Retrieving Text-Based Surrounding Objects in Spatial Databases

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Abstract. Retrieval of textually relevant non-dominated surrounding data objects has many potential applications in spatial databases such as textually relevant nearby point-of-interest retrieval surrounding a user. This paper presents a novel query, called textually-relevant direction-based spatial skyline (TDSS), for retrieving textually relevant non-dominated surrounding data objects in spatial databases. The paper also presents efficient algorithms for processing TDSS queries in spatial databases by designing novel data pruning techniques using keyword inverted index and R-Tree data indexing scheme. The effectiveness and efficiency of the proposed algorithms are demonstrated by conducting extensive experiments.

1 Introduction

The retrieval of textually relevant non-dominated surrounding data objects has potential applications in spatial databases. For example, consider a user who is looking for nearby restaurants surrounding her (green point as shown in Fig. 1) that provide "Shushi". A textually-relevant direction-based spatial skyline (TDSS) query can return a number of restaurants surrounding her by trading off the direction and distance $\{r_2, r_3, r_4, r_5, r_6\}$ as shown in Fig. 1 as well as matching her preferred food item. Though $\{r_1, r_8\}$ and r_7 also provide "Shushi", they are in the same directions as r_2 and r_6, respectively and are also far from the user in comparison to r_2 and r_6, respectively. There exists plenty of works on the retrieval of textually relevant objects in spatial databases ([2,3,6,20,22,25] for survey). Unfortunately, none of these works incorporates surroundingness in the retrieval of textually relevant data objects from spatial databases.

The first work on direction based spatial skyline query (DSQ) for retrieving surrounding data objects in spatial databases is proposed by Guo et al. [7,8]. The DSQ query retrieves all data objects that are closest to the given query point and that are not dominated by other data objects in their directions w.r.t. query point. The authors propose that a data object p_i should dominate another data object p_j w.r.t. the query object q if (i) both p_i and p_j are in the same direction according to the user-given acceptance angle, i.e., $\measuredangle p_i q p_j \leq \tau$, where τ

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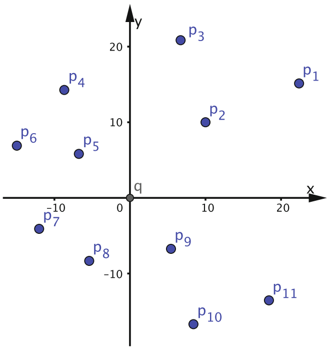
Fig. 1. An application of TDSS queries for retrieving surrounding objects (results produced by our query model)

is the user-given acceptance angle and (ii) p_i is closer to q than p_j, i.e., $d(q, p_i) < d(q, p_j)$, where $d(q, p_i)$ denotes the Euclidean distance between q and p_i. This query model does not consider to emphasize textual relevance on surrounding objects retrieval. The DSQ query also has two major problems as given as follows: (i) missing result and (ii) instability. The missing result problem is caused by the fact that a non-resultant data object can dominate and filter other data objects. The instability problem is caused by the settings of the user given acceptance angle. A small change in the acceptance angle can provide a completely different result set and causes the instability issue.

Another work on surrounding objects retrieval is the *nearest surrounder queries* (NSQ) proposed by Lee et al. [13,14]. The authors propose an approach to retrieve nearest surrounder objects of arbitrary shapes w.r.t. the given query point and argue that surrounder objects should be visible from the query point. Unfortunately, none of these works [7,8,13,14] considers textual relevance in their approaches.

To fill the research gap and alleviate the missing result and instability problems of DSQ queries [7,8], we propose a novel query called, Textually-relevant Direction-based Spatial Skyline (TDSS), for retrieving textually relevant non-dominating surrounding data objects in spatial databases. We propose directional zone (DZ) to measure directional similarities among spatial data objects. We also develop novel data pruning techniques based on keyword inverted list and R-tree data indexing and propose two different algorithms to process TDSS queries in spatial databases. To be specific, our main contributions are summarized below:



