Multimedia Systems 10: 56–71 (2004)
Digital Object Identifier (DOI) 10.1007/s00530-004-0137-4

Multimedia Systems
© Springer-Verlag 2004

MINDEX: An efficient index structure for salient-object-based queries in video databases

Lei Chen[1], **M. Tamer Özsu**[1], **Vincent Oria**[2]

[1] School of Computer Science, University of Waterloo, Canada
e-mail: {l6chen, tozsu}@uwaterloo.ca
[2] Department of Computer Science, New Jersey Institute of Technology, Newark, NJ, USA
e-mail: oria@cis.njit.edu

Abstract. Several salient-object-based data models have been proposed to model video data. However, none of them addresses the development of an index structure to efficiently handle salient-object-based queries. There are several indexing schemes that have been proposed for spatiotemporal relationships among objects, and they are used to optimize *timestamp* and *interval* queries, which are rarely used in video databases. Moreover, these index structures are designed without consideration of the granularity levels of constraints on salient objects and the characteristics of video data. In this paper, we propose a multilevel index structure (MINDEX) to efficiently handle the salient-object-based queries with different levels of constraints. We present experimental results showing the performance of different methods of MINDEX construction.

Keywords: Content-based video retrieval – Video data model – Salient-object-based queries – Multilevel indexes

1 Introduction

Content-based video retrieval has been used in many application fields such as sports video analysis, surveillance video monitoring systems, digital news libraries, etc. However, current computer vision and image processing techniques can only offer limited query ability on primitive audiovisual features. The query techniques that have been used in image databases, such as query-by-example [23], cannot be easily applied to video retrieval because of the limited number of video examples. Based on the characteristics of video data, content-based video retrieval approaches can be classified into the following three categories:

1. *Visual-feature-based retrieval* [20,32]: In this approach, a video is recursively broken down into *scenes*, *shots*, and *frames*. Key frames are extracted from the shots and the scenes to summarize them, and visual features from the key frames are used to index them. With indexed key frames, this approach converts the video retrieval problem into the retrieval of images from image databases.
2. *Keywords or free-text-based retrieval* [15,26]: In this approach, a content description (annotation) layer is put on top of the video stream. Each descriptor can be associated with a logical video sequence or physically segmented shots or scenes. Content-based video retrieval is converted into a search for the specified text in annotation data.
3. *Salient-object-based retrieval* [6, 11, 16, 19, 21]: In this approach, salient objects are extracted from the videos and the spatiotemporal relationships among them are described to express events or concepts. The salient objects are the physical objects appearing in video data (e.g. houses, cars, people) that are of interest in one or more applications.

Visual-feature-based retrieval has the advantage that visual feature extraction and comparison can be automatically performed, with very little interpretation required on visual features. However, it is not realistic to expect users to be knowledgable about low-level visual features. Most importantly, high-level semantic similarity may not correspond to the similarity of low-level features. For example, sky and sea have a similar visual component, "blue color"; however, they express totally different concepts. Keyword or free-text-based retrieval is directly related to the semantics of video content and is easier for users to understand and use. It remains the most popular approach in current video database systems such as news video and documentary video databases. However, this approach requires too much human effort to annotate video data, and annotations are subjective. Furthermore, text annotations cannot cover all aspects of video data content. For example, it is very difficult to textually describe the moving trajectory of a salient object. Compared to these, salient-object-based search is more intuitive and more suitable for human understanding, especially for naive users. Users can directly manipulate salient objects, their properties, and the spatiotemporal relationships among them. They can also construct queries to retrieve videos that contain events the user is interested in. These events can be expressed through the spatial or temporal relationships among the salient objects. For example, an interleaving pattern of the temporal relationship *"before"* between two cars can be used to express a car chase event. Queries related to the spatiotemporal relationships of salient objects can be classified into four types:

1. *Salient-object existence*. In this type of query, the user is only interested in the appearance of an object. For example, given a movie database, a director may submit the query "give me all the video shots in which actor a appears" in order to observe the acting skills of the actor.
2. *Temporal relationships*. These queries involve temporal relationships among objects in videos. One possible application for this type of query is to extract interesting shots from movies and construct a trailer. For example, to use the shot/reverse shot patterns [2] to construct a car chase scene in a movie trailer, a video editor may first submit two queries – "Give me all the video shots in which car a appears before car b" and "Give me all the video shots in which car b appears before car a". After that, he/she can choose the shots from two results and concatenate them in an interleaving pattern to build a chase scene between cars a and b.
3. *Spatial relationships*. In these queries, users express simple directional or topological relationships among salient objects. These queries may be useful, for example, in sport video analysis. Consider a coach who may want to analyze Michael Jordan's movements when he is under the backboard in order to train his defense team. A query that he may submit over a NBA video database is: "Give me all the shots in which Michael Jordan has an $under$ relationship with the backboard."
4. *Spatiotemporal relationships*. In these queries users are concerned with the spatiotemporal relationships among salient objects. This type of query is useful, for example, in surveillance video systems. Consider the case where one may want to retrieve all the shots in which suspect a enters bank b by submitting a query "Give me all the shots in which *a enters b* ".

A major problem in video databases is to find an effective index that can optimize video query processing. In the four types of queries listed above, the query constraints are set on the spatial or temporal relationships among salient objects. Therefore, it may appear that well-developed spatiotemporal index structures, such as 3DR-tree [28], HR-tree [22], RT-tree [31], and MVR-tree [27], may be used to improve the query efficiency of salient-object-based queries. However, these index structures are mainly designed to optimize *timestamp* and *interval* queries [31], which are common in spatiotemporal databases but not in video databases. Timestamp queries retrieve all objects that intersect with a value range window at a specific time. Interval queries consider sequences of timestamps.

These types of queries are rarely, if ever, used in video databases because they require users to have a comprehensive knowledge of the story line of a video. It is very difficult for users to accurately specify the timestamp or time interval in which the events that they are interested in occur, even though they may be interested in finding the timestamps or intervals of interesting events. In this paper, we focus on index structures to improve efficiency of salient-object-based queries.

Two aspects need to be considered when we design an index structure for video databases:

1. Characteristics of queries: Creating index structures without knowing the characteristics of queries may result in the maintenance of redundant information. For example, if we create an independent index for each type of salient-object-based query, the index on spatial relationships also contains the information about object existence. Salient-object-based queries allow users to set constraints on salient objects at four different granularity levels corresponding to the four types of queries described above. Different amounts of information are required for different constraints.
2. Characteristics of video data: Characteristics of video data may affect effectiveness and efficiency of an index structure. For example, in movies, it rarely happens that more than four actors appear in the same frame. Therefore, an index structure on spatial relationships that relate to more than three objects will be less useful compared to an index structure on pairwise spatial relationship since most of the time video frames contain only two actors. Another interesting characteristic of video data is due to the shot/reverse shot techniques, which are often used by video editors to construct dialog and action scenes [2]. Even in sports videos, shot/reverse shots are often used to give the audience different points of view. These techniques cause similar spatial layouts of salient objects to appear in an interleaving pattern.

In this paper, we propose a multilevel index structure, called MINDEX, that is based on a video data model [8] to improve the efficiency of salient-object-based queries; the proposed index structure takes into account the above two points. At the first level, an extendable hash is created to find the ID of a salient object from its name. A B^+-tree is set up at the second level to index pairwise temporal relationships between two salient objects. Finally, at the third level, a perfect hash is developed to index the spatial relationships among salient objects that appear in each shot. To find the optimal index methods for MINDEX, we also propose alternative approaches: signature files and inverted files as the second and third level of MINDEX.

The rest of the paper is organized as follows. Section 2 presents some related works on index structures. The video data model that forms the base of our index structure is introduced in Sect. 3. Section 4 presents MINDEX. In Sect. 5 we give experimental results on the performance comparison of different methods of MINDEX construction. We conclude in Sect. 6.

2 Related work

As mentioned earlier, there has not been much work on indexing salient objects and their spatiotemporal relationships in video data. Several related index structures are proposed for spatiotemporal databases, image databases, and video databases. We briefly review some of the index proposals in this section.

The 3DR-tree [30] was originally proposed to speed up the operations of multimedia object composition and synchronization. It requires that indexed objects not change their locations over time. Three-dimensional minimum bounding boxes (MBBs) are used to encapsulate objects over which a 3DR-tree is constructed. With the 3DR-tree, an interval query can be efficiently answered by finding the intersection between the 3D MBB of the query and the MBBs in the 3DR-tree. However, MBBs of moving objects that cover a large portion of the data space may lead to high overlap and low discrimination ability of the 3DR-tree.

RT-trees [31], HR-trees [22], and MVR-trees [27] have been proposed to index spatiotemporal relationships. The RT-tree is a spatiotemporal version of the R-tree; it indexes all the spatiotemporal information in one R-tree, which makes it unmanageable when the number of changing objects is large. The MVR-tree can be considered a variation of the 3DR-tree in that it combines the concepts of multiversion B tree [3] and the 3DR-tree. An HR-tree can efficiently handle timestamp queries since such a query can be converted into a search over a static R-tree. However, for an interval query, all the trees whose timestamps are located inside the interval have to be searched. The aim of these index structures is to improve the efficiency of the system in dealing with the *timestamp* and *interval* queries. In order to answer queries that involve salient objects, all the timestamped R-trees have to be searched in the HR-tree or a large number of timestamp queries have to be executed against the 3DR-tree.

Several approaches have been proposed to improve the efficiency of spatial-relationship-based queries on image databases [4, 12, 14, 17]. Basically, three index structures or their variations exist: inverted file, hash table, and signature file. Inverted files [14] index the appearance of objects in images by creating an index on the name of each object. Querying multiple objects requires taking the intersection of the results of multiple queries over each of the objects. Building a perfect hash over pairwise spatial relationships has been proposed [4]. Again, querying over multiple pairs of spatial relationships requires multiple queries. Furthermore, the perfect hash structure requires a priori knowledge of all the images. Finally, various signature file structures have been proposed to represent 2D strings [5] in image databases. A two-level signature file [17] creates an image signature based on spatial relationships among the objects in an image and forms a block signature from all the objects of the images in the block. The block here refers to a set of images. This technique is improved by a multilevel signature file structure [18] that creates higher-level signatures with larger size blocks. A two-signature-based multilevel signature file structure has also been proposed to handle a wider set of queries over 2D strings [12].

