Time-aware Collective Spatial Keyword Query

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Abstract. The collective spatial keyword query is a hot research topic in the database community in recent years, which considers both the positional relevance to the query location and textual relevance to the query keywords. However, in real life, the temporal information of object is not always valid. Based on this, we define a new query, namely time-aware collective spatial keyword query (TCoSKQ), which considers the positional relevance, textual relevance, and temporal relevance between objects and query at the same time. Two evaluation functions are defined to meet different needs of users, for each of which we propose an algorithm. Effective pruning strategies are proposed to improve query efficiency based on the two algorithms. Finally, the experimental results show that the proposed algorithms are efficient and scalable.

Keywords: Collection of objects, TR-tree, Valid time of the objects, Keyword query.

1. Introduction

As textual information on location-based geographic information has been paid more and more attention, spatial keyword query technology is proposed [8]. With the continuous development of spatial keyword query, in some practical applications, people begin to pay attention to the valid time of geo-spatial objects. For example, visitors want to plan a trip based on the opening time of geo-spatial objects, which is the time-aware spatial keyword query [5]. However, [5] only considers the case that a single object contains all the query keywords. As far as we know, there is no work to consider the valid time of objects based on the collective spatial keyword query. The collective spatial keyword query refers to finding a group of objects that together contain all of the query keywords and are near to the query location. Therefore, this paper proposes a new query, i.e., time-aware collective spatial keyword query (TCoSKQ). An example is illustrated in Fig. 1 where a user (at the location of q) plans to visit a “gym” from 7:00 to 8:30, and a “restaurant” from 9:00 to 10:00. Collective spatial keyword query may return \{o₁, o₂\}, while TCoSKQ may return \{o₃, o₂\}. The reason of the difference is that TCoSKQ considers the valid time of the objects. Although [6] is closely related to ours, they do not consider the case that there exists a query point. [21] considers the valid time of the objects too, but it aims to find a set of k objects ranked the highest according to a ranking function.

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TCoSKQ considers the positional relevance, textual relevance and temporal relevance between the objects and the query at the same time. In order to solve the TCoSKQ problem, we define two evaluation functions to meet different needs of users, i.e., $score_1$ and $score_2$, which are suitable for the cases that the object containing the query keyword is close to and far from the query position, respectively. Then, TCoA1 algorithm and TCoA2 algorithm are designed for the two evaluation functions, respectively. Both algorithms use multiple Time-aware R-tree (TR-tree) [6] to index the valid time information and the spatial information of objects, that is, objects containing the same keyword are on the same TR-tree. TCoA1 algorithm finds feasible solutions by the distance dominators, which are searched from near to far, starting from the query location. Finally, the feasible solution with the largest $score_1$ is the final result. In order to improve the efficiency of the query, we propose effective pruning strategies for pruning the distance dominators that are unlikely to appear in the final result. TCoA2 algorithm searches for the center object from near to far from the query location, in which TCoA1* algorithm is called to find the feasible solution. TCoA1* algorithm is got by modifying TCoA1 algorithm. The feasible solution with the largest $score_2$ is the optimal solution, and effective pruning strategies are proposed to improve the query efficiency.

![Fig. 1. Example of a TCoSKQ](image)

To summarize, the main contributions of this paper are:

1. We propose a new query, i.e., time-aware collective spatial keyword query (TCoSKQ).
2. We propose two evaluation functions (i.e., $score_1$ and $score_2$), and propose effective pruning strategies and algorithms (i.e., TCoA1 and TCoA2) for these two functions to solve TCoSKQ.
3. We conduct extensive experiments using the data sets to demonstrate the efficiency and scalability of our algorithms.

This paper introduces related work in Section 2, Section 3 gives problem definition. Section 4 gives the TR-tree indexing structure. Section 5 and 6 elaborates TCoA1 and TCoA2 algorithm, respectively. Section 7 gives the experimental results and analysis. Section 8 concludes the paper.
2. Related Work

In recent years, spatial keyword query has attracted much attention from the spatial database community. Scholars have proposed effective techniques to deal with spatial keyword query. The early spatial keyword query is mainly for the case of retrieving a single object containing all query keywords and close to the query position. It is roughly divided into three types: Boolean kNN query [2], ranked kNN query [14] and Boolean range query [19].

As people’s needs increase, [1] observed that there may be situations where a single object cannot meet the needs of users, therefore, they first proposed collective spatial keyword query (CoSKQ). CoSKQ refers to retrieving a group of spatial web objects such that the group’s keywords cover the query’s keywords and such that objects are nearest to the query location and have the lowest inter-object distances. Based on two types of cost function, they study two instances of this problem, both of which are NP-complete. So they proposed effective approximate algorithms and exact algorithms to solve the two instances. Based on the shortcomings of the query in [1], [15] defined a new cost function describing the quality of set, proposed a new collective query processing method based on spatial keyword, and devised the corresponding approximate algorithm and exact algorithm.

With the intensive study of the collective spatial keyword query, some variants of the collective spatial keyword query have been proposed. [7] focused on specific spatial keyword set search in specific direction, and proposed a query algorithm based on grid index. [3] proposed an inherent-cost aware collective spatial keyword query, which takes into account the inherent cost of each object, and gave an exact algorithm and approximate algorithm that can solve the problem. Considering the importance of keyword level, [20] proposed a level-aware collective spatial keyword query, the corresponding cost function, the exact algorithm, and the approximate algorithm. Group-based collective keyword querying was proposed in [17], which considers the case of group of users. The query aims to find a region containing a set of objects that covers all the query keywords and these objects are close to the group of users and are close to each other. [9] and [22] have successively proposed methods for solving collective spatial keyword query on the road network. [11] considered the problem of scalable collective spatial keyword queries and proposed a distributed method to solve this problem effectively. In [4], a unified cost function and a unified method are proposed for the collective spatial keyword query problem to systematically solve the query problem.

With the in-depth study of spatial keyword queries, the valid time information of objects has attracted people’s attention. [5] proposed a time-aware Boolean spatial keyword query (TABSKQ), which returns the $k$ objects that satisfy users’ spatio-temporal description and textual constraint, designed TA-tree index structure, and proposed algorithms to process TABSKQ efficiently. [21] proposed time-aware spatial keyword queries on road networks, which finds the $k$ objects satisfying users’ spatio-temporal description and textual constraint, and devised several effective algorithms using the TG index. [6] proposed a time-aware spatial keyword cover query (TSKCQ), devised a TR-tree for indexing the temporal information and the spatial information of objects, and proposed an exact algorithm to tackle TSKCQ.