Object	Distance	Angle	Keywords
p_1	27	34°	Australian, Burger, Fries
p_2	14	45°	Australian, Steak, Dessert
p_3	22	72°	Australian, Pizza
p_4	17	121°	Australian, Burger, Fries
p_5	9	139°	Chinese, Noodle, Dessert
p_6	16	155°	Australian, Burger, Fries
p_7	13	199°	Italian, Pizza, Risotto, Dessert
p_8	10	237°	Australian, Burger, Fries, Dessert
p_9	9	309°	Australian, Pizza, Dessert
p_{10}	19	297°	Australian, Burger, Fries
p_{11}	23	324°	Japanese, Sushi

Fig. 2. A toy dataset for exemplifying the definitions and algorithms in this paper

1. we propose directional zone to measure directional similarity between two spatial data objects (Sect. 2);
2. we present a novel query called TDSS to retrieve textually relevant non-dominating surrounding point data objects (Sect. 2);
3. we propose efficient algorithms to process TDSS queries in spatial databases by designing novel pruning techniques based on keyword inverted list and R-tree data indexing scheme (Sect. 3); and
4. we experimentally evaluate our proposed algorithms (Sect. 4).

2 Preliminaries

Data Model. We assume that P is a set of spatial data objects and an individual data object $p \in P$ is modeled as a point in xy plane. The x and y coordinates of $p \in P$ are denoted by p^x and p^y, respectively. The query object is also a point in xy plane and is denoted by q. Each object $p \in P$ is associated with a set of keywords and is denoted by $p.\psi$. The query keywords set is denoted by $q.\psi$. Data objects and points are used interchangeably in this paper. We use the toy dataset given in Fig. 2 to exemplify the definitions and algorithms provided the paper.

Definition 1. A data object p is said to be a keyword-match object iff $p.\psi = q.\psi$.

Definition 2. A keyword match data object p_i dominates another keyword-match data object p_j w.r.t. a given query object q, denoted by $p_i \prec p_j$, iff the following holds: (a) p_j is directionally similar to p_i w.r.t. q; and (b) $d(q, p_i) < d(q, p_j)$, where $d(q, p_i)$ denotes the distance between q and p_i.

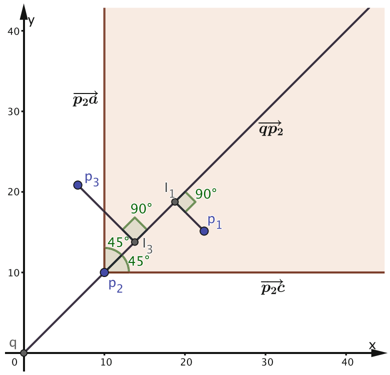


Fig. 3. The directional zone of p_2

From Definition 2, it is obvious that we need to establish (i) *directional similarity metric* and (ii) *distance metric* to decide on the dominance between two spatial data objects. For the *distance metric*, we rely on the Euclidean distance measure. For *directional similarity metric*, in this paper we propose *directional zone* to model the directional similarity among the spatial data objects. Firstly, the direction of an arbitrary point object p_i w.r.t. the query q is modeled by $\overrightarrow{qp_i}$. Assume that the intersection point of the perpendicular line from point p_j to $\overrightarrow{qp_i}$ is denoted by $I(p_j, \overrightarrow{qp_i})$. The distance $d(p_j, I)$ can be used to measure how far p_j deviates from the direction of p_i w.r.t. q. On the other hand, $d(p_i, I)$ can be used to measure how far p_j is away from p_i according to the direction $\overrightarrow{qp_i}$. We consider p_j has the same direction as p_i w.r.t. q if $d(p_i, I) > d(p_j, I)$. To model the above, we rotate the ray $\overrightarrow{qp_i}$ by 45° (up to this limit we get $d(p_i, I) > d(p_j, I)$) both in clockwise and anticlockwise considering p_i as the center of origin. Assume that these rays are $\overrightarrow{p_i c}$ and $\overrightarrow{p_i a}$, respectively. Now, the directional zone of p_i, denoted by $DZ(p_i)$, is formed by the area bounded by $\overrightarrow{p_i a}$ and $\overrightarrow{p_i c}$ as illustrated in Fig. 3 for data object p_2.

Definition 3. A data object p_j is considered to be directionally similar to a data object p_i w.r.t. the given query object q in spatial data space if $p_j \in DZ(p_i)$.