In video databases, in addition to spatial relationships, temporal relationships are important for describing the characteristics of salient objects. A content-based video query language (CVQL) is proposed in [16] that supports video retrieval by specifying spatial and temporal relationships of content objects. The queries are processed in two phases: the elimination-based processing phase and the query predicate evaluation phase. The elimination phase is proposed to eliminate the unqualified video without accessing the video data, and the *behavior-based* function evaluation phase is introduced to examine video functions that are specified in query predicates for retrieving query results. The behavior of salient objects is classified into static, regular moving, and random moving. To improve the efficiency of evaluating video functions, an index structure named M-index is proposed to store the behaviors of its content objects. For each type of behavior in a video, an independent index structure is created (e.g., Hash, B^+-tree, or R^+-tree). However, M-index only indexes the spatial position information of salient objects, while the temporal relationships among salient objects are not considered.

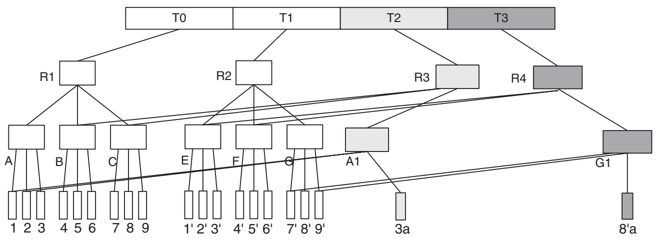


Fig. 1. Example of VHR-tree

Döndeler et al. [11] propose a rule-based video database system that supports salient-object-based spatiotemporal and semantic queries. In their system, video clips are first segmented into shots whenever the current set of relationships among the salient objects is changed. The frame at which the change occurs is selected as a key frame. The directional, topological, and 3D relations of salient objects in a shot are stored as Prolog facts of a knowledge base. The comprehensive set of inference rules of the system helps reduce the number of facts to be stored. However, the system does not provide explicit index structures to support salient object appearance or spatiotemporal queries. It relies on the implicit indexes provided by the implementation language SWI-prolog. Therefore, the indexes in their system are implementation dependent.

In an earlier work [7], we proposed a two-level index structure for salient-object-based queries. A *Salient Object Inverted List* acts as the first level of the index structure to index key frames in which salient objects appear. A variation of HR-tree (called VHR-tree) is used to index the spatial relationships among the salient objects in key frames, which comprises the second level of the index structure. VHR-trees are designed with the consideration of shot/reverse shot patterns. Figure 1 shows how a VHR-tree handles the spatial patterns brought by shot/reverse shots. At timestamp T1, all the salient objects that appear at T0 disappear, and a new set of nine salient objects appears, thus setting up a new R-tree at T1. At timestamp T2, instead of only searching its immediate precedent R2 at T1 as the HR-tree does, the VHR-tree checks the R-trees at T1 and T0 and uses the unchanged part of the R-tree at T0. The same construction procedure applies for timestamp T3.

However, the two-level index structure does not consider the temporal relationships among the salient objects, and sequential scan has to be used to answer temporal and spatiotemporal queries.

3 Modeling video data

3.1 Overview of the video data model

We use a video data model [8] that captures the structural characteristics of video data and the spatiotemporal relationships among salient objects that appear in the video. The model extends the DISIMA model [24] by adding a video data layer. Figure 2 shows an overview of the improved video data model and its links to the DISIMA image data model.

The DISIMA model captures the semantics of image data through salient objects, their shapes, and the spatial relationships among them. It is composed of two main blocks (a block is defined as a group of semantically related entities), as shown on the right-hand side of Fig. 2: the image block and the salient-object block. The image block consists of two layers: the *image* layer and the *image representation* layer. The DISIMA model captures both specific information on every appearance of a salient object in an image (by means of *physical salient objects* and properties) and the semantics of the salient object (by means of *logical salient objects*). The DISIMA model supports a wide range of queries, from semantic-based to feature-based queries.

A video is often recursively decomposed into scenes and shots. Shots are summarized by key frames. A frame is an image with some specifics (time information, shot it is extracted from, etc.) that can be represented as a special kind of image (subclass of image). A new video block, as shown on the left-hand side of Fig. 2, is introduced to capture the representation and the recursive composition of videos. The lowest level in the video block is the shot, and a shot is linked to its key frames stored as images in the image block. The video block has four layers: *video*, *scene*, *shot*, and *video representation*. Because a video *frame* is treated as a special type of image, it inherits all the attributes defined for image entities in addition to a time-related attribute that models the temporal characteristics. The relationship between key frames and shots sets up the connection between a video block and a DISIMA image block.

3.2 Components of the video data model

The definitions of components of the video data model are given below.

Definition 1. A *key frame* is a video frame that is selected from a shot to represent the salient contents of the shot. A key frame KF_i is defined as a six-tuple

$$< i, R_i, C_i, D_i, SH_i, LS_i >$$

where

- i is the unique frame identifer;
- R_i is a set of representations of the raw frame (e.g., JPEG, GIF);
- C_i is the content of a key frame KF_i (Definition 3);
- D_i is a set of descriptive alphanumeric data associated with KF_i;
- SH_i is the shot (Definition 5) to which KF_i belongs;
- LS_i is the *lifespan* of the frame represented as a closed time interval $[T_s, T_e]$ that specifies the portion of the shot that KF_i represents. Since LS_i is within the shot, it must satisfy $LS_i \preccurlyeq SH_i.I_i$, where $\preccurlyeq$ is a "subinterval" operation, defined as follows. Given two time intervals I_A and I_B, $I_A \preccurlyeq I_B$ if and only if $I_B.T_s \leq I_A.T_s$ and $I_A.T_e \leq I_B.T_e$, where T_s and T_e are the start and end times of an interval.

In this data model, key frames are first selected through the automatic processes (using any of the existing key frame selection algorithms; e.g., [33]) and manual interpretation processes are used to mark out the changes of salient objects. With these two steps, a key frame is selected to represent a duration within a shot in which the spatial relationships among salient objects contained in that video frame hold.

We identify, as in DISIMA, two kinds of salient objects: physical and logical.

Definition 2. A *physical salient object* is a part of a key frame and is characterized by a position (i.e., a set of coordinates) in the key frame space. A *logical salient object* is an abstraction of a set of physical salient objects and is used to give semantics to that set.

Based on the definitions of physical and logical salient objects, we define the content of a key frame as follows:

Definition 3. C_i, the content of key frame KF_i, is defined by a triple

$$< \mathcal{P}_i, s, Triplelist >$$

where

- $\mathcal{P}_i$ is the set of physical salient objects that appear in KF_i and $\mathcal{P}$ is the set of all physical salient objects ($\mathcal{P} = \cup_i \mathcal{P}_i$);
- $s : \mathcal{P}_i \to \mathcal{L}$ maps each physical salient object to a logical salient object, where $\mathcal{L}$ is the set of all logical salient objects;
- $Triplelist$ is a list of *spatial triples* (Definition 4) that is used to represent the spatial relationships among objects that appear in KF_i.

Definition 4. A *spatial triple* is used to represent the spatial relationship between two salient objects, denoted by

$$< O_i, O_j, SR_{ij} >$$

where

- O_i and O_j are the physical objects that appear in the key frame;
- SR_{ij} is the spatial relation between O_i and O_j with O_i as the reference object. The spatial relations consist of eight directional relations (*north, northwest, west, southwest, south, southeast, east, northeast*) and six topological relations (*equal, inside, cover, overlap, touch, disjoint*).

Given n salient objects in a key frame, we need to store $n \times (n-1)/2$ pairwise spatial relations in order to capture all the spatial relationships among the salient objects.

Definition 5. A *shot* is an unbroken sequence of frames recorded from a single camera operation. A shot SH_j is defined as a five-tuple

$$< j, I_j, KFS_j, SC_j, D_j >$$

where

- j is the unique shot identifier;
- I_j is a time interval that shows the start and end time of SH_j;
- SC_j is the scene (Definition 6) to which SH_j belongs. Since SH_j is within SC_j, it satisfies: $I_j \preccurlyeq SC_j.I_j$;
- KFS_j is a sequence of key frames $[KF_{j,1}, \ldots, KF_{j,m}]$, where m is the number of key frames in SH_i. KFS_j is used to represent the content of a shot;
- D_j is as given in Definition 1.

Definition 6. A *scene* is a sequence of shots that are grouped together to convey the concept or story. A scene SC_k is

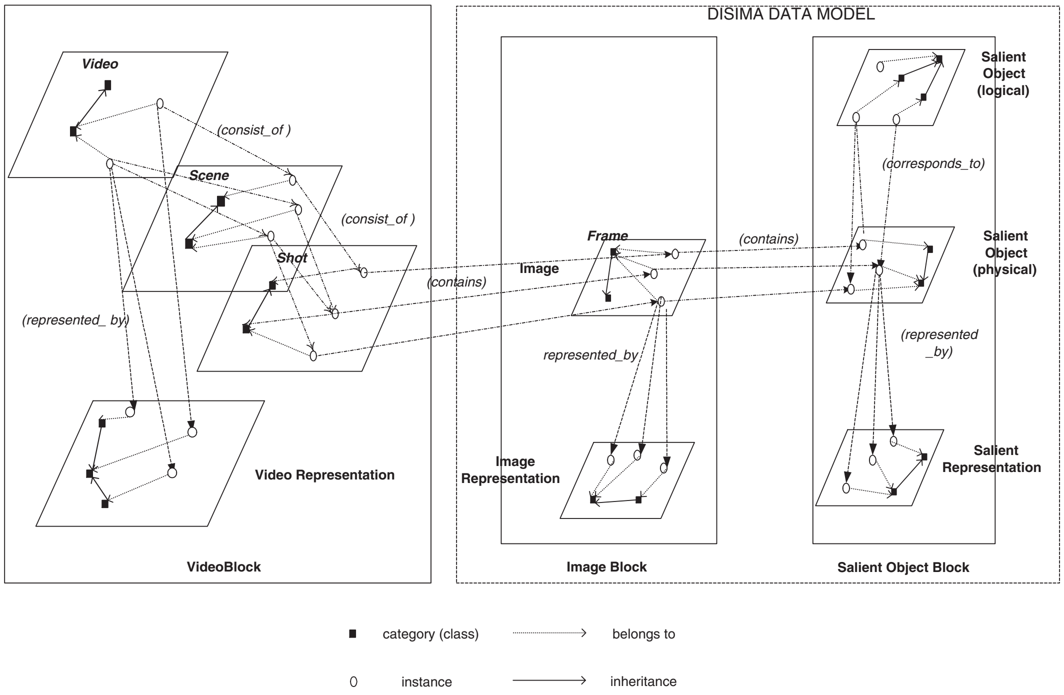


Fig. 2. Overview of the video data model and its links to the DISIMA data model

defined by a five-tuple

$$< k, I_k, SHS_k, V_k, D_k >$$

where

- k is the unique scene identifer;
- I_k is a time interval that shows the start and end times of the SC_k;
- V_k is the video (Definition 7) to which SC_k belongs. SC_k is a part of V_k; therefore, SC_k satisfies $I_k \preccurlyeq V_k.I_k$;
- SHS_k is a sequence of shots $[SH_{k,1}, \ldots, SH_{k,m}]$, where m is the number of shots in SC_k. SHS_k is used to construct SC_k;
- D_k is as given in Definition 1.

