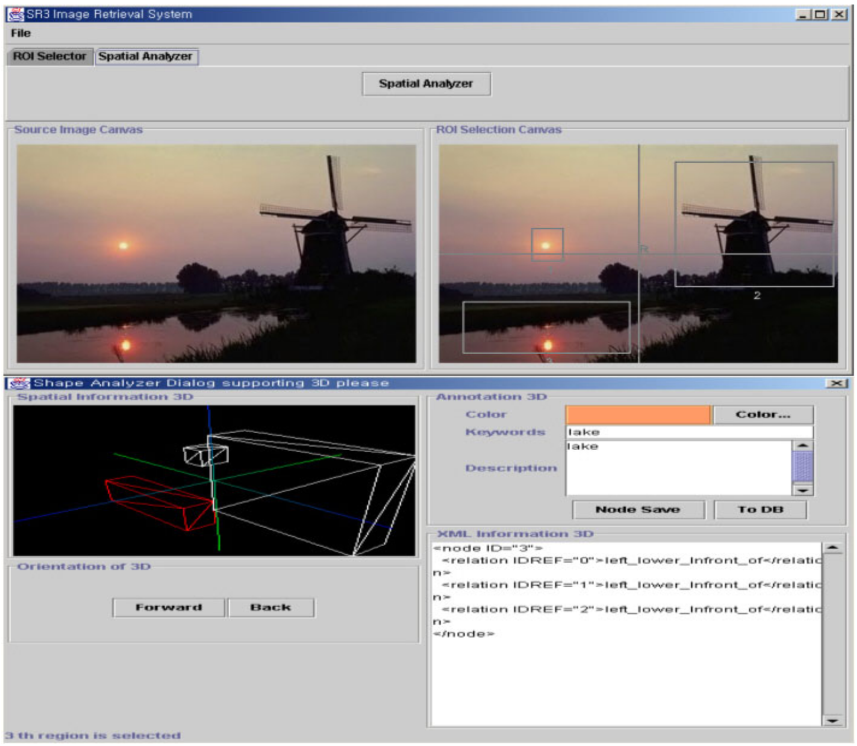

Fig. 2. Image analyzer interface.

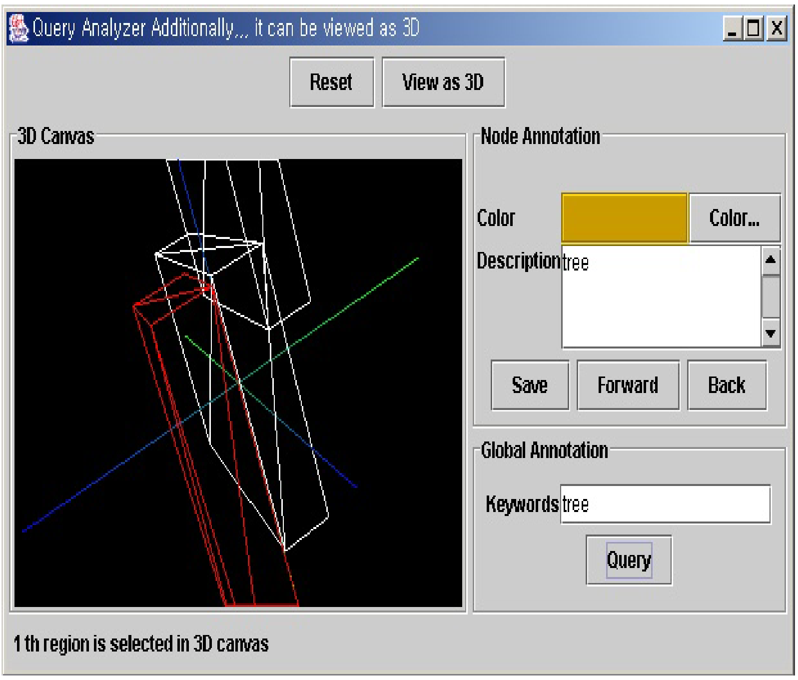

Fig. 3. Query interface on the 3D canvas.

