Nearest Neighbor Search on Moving Object Trajectories

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Abstract. With the increasing number of Mobile Location Services (MLS), the need for effective *k*-NN query processing over historical trajectory data has become the vehicle for data analysis, thus improving existing or even proposing new services. In this paper, we investigate mechanisms to perform NN search on R-tree-like structures storing historical information about moving object trajectories. The proposed branch-and-bound algorithms vary with respect to the type of the query object (stationary or moving point) as well as the type of the query result (continuous or not). We also propose novel metrics to support our search ordering and pruning strategies. Using the implementation of the proposed algorithms on a member of the R-tree family for trajectory data (the TB-tree), we demonstrate their scalability and efficiency through an extensive experimental study using synthetic and real datasets.

1 Introduction

With the integration of wireless communications and positioning technologies, the concept of Moving Object Databases (MOD) has become increasingly important, and has posed a great challenge to the database community. In such implicitly formulated location-aware environments, moving objects are continuously changing locations; nevertheless existing DBMSs are not well equipped to handle continuously changing data. Emerging location-dependent services (including nearby information accessing and enhanced 911 services) call for new query processing algorithms and techniques to deal with both the spatial and temporal domains.

Unlike traditional databases, MODs have some distinctive characteristics: First of all, spatio-temporal queries are continuous in nature. In contrast to snapshot queries, which are invoked only once, continuous queries require continuous evaluation as the query result becomes invalid after a short period of time. Secondly, we typically have to deal with vast volumes of historical data which correspond to a large number of mobile and stationary objects. As a consequence, querying functionality embedded in an extensible DBMS that supports moving objects has to present robust behavior in the above mentioned issues.

An important class of queries that definitely turns out to be useful for MOD processing is the so-called *k* nearest neighbor (*k*-NN) queries, where one is interested in finding the k closest trajectories to a predefined query object *Q*. To our knowledge, in the literature such queries primarily deal with either static ([8], [2], [4]) or continuously moving query points ([11], [13]) over stationary datasets, or queries about the future positions of a set of continuously moving points ([1], [12], [5]). Apparently, these types of queries do not cover NN search on historical trajectories.

The challenge accepted in this paper is to describe diverse mechanisms to perform *k*-NN search on R-tree-like structures [6] storing historical information. To illustrate the problem, consider an application tracking the positions of rare species of wild animals. Such an application is composed of a MOD storing the location dependent data, together with a spatial index for searching and answering *k*-NN queries in an efficient manner. Experts in the field would be advantaged if they could pose queries about the nearest trajectories of animals to a stationary point (lab, source of food or other non-emigrational species) or an animal moving from location P_1 to P_2 during a period of time. By these types of queries an expert may figure out motion habits and patterns of wild species or deviations from natural emigration, which could be interrelated with environmental and/or ecological changes or destructions. Having in mind that users of MODs are usually interested in continuous types of queries, the above queries can be extended to their continuous counterparts, where the result is a time-varying number (the nearest distance depends on time) along with a collection of trajectory ids and the appropriate time intervals for which each moving object is valid.

To make the previous example more intelligible, Fig. 1 illustrates the trajectories of six moving animals $\{O_1, O_2, O_3, O_4, O_5, O_6\}$ along with two stationary points (Q_1 and Q_2) representing two sources of food. Now, consider the following queries demonstrated in Fig. 1 (Queries 2 and 4 are the continuous counterparts of Queries 1 and 3, respectively):

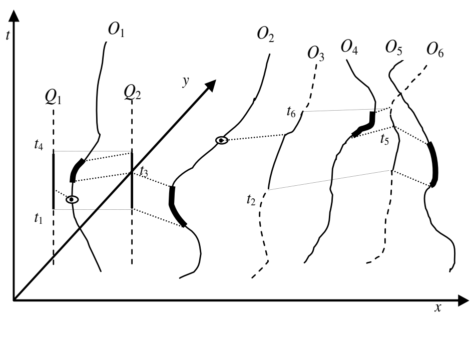


Fig. 1. Continuous and non-continuous point and trajectory NN queries over moving objects trajectories

- Query 1. "*Find which animal was nearest to the stationary food source Q_1 during the time period $[t_1, t_4]$*", resulting to animal O_1.