Definition 7. A video consists of a sequence of scenes. A *video* V_n is defined by a five-tuple

$$< n, I_n, R_n, SCS_n, D_n >$$

where

- n is the unique video identifer;
- I_n is a time interval that describes the start and end times of the video V_n. $I_n.T_s = 0$ since all the videos start at time 0;
- SCS_n is a sequence of scenes $[SC_{n,1}, \ldots, SC_{n,m}]$ that is contained by V_n, where m is the number of scenes in V_n;
- R_n is a set of representations of V_n. We consider two main representation models for videos: *raster* and *CAI*. Raster representations are used for video presentation, browsing, and navigation, while CAI (common appearance interval) representations are used to express spatiotemporal relationships among salient objects and moving trajectories of moving objects. The raster presentation may be one of MPEG-1, MPEG-2, AVI, NTSC, etc. Shots and scenes are not directly represented in the representation layer. Through time intervals that record durations of shots or scenes and video identifiers that indicate the video to which shots or scenes belong, portions of video representations can be quickly located and used as the representation for shots or scenes;
- D_n is as given in Definition 1.

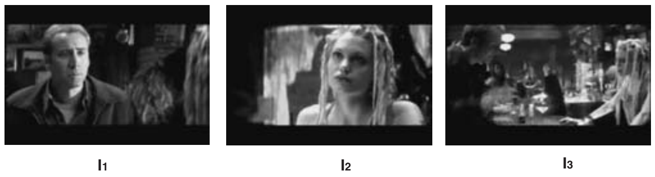


Fig. 3. CAIs of an example shot

3.3 Modeling temporal relationships within a shot

In our proposed video data model, the video shot is the smallest querying unit. Therefore, efficient capture of the appearance of salient objects and the temporal relationships among them directly affects the performance of salient-object-based queries.

The CAI model [6] captures the appearance and disappearance of the salient objects. A video shot can be represented as a sequence of CAIs, each representing an interval in which salient objects appear together. Figure 3 shows an example shot extracted from the movie "Gone in 60 seconds". In this video, object O_1 is Randall and object O_2 is Sara, $CAI(O_1) = I_1$, $CAI(O_2) = I_2$, and $CAI(O_1, O_2) = I_3$.

For any two salient objects that appear in a video shot, we define two types of temporal relationships between them: *appear_together* and *appear_before*:

Definition 8. Given two salient objects O_i and O_j that appear in shot SH_k, if there exists a time interval $[T_s, T_e] \preccurlyeq SH_k.I_k$ such that both O_i and O_j appear in $[T_s, T_e]$, we say O_i and O_j *appear_together* in SH_k, denoted by $O_i \simeq O_j$.

Definition 9. Given two salient objects O_i and O_j that appear in shot SH_k, if O_i and O_j appear in two time intervals $[T_s^i, T_e^i]$ and $[T_s^j, T_e^j]$, respectively, and $T_e^i \leqslant T_s^j$, then O_i is said to *appear_before* O_j, denoted as $O_i \lesssim O_j$.

The temporal relationships *appear_together* and *appear_before* can be used to construct other temporal relationships [1]. For example, $O_1 \lesssim O_1 \simeq O_2 \lesssim O2$ represents that $O1$ *overlaps* O_2.

Definition 10. Given a shot SH_i with n salient objects $O_1, O_2, \ldots, O_n$, the *temporal string* of SH_i is $O_1\theta O_2\theta \ldots \theta O_n$ ($\theta \in \{\simeq, \lesssim\}$). A temporal string represents the temporal relationships among salient objects that appear in a shot.

For the sample shot in Fig. 3, a temporal string is: $O_1 \lesssim O_2 \lesssim O_1 \simeq O_2$. Since $\simeq$ is symmetric, another valid temporal string of this shot is: $O_1 \lesssim O_2 \lesssim O_2 \simeq O_1$. Note that non-intuitive relationships such as $O_2 \lesssim O_2$ are acceptable since they represent occurrences in different intervals (e.g., frames) and the relationship is temporal.

4 MINDEX: a multilevel index structure

An analysis of the four types of salient-object-based queries discussed earlier reveals the following:

(1) For salient-object existence queries, it is only necessary to find all the shots in which the specified salient objects appear without any regard to their temporal appearance orders.
(2) For queries related to temporal relationships among salient objects, in addition to checking the existence of the salient objects, it is necessary to investigate the temporal relationships among the salient objects.
(3) For spatial queries, all the shots should be retrieved in which the specified salient objects appear, followed by a filtering of the shots in which the specified salient objects have *appear_together* temporal relationships. These are kept as candidate shots over which the spatial relationships among the salient objects are checked.
(4) For spatiotemporal queries, besides following the same steps as (3), temporal relationships among the salient objects in the candidate shots are also checked.

Among these four different granularity levels of constraints on salient objects, object existence queries help remove the shots that do not contain the specified salient objects; these shots also do not satisfy the other three types of queries. Similarly, the temporal queries with *appear_together* constraints can be considered as filters to avoid unnecessary searches for spatial and spatiotemporal queries because the shots in which the salient objects do not appear together cannot satisfy any spatial relationships. Therefore, we create an index that considers different granularity levels of constraints on salient objects. Figure 4 shows an overview of MINDEX. The first level is a hash table on names of salient objects; a B$^+$-tree is used to index pairwise temporal relationships and acts as the second level of the index structure. At the third level, a perfect hash table is created to index all the spatial triples that are contained in each shot. Figure 4 only shows one possible construction of MINDEX; we also propose two other alternative approaches: signature files and inverted files [7]. The construction using signature files is presented in this paper, and details for inverted files is described in [7].

4.1 First-level index structure: hash on names

It is more natural for users to query video databases using names of salient objects instead of their IDs (e.g., "give me all the shots in which Tom Cruise appears" is more intuitive than "give me all the shots in which salient object 001 appears"). Furthermore, generally, users do not know salient object IDs. Therefore, we create an extendable hash on the names of salient objects as the first-level index structure. A hash is selected because it offers $O(1)$ access time on data files. We assume that a name is assigned to a salient object when the video is added to the video database. Among the many possibilities, we select the *shift-add-xor* hash function [25] due to its low collision rate. We use $L = 5$ and $R = 2$ in our index structure as suggested in [25].

Since there exists the possibility that different name strings have the same hash value, chained lists are used to handle collisions (Fig. 4). Each data bucket of the hash table stores the ID of a salient object and a pointer that points to the next data bucket in the chain. Each salient object is stored in a object record structure, which is defined as

struct object record$\{$
$$\begin{aligned} int \quad & ID; \\ string \quad & name; \\ pointer \quad & rootnode; \\ \} \end{aligned}$$

where "rootnode" refers to a root node of a B$^+$-tree that is created as the second level of the index structure.

4.2 Second-level index

The second level of MINDEX is proposed to quickly filter out the false alarms in answering salient-object existence queries and temporal relationship queries. We propose three approaches, a B$^+$-tree, a multilevel signature file filter, and an inverted file. In the experiment section, we compare the performance of these three access methods.

4.2.1 A B$^+$-tree on pairwise temporal relationships

Spatial, temporal, and spatiotemporal relationship queries set constraints on at least a pair of salient objects since there is no spatial or temporal relationship for a single salient object. Queries that involve more than two salient objects can be handled by taking the intersection of a set of query results on pairs of objects. Therefore, for each salient object O_i, we create a B$^+$-tree to index all pairwise temporal relationships between