Lemma 1. *If $p_j \in DZ(p_i)$, then we get $d(q, p_i) < d(q, p_j)$.*

Lemma 2. *If $p_j \in DZ(p_i)$, then we get $p_i \prec p_j$.*

Definition 4. Given a set of spatial data objects P and a query point q, a textually-relevant direction-based spatial skyline (TDSS) query for q, denoted by $TDSS(q)$, retrieves all keyword match data object $p_i \in P$ if any of the following holds:

1. $\nexists p_j \in P$ such that $p_j \prec p_i$, where p_j is a keyword match data object; and
2. $\nexists p_k \in TDSS(q)$ and $p_j \in P$ such that $p_k \prec p_j$ and $p_j \prec p_i$ but $p_k \not\prec p_i$, where both p_j and p_k are keyword match data objects.

The above definition of TDSS queries for retrieving the surrounding data objects closely matches the idea of global skyline [5] (i.e., union of the skylines in each quadrant of the query point in 2D) which is rotationally invariant in spatial context. Here, we also emphasize textual relevance through Definition 1, i.e., a TDSS query retrieves only textually relevant non-dominated surrounding data objects.

3 Our Approach

This section presents our approach of processing TDSS queries in spatial databases.

3.1 Dominance Checking

Here, we explain our idea of checking the directional dominance between a pair of spatial data points p_i and p_j. Firstly, we identify the perpendicular intersection point I from the point p_j to the ray $\overrightarrow{qp_i}$ and derive the following vector based calculation to calculate the coordinates of the perpendicular intersection point I.

$$I^x = q^x + t({p_i}^x - q^x) \tag{1}$$
$$I^y = q^y + t({p_i}^y - q^y) \tag{2}$$
$$0 = (I_x - {p_j}^x)({p_i}^x - q^x) + (I^y - {p_j}^y)({p_i}^y - q^y) \tag{3}$$

By substituting the first two equations into the third, we get the following:

$$t = \frac{({p_j}^x - q^x)({p_i}^x - q^x) + ({p_j}^y - q^y)({p_i}^y - q^y)}{({p_i}^x - q^x)^2 + ({p_i}^y - q^y)^2} \tag{4}$$

Now, the directional dominance between p_i and p_j can be decided by comparing the distance $d(p_i, I)$ and $d(p_j, I)$. However, we need to ensure that the intersection point I follows p_i on the ray $\overrightarrow{qp_i}$, so that the p_j can be directionally dominated by p_i. For the above, we derive the following property: $d(q, I) > d(q, p_i)$ and $d(q, I) > d(p_i, I)$ from observation. Finally, for p_j to appear inside $DZ(p_i)$ we check the following condition: $d(p_i, I) \geq d(p_j, I)$. Otherwise, the point p_j deviates from the direction $\overrightarrow{qp_i}$ and it must not be inside the $DZ(p_i)$. Based on the above formulation, we can decide that $p_2 \prec p_1$ and $p_2 \not\prec p3$ as illustrated in Fig. 3.

3.2 TDSS Query Processing

This section proposes two algorithms for processing the TDSS queries in spatial databases. Our first algorithm is called Keyword Filtering Based Approach (KFBA). KFBA algorithm utilizes the keyword inverted index data structure to filter out the non-keyword match objects based on the query keywords. The second approach is a Branch and Bound Keyword Matching (BBKM) approach which progressively matches query keywords after indexing the database objects into an R-tree. BBKM also exploits the directional dominance between the current skyline points and the bounding boxes in R-Tree data indexing to expedite the query processing.

3.2.1 Keyword Filtering Based Approach

The main idea of keyword filtering based approach (KFBA) is to take advantage of the pruning power of the keyword inverted index, which is a mapping between the database objects and the keywords. They keyword inverted index allows us to quickly search for the objects that contain a specific keyword and can help us to filter out the objects that do not match the query keywords $q.\psi$. Consider our toy dataset given in Fig. 2 as an example, which contains a set of restaurants and the corresponding keywords which describe the foods provided by each restaurant. The inverted index lists all the keywords appeared and the corresponding objects in our toy dataset as shown in Table 1. Now, if the user is only interested in the restaurants which provide Australian food, then the objects $\{p_1, p_2, p_3, p_4, p_6, p_8, p_9, p_{10}\}$ are returned as keyword match objects. For multiple query keyword, we can simply calculate the intersection set among keyword match objects of each query keyword. After filtering data objects based on keyword inverted index, the next step is to perform the dominance checking among them. However, the access order of the database objects cannot be random as per the following lemma.