6. EXPERIMENTAL RESULTS

In order to show the effectiveness of our scheme, in this section, we describe a comparative analysis of the three querying modes: (i) querying by spatial relationships in the 3D space (QbS^3), as proposed in this paper, (ii) querying by spatial relationships in the 2D space (QbS^2), and (iii) querying by content (QbC).

A database of 1000 images was used for this experiment. The images in the database were collected from diverse sources such as screenshots of computer graphics animations, personal video sequences of natural landscapes, and paintings representing real-world landscapes.

For the performance comparison, we executed three different types of tasks and measured their retrieval effectiveness and efficiency. The three different tasks are:

Task A: Retrieving images that have a similar structure (layout), but which differ from each other in terms of some of the details.

Task B: Retrieving images that have a similar structure, but which differ from each other in terms of their color and boundary orientation.

Task C: Retrieving images that have a dissimilar structure. These images are usually obtained from video sequences of complex scenes.

6.1 Effectiveness

In order to compare the three querying modes for different types of tasks, we measured the retrieval effectiveness $P(i)$, which is defined as the ratio of the number of target images to the images retrieved in each elaboration i for a given user query:

$$P(i)= \frac{\text{Number of images which belong to the target set}}{\text{Number of images retrieved with the } i^{th} \text{ query}}$$

Fig. 4 shows the overall retrieval effectiveness of QbS^3, QbS^2 and QbC for the different types of tasks. For example, after three query attempts, we could see the following effectiveness: $P_{QbS^3}(3) = 0.81$, $P_{QbS^2}(3) = 0.66$, and $P_{QbC}(3) = 0.54$. The figure shows that QbS^3 achieves the highest retrieval effectiveness. QbS^2 and QbC achieve similar level of retrieval performance only after a number of attempts.

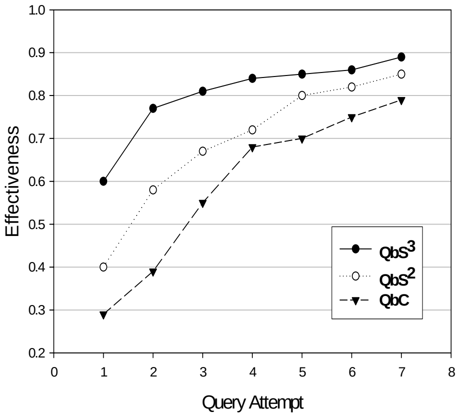

Fig. 4. Overall retrieval effectiveness.

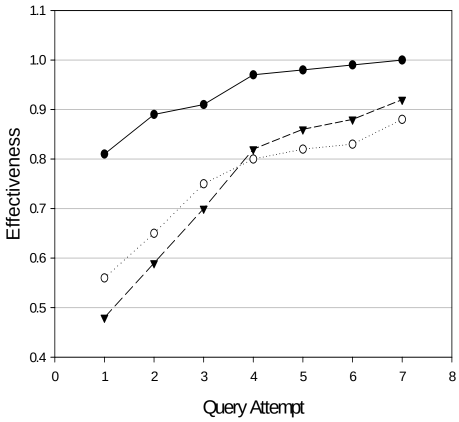

Fig. 5. Retrieval effectiveness of task *A*.

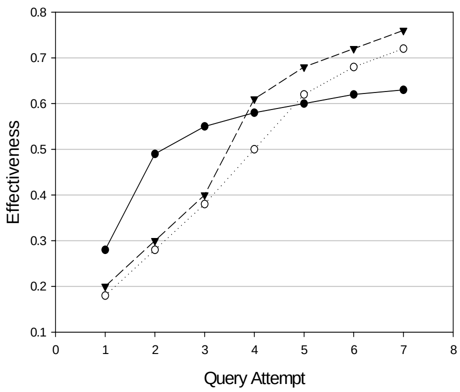

Fig. 6. Retrieval effectiveness of task *B*.