As far as we know, the previous work on collective spatial keyword query does not consider the importance of the object’s valid time information. Therefore, we propose
a new query, that is, time-aware collective spatial keyword query, which considers the object’s valid time based on the collective spatial keyword query.

3. Problem Definition

In spatial dataset, each object may be associated with one or multiple keywords. We convert the object with multiple keywords into multiple objects in the same location. For any object \( o \) with \( m (m > 1) \) keywords, we will create \( m - 1 \) other objects with the same location of \( o \) so that each of the \( m \) objects has only one different keyword. Let \( D \) be a set of objects. Each \( o \in D \) is associated with a location denoted by \( o.\lambda \), a keyword denoted by \( o.k \) and a valid time denoted by \( o.t \), where \( o.t \) is in the form of \((st, et)\) with \( st \) and \( et \) being the starting time stamp and the ending time stamp of \( o \), respectively. Similar to [5] and [6], we integerize \( st \) and \( et \) of \( o \), and take one hour as a time unit. As an example, any time stamp among \([13:00, 14:00)\) can be converted to a time unit 13. \((13:10, 18:00)\) can be converted to \((13, 18)\). For simplicity, let \( et, st \in [0, 24] \) and \( st \leq et \). The input of a time-aware collective spatial keyword query (TCoSKQ) is \( q = (\lambda, K, T) \), where \( q.\lambda \) is the query location, \( K = \{k_1, ..., k_m\} \), \( T = \{t_1, ..., t_m\} \), \( k_i (1 \leq i \leq m) \) is the \( i \)th query keyword, and \( t_i \) is a time interval specified in the query for \( k_i \). For the query \( q \), the object set \( S = \{o_1, ..., o_m\} (S \subseteq D) \) containing all the keywords in \( K \) is called the feasible solution.

Definition 1. (Time-aware collective spatial keyword query (TCoSKQ)) Given a spatial database \( D \) and a query \( q = (\lambda, K, T) \), TCoSKQ returns an optimal solution \( S \) (which is also a feasible solution), such that \( \text{score}(q, S) \geq \text{score}(q, S') \), where \( S' \) is any feasible solution.

According to the two different needs of users, we give the definition of \( \text{score}(q, S) \):

\[
\text{score}(q, S) = \begin{cases} 
\text{score}_1(q, S), & \text{the first evaluation function} \\
\text{score}_2(q, S), & \text{the second evaluation function} 
\end{cases}
\] (1)

where \( \text{score}_1 \) and \( \text{score}_2 \) are evaluation functions that satisfy the user’s first and second requirement, respectively.

(a) The \( \text{score}_1 \) is defined as:

\[
\text{score}_1(q, S) = \alpha (1 - \max_{o \in S} \frac{\text{dist}(q, o)}{\text{max}\_\text{dist}}) + (1 - \alpha) \min_{o \in S, k_i \in K, o.k = k_i} \frac{|t_i \cap o.t|}{|t_i|} \tag{2}
\]

where \( \text{dist}(q, o) \) is the Euclidean distance between \( q \) and \( o \), \( \text{max}\_\text{dist} \) is the maximum distance between any two objects in the spatial database \( D \), and \( \alpha (0 < \alpha < 1) \) is a specified parameter. Let \( \Gamma_o = \frac{|t_i \cap o.t|}{|t_i|} \), where the object \( o \) contains the keyword \( k_i \) in \( K \).

(b) The \( \text{score}_2 \) is defined as:

\[
\text{score}_2(q, S) = \max_{o \in S} \text{score}(q, S, o) \tag{3}
\]

\[
\text{score}(q, S, o) = \beta (1 - \frac{\text{dist}(q, o)}{\text{max}\_\text{dist}}) + (1 - \beta) \text{score}_1(q', S), o \in S \tag{4}
\]
where \( q' = (o.\lambda, q.K, q.T) \). According to (3), a function value is obtained by centering on each object in \( S \), so that such an object is called the center object of \( S \). We call \( o' \) the best center object if \( o' = \arg \max_{o \in S} \text{score}(q, S, o) \).

For \( \text{score}_1 \) and \( \text{score}_2 \), the user could choose the function according to the query location. If the user is in the downtown area at present, \( \text{score}_1 \) may be chosen to find the result. But if the user is far away from downtown now, the user may have to choose \( \text{score}_2 \) to find the result.

The notations used in this work are summarized in Table 1.

Table 1. Symbols and Description

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D )</td>
<td>a set of objects</td>
</tr>
<tr>
<td>( \Gamma_o )</td>
<td>the temporal overlap ratio of the object ( o )</td>
</tr>
<tr>
<td>( \text{score}_1 )</td>
<td>the evaluation function that satisfies the user’s first requirement</td>
</tr>
<tr>
<td>( \text{score}_2 )</td>
<td>the evaluation function that satisfies the user’s second requirement</td>
</tr>
<tr>
<td>( \text{TR}_k )-tree</td>
<td>the time-aware R-tree for keyword ( k )</td>
</tr>
<tr>
<td>( d(q, \text{elem}) )</td>
<td>the distance (or minimum distance) from query ( q ) to object (or node) ( \text{elem} )</td>
</tr>
<tr>
<td>( C(q, r) )</td>
<td>a circle with ( q ) as the center and ( r ) as the radius</td>
</tr>
<tr>
<td>( \text{NN}(q, k) )</td>
<td>( k )-keyword nearest neighbor of ( q )</td>
</tr>
</tbody>
</table>

4. TR-tree Index Structure

To process TCoSKQ, we use TR-tree [6] as the index structure of the algorithms, which is an extension of R-tree [10]. On the basis of R-tree, a new dimension is added for indexing valid time of objects.

As far as we know, the current collective spatial keyword queries use the index structure of a single tree, that is, a tree indexes objects in all geographic locations. A single tree structure suits the situation that most keywords are query keywords. However, in practice, users will only use a small fraction of keywords as query keywords. So, multiple trees are also used in this work, one for each keyword. The TR-tree for keyword \( k_i \) is denoted as \( \text{TR}_k \)-tree.