Table 1. The keyword inverted index of the toy dataset given in Fig. 2

Keyword	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}
Australian	1	1	1	1	0	1	0	1	1	1	0
Chinese	0	0	0	0	1	0	0	0	0	0	0
Italian	0	0	0	0	0	0	1	0	0	0	0
Japanese	0	0	0	0	0	0	0	0	0	0	1
Burger	1	0	0	1	0	1	0	1	0	1	0
Fries	1	0	0	1	0	1	0	1	0	1	0
Steak	0	1	0	0	0	0	0	0	0	0	0
Dessert	0	1	0	0	1	0	1	1	1	0	0
Pizza	0	0	1	0	0	0	1	0	1	0	0
Risotto	0	0	0	0	0	0	1	0	0	0	0
Sushi	0	0	0	0	0	0	0	0	0	0	1
Noodle	0	0	0	0	1	0	0	0	0	0	0

Lemma 3. *The TDSS of a query point q will be correct if and only if we access the database objects in order of their distances to q given that we compare their dominances with the objects accessed so far.*

Proof. Assume that there are three points $\{p_1, p_2, p_3\}$ and the following relationships hold: (a) $d(q, p_1) < d(q, p_2) < d(q, p_3)$; (b) $p_2 \in DZ(p_1)$; (c) $p_3 \in DZ(p_2)$ and (d) $p_3 \notin DZ(p_1)$. Now, assume again that we access these points from the database in the following order: first p_2, then p_1 and p_3 and compare their directional dominances with the points accessed so far only. The TDSS result for the

Algorithm 1. Keyword Filtering Based Approach (KFBA)

Input : q: query point, P: dataset
Output : S: a list of textually relevant spatial skyline objects
Initialization: $S \leftarrow \emptyset$
invertedIndex$\leftarrow$ buildInvertedIndex(P); `// build inverted index`
$P' \leftarrow$ searchKeywordMatchObjects(invertedIndex, $q.\psi$); `// find keyword match objects`
$\mathscr{H} \leftarrow$ insert(P'); // insert P' into min heap $\mathscr{H}$
while $\mathscr{H} \neq \emptyset$ **do**
  $e \leftarrow \mathscr{H}$.pop() ; `// pop the root element`
  if $\nexists s \in S : s \prec e$ **then**
    $S \leftarrow$ append(e); // e is a spatial skyline object
return S; `// final spatial skyline set`

above would be $\{p_1, p_2\}$, which is incorrect as per Definition 4. However, if we access them in the following order: first p_1, then p_2 and p_3, the TDSS result would be $\{p_1, p_3\}$, which is correct as per Definition 4. Hence, the lemma.

Algorithm Steps. The KFBA algorithm firstly constructs the keyword inverted index of the dataset P. Then, it performs keyword based filtering to find keyword match objects, $\forall p \in P : p.\psi = q.\psi$. After that, a min heap $\mathscr{H}$ is created by inserting the filtered database objects $P\prime$ in order of their distances to the query point q. Finally, we initialize the spatial skyline set S to $\emptyset$, then repeatedly retrieve the root element e from $\mathscr{H}$ until $\mathscr{H}$ become $\emptyset$ and append e to S iff $\nexists s \in S : s \prec e$. The above steps are pseudo-coded in Algorithm 1.

3.2.2 Branch and Bound Keyword Matching

In this section, we present our branch and bound keyword matching approach which is based on the R-tree indexing structure. The main idea of the BBKM approach is to avoid the object-to-object dominance checking as much as possible by pruning R-tree bounding boxes as per the following lemma.