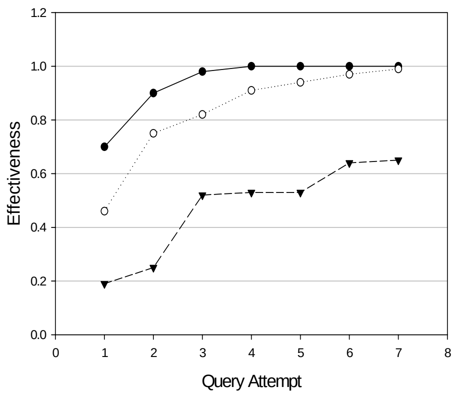

Fig. 7. Retrieval effectiveness of task *C*.

Figs. 5, 6 and 7 show the retrieval effectiveness of three querying modes for tasks *A*, *B* and *C*, respectively. Fig. 5 shows that QbS^3 performs best for the task *A*, while QbS^2 performs worst. With QbS^3, the users selected a scene and populated it with objects having appropriate spatial relationships, in order to obtain a suitable view. The specification of query images reproducing relevant features was difficult with QbS^2. With QbC, the users found it difficult to find images in the result, whose contents were similar to those of the target image. With QbS^3, the users were first provided with a query canvas comporting an image selected from a database at the beginning of the experimental session. The users selected objects of interest from the canvas and their edges of these objects were extracted. Only a few users used this function to search for images with different skylines in their subsequent query attempts. The other users performed extensive navigation in an attempt to find similar skylines within the 3D scene. Nevertheless, one of the users succeeded in retrieving 10 out of the 12 images of set *B*, which was the second highest score.

Fig. 6 shows that QbS^2 and QbC have similar performances and that both ultimately perform better than QbS^3 in the task *B*, but only after a relatively large number of query attempts. This is due to the fact that the images in the target set have simple scenes with two colored regions and that they have different boundaries. This situation is well-suited to the querying-by-spatial relationships using 2D.

Fig. 7 shows that QbS^3 and QbS^2 outperform QbC for the task *C*. The target set includes images of the same scene taken from viewpoints at different distances. With QbS^3, once the 3D scene has been populated according to the task objective, queries were easily constructed by navigating the 3D scene and taking photographs from appropriate view points. The complexity of the scene in the target images is the cause of the poor retrieval performance of QbS^2.

6.2 Efficiency

For the efficiency of the three modes, we measured the average time spent by users to accomplish the tasks (T_{task}). The results are summarized in Table 2. According to this result, QbC shows better performance than QbS^3 and QbS^2 in all three tasks. QbS^2 exhibits the worst performance, except in task *B*.

Table 2. Average time for tasks.

Scheme	$T_{\text{task } A}$	$T_{\text{task } B}$	$T_{\text{task } C}$
QbS^3	4.4	17.0	8.1
QbS^2	11.6	10.6	16.1
QbC	3.7	6.9	4.1

The total amount of time spent by each subject is equal to the sum of the time spent on each query attempt. This includes the time spent on the construction of the query, matching, result visualization, and user's feedback:

$$T_{\text{task}} = \sum_{q=1}^{n} T_{\text{query}}(q), \text{ where } T_{\text{query}}(q) = T_{\text{specify}}(q) + T_{\text{match}}(q) + T_{\text{visualize}}(q) + T_{\text{feedback}}(q).$$

T_{match} is slightly higher for QbS^3 and QbS^2 than for QbC since querying by QbS^3 and QbS^2 required spatial information of the sample image to be analyzed and extracted during the execution time. T_{specify} was measured from the logs of the experiment sessions and summarized in Table 3.

Table 3. Average time spent on query specification.