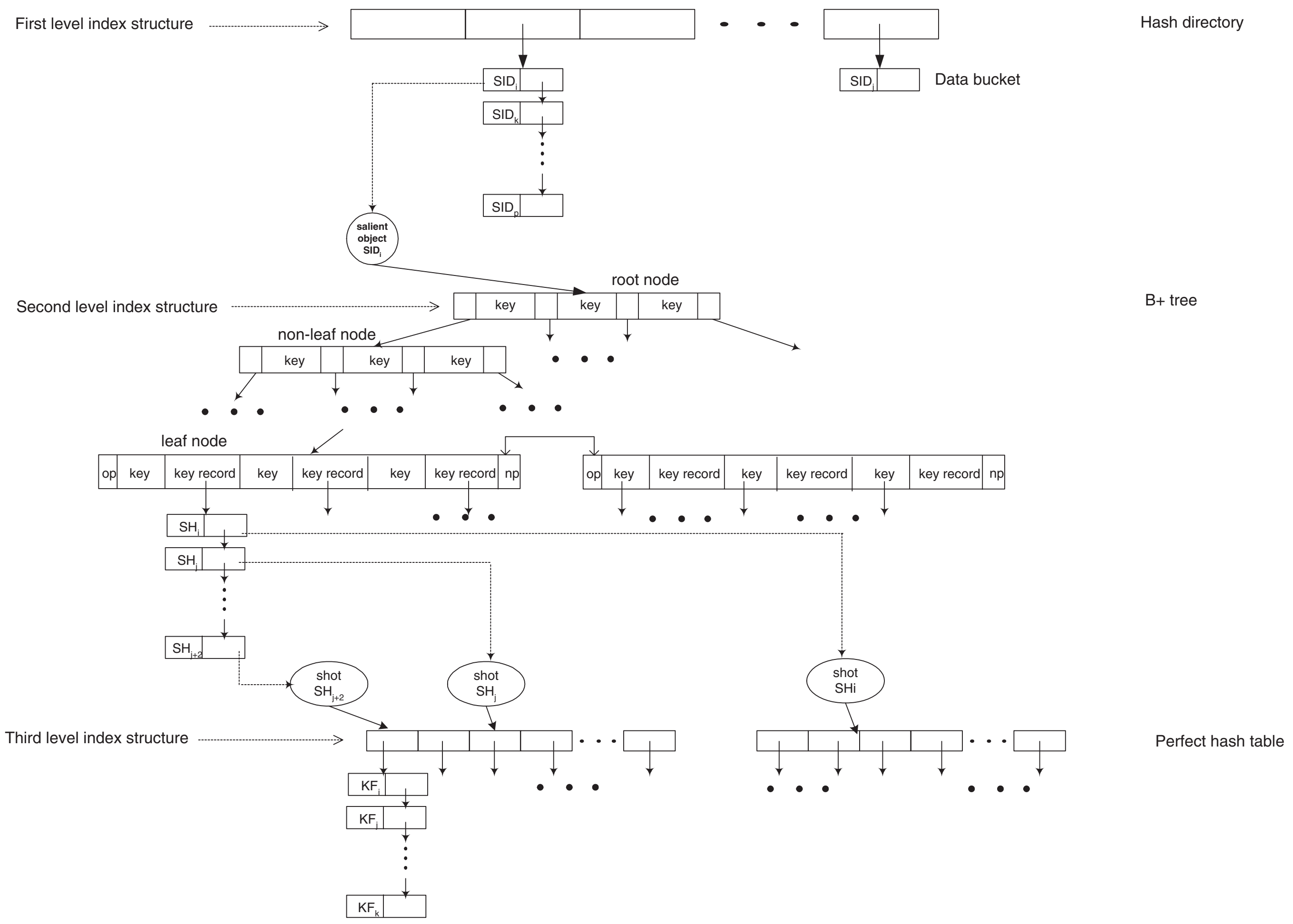


Fig. 4. Overview of MINDEX

overflow page	key$_1$	record of the key$_1$	key$_2$	record of the key$_2$	......	next page

Fig. 5. Layout of the leaf node of the B$^+$-tree

O_i and other salient objects. IDs of salient objects are used as keys. Each nonleaf node contains $q+1$ pointers and q entries for keys. The structure of a leaf node is shown in Fig. 5. The value of “key” is the ID of a salient object, which is an integer, “overflow page” is a pointer to the overflow pages, and “next page” points to the next leaf node. The internal structure of “record of the key” is defined as follows:

```
struct record of the key{
                    int    tempRel;
                  string linkedList;
                 }
```

where $tempRel$ is used to store the temporal relationship; it is a mapped integer value from a temporal relationship. The IDs of shots in which the *tempRel* relationship hold are stored in the $linkedList$.

4.2.2 A two-signature-based multilevel signature filter

Signature files have been widely used in information retrieval [10,13,18]. Recently, they have been used in spatial-similarity-based image retrieval [12,17,29]. The steps to construct signatures for images are as follows:

1. For each salient object in an image, we transform it into a binary code word using a hash function. The binary code is m (signature width) bits wide and contains exactly w (signature weight) 1s.
2. Each image signature is formed by superimposing (inclusive OR) of all the binary codes of salient objects contained in the image.

When querying the appearance of salient objects, the objects that are specified in the query are also transformed into binary codes and all the binary codes are superimposed together to form a query signature. The query signature is checked ($ANDed$) with each image signature. However, due to the false drop probability P_f of signature files (the probability that the signature is identified as containing the query signature, but the real record does not contain the query terms [13]), the images that are pointed to by matched signatures need to be further verified to remove false drops. With P_f, the number of images n, and the number of distinct salient objects s

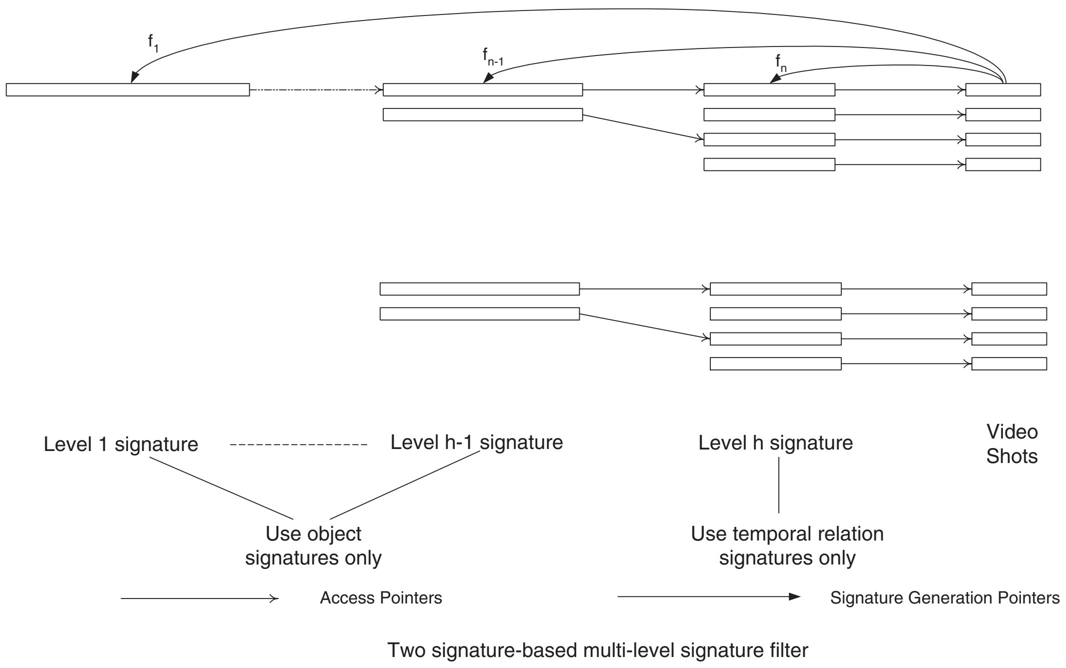

f1
fn-1
fn
Level 1 signature
Level h-1 signature
Level h signature
Video Shots
Use object signatures only
Use temporal relation signatures only
Access Pointers
Signature Generation Pointers
Two signature-based multi-level signature filter

Fig. 6. Two-signature-based multilevel signature filter

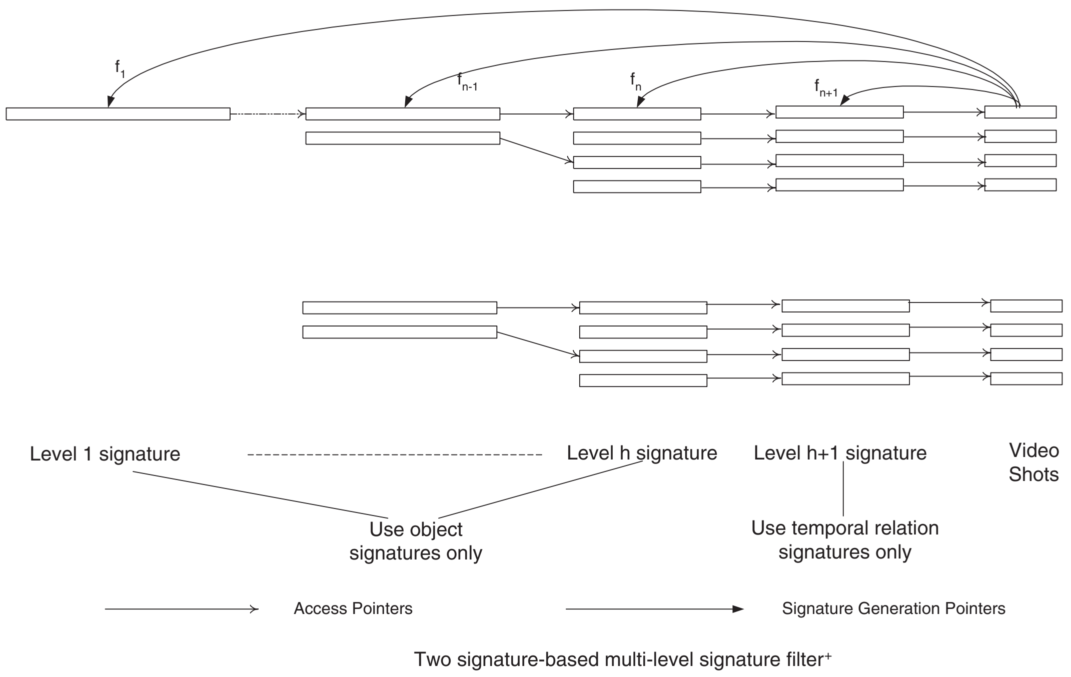

f1
fn-1
fn
fn+1
Level 1 signature
Level h signature
Level h+1 signature
Video Shots
Use object signatures only
Use temporal relation signatures only
Access Pointers
Signature Generation Pointers
Two signature-based multi-level signature filter+

Fig. 7. Two signature-based multi-level signature filter $^+$

we can compute the optimal values of signature width m and signature weight w [18].

The image signatures that are generated using only salient objects are called salient-object-based signatures. We can also use the same steps as above to generate spatial-relation-based image signatures by coding the spatial relationship pair of salient objects that appear in the images. El-Kwae and Kabuka [12] integrate two signatures into a single index structure, called a two-signature-based multilevel signature filter (2SMLSF), to index appearance of salient objects and spatial relationships among objects in images.

In this paper, we use 2SMLSF to index the appearances of salient objects and pairwise temporal relationships among salient objects in video shots.

As shown in Fig. 6, a 2SMLSF file is a forest of b-ary trees. Every nonleaf node has b child nodes. There are h levels in the 2SMLSF. Assume all the trees are complete b-ary trees; the number of nodes in the structure is: $n = b^h$. We generate salient-object-based shot signatures by superimposing binary codes of salient objects that appear in the shots and temporal-relation-based shot signatures from the temporal relation pairs in the shots. The temporal-relation-based shot signatures are used as leaf nodes of the 2SMLSF; the remaining nonleaf (block) signatures are only based on salient objects. We also propose a modified version of 2SMLSF called 2SMLSF$^+$. Compared to 2SMLSF, we add one more level of signatures to the 2SMLSF that are generated from salient objects. As shown in Fig. 7, in 2SMLSF$^+$, the level 1 to h signatures are generated from signatures of salient objects and level $h + 1$ signatures (same as h level in 2SMLSF) are generated from temporal relationships among the salient objects. Due to one more level of filtering, 2SMLSF$^+$ can remove more false alarms when it is used to answer salient-object appearance and temporal relationship queries. Our experimental results, presented in Sect. 5, confirm this claim.