Lemma 4. *A bounding box R_k in R-Tree can be safely pruned if $\exists s \in S$ such that all of the vertices of R_k are inside $DZ(s)$, where S is the current skyline of the database objects accessed so far in order of their distances to the query point q.*

Proof. Every database object $p \in R_k$ is bounded by the vertices of the bounding box R_k in R-Tree. These vertices are the corner points of the minimum bounding box R_k in R-Tree. Therefore, every $p \in R_k$ is inside $DZ(s)$ as all the vertices of R_k are inside $DZ(s)$, i.e., $p \in DZ(s_i)$, $\forall p \in R_k$. Now, every database object $p \in R_k$ has the same direction as s w.r.t. q as well as $d(q, s) < d(q, p)$ as $p \in DZ(s)$ (as per Sect. 2 and Lemma 1). Therefore, we get $s \prec p$, $\forall p \in R_k$ and the bounding box R_k can be pruned safely without further processing. Hence, the lemma.

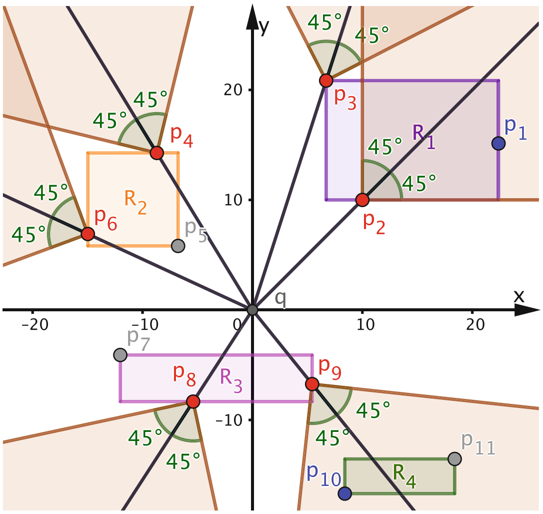


Fig. 4. R-Tree (MAX #entries = 4) bounding boxes of the data in Fig. 2 and dominance checking for BBKM

Consider the dataset given in Fig. 2 and the R-tree indexing given in Fig. 4. Assume that a user wants to search for the surrounding restaurants around her which provide Australian food. In this case, the query keyword is $q.\psi =$ {"Australian"}. Here, the bounding box R_4 can be directly eliminated as it is directionally dominated by the data objects p_9 as per Lemma 4. Also, the data objects p_5 and p_7 are ignored during the processing as these two data objects do not contain the keyword "Australian", i.e., are nor keyword match objects.

Algorithm Steps. Based on Lemmas 3 and 4, the BBKM approach can be explained as given below. Firstly, the algorithm index the dataset P into an R-tree, initialize the skyline result set S to $\emptyset$ and insert the root element e of R-Tree into a min-heap $\mathscr{H}$. The BBKM keep accessing the top element e from $\mathscr{H}$ until $\mathscr{H}$ becomes $\emptyset$, the element e is examined further if $\nexists s \in S : s \prec e$. There are three case to consider as follows: (i) e is an intermediate node: we insert each child e_i of e, which is a R-tree node, into $\mathscr{H}$ iff $\nexists s \in S : s \prec e_i$; (ii) e is a leaf node, then we insert each child e_i of e, which is a database object, into $\mathscr{H}$ iff $\nexists s \in S : s \prec e_i$ and e_i is a keyword match object; and (iii) e is a database object and is a keyword match for q, i.e., $e.\psi = q.\psi$, we insert e into the skyline result set S. The above steps are pseudo-coded in Algorithm 2. It should be noted that the min heap $\mathscr{H}$ stores only the R-tree nodes and keyword match objects.

Algorithm 2. Branch and Bound Keyword Matching (BBKM)

```
Input          : q: query point, R: R-Tree indexing of dataset P
Output         : S: a list of textually relevant spatial skyline objects
Initialization: S ← ∅;
ℋ ←insert(getRoot(R)) ;                       // insert root of R into min-heap ℋ
while ℋ ≠ ∅ do
    e ← ℋ.pop() ;                                       // pop the root element
    if ∄s ∈ S : s ≺ e then
        if e ≠leaf then                          // intermediate node in R-Tree
            foreach child e_i of e do
                if ∄s ∈ S : s ≺ e_i then
                    ℋ ←insert(e_i) ;              // insert box e_i into heap ℋ
        else if e ==leaf then                            // leaf node in R-Tree
            foreach child e_i of e do
                if ∄s ∈ S : s ≺ e_i and isKeywordMatch(e_i) then
                    ℋ ←insert(e_i) ;          // insert object e_i into heap ℋ
        else                                               // a database point
            S ← append(e);                         // e is a spatial skyline point
return S;                                          // final spatial skyline set
```