In the case of knowing the query keywords, we only need to find the TR-tree corresponding to the query keyword, which greatly reduces the number of objects to be considered in the query.

Next, we introduce the non-leaf nodes and leaf nodes of TR-tree in detail:

Non-leaf nodes of TR-tree contain entries of the form \( N(ptrs, mbr, UT) \), where \( ptrs \) is the address of a child node of \( N \), \( mbr \) is the minimum bounding rectangle (MBR) of all rectangles in entries of the child node, and \( UT \) is a set of the time intervals that are the union of the valid times of the objects in \( N \).

Leaf nodes of TR-tree contain entries of the form \( o(id, l, t) \), where \( id \) refers to the object \( o \), \( l \) represents the coordinates of \( o \), and \( t \) is the valid time of \( o \).
Fig. 2a gives the placement of objects containing the keyword “restaurant”. Objects and valid time of objects are shown in Fig. 2b. The TR$_k$-tree for keyword “restaurant” is created, and the nodes and their corresponding valid time of the tree are shown in Fig. 2c.

![Diagram](image)

(a) Object placement  (b) Objects and valid time of objects

<table>
<thead>
<tr>
<th>Object</th>
<th>Valid time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$o_1$</td>
<td>(6:00, 10:00)</td>
</tr>
<tr>
<td>$o_2$</td>
<td>(7:00, 9:00)</td>
</tr>
<tr>
<td>$o_3$</td>
<td>(7:00, 11:00)</td>
</tr>
<tr>
<td>$o_4$</td>
<td>(13:00, 17:00)</td>
</tr>
<tr>
<td>$o_5$</td>
<td>(21:00, 24:00)</td>
</tr>
<tr>
<td>$o_6$</td>
<td>(9:00, 14:00)</td>
</tr>
</tbody>
</table>

(c) Nodes and time intervals of nodes

<table>
<thead>
<tr>
<th>Node</th>
<th>Valid time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_1$</td>
<td>(6:00, 11:00)</td>
</tr>
<tr>
<td>$N_2$</td>
<td>(9:00, 17:00), (21:00, 24:00)</td>
</tr>
<tr>
<td>$N_3$</td>
<td>(6:00, 17:00), (21:00, 24:00)</td>
</tr>
</tbody>
</table>

Fig. 2. Example of a TR-tree

TR-tree inherits the important features of R-tree: the minimum distance from the query to the parent node is less than or equal to the minimum distance to the child node.

Example 1. In Fig. 2, we assume that the time interval specified in the query for the query keyword “restaurant” is (8:00, 19:00). Thus, we have $\Gamma_{o_1} = 2/11$, $\Gamma_{o_2} = 1/11$, $\Gamma_{o_3} = 3/11$, $\Gamma_{o_4} = 4/11$, $\Gamma_{o_5} = 0$, $\Gamma_{o_6} = 5/11$.

Definition 2. (MinDist Distance [16]) In Euclidean space of dimension $n$, the minimum distance between a point $q$ and MBR $N(s, u)$ is denoted by $MinDist(q, N(s, u))$, which is defined as follows:

$$MinDist(q, N) = \sum_{i=1}^{n} |q_i - r_i|^2, r_i = \begin{cases} s_i, & q_i < s_i \\ u_i, & q_i > u_i \\ q_i, & \text{otherwise} \end{cases}$$ (5)

Given a query $q$,

$$Dist(q, \text{elem}) = \begin{cases} dist(q, \text{elem}), & \text{elem is an object} \\ MinDist(q, \text{elem}), & \text{elem is a node} \end{cases}$$ (6)

$$d(q, \text{elem}) = \frac{Dist(q, \text{elem})}{\max_{\text{dist}}}$$ (7)
5. TCoA1 algorithm

We propose TCoA1 algorithm for the evaluation function \( \text{score}_1(q, S) \) to solve the TCoSKQ problem. Before we introduce TCoA1 algorithm, we first introduce some notations.

Given a query \( q = (\lambda, K, T) \), let \( S \) be a solution that satisfies the query, then

1. The distance dominator of \( S \) is defined to be the object \( o \in S \) that is most far away from \( q \) (i.e., \( o = \arg \max_{o \in S} \text{dist}(q, o) \)).
2. Let \( o \) be the distance dominator of \( S \). A circle with \( q \) as the center and \( d(q, o) \) as the radius is denoted by \( C(q, r) \), where \( r = d(q, o) \).
3. Given a keyword \( k \), for the objects containing \( k \), the one who is closest to \( q \) is called the \( k \)-keyword nearest neighbor of \( q \), denoted by \( \text{NN}(q, k) \).

5.1. Pruning Strategies

The idea of TCoA1 algorithm is to find feasible solutions with the help of distance dominators. However, not every object can be distance dominators, so we will find the lower bound of distance to \( q \) for distance dominators by the following theorem.

**Theorem 1.** Given a query \( q = (\lambda, K, T) \), let \( F S \) be a feasible solution, let \( o \) be the distance dominator of \( F S \), and let \( S = \{ \text{NN}(q, k_1), \text{NN}(q, k_2), ..., \text{NN}(q, k_m) \} \). Then, we have

\[
\frac{d(q, o)}{\max_{o' \in S} \text{dist}(q, o')} \geq \frac{d(q, o)}{d_{LB}},
\]

where \( d_{LB} = \max_{o \in S} \text{dist}(q, o') \).

**Proof.** Assume \( d(q, o) < d_{LB} \). Let \( o_f \) be the distance dominator of \( S \), i.e., \( d_{LB} = d(q, o_f) \), and \( o_f \) contains the keyword \( k_f \). Since \( d(q, o) < d_{LB} \), we get \( o_f \notin FS \), and there must be an object \( o_f' \in FS \) containing \( k_f \), such that \( d(q, o_f') \leq d(q, o) \). Therefore, we have \( d(q, o_f') < d_{LB} \). This conclusion contradicts that \( o_f \) is \( \text{NN}(q, k_f) \), so it is true that \( d(q, o) \geq d_{LB} \).

If some distance dominators are too far from \( q \), then the solutions obtained by such distance dominators would not be the optimal solution. Therefore, such distance dominators can be pruned by the following theorem.