4.3 Third-level index: perfect hash for spatial relationships

Both spatial and spatiotemporal queries relate to spatial relationships among salient objects; therefore, an index structure on spatial relationships will be helpful to answer these queries. In our video data model, a sequence of key frames is chosen to represent a shot. The spatial relationships among the salient objects in each key frame are described by a list of spatial triples. Although the number of key frames that are selected to represent a shot may not be large, scanning each key frame to find the specified spatial relationship is still time consuming, especially when there exists a large number of candidate shots. We use a hash table as the third-level index structure to index pairwise spatial relationships in each shot and adapt the technique described in [4] for this purpose. As depicted in Fig. 4, key frames that contain the same spatial triple (O_i, O_j, SR_{ij}) will be mapped to the same hash entry, and IDs of these key frames are linked together. For each shot, since the number of key frames and the spatial relationships among salient objects in each key frame are known, a minimum perfect hash algorithm can be employed to reduce the storage and avoid the conflicts. Fourteen integers are used to denote spatial relationships (eight directional and six topological). The hash address of a spatial triple (O_i, O_j, SR_{ij}) is

$$h(O_i, O_j, SR_{ij}) = SR_{ij} + \text{associated value of } O_i \\ + \text{associated value of } O_j .$$

To assign the associated values to symbols of spatial tuples, we use Cook and Oldehoeft's algorithm [9], which is also used in [4].

The third-level index structure is not created for each shot. We define a shot as *spatial indexable* if there are at least two salient objects that appear together in the shot. Shots in which only one salient object appears or no salient objects appear together do not need indexes on spatial relationships since there are no spatial relationships that can be derived from these shots. However, creating a hash table for each spatial indexable shot induces redundant information because shots/reverse shots cause similar spatial layouts to appear in an interleaving pattern. Figure 8 shows an example of this interleaving pattern, which appears in a dialog scene between “Maximus” and “Princess” in the movie “Gladiator”. In the four example shots, SH_1 has a spatial layout similar to that of SH_3 as well as to SH_2 and SH_4. Therefore, when we create a hash table for an indexable shot SH_i and $(i > 1)$, two precedent shots SH_{i-2} and SH_{i-1} are checked first. If SH_{i-2} or SH_{i-1} has exactly the same spatial triples as those of SH_i, we define the corresponding hash table as *sharable* to SH_i. Thus, instead of creating a new hash table for SH_i, the hash table pointer of SH_i is pointed to the *sharable* hash table, which removes the possible redundant information from the index structure. Figure 4 shows an example of SH_{j+2} and SH_j sharing a hash table.

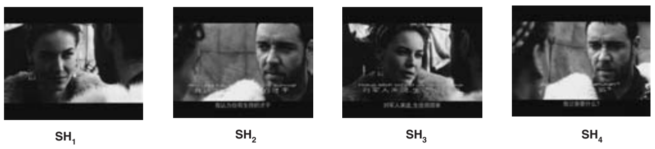


Fig. 8. Example of shot/reverse shot pattern in a dialog scene

We also implement two other alternative approaches to third-level indexes: spatial-relation-based image signature files and inverted files. The pairwise spatial relationships between two salient objects that exist in a key frame are hashed into binary code words, and all the binary code words of the key frame are superimposed to get the image signature of that key frame. Since there are a limited number of key frames for each shot, we store the image signatures sequentially. The inverted files are used to index each distinct pairwise spatial relationship of each shot.

4.4 Creation of the multilevel indexing structure

In general, given a set of n shots, three steps are needed to create a MINDEX when we use a B$^+$-tree as the second level of MINDEX:

1. For all salient objects of each shot, use their names to find their IDs in the hash (the first-level index) and update the hash directory if these objects are new ones.
2. For all the temporal relationships in the shot, use IDs of involved salient objects to update the corresponding B$^+$-tree (the second-level index structure).
3. For all the spatial relationships in the shot, create a new perfect hash table (the third-level index structure) for all the spatial triples contained in the shot if there is no sharable hash table in the two preceding shots.

In the first step, besides finding the IDs for salient objects, we also need to create an ID for the new salient object and insert it into the hash directory. We consider a salient object a new one if $NULL$ is returned after searching the data bucket that is pointed to by the hash directory entry of the salient object. Algorithm 1 presents the steps that are followed to update the second-level index structure. The standard update operation of B$^+$-tree is used in the algorithm. When we use signature files at the second and third levels of MINDEX, we can use the first step that we use for creating MINDEX with

B$^+$-tree as the second level. The second and third steps are described as follows:

Algorithm 1 The algorithm for updating second-level index structure

```
Require: /*input: the IDs of all salient objects in a given shot $SH_i$*/
Ensure: /*output: updated B$^+$-tree of each object record*/
1: Compute all distinct pairwise temporal relationships between two salient objects from temporal strings of $SHi$
2: For each temporal relationship $TR_{ij}$ ($appear\_together$ or $appear\_before$) between two salient objects whose IDs are $ID_i$ and $ID_j$, respectively
3: Insert $ID_j$ and $TR_{ij}$ into the B$^+$-tree of the object record that is identified by $ID_i$
4: Insert $ID_i$ and $TR_{ij}$ into the B$^+$-tree of the object record that is identified by $ID_j$
```

Algorithm 2 The searching algorithm for salient-object existence queries using B$^+$-trees

```
Require: /*input: the names of salient objects */
Ensure: /*output: the set of IDs of shots that the specified salient objects appear*/
1: find IDs of all the salient objects specified in the queries through the first level of MINDEX
2: the object records that stored specified salient objects are identified through IDs
3: select one B$^+$-tree that pointed to one of the identified object records
4: if only one object in the query then
5:   insert all the IDs of shots stored in the leaf node of the B$^+$-tree into result set $Reset$
6: end if
7: search the B$^+$-tree with the remaining object IDs and get the intersection of all the searching result sets as the result set $Reset$
8: return the result set $Rset$
```

1. Determine the height h of 2SMLSF and 2SMLSF$^+$ according to the number of shots n, the maximum number of distinct salient objects of each shot s, and the global false drop probability p^f. For each level, compute the signature width and weight.
   - For each shot, compute all distinct pairwise temporal relationships between two salient objects from the temporal string of that shot. For each pairwise temporal relationship, generate a signature to represent it and superimpose all the signatures of pairwise temporal relationships to construct the temporal-relation-based shot signature as a leaf node of 2SMLSF or 2SMLSF$^+$. A pointer is used to link the leaf node and the logical shot.
   - For each shot, generate $h-1$ salient-object-based signatures (h signatures for 2SMLSF$^+$) that are based on salient objects of the shot. For each level i, superimpose b^{h-i} salient-object-based signatures to get block signature at that level.
2. For each key frame in a shot, generate a signature for each distinct pairwise spatial relationship and superimpose all the signatures of spatial pairs to construct a spatial-relation-based image signature for the key frame. Store all the image signatures of the shot sequentially in a file. This step is similar to the creation of 2SMLSF for image databases [12].

4.5 Query processing using multilevel indexing structure

In this section, we discuss how the four types of queries are executed using MINDEX. To answer object existence and pure temporal relationship queries, only the first- and second-level indexes are needed, while for queries involving spatial and spatiotemporal relationships all three levels are used. We first present the algorithms in answering different types of queries when a B$^+$-tree is used as the second level of MINDEX.

1. *Salient-object existence queries*: Algorithm 2 presents the steps in answering salient-object existence queries.
2. *Temporal relationship queries*: Algorithm 2 can be used to search results for temporal relationship queries; the only additional work is to check the temporal relationship stored at the leaf node of the B$^+$-tree.
3. *Spatial relationship queries*: Algorithm 3 presents the steps in answering spatial relationship queries.

Algorithm 3 The searching algorithm for spatial relationship queries using B$^+$-tree

```
Require: /*input: the names of salient objects and spatial relationships among them*/
Ensure: /*output: the set of IDs of shots that contain salient objects and specified spatial relationships*/
1: find IDs of all the salient objects specified in the queries through the first level of MINDEX
2: the object records that stored specified salient objects are identified through IDs
3: select one B$^+$-tree that pointed to one of the identified object records
4: search the B$^+$-tree with the remaining object IDs and get the intersection of all the searching result sets as candidate set $CanSet$
5: for all each candidate shot in $CanSet$ do
6:   compute the hash address of the third-level index structure for the spatial triple that is constructed from the object IDs and the specified spatial relationships
7:   load the corresponding hash table that is referred by the candidate shot
8:   if the hash entry of the computed hash address is not empty then
9:     insert the ID of the candidate shot into $Rset$
10:  end if
11: end for
12: return the result set $Rset$
```

4. *Spatiotemporal relationship queries*: Steps similar to Algorithm 3 are followed to find the candidate shots that contain the specified salient objects and spatial relationships. The candidate shots are further checked to verify whether the specified temporal relationships are satisfied among the spatial relationships in the candidate shots.

When we use signature files as the second and third levels of MINDEX, the following algorithms are used to answer different types of queries:

1. *Salient-object existence queries:* The steps in answering salient-object existence using 2SMLSF is described in Algorithm 4.

Algorithm 4 The searching algorithm for salient-object existence queries using 2SMLSF

```
Require: /*input: the names of salient objects */
Ensure: /*output: the set of IDs of shots that the specified salient objects appear*/
1: find IDs of all the salient objects specified in the queries through the first level of MINDEX
2: generate $h-1$ salient-object-based shot signatures as query signatures: $S_q^1, S_q^2, \dots, S_q^{h-1}$
3: check (AND operation) $S_q^1$ with root signatures of 2SMLSF
4: if the result equals to $S_q^1$ then
5:   put the access pointer of the root into the candidate block set $CanBlkSet_1$
6: end if
7: level $i \leftarrow 2$
8: while level $i \neq h$ do
9:   if $CanBlkSet_{i-1}$ is empty then
10:     return NULL
11:   end if
12:   check (AND operation) $S_q^i$ with the block signature at level $i$, which is pointed to by the access pointer in $CanBlkSet_{i-1}$
13:   if the result equals to $S_q^i$ then
14:     put the access pointer of the block signature into the candidate block set $CanBlkSet_i$
15:   end if
16:   level $i \leftarrow i+1$
17: end while
18: if $CanBlkSet_{h-1}$ is empty then
19:   return NULL
20: else
21:   check each shot pointed to by the access pointers in $CanBlkSet_{h-1}$
22:   if the shot contains the IDs of salient objects specified in the query then
23:     insert the ID of the shot into the result set $Reset$
24:   end if
25: end if
26: return $Reset$
```

2. *Temporal relationship queries*: Algorithm 5 presents the steps in answering temporal relationship queries using 2SMLSF. Algorithms 4 and 5 can be applied to 2SMLSF$^+$ by slightly modifying the searching level and generating query signatures.
3. *Spatial and spatiotemporal queries*: Due to space constraints, the detailed algorithms are not given here, and we briefly describe the steps as follows:
   (a) Algorithm 5 is used to find the candidate shots that contained specified query objects and temporal relations.
   (b) Check the spatial-relation-based query signature with each image signature of the candidate shots.
   (c) If the result is equal to the spatial query signature, the corresponding key frame will be checked to see if it indeed contains the specified spatial relations. If this is the case, insert the candidate shot into the result set.
   (d) Return the result set.