4 Experiments

Setup. The experiments are conducted on both real and synthetic datasets. The real dataset is a POI dataset, which contains 104770 locations in California (CA) [16]. We randomly select 25K, 50K, 75K and 100K points from this dataset as candidate points. We also generate synthetic (SYN) datasets consisting of 125K, 250K, 375K and 500K uniformly distributed points. We randomly create 50 query points following the distribution of the datasets to report the performance of the tested algorithms. Each point is assigned 10 random keywords from a keyword pool of 63 keywords. We randomly create 50 query points by following the distribution of the dataset and assign 1–4 keywords to conduct our experiments. To index the datasets in R-tree, we set MAX #entries in a R-Tree node to 20–50 and default setting is 30. The algorithms are implemented in Java and experiments are conducted on a Mac Laptop with 2 GHz Intel Core i7 CPU and 8 GB 1600 MHz DDR3 main memory.

4.1 Effectiveness Study

Here, we demonstrate the usefulness of our TDSS query model through a case study. The case study result for an arbitrary user (query) in CA dataset is visualized in Fig. 5, where the user is shown as green point. The gray points represent the non-keyword matched POI objects, whereas the candidate keyword match POI objects and the resultant objects are shown as blue and red, respectively. It is obvious that our proposed TDSS query model can retrieve non-dominated surrounding keyword match objects for an arbitrary user by trading-off the direction and distance.

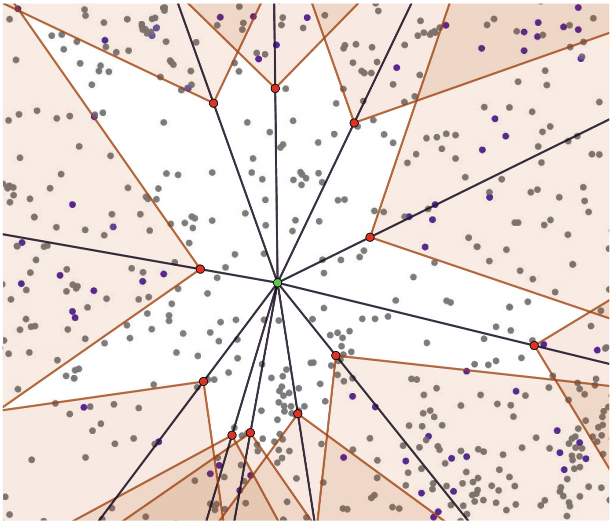
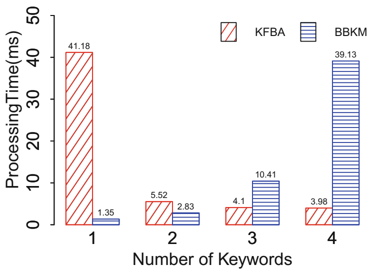


Fig. 5. Non-dominated keyword match surrounding objects retrieval for an arbitrary user via TDSS query model in CA dataset

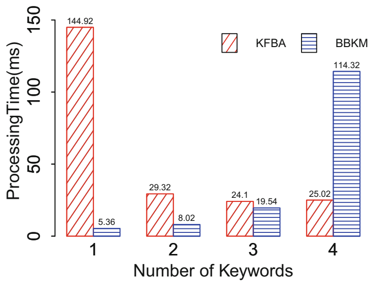
4.2 Efficiency Study

This section presents the efficiency study of the proposed algorithms.