**Theorem 2.** Given a query \( q = (\lambda, K, T) \), and the current optimal solution \( S \). Let \( S' \) be any feasible solution, and let \( o \) be the distance dominator of \( S' \). If \( d(q, o) \geq d_{UB} \), where \( d_{UB} = (1 - \text{score}_1(q, S))/\alpha \), then we have \( \text{score}_1(q, S') \leq \text{score}_1(q, S) \).

**Proof.** Assume when \( o \) is the distance dominator of \( S' \) and \( d(q, o) \geq d_{UB} \), there is

\[
\text{score}_1(q, S') > \text{score}_1(q, S).
\]

Since

\[
\text{score}_1(q, S') = \alpha(1 - d(q, o)) + (1 - \alpha) \min_{o_j \in S'} \text{score}_1(q, o_j) \leq \alpha(1 - d(q, o)) + (1 - \alpha),
\]

we have \( \alpha(1 - d(q, o)) + (1 - \alpha) > \text{score}_1(q, S) \), i.e.,

\[
d(q, o) < (1 - \text{score}_1(q, S))/\alpha, \text{ that is, } d(q, o) < d_{UB}, \text{ which contradicts the hypothesis.}
\]

Fig. 3 shows the distance constraint when looking for distance dominators. Suppose \( o_1, o_2, o_3, o_4, o_5 \), and \( o_6 \) contain one query keyword in \( K \) respectively. Initially, we only need to consider the objects in the gray area (i.e., \( o_2, o_3, o_5 \)) to be distance dominators. As the current optimal solution \( S \) changes, the upper bound \( d_{UB} \) will become smaller and smaller.
5.2. TCoA1 Algorithm Description

The steps of the algorithm are as follows:

Step 1: For each query keyword $k_i$ in $K$, $NN(q, k_i)$ is found to form the current optimal solution $S$.
   (1) For the $m$ query keywords in $K$, the $m$ TR-trees are found, respectively;
   (2) For each TR$_{k_i}$-tree, a min heap $Minheap_i$ is created, with $d(q, elem)$ as the key, where $elem$ is the node or object of TR$_{k_i}$-tree;
   (3) We create a max heap $maxHeap_i$ for each TR$_{k_i}$-tree, with $\Gamma_o_i$ as the key, where $o_i$ represents the object accessed in the TR$_{k_i}$-tree;
   (4) For each TR$_{k_i}$-tree, $NN(q, k_i)$ is found with the best-first strategy [12] to form the current optimal solution $S$, i.e., $S = \{NN(q, k_1), NN(q, k_2), ..., NN(q, k_m)\}$.

The process of finding $NN(q, k_i)$ is as follows: The root node of TR$_{k_i}$-tree is kept in $Minheap_i$. Determine whether the top element of $Minheap_i$ is a node or an object. If it is a node, remove the node and store its children in $Minheap_i$. This process is repeated until the top element is an object, and the object is $NN(q, k_i)$.

Example 2. Fig. 4 shows an example. Assume that the query keywords are “restaurant” and “gym”. The initial state of $Minheap_1$ and $Minheap_2$ is shown in Fig. 4. When $S$ is found by using the best-first strategy for each TR-tree, the state of $Minheap_1$ and $Minheap_2$ is shown in Fig. 4. we know that $NN(q, k_1) = o_3$, $NN(q, k_2) = o_7$, therefore, we have $S = \{o_3, o_7\}$.

Step 2: Using $S$, we can determine $d_{LB}$, which is used to identify the distance dominator. The object $o \in D$ will be put into the $maxHeap$ in ascending order $d(q, o)$. Once a distance dominator is put into the $maxHeap$, it will be used to find a feasible solution $S'$.

(1) Let $o_f = \arg \max_{o_j \in S} d(q, o_f)$, $d_{LB} = d(q, o_f)$;

(2) For each $o \in Minheap_i (1 \leq i \leq m)$, if $d(q, o) < d_{LB}$, then remove $o$ from $Minheap_i$, and put it into $maxHeap_i$. All these objects will not be distance dominators according to Theorem 1.

(3) With best-first strategy, we look for a distance dominator $minobject$ from $Minheap_j (1 \leq j \leq m)$, and put it into $maxHeap_j$ to find a new feasible solution $S'$, which is formed by $minobject$ and the heads of all the max heaps except $maxHeap_j$. If $score_1(q, S) < score_1(q, S')$, $S$ is replaced by $S'$.
(4) According to Theorem 2, if \( d(q, \text{minobject}) < \frac{(1 - \text{score}_1(q, S))}{\alpha} \), then we repeat (3), otherwise the algorithm terminates.

In (3), once a distance dominator \( \text{minobject} \) is found, all the objects in \( C(q, d(q, \text{minobject})) \) have been put into the max heaps. But we need not combine all the objects in the max heaps with \( \text{minobject} \) to find the feasible solution with the largest \( \text{score}_1 \). Instead, we only get the feasible solution \( S' \), which is formed by \( \text{minobject} \) and the heads of all the max heaps except the max heap of \( \text{maxHeap}_j \). The reason is that \( \text{minobject} \) is the distance dominator of \( S' \), that is, \( \text{minobject} \) is the object furthest away from \( q \) in \( S' \). Since \( \text{score}_1(q, S') = \alpha(1 - d(q, \text{minobject})) + (1 - \alpha) \min_{o \in S'} \Gamma_o \), we know that \( \alpha(1 - d(q, \text{minobject})) \) is a fixed value when we compute \( \text{score}_1(q, S') \). Therefore, we create corresponding max heap \( \text{maxHeap}_i \) for each \( \text{TR}_{k_i} \)-tree, with \( \Gamma_o \) as the key, and just take the head of all the max heaps except \( \text{maxHeap}_j \) to form \( S' \), which has the largest \( \text{score}_1 \) among all the combinations.

**Example 3.** From Example 2, it is known that \( d_{LB} = d(q, o_7) \). Assume that the current state of \( \text{Minheap}_1, \text{Minheap}_2, \text{maxHeap}_1, \) and \( \text{maxHeap}_2 \) is shown in Fig. 5a. Next, we first compare \( d(q, o_6) \) with \( d(q, o_9) \). From Fig. 4a, we know that \( d(q, o_6) < d(q, o_9) \). Then, \( o_6 \) is removed from \( \text{Minheap}_1 \), and \( \Gamma_{o_6} \) is calculated and stored in \( \text{maxHeap}_1 \). The state of all the heaps is shown in Fig. 5b. Since \( d(q, o_6) > d_{LB}, o_6 \) will be the distance dominator of the next feasible solution \( S' \), we get \( S' = \{o_6, o_7\} \).