Algorithm 5 Searching algorithm for temporal relationship queries using 2SMLSF

```
Require: /*input: the names of salient objects and temporal relationships among them */
Ensure: /*output: the set of IDs of shots that contain specified salient-object and temporal relations */
1: find IDs of all the salient objects specified in the queries through the first level of MINDEX
2: generate $h-1$ salient-object-based shot signatures $S_q^1, S_q^2, \dots, S_q^{h-1}$ and one temporal-relation-based shot signatures $S_q^h$ as query signatures
3: check (AND operation) $S_q^1$ with root signatures of 2SMLSF
4: if the result equals $S_q^1$ then
5:   put the access pointer of the root into the candidate block set $CanBlkSet_1$
6: end if
7: level $i \leftarrow 2$
8: while level $i \neq h+1$ do
9:   if $CanBlkSet_{i-1}$ is empty then
10:     return NULL
11:   end if
12:   check (AND operation) $S_q^i$ with the block signature at level $i$, which is pointed to by the access pointers in $CanBlkSet_{i-1}$
13:   if the result equals $S_q^i$ then
14:     put the access pointer of the block signature into the candidate block set $CanBlkList_i$
15:   end if
16:   level $i \leftarrow i+1$
17: end while
18: if $CanBlkSet_h$ is empty then
19:   return NULL
20: else
21:   check each shot pointed to by the access pointers in $CanBlkSet_h$
22:   if the shot contains the IDs of salient objects and temporal relationships specified in the query then
23:     insert the ID of the shot into the result set $Reset$
24:   end if
25: end if
26: return $Reset$
```

5 Experiment results and discussion

We have run experiments to compare the performance of different methods of MINDEX construction in answering salient-object-based queries. Due to the lack of sufficient annotated video data, we generated synthetic data to test the performance of MINDEX.

5.1 Experiment setup

In order to generate synthetic data that are similar to real movie data, we investigated the appearance frequencies of salient objects in each key frame and the number of salient objects in

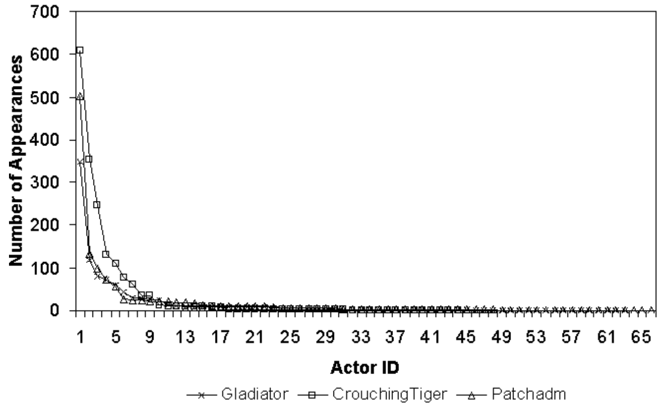


Fig. 9. Appearance distribution of actors

each shot in three movies.[1] As expected, the appearance frequencies of the main actors are higher than those of supporting actors and the number of actors that appear frequently is much less than that of actors who appear only once or twice in the whole movie. Figure 9 shows the number of appearances of actors in the three movies. The horizontal axis denotes the actor IDs; the lower IDs are given to the main actors. The vertical axis indicates the number of shots in which an actor appears. This data distribution is very similar to the ZIPF distribution [34]: $P_i \sim 1/i^a$, where P_i is the frequency of occurrence of the i-th ranked event, i is the rank of the event that is determined by the above frequency of occurrence, and a is close to 1. Thus, a few events occur very often while many others occur rarely.

We also found that there are at most five salient objects that appear in one frame (not counting the crowd), and the number of salient objects that appear in key frames also follows a ZIPF-like distribution (Fig. 10).

According to the changes of spatial relationships among the salient objects that appear in a shot, we manually selected the key frames for each segmented shot of these movies. We found that, for each shot, the number of selected key frames is around 1 to 5. In these experiments, we assumed that all salient objects are people and created synthesized names from a list of the top 1000 given names with an appearance probability of each name.[2] We do not use randomly generated strings as

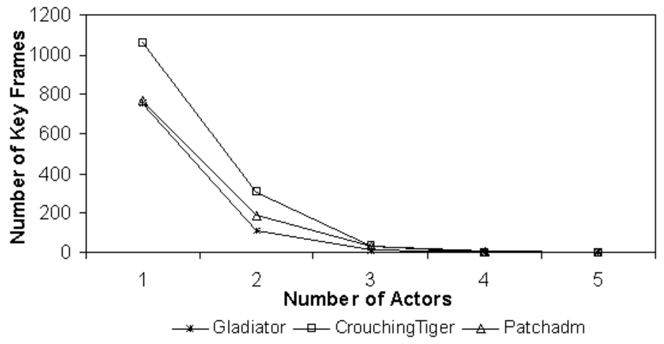


Fig. 10. Distribution of number of actors

[1] 1. "Gladiator", 2000; 2. "Crouching Tiger Hidden Dragon", 2000; 3. "Patch Adams", 1998.

[2] Obtained from http://www.ssa.gov/OACT/babynames/index.html.

names for the salient objects simply because it is not realistic. Furthermore, since the hash value is computed based on each character of a string, randomly generated strings do not reflect the real data distribution of each character as it appears in person names. A random number generator with a ZIPF distribution was used to select object IDs that may appear in each key frame. We used another random number generator with a ZIPF data distribution to simulate the number of salient objects that may appear in each key frame. Five data sets were created with different numbers of shots and different numbers of salient objects. For each shot, 1 to 5 key frames are randomly generated.

1. 4,096 shots with 41 salient objects;
2. 8,192 shots with 82 salient objects;
3. 16,384 shots with 164 salient objects;
4. 32,768 shots with 328 salient objects;
5. 131,072 shots with 1311 salient objects.

We generated the number of shots as the power of 2 in order to satisfy the assumption of complete b-ary ($b = 2$) trees of 2SMLSF and 2SMLSF$^+$. We set the false drop probability of signature files as $1/n$, where n is the number of shots in the data set. We randomly generated three types of queries: salient object existence, temporal relationship, and spatial relationship queries, with a uniform distribution and a ZIPF distribution, 100 queries for each type. Spatiotemporal relationship queries were not tested. In order to answer spatiotemporal relationship queries, MINDEX is used to find the candidate shots that satisfy the specified spatial relationships first, and then within those shots the temporal relationships among the spatial relationships are checked. Therefore, we only need to test spatial relationship queries. For object existence queries, the randomly generated queries specify the appearances of 1–5 salient objects. For temporal and spatial queries, the number of objects that are specified is 2 to 5. All the results are averages obtained from 100 query results.

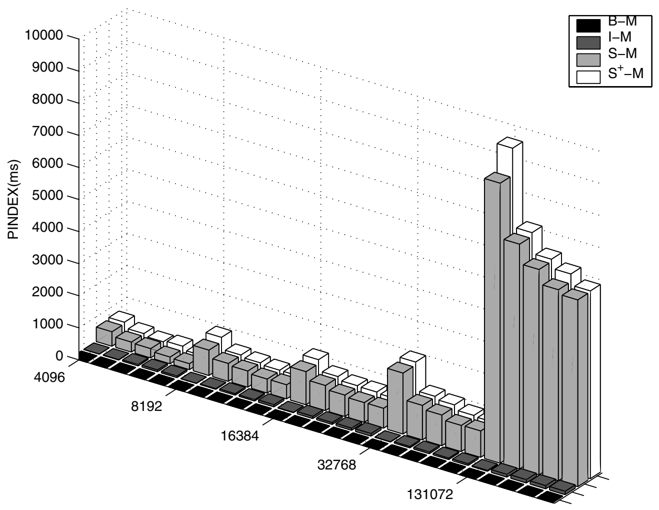
The experiments were run on a Sun Blade 1000 workstation with 512 MB RAM under Solaris 2.8.