Effect of Query Keywords. Here, we examine of the effect of query keywords on the efficiency of the proposed algorithms and the results are illustrated in Fig. 6. It is evident from Fig. 6 that the proposed BBKM algorithm outperforms our KFBA algorithm for lower number of query keywords (1–3). On the other

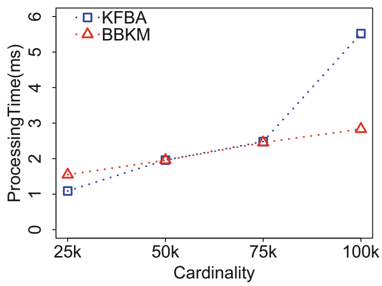


(a) CA dataset (100K)

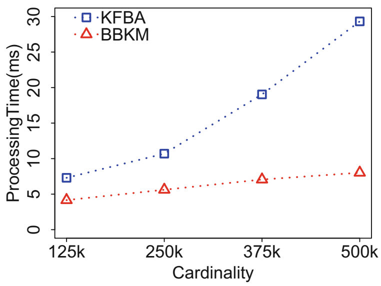


(b) SYN dataset (500K)

Fig. 6. Effect of keywords: avg. processing time (ms) in (a) CA and (b) SYN datasets



(a) CA dataset



(b) SYN dataset

Fig. 7. Effect of cardinality: avg. processing time (ms) in (a) CA and (b) SYN datasets ($|q.\psi| = 2$)

hand, KFBA algorithm performs better for higher number of query keywords (3–4 and more). This is because, the KFBA algorithm ends up having only a few data objects after keyword filtering and thereby, reduces the size of the heap significantly at run time.

Effect of Data Cardinality. Here, we examine the effect of cardinality on the efficiency of our proposed algorithms and the results are shown in Fig. 7. From Fig. 7(a), it is evident that the KFBA algorithm runs faster than the BBKM algorithm for lower cardinality (25K–50K). On the other hand, the BBKM algorithm performs much better for higher cardinality settings. From Fig. 7(b), it is obvious that the BBKM algorithm outperforms our KFBA algorithm for all cardinality settings in SYN dataset. This is because the KFBA algorithm is time-consuming when there are many objects after keyword filtering. Also, multiple keywords searching in inverted index structure for higher cardinality setting is time consuming.

Effect of R-Tree Parameter. Here, we examine the effect of R-tree parameter on the efficiency of BBKM algorithm and the results are shown in Table 2 for $|q.\psi| = 2$. The proposed BBKM algorithm is tolerant in all different R-tree MAX #entries for both CA and SYN datasets. However, it is hard to decide which R-tree parameter setting is optimum. For the larger R-tree parameter setting, the BBKM algorithm may need to examine more objects to find the TDSS result. However, the larger R-tree MAX #entries may also have the advantage of pruning more objects that are inside a bounding box.

Table 2. Avg. running time (ms) of BBKM algorithm in CA and SYN datasets for different settings of MAX #entries in a R-tree node

Approach	20	30	40	50
CA dataset	2.877	2.830	2.324	2.758
SYN dataset	5.92	8.02	9.18	7.4

5 Related Work

The skyline operator proposed by Borzsony et al. [1] has gained significant attention among the researchers [4,5,9–12,18,19] including the spatial database community [15,17,21,23,24]. However, none of these approach considers surroundingness in the non-dominating objects retrieval by trading off the distance and direction.

The direction-based spatial skyline query (DSQ) was first discussed by Guo et al. [7,8] and they propose to retrieve data objects that surround the query point based on user given angle threshold. The DSQ queries have missing result and instability problems as discussed in Sect. 1. The *nearest surrounder queries* (NSQ) proposed by Lee et al. [13,14] retrieve nearest surrounder objects of arbitrary shapes that are visible from the given query point. Both DSQ and NSQ queries do not emphasize textual relevance of the retrieved objects.

Existing works on the retrieval of textually relevant objects in spatial databases are quite established ([2,3,6,20,22,25] for survey). These works emphasize on trading off the spatial proximity and the textual relevance in spatio-textual data context, rather than distance and direction. As these works do not consider surroundingness in their retrieval system, they may return multiple objects in the same direction.

Our work differs from the existing works in the sense that we emphasize not only the textual relevance in the retrieved objects, but also we trade off the direction and distance to retrieve non-dominating surrounding objects for a given query point. Our TDSS queries are also fair and free from missing result and instability problems.

6 Conclusion

In this paper, we have presented a novel query called textually-relevant direction-based spatial skyline (TDSS) for retrieving textually relevant non-dominating surrounding data objects in spatial databases. We have also presented efficient algorithms to process TDSS queries in spatial databases. The proposed algorithms have been evaluated by experimenting with both real and synthetic datasets.

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