The pseudo-code of TCoA1 algorithm is presented in Algorithm 1. The \( m \) min heaps are initialized, and \( \text{Minheap}_i \) is used to store objects or nodes in the \( \text{TR}_{k_i} \)-tree (line 1).
Algorithm 1: TCoA1\( (D, q) \)

**Input:** A spatial database \( D \), a query \( q = (\lambda, K, T) \), where \( K = \{k_1, ..., k_m\} \), \( T = \{t_1, ..., t_m\} \)

**Output:** The result \( S \)

1. Initialize \( m \) min heaps \( \text{Minheap}_1, ..., \text{Minheap}_m \) with \( d(q, \text{elem}) \) as key;
2. Initialize \( m \) max heaps \( \text{maxHeap}_1, ..., \text{maxHeap}_m \) with \( \Gamma_{\text{elem}} \) as key;
3. Lists = \( \emptyset \), \( S = \emptyset \);
4. for each query keyword \( k_i \in K \) do
   5. \( \text{Minheap}_i \leftarrow \) the root in \( \text{TR}_{k_i} \)-tree;
   6. \( \text{Minheap}_i = \text{FindN}(q, \text{Minheap}_i, \text{TR}_{k_i} \)-tree);
   7. \( S \leftarrow \text{Minheap}_i.\text{head} \);
   8. Lists \( \leftarrow \text{Minheap}_i \);
   9. \( d_{LB} = \max_{o \in S} d(q, o) \);
5. while Lists \( \neq \emptyset \) do
   6. \( \text{Minheap}_j = \arg \min_{\text{Minheap}_i \in \text{Lists}} d(q, \text{Minheap}_i.\text{head}) \);
   7. minobject \( = \text{Minheap}_j.\text{head} \);
   8. Remove \( \text{Minheap}_j.\text{head} \) from \( \text{Minheap}_j \);
   9. \( \text{maxHeap}_j \leftarrow \text{minobject} \);
10. if \( \text{Minheap}_j = \emptyset \) then
11.   Remove \( \text{Minheap}_j \) from Lists;
12. else
13.   \( \text{Minheap}_j = \text{FindN}(q, \text{Minheap}_j, \text{TR}_{k_j} \)-tree);
14. if \( d(q, \text{minobject}) < d_{LB} \) then
15.   continue;
16. else
17.   if \( d(q, \text{minobject}) < (1 - \text{score}_1(q, S))/\alpha \) then
18.     \( S' = \emptyset \);
19.     for \( (x = 1; x \leq m; x + +) \) do
20.       if \( x == j \) then
21.         \( S' \leftarrow \text{minobject} \);
22.       else
23.         \( S' \leftarrow \text{maxHeap}_x.\text{head} \);
24.       if \( \text{score}_1(q, S') > \text{score}_1(q, S) \) then
25.         \( S = S' \);
26.       else
27.         break;
28.     end
29. end
30. return \( S \);
The $m$ max heaps are initialized, and $maxHeap_i$ is used to store objects with keyword $k_i$ (line 2). In lines 4-8, for each TR$_k_i$-tree corresponding to the query keyword $k_i$, Algorithm 2 is called to find $NN(q,k_i)$ (line 6). In line 7, $Minheap_i.head$ is $NN(q,k_i)$. After all the keyword nearest neighbors are found, the current optimal solution $S'$ is formed. In lines 10-32, for the heads of all the min heaps in $Lists$, the head $minobject$ with the smallest key is found and moved from $Minheap_j$ to $maxHeap_j$. After that, if $Minheap_j$ is not empty, the heap is processed until the head is an object. We process $minobject$ with $d_{UB}$ and $d_{LB}$. In lines 22-30, for a distance dominator $minobject$, if $d_{LB} \leq d(q,minobject) < d_{UB} = (1 - score_1(q,S))/\alpha$, then a new feasible solution $S'$ will be found. The current optimal solution will be updated by $S'$ when $score_1(q,S') > score_1(q,S)$.

The pseudo-code of FindN algorithm for finding an object is presented in Algorithm 2. In lines 1-8, if the heap is not empty, then the heap will be traversed in the best-first strategy until the head of the heap is an object. In line 9, the changed heap is returned.

5.3. Time Complexity of TCoA1 Algorithm

We assume that the objects are uniformly distributed. According to [12], after finding the $k$ nearest neighbors, the total cost is $O(klogk)$. In TCoA1 algorithm, there are $m$ min heaps, which are used to find the nearest neighbor in the best-first strategy [12]. Each min heap is used separately. Each time only one of the min heap is chosen to find the nearest neighbor incrementally. And the found nearest neighbor will be put into the corresponding max heap. After the $k$ nearest neighbors are put into a max heap, the total cost is $O(klogk)$. Once a distance dominator minobject from $Minheap_j$ is put into a max heap, a feasible solution is formed by minobject and the heads of all the max heaps except the max heap of $maxHeap_j$. The cost is $O(1)$. Let the maximum number of nearest neighbors found by min heap be $k_a$. So the time complexity of TCoA1 algorithm is $O(mk_a log k_a)$. 

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(a) Current state of all heaps

(b) Changed state of all heaps

**Fig. 5.** An example of step 2
Algorithm 2: FindN(q, heap, TRk_i-tree)

Input: a query q, a min heap heap for keeping nodes or objects of TRk_i-tree, TRk_i-tree
for the query keyword k_i

Output: heap

1 while heap ≠ ∅ do
2 elem = heap.head;
3 if elem is a node then
4 Remove elem from heap;
5 for each child e of elem do
6 heap ← e;
7 else
8 break;
9 return heap;

6. TCoA2 Algorithm

We propose TCoA2 algorithm for the evaluation function score_2(q, S) to solve the TCoSKQ problem.

The idea of TCoA2 algorithm is to find the central object o in ascending order of d(q, o), which is used to find a feasible solution. We propose the following theorem to prune the central object that cannot form the optimal solution.