5.2 Query performance

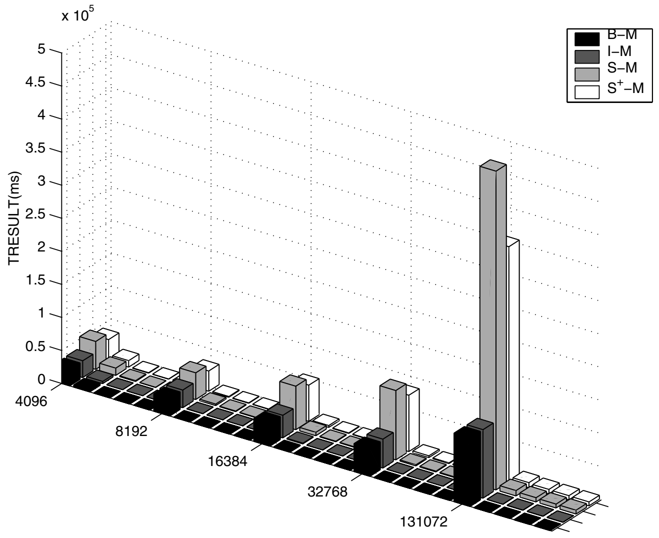
The first experiment was designed to test the performance of MINDEX with different construction on answering salient-object existence queries. We use the following abbreviations for four types of MINDEX: B-M for using B$^+$-tree in MINDEX, S-M for using 2SMLSF, S$^+$-M for using 2SMLSF$^+$, and I-M for using inverted file. We use two performance measures. One is the time spent on index retrieval and processing time, called $PINDEX$. For queries that are related to more than two salient objects, $PINDEX$ includes the time spent on finding the intersection of candidate sets for B$^+$-tree and inverted files. The other one is the total time spent on index retrieval and processing and retrieving the results and is called $TRESULT$. For signature files, $TRESULT$ includes the time to remove the false drops. Table 1 presents the selectivity ratios of queries and shows that object existence queries generated from a ZIPF (Z) distribution have much higher selectivity ratios compared to those of queries from uniform (U) distribution. We tested both types of queries. Figure 11 shows the $PINDEX$ and $TRESULT$ values of four types of MINDEX in answering salient-object existence queries generated

Table 1. Selectivity ratios of two types of salient-object-based existence queries on five data sets

	4096		8192		16384		32768		131072	
No. obj.	U	Z	U	Z	U	Z	U	Z	U	Z
1	0.087	0.797	0.047	0.093	0.031	0.416	0.018	0.243	0.011	0.067
2	0.011	0.602	0	0.031	0.001	0.159	0	0.069	0	0.005
3	0	0.095	0	0	0	0.092	0	0.037	0	0.002
4	0	0.016	0	0	0	0.055	0	0.015	0	0.001
5	0	0.006	0	0	0	0.028	0	0.009	0	0

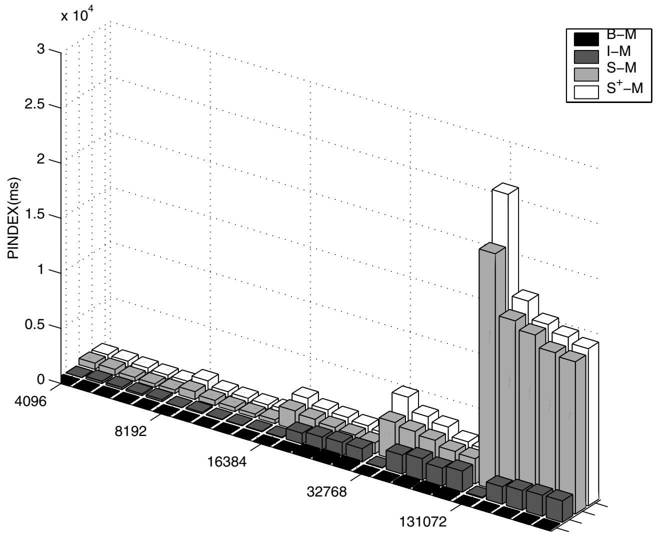


a

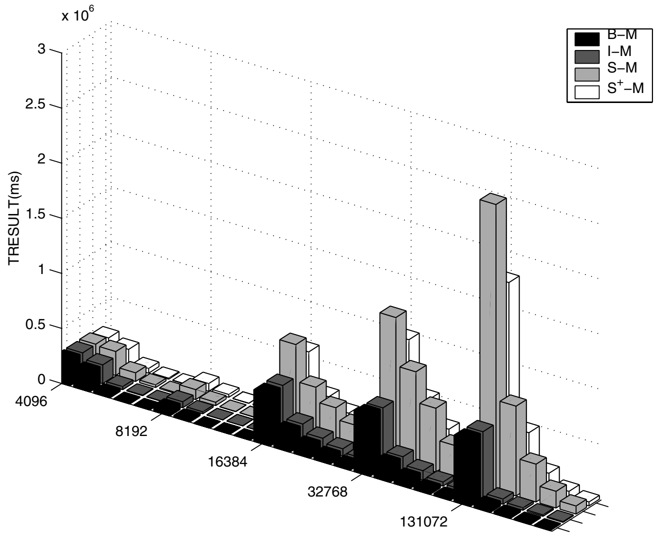


b

Fig. 11. Comparison of four types of MINDEX on salient-object existence queries (Uniform)

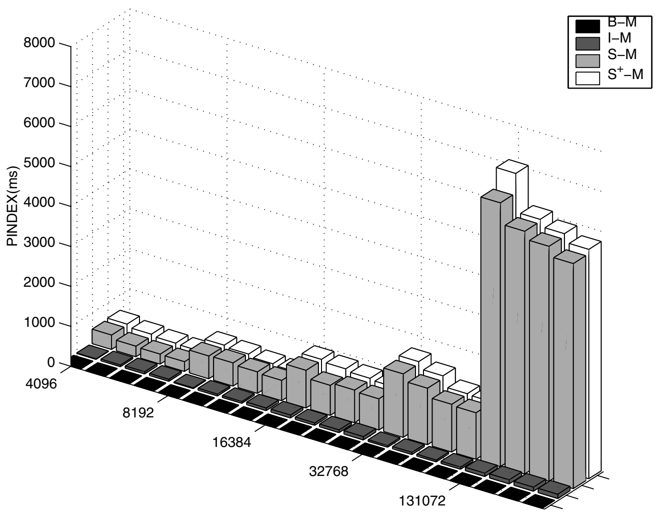


a

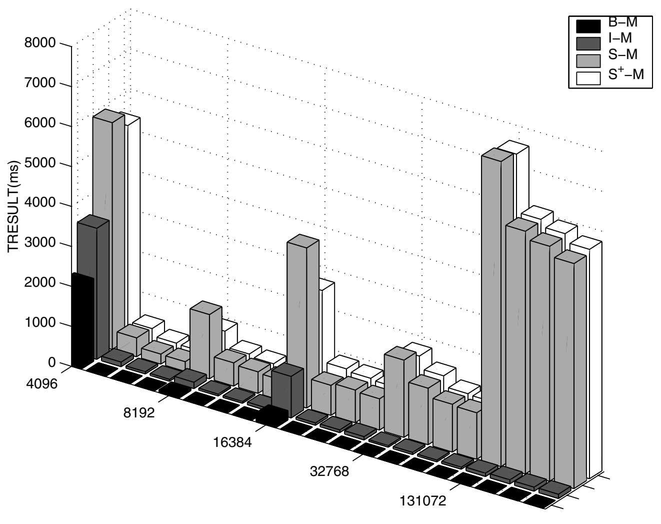


b

Fig. 12. Comparison of four types of MINDEX on salient-object existence queries (ZIPF)

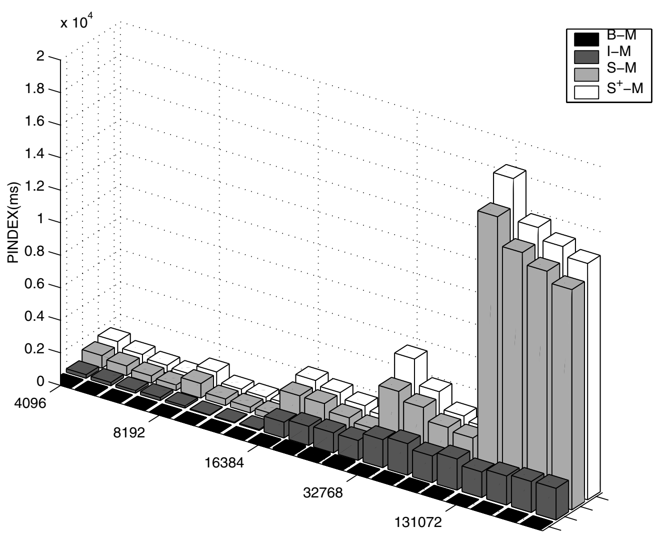


a

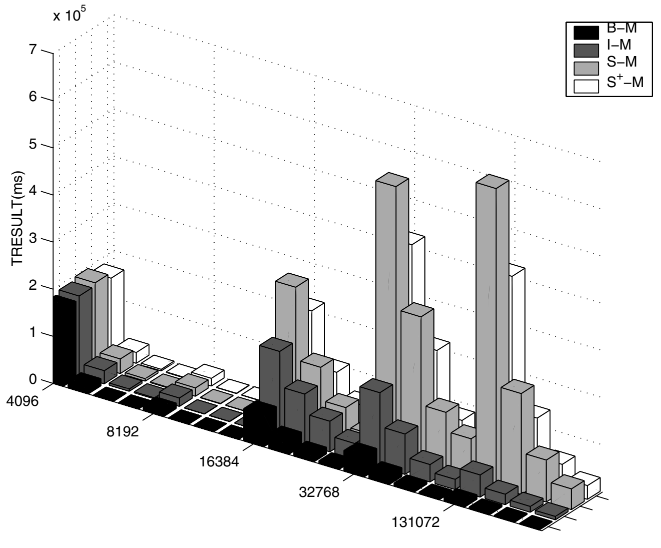


b

Fig. 13. Comparison of four types of MINDEX on temporal relationship queries (Uniform)



a



b

Fig. 14. Comparison of four types of MINDEX on temporal relationship queries (ZIPF)

from a uniform distribution, and Fig. 12 shows the same for a ZIPF distribution. The horizontal axis denotes the different sizes of data sets. For each data set (e.g., data set 4096), the results of queries on one to five salient objects are shown sequentially starting from the position of the label. The vertical axis indicates the time spent on $PINDEX$ or $RRESULT$ in milliseconds.

As shown in Fig. 11a, considering index processing time, B-M outperforms the other three index structures. When the selectivity ratio is low, B-M and I-M are always better than S-M or S^+M because of the false drops that are introduced by signature files. Since B-M uses B^+-trees to index pairs of salient objects, it produces fewer candidate shots compared to that of I-M, which creates an inverted list for each individual object. As a consequence, B-M needs less time to find the intersection from candidate sets. This has been shown in both figures, especially in Fig. 12a in which I-M spent much more time in finding the intersection of candidate sets. We also find that the index processing time for S^+-M is nearly the same as that of S-M because signature files are binary words and the time for loading and comparing one more level of signature files is minimal, especially when we use multilevel filtering. Considering the total time that is used to retrieve the answers (Figs. 11b and 12b), B-M is also the best. However, the difference between B-M and I-M is very slight when the selectivity ratio is higher since the time spent on index processing only counts for a very small portion of total retrieval time. There is another interesting fact that is shown in Figs. 11b and 12b: the difference between S$^+$-M and S-M on $TRESULT$ becomes larger with the increasing of the size of the data set. This confirms that S$^+$-M can remove more false drops than S-M; the greater the size of the data set, the more false drops can be removed by S$^+$-M.