Scheme	T_{specify}
QbS^3	1.89
QbS^2	1.65
QbC	1.04

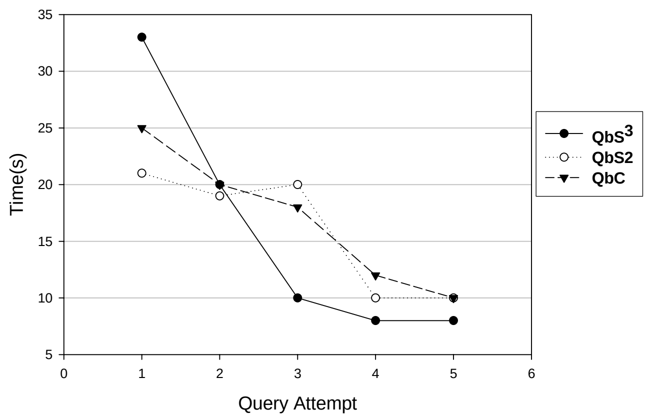

Fig. 8. Time spent to specify a query in a sample test session.

The experiment showed that the time for the query specification during successive attempts had different patterns for the three querying modes. Fig. 8 shows a plot of T_{specify} versus the number of query attempts in a representative sample test session.

It can be noticed that the time required by the user to construct the query decreases as the number of query attempts increases for both QbS^3 and QbS^2, while it stays almost constant for QbC. This means that, in the case of QbS^3 and QbS^2, the users spent more time constructing the first query and then just made minor adjustment, in order to specify the subsequent queries. On the other hand, in the case of QbC, almost the same effort was required for each query, since this paradigm includes only a limited number of operations which allows for the refinement of the query or the specification of a new one. However, with QbS^3, the longer the time it took to specify the first query, the higher the number of relevant images that were retrieved at the first attempt.

7. CONCLUSIONS

In this paper, we addressed the issue of how to retrieve images from databases using the 3D relationships among image objects. Here, the database and query images are referred to by considering the spatial relationships between the objects in their 3D space. These spatial relationships are extracted by means of a semi-automatic method and annotated into an XML document.

We also presented a set of reduction rules designed to minimize the number of spatial relationships obtained from a given set of relationships. That is, some of the relationships are necessarily redundant, in that they can be inferred from other existing relationships.

We built a prototype system based on this method, and performed several experiments in order to see how well it works for typical image retrieval tasks. The prototype system is equipped with several tools for analyzing, annotating, querying, and browsing images in a user friendly way. From the experimental evaluation, we concluded that these tasks are effectively supported by the proposed QbS^3 method, in terms of both effectiveness and efficiency.

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Soo-Cheol Lee received the B.S. degree in Computer Engineering from Hannam University, Taejeon, Korea, in 1998, the M.S. and Ph.D. degrees in Graduate School of Information and Communication, Ajou University, in 2000 and 2005, respectively. He was a Senior Researcher of KISTI (Korea Institute of Science and Technology Information). Currently, he is a senior researcher of ETRI (Electronics and Telecommunications Research Institute), Daejeon, Korea. His current research interests include database systems, multimedia systems, image retrieval, heterogeneous information integration, and web applications.

EenJun Hwang received his B.S. and M.S. degrees in Computer Engineering from Seoul National University, Seoul, Korea, in 1988 and 1990, respectively; and the Ph.D. degree in Computer Science from the University of Maryland, College Park, in 1998. He was an Associate Professor of Information and Communication College, Ajou University, Suwon, Korea from 1999 to 2004. Currently, he is a member of the faculty in the Department of Electronics and Computer Engineering, Korea University, Korea. His current research interests include database systems, multimedia systems, information retrieval, XML and web applications.

Jung-Geun Han received the B.S. degree in Civil Engineering from Chung-Ang University, Seoul, Korea, in 1988, and the M.S. and Ph.D. degrees in Geotechnical Engineering from Chung-Ang University, Seoul, Korea, in 1990 and 1997, respectively. He is an Associate Professor of the Department of Civil and Environmental Engineering of the Chung-Ang University from March 2003. He was a full time instructor of the Department of Civil, Environmental and Information Engineering of Daelim College, Anyang, Korea, from March 1999 to February 2003. He was a visit researcher in the Department of Civil Engineering of Osaka University, Osaka, Japan, from December 1995 to February 1997. His areas of research include geotechnical and geoenvironmental engineering, embedded numerical analysis.