The current optimal solution obtained during the search process is defined as follows: If S is the current optimal solution found by o, then for any result set S_i found by o_i so far, we have score(q, S_i, o_i) ≤ score(q, S, o).

Theorem 3. Given a query q = (λ, K, T), the current optimal solution S found by o. Let S' be any feasible solution, whose best center object is o'. If d(q, o') ≥ (1 − score(q, S, o))/β, we have score_2(q, S') ≤ score(q, S, o).

Proof. Assume that if d(q, o') ≥ (1 − score(q, S, o))/β, we have score_2(q, S') > score(q, S, o). Since o' is the best center object of S', we have score_2(q, S') = β(1 − d(q, o')) + (1 − β)score_1(q', S') ≤ β(1 − d(q, o')) + (1 − β), where q' = (o′.λ, K, T). Thus, β(1 − d(q, o')) + (1 − β) > score(q, S, o), that is, d(q, o') < (1 − score(q, S, o))/β, which contradicts the hypothesis.

It can be known from Theorem 3 that when the central object is searched from near to far, if the distance from the central object to the query reaches an upper bound, then it is not necessary to continue to search for the central object, and the search process can be terminated early.

The following example demonstrates that the center object found firstly may not be the best central object.

Example 4. Fig. 6 shows an example. Let max_dist = 100, dist(q, o_1) = 70, dist(o_1, o_3) = 20, dist(o_2, o_1) = 10, α = 0.5, β = 0.3, the feasible solution S = {o_1, o_2, o_3}, and min ∏_{o_j ∈ S} = 0.5.
(1) When $S$ is found by the center object $o_1$, we have $\text{score}(q, S, o_1) = \beta(1 - d(q, o_1)) + (1 - \beta)\text{score}_1(q', S) = \beta(1 - d(q, o_1)) + (1 - \beta)(\alpha(1 - d(o_1, o_3)) + (1 - \alpha) \min_{o_j \in S} \Gamma_o) = 0.3 \ast (1 - 70/100) + 0.7 \ast (0.5 \ast (1 - 20/100) + 0.5 \ast 0.5) = 0.545$.

(2) When $S$ is found by the center object $o_2$, we have $\text{score}(q, S, o_2) = \beta(1 - d(q, o_2)) + (1 - \beta)\text{score}_1(q', S) = \beta(1 - d(q, o_2)) + (1 - \beta)(\alpha(1 - d(o_2, o_1)) + (1 - \alpha) \min_{o_j \in S} \Gamma_o) = 0.3 \ast (1 - 80/100) + 0.7 \ast (0.5 \ast (1 - 10/100) + 0.5 \ast 0.5) = 0.55$.

(3) When $S$ is found by the center object $o_3$, we have $\text{score}(q, S, o_3) = \beta(1 - d(q, o_3)) + (1 - \beta)\text{score}_1(q', S) = \beta(1 - d(q, o_3)) + (1 - \beta)(\alpha(1 - d(o_3, o_1)) + (1 - \alpha) \min_{o_j \in S} \Gamma_o) = 0.3 \ast (1 - 90/100) + 0.7 \ast (0.5 \ast (1 - 20/100) + 0.5 \ast 0.5) = 0.485$.

According to the above result, it can be seen that only $o_2$ is the best central object of $S$.

![Diagram](Fig. 6. Find the best central object for $S$)

**Example 5.** Consider Example 4 again. Assume that the current best solution $S'$ is found by $o'$ and $\text{score}(q, S', o') = 0.775$. By Theorem 3, we have $(1 - \text{score}(q, S', o'))/\beta = 0.75$. Since $d(q, o_1) = 0.7 < 0.75$, we should compute $\text{score}(q, S, o_1)$, which is 0.545. Because $0.545 < 0.775$, the current optimal solution is unchanged. Since $d(q, o_2) = 0.8 > 0.75$, the query is terminated according to Theorem 3. It is no longer necessary to calculate $\text{score}(q, S, o_2)$.

The main idea of TCoA2 algorithm is shown in Fig. 7.

The pseudo-code of TCoA2 algorithm is presented in Algorithm 3. The $m$ min heaps are initialized, and $heap_i$ is used to store objects or nodes in the TR's tree (line 1). For each TR's tree, we store its root node in the corresponding heap (lines 3-5). In lines 6-23, for the head of each heap in Lists, the element elem with the smallest key is found and removed. If elem is a node, all children of elem are stored in the corresponding heap. If elem is an object, then it is a central object, which is used to find $S'$. In lines 16-21, if $d(q, elem) < (1 - C\text{score})/\beta$, then it is possible to find the optimal solution by elem according to Theorem 3. TCoA1* algorithm is called to find a feasible solution, and the final solution is updated.

TCoA1* algorithm is got by modifying TCoA1 algorithm as follows:

a. Different input. TCoA1* algorithm needs to know which object is to be the center object to find the result set;
Algorithm 3: TCoA2(D, q)

Input: A spatial database D, a query q = (λ, K, T), where K = {k₁, ..., kₘ},
       T = {t₁, ..., tₘ}

Output: The result S
1 Initialize m min heaps heap₁, ..., heapₘ with d(q, elem) as key;
2 Lists = ∅, S = ∅, Cscore = 0;
3 for each query keyword kᵢ ∈ K do
4    heapᵢ ← the root in TRₖᵢ-tree;
5    Lists ← heapᵢ;
6 while Lists ≠ ∅ do
7    heapⱼ = arg min_{heapᵢ ∈ Lists} d(q, heapᵢ.head);
8    elem = heapⱼ.head;
9    Remove heapⱼ.head from heapⱼ;
10   if elem is a node then
11      for each child e of elem do
12         heapⱼ ← e;
13   else
14      if heapⱼ = ∅ then
15         Remove heapⱼ from Lists;
16         if d(q, elem) < (1 − Cscore)/β then
17            q' = (elem.λ, K, T);
18            S' = TCoA1*(D, q', elem);
19            if score(q, S', elem) > Cscore then
20               S = S';
21               Cscore = score(q, S', elem);
22         else
23            break;
24 return S;
1) For each heap, update until the top of the heap is the object \((NN(o, k_i))\), and form \(S_1\);
2) Find the distance dominator \(o'\) in ascending order of \(d(q, o')\), and use \(o'\) to find a feasible solution.