The second experiment was designed to test the query performance of four different types of MINDEX on answering temporal-relationship-based queries. We present results of queries from uniform and ZIPF distributions in Figs. 13 and 14, respectively. As in Figs. 11 and 12, the horizontal axis denotes the different sizes of data sets. For each data set, the results of queries on two to five salient objects are shown sequentially.

Figures 13 and 14 show that B-M saves a significant amount of time in $PINDEX$ and $TRESULT$. Since B-M encodes the pairwise temporal relationship into the key record of B$^+$-tree, the size of candidate sets that are obtained from B-M is much smaller than those from I-M. Therefore, B-M saves time on both index processing (finding the intersection set) and retrieving results (removing false alarms). I-M only creates an index on the appearance of salient objects. Further examination on the candidate shots is required to confirm the existence of the query temporal relationships. The existence of false drops for signature files again leads to the inefficiency in answering temporal relationship queries. As shown in Figs. 13b and 14b, S$^+$-M again performs better than S-M in terms of total retrieval time.

From the above two experiments, we conclude that B$^+$-tree on pairwise salient objects is the best index structure that acts as the second level of MINDEX. As discussed in Sect. 4.5, spatial relationship queries help to identify the candidate shots for spatiotemporal queries. Therefore, the last experiment was designed to check the performance of processing spatial queries on different index structures for the third level of MINDEX. In this experiment, we use B$^+$-tree as the second level of MINDEX, and three index structures are tested: perfect hash table (HT), sequentially stored signature files (SSF), and inverted files (IF). Compared to salient-object existence and pure temporal queries, spatial queries incur extra reading costs in key frames to obtain spatial information. Figure 15 shows the $TRESULT$ of retrieval key frames to answer spatial queries on two salient objects generated from ZIPF distribution. The reason we select queries on two salient objects is that they have higher selectivity ratios. The results show that HT is the best candidate for the third level of MINDEX.

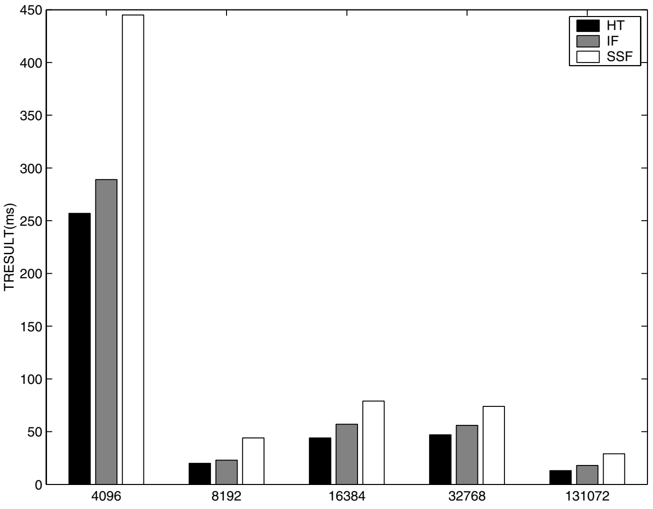


Fig. 15. Performance of spatial relationship queries on two salient objects

6 Conclusions

Several approaches have been proposed in the literature for salient-based queries on video databases. However, most of them focus on modeling video data using salient objects, and sequential search is used to answer these queries. However, when the size of a video database grows, it is quite time consuming to answer queries using sequential scan. Very few indexes have been proposed to quickly answer salient-object-based queries, and these either create indexes only for spatial relationships or rely on an implicit indexing mechanism provided by the implementation languages. Querying video databases on salient objects is quite different from querying spatiotemporal databases. The two fundamental types of queries in spatiotemporal databases, *timestamp* and *interval* queries, are rarely used in salient-object-based video databases since users normally do not have any knowledge about the timestamps or intervals in which some specified event happens. What they are interested in is retrieving those timestamps or intervals! Therefore, the index structures on spatiotemporal databases cannot be directly applied to salient-object-based video databases.

In this paper, we present a multilevel index structure (MINDEX) for salient-object-based queries. The index structure considers the different levels of constraints on salient objects that users may have when they pose queries to the video database. An extendable hash table is created for quickly locating IDs of salient objects through their names, which act as the first level of the index structure. Four candidate index structures, B$^+$-tree, two types of multilevel signature files, and inverted files, are proposed for the second level of MINDEX. Perfect hash tables, sequential stored signature files, and inverted files are selected as candidates for the third level. All the index structures have been tested with various sizes of synthetic data generated according to the data distribution of real movies. Based on the experimental results, we conclude that a B$^+$-tree used to index pairwise temporal relationships between two salient objects is the best one for the second-level index structure. The ideal index structure for the third level of MINDEX is a perfect hash table that indexes all the pairwise spatial relationships within a shot. The characteristic of video data brought by shot/reverse shots is utilized to share hash tables of the third-level index, which avoids saving redundant information.

References

1. Allen JF (1983) Maintaining knowledge about temporal intervals. ACM Commun 26(11):832–843
2. Arijon D (1976) Grammar of the film language. Focal Press, Burlington, MA
3. Becker B, Gschwind S, Ohler T, Seeger B (1996) An asymptotically optimal multi-version B tree. VLDB J 5(4):264–275
4. Chang CC, Lee SY (1991) Retrieval of similar pictures on pictorial databases. Patt Recog 24(7):675–680

5. Chang SK, Shi QY, Yan CW (1987) Iconic indexing by 2D strings. IEEE Trans Patt Anal Mach Intell 9(3):413–428
6. Chen L, Özsu MT (2002) Modeling video objects in video databases. In: Proceedings of the 2002 IEEE international conference on multimedia and expo, pp 171–175
7. Chen L, Oria V, Özsu MT (2002) A multi-level index structure for video databases. In: Proceedings of the 8th international workshop on multimedia information system, pp 28–37
8. Chen L, Özsu MT, Oria V (2003) Modeling video data for content based queries: extending the DISIMA image data model. In: Proceedings of the 9th international conference on multimedia modeling, pp 169–189
9. Cook CR, Oldehoeft R (1982) A letter-oriented minimal perfect hashing function. ACM SIGPlan Notices 17(9):18–27
10. Davis RS, Kamamohanarao K (1983) A two-level superimposed coding scheme for partial match retrieval. Inf Sys 8(4):273–280
11. Dönderler ME, Ulusoy Ö, Güdükbay U (2002) A rule-based video database system architecture. Inf Sci 143(1):13–45
12. El-Kwae EA, Kabuka MR (2000) Efficient content-based indexing of large image databases. ACM Trans Inf Sys 18(2):171–210
13. Faloutsos C, Christodoulakis S (1984) Signature files: an access method for documents and its analytical performance evaluation. ACM Trans Inf Sys 2(4):267–288
14. Gudivada VN, Jung GS (1995) An algorithm for content-based retrieval in multimedia databases. In: Proceedings of the 2nd international conference on multimedia and computing system, pp 90–97
15. Jiang HT, Montesi D, Elmagarmid AK (1997) VideoText database systems. In: Proceedings of the 4th international conference on multimedia and computing systems, pp 344–351
16. Kuo TCT, Chen AL (2000) Content-based query processing for video databases. IEEE Trans Multimedia 2(1):1–13
17. Lee S-Y, Shan M-K (1990) Access methods of image database. Int J Patt Recog Artif Intell 4(1):27–42
18. Lee DL, Kim YM, Patel G (1995) Efficient signature file methods for text retrieval. IEEE Trans Knowl Data Eng 7(3)
19. Li JZ, Özsu MT, Szafron D (1997) Modeling of moving objects in a video database. In: Proceedings of the 4th international conference on multimedia and computing systems, pp 336–343
20. Mahdi W, Ardebilian M, Chen LM (2000) Automatic video scene segmentation based on spatial-temporal clues and rhythm. Network Inf Sys J 2(5):1–25
21. Nabil M, Ngu AHH, Shepherd J (1997) Modeling moving objects in multimedia database. In: Proceedings of the 5th international conference on database systems for advanced applications, Melbourne, Australia, pp 67–76
22. Nascimento MA, Silva JRO (1998) Towards historical R-trees. In: Proceedings of the 1998 ACM symposium on applied computing, pp 235–240
23. Niblack W, Barber R, Equitz W, Flickner M, Glasman E, Petkovic D, Yanker P, Faloutsos C, Taubin G (1993) The QBIC project: querying images by content using color, texture and shape. In; Proceedings of the 5th international symposium on storage and retrieval for image and video databases (SPIE), pp 173–185
24. Oria V, Özsu MT, Liu L, Li X, Li JZ, Niu Y, Iglinski P (1997) Modeling images for content-based queries: The DISIMA approach. In: Proceedings of the 2nd international conference on visual information systems, pp 339–346
25. Ramakrishna MV, Zobel J (1997) Performance in practice of string hashing functions. In: Proceedings of the 5th international conference on database systems for advanced applications, pp 215–224
26. Smith TGA, Davenport G (1992) The stratification system: a design environment for random access video. In: Proceedings of the international workshop on networking and operating system support for digitial audio and video
27. Tao YF, Papadias D (2001) MV3R-tree: a spatio-temporal access method for timestamp and interval queries. In: Proceedings of the 27th international conference on very large data bases, Rome, Italy pp 431–440
28. Theodoridis Y, Sellis T, Papadopoulos AN, Manolopoulos Y (1998) Specifications for efficient indexing in spatiotemporal databases. In: Proceedings of the 1998 IEEE international conference on SSDBM, pp 242–245
29. Tseng G, Hwang T, Yang W (1994) Efficient image retrieval algorithms for large spatial databases. Int J Patt Recog Artif Intell 8(4):919–944
30. Vazirgiannis M, Theodoridis Y, Sellis T (1998) Spatio-temporal composition and indexing for large multimedia applications. In: Proceedings of the 6th ACM international conference on multimedia, 6:284–298
31. Xu X, Han J, Lu W (1990) RT-tree: An improved R-tree index structure for spatiotemporal databases. In: Proceedings of the 4th international symposium on spatial data handling, pp 1040–1049
32. Zhang HJ, Kankanhalli A, Smoliar SW (1993) Automatic partitioning of full-motion video. ACM Multimedia Sys 1:10–28
33. Zhang HJ, Low CY, Smoliar SW, Wu JH (1995) Video parsing, retrieval and browsing: An integrated and content based solution. In: Proceedings of the 3rd ACM international conference on multimedia, pp 15–24
34. Zipf GK (1965) The psycho-biology of language. MIT Press, Cambridge, MA