**Fig. 7.** The main idea of TCoA2 algorithm

b. For the input central object \(o\), TCoA1* algorithm does not need to create a min heap and a max heap for the TR-tree corresponding to the keyword contained in \(o\);

c. All result sets found by TCoA1* algorithm must contain the input central object.

To support the correctness of TCoA1* algorithm, we give the following Theorems by rewriting Theorem 1 and 2, respectively.

**Theorem 4.** Given \(q'(o_i, \lambda, q.K, q.T)\), where \(o_i\) is a central object, let \(FS\) be a feasible solution containing \(o_i\), let \(o\) be the distance dominator of \(FS\), and let \(S = \{NN(q', k_1), ..., o_i, ..., NN(q', k_m)\}\). Then, we have \(d(q', o) \geq d_{LB}\), where \(d_{LB} = \max_{o' \in S} d(q', o')\).

**Proof.** The proof is similar to that of Theorem 1.

**Theorem 5.** Given \(q'(o_i, \lambda, q.K, q.T)\), where \(o_i\) is a central object, and the current optimal solution \(S\) containing \(o_i\). Let \(S'\) be any feasible solution containing \(o_i\), and let \(o\) be the distance dominator of \(S'\). If \(d(q', o) \geq d_{UB}\), where \(d_{UB} = (1 - score_1(q', S)) / \alpha\), then we have \(score_1(q', S') \leq score_1(q', S)\).

**Proof.** The proof is similar to that of Theorem 2.

For each found central object \(o\), TCoA1* algorithm is called to find feasible solution \(S'\) containing \(o\), where \(S'\) is the best solution with \(o\) being a central object according to Theorem 4 and 5.

**Correctness analysis of TCoA2 algorithm:** According to Definition 1, for any feasible solution \(S\), it is necessary to calculate \(score(q, o_i)\), where \(o_i\) is a best central object. But for \(S\), we could not predict which object in \(S\) is the best central object, so we have to try each object \(o\) as a central object in ascending order of \(d(q, o)\). For
TCoA2 algorithm, assume that the current optimal solution $S_p$ is found by $o_p$, and the best central object of any feasible solution $S$ is $o$. According to Theorem 3, if $d(q, o) \geq (1 - \text{score}(q, S_p, o_p))/\beta$, then we have $\text{score}_2(q, S) \leq \text{score}(q, S_p, o_p)$. Therefore, TCoA2 algorithm can return the correct result.

**Time complexity of TCoA2 algorithm:** We assume that the objects are uniformly distributed. In TCoA2 algorithm, there are $m$ min heaps, which are used to find the nearest neighbor in the best-first strategy [12]. Once a nearest neighbor is found, it is used to call TCoA1* algorithm, whose time complexity is the same with that of TCoA1 algorithm. Let the maximum number of nearest neighbors found by min heap be $k_b$, and let the maximum number of nearest neighbors found by min heap in TCoA1* algorithm be $k_a$. So the time complexity of TCoA2 algorithm is $O(mk_b \log k_b + mk_bmk_a \log k_a)$.

7. **Experiment and Result Analysis**

All the algorithms are implemented in Java 1.7.0. All the experiments have been performed on a Windows 7 PC with an Intel(R) Core(TM) i5-2450M CPU and 4G RAM.

We use the datasets Oldenburg (https://www.cs.utah.edu/~lifeifei/SpatialDataset.htm) and GN (extracted from the Geographic Names Information System in USA, https://www.usgs.gov/), and generate randomly keyword information and valid time information for each object in the datasets. Oldenburg contains 6,105 objects and 59 different keywords. GN contains 2288631 objects and 1865 different keywords. We assign one keyword to each object using the Zipf distribution [13] in both datasets. The starting time stamp of objects in both datasets is set to follow the Gaussian distribution, and the ending time stamp of objects is computed by the starting time stamp plus the length of time interval which is in the range of [6, 12]. Each query location is randomly read from the dataset, and the query keywords and query time interval are randomly assigned to the query. We randomly produce 100 queries and report the average results.

7.1. **TCoA1 algorithm and Baseline algorithm**

The max heaps are used to obtain a feasible solution in step 2 of TCoA1 algorithm. In order to test the performance of those max heaps, we propose a baseline algorithm (Baseline) for comparison.

Baseline algorithm is got by modifying TCoA1 algorithm as follows:

- **a.** In step 1 (3) in section 5.2, the max heaps are replaced by lists. For each TR$_{k_i}$-tree, the list $list_i$ is created, which keeps objects that have been visited in the TR$_{k_i}$-tree.

- **b.** In step 2 (3) in section 5.2 after finding the distance dominator minobject, we combine minobject with all objects in each list except the list containing minobject to get multiple feasible solutions. In each feasible solution, one object is taken from each list. We retain the solution $S'$ with the largest score$_1$. Finally, the final result is updated with $S'$. We should note that the pruning strategies for the distance dominators in TCoA1 algorithm are applicable in Baseline algorithm. Therefore, Baseline algorithm uses the pruning strategies too.

1. Effect of the number of query keywords $m$
Fig. 8 shows the influence of $m$ on the query time of TCoA1 algorithm and Baseline algorithm. We set $\alpha = 0.6$. According to Fig. 8, TCoA1 algorithm is faster than Baseline algorithm. It is because after finding the distance dominator $minobject$, TCoA1 algorithm directly obtains head of each heap except the heap containing $minobject$, and then combines with $minobject$ to get a feasible solution. However, Baseline algorithm needs to obtain all the objects in each list except the list containing $minobject$, and to combine with $minobject$ to get a large number of feasible solutions. Finally, we retain the feasible solution with the largest $score_1(q, S')$ to update the final result. The query time of both algorithms increases when $m$ increases. This is because the total number of objects containing query keywords may increase when $m$ increases. This may result in an increase in the total number of the distance dominators used. It can also be seen from Fig. 8 that TCoA1 algorithm are scalable.

(2) Effect of $\alpha$

The $\alpha$ is a parameter used to adjust the distance and time. When $\alpha$ changes from 1 to 0, more weight is assigned to temporal relevance. When $\alpha$ is close to 1, TCoSKQ is more related to positional relevance.

Fig. 9 shows the influence of $\alpha$ on the query time of TCoA1 algorithm and Baseline algorithm. We set $m = 4$. According to Fig. 9 with $\alpha$ increasing, the query time of TCoA1 algorithm and Baseline algorithm decreases. This is because when $\alpha$ increases, the smaller $\max_{o\in S} d(q, o)$ is, the larger the $score_1(q, S)$ is. TCoSKQ prefer finding the result close to the query location. It is easier to find the result that satisfies the condition in a small range, so that few distance dominators are used.

7.2. TCoA1 algorithm and TCoA1NoPrune algorithm

In order to test the pruning effect on the total number of the distance dominators used ($N_{du}$), we remove a pruning strategy of TCoA1 algorithm (i.e., Theorem 2), then get TCoA1NoPrune algorithm. Next, we compare TCoA1 algorithm and TCoA1NoPrune algorithm on $N_{du}$ and query time using the two datasets.

(1) Effect of $m$
Fig. 9. Query time versus $\alpha$

Fig. 9 shows the influence of $m$ on $N_{du}$ in the query. We set $\alpha = 0.6$. According to Fig. 9, TCoA1 algorithm uses less total number of distance dominators than TCoA1NoPrune algorithm does. This is because TCoA1 algorithm uses pruning strategy to prune a large number of distance dominators. $N_{du}$ in TCoA1NoPrune algorithm is the total number of objects containing the query keywords and the distance to $q$ is not less than $d_{LB}$. With $m$ increasing, $N_{du}$ in TCoA1 algorithm and TCoA1NoPrune algorithm increases. This is because the total number of objects containing query keywords may increase when $m$ increases.

Fig. 10 shows the influence of $m$ on query time. We set $\alpha = 0.6$. According to Fig. 10, TCoA1 algorithm is faster than TCoA1NoPrune algorithm. As $m$ increases, the query time of TCoA1 algorithm and TCoA1NoPrune algorithm increases. This is because the query time of the algorithms is related to $N_{du}$.

Fig. 10. $N_{du}$ versus $m$

(2) Effect of $\alpha$

Fig. 11 shows the influence of $\alpha$ on $N_{du}$ in the query. We set $m = 4$. According to Fig. 11, $\alpha$ has no impact on $N_{du}$ in TCoA1NoPrune algorithm. This is because the distance dominator is not pruned in TCoA1NoPrune algorithm, and $N_{du}$ is the total number of objects containing the query keywords and the distance to $q$ is not less than $d_{LB}$.
As $\alpha$ increases, $N_{du}$ in TCoA1 algorithm decreases. This is because when $\alpha$ increases, TCoSKQ prefer positional relevance. It is easier to find the result that satisfies the condition in a small range, so that few distance dominators are used.

Fig. 13 shows the influence of $\alpha$ on query time. We set $m = 4$. As shown in Fig. 13, $\alpha$ has no impact on the query time of TCoA1NoPrune algorithm, and the query time in TCoA1 algorithm decreases with $\alpha$ increasing. This is because the query time of the algorithms is related to $N_{du}$.

7.3. TCoA2 algorithm and TCoA2NoPrune algorithm

In order to test the pruning effect on the total number of center objects used ($N_{co}$), we remove the pruning strategy of TCoA2 algorithm (i.e., Theorem 3), then get TCoA2NoPrune algorithm. Next, we compare TCoA2 algorithm and TCoA2NoPrune algorithm on $N_{co}$ and query time using the two datasets.

(1) Effect of $m$

Fig. 14 shows the influence of $m$ on $N_{co}$ in the query. We set $\alpha = 0.6$ and $\beta = 0.6$. According to Fig. 14, $N_{co}$ in TCoA2 algorithm is less than TCoA2NoPrune algorithm.
This is because TCoA2 algorithm uses pruning strategy to prune a large number of center objects. \(N_{co}\) in TCoA2NoPrune algorithm is the total number of objects containing the query keywords. When \(m\) increases, \(N_{co}\) in TCoA2 algorithm and TCoA2NoPrune algorithm increases. This is because the total number of objects containing query keywords may increase when \(m\) increases.

Fig. 13 shows the influence of \(m\) on query time. We set \(\alpha = 0.6\) and \(\beta = 0.6\). With \(m\) increasing, the query time of TCoA2 algorithm and TCoA2NoPrune algorithm increases, and TCoA2 algorithm is faster than TCoA2NoPrune algorithm. This is because the query time of the algorithms is related to \(N_{co}\).

(2) Effect of \(\beta\)

The \(\beta\) is a parameter used to adjust the distance and \(score_1\). When \(\beta\) changes from 1 to 0, more weight is assigned to \(score_1\). When \(\beta\) is close to 1, TCoSKQ is more related to positional relevance.

Fig. 14 shows the influence of \(\beta\) on \(N_{co}\) in the query. We set \(m = 4\) and \(\alpha = 0.6\). According to Fig. 14, \(\beta\) has no impact on \(N_{co}\) in TCoA2NoPrune algorithm. This is because there is no pruning strategy in TCoA2NoPrune algorithm, and \(N_{co}\) is the total number of objects containing the query keywords. As \(\beta\) increases, \(N_{co}\) in TCoA2 algo-
Fig. 15. Query time versus $m$

Algorithm decreases. This is because when $\beta$ increases, TCoSKQ prefer positional relevance. It is easier to find the result that satisfies the condition in a small range, so that few center objects are used.

Fig. 16. $N_{co}$ versus $\beta$

Fig. 17 shows the influence of $\beta$ on query time. We set $m = 4$ and $\alpha = 0.6$. As shown in Fig. 17, $\beta$ has no impact on the query time of TCoA2NoPrune algorithm, and the query time in TCoA2 algorithm decreases with $\beta$ increasing. This is because the query time of the algorithms is related to $N_{co}$.

8. Conclusions

This paper presents a new query, time-aware collective spatial keyword query (TCoSKQ). For different needs of users, we define two new evaluation functions, $score_1$ and $score_2$, and adopt the TR-tree index structure. For the evaluation function $score_1$, we propose pruning strategies for effectively pruning the number of the distance dominators used, and give TCoA1 algorithm for solving the query problem. For the evaluation function $score_2$, we propose effective pruning strategies to prune the number of the center objects used.
Fig. 17. Query time versus $\beta$

and give TCoA2 algorithm. Finally, the efficiency and scalability of the two algorithms are verified. In the future work, other evaluation functions could be proposed.

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