- Query 2. "*Find which animal was nearest to the stationary food source Q_2 at any time instance of the time period $[t_1\ t_4]$*", resulting to a list of objects: O_2 for the interval $[t_1,t_3)$; O_1 for the interval $[t_3,t_4]$.
- Query 3. "*Find which animal was nearest to animal O_3 during the time period $[t_2,t_6]$*", resulting to O_2.
- Query 4. "*Find which animal was nearest to animal O_6 at any time instance of the time period $[t_2,t_6]$*", resulting to a list of objects: O_5 for the interval $[t_2,t_5)$; O_4 for the interval $[t_5,t_6]$.

To the best of our knowledge, this is the first work on continuous *k*-NN query processing over historical trajectories of moving objects. Outlining the major issues that will be addressed in this paper, our main contributions are as follows:

- We propose a set of four query processing algorithms to perform NN search on R-tree-like structures storing historical information about moving objects. The description of our branch-and-bound traversal algorithms for different queries depends on the type of the query object as well as on whether the query itself is continuous or not. The algorithms are generalized to find the k nearest neighbors.
- We propose novel metrics to support our search ordering and pruning strategies. More specifically, the definition of the minimum distance metric MINDIST between points and rectangles, initially proposed in [8] and extended in [13], is further extended in order for our algorithms to calculate the minimum distance between trajectories and rectangles.
- We conduct a comprehensive set of experiments over synthetic and real datasets demonstrating that the algorithms are highly scalable and efficient in terms of node accesses and pruned space.

The rest of the paper is structured as follows. Related work is discussed in Section 2, while Section 3 introduces, at an abstract level, the set of k-NN algorithms over moving object trajectories, as well as the metrics that support our search ordering and pruning strategies. Sections 4 and 5 constitute the core of the paper describing in detail the query processing algorithms to perform NN search over historical trajectory information (Section 4) together with their continuous counterparts (Section 5). Section 6 presents the results of our experimental study and Section 7 provides the conclusions of the paper and some interesting research directions.

2 Related Work

In the last decade, NN queries have fueled the spatial and spatiotemporal database community with a series of interesting noteworthy research issues.

The first algorithm for *k* nearest neighbor search over a moving query point was proposed in [11]. The algorithm assumes that sites (landmark points) are static and their locations (known in advance) are stored in an R-tree-like structure. A discrete time dimension is assumed, thus a periodical sampling technique is applied on the trace of the moving query point. The location of the query point that lies between two consecutive sampled locations is estimated using linear or polynomial splines.

Using the TPR-tree (Time Parameterized Tree) structure [9], Benetis et al. [1] presented efficient solutions for NN and RNN (Reverse Nearest Neighbor) queries for moving objects. (An RNN query returns all the objects that the query object is the nearest neighbor of.) The proposed algorithm was the first to address continuous RNN queries, since previous existing RNN algorithms were developed under the assumption that the query point is stationary. The algorithms for both NN and RNN queries in [1] refer to future (estimated) locations of the query and data points, which are assumed to be continuously moving on the plane. In the same paper, an algorithm for answering CNN queries is also proposed.

Tao et al. [13] also studied CNN queries and proposed an R-tree based algorithm (for moving query points and static data points) that avoids the pitfalls of previous ones (false misses and high processing cost). The proposed tree pruning heuristics exploit the MINDIST metric presented in [8]. At each leaf entry, the algorithm focuses on the accurate calculation of the split points (the points of the query segment that demonstrate a change of neighborhood). A theoretical analysis of the optimal performance for CNN algorithms was presented and cost models for node accesses were proposed. Finally, the CNN algorithm was extended for the case of *k* neighbors and trajectory inputs.

Shahabi et al. [10] presented the first algorithm for processing the *k*-NN queries for moving objects in road networks. Their proposed algorithm, which utilizes the network distance between two locations instead of the Euclidean, is based on transforming the road network into a higher dimensional space, in which simpler distance functions can be applied. Using this embedding space, efficient techniques are proposed for finding the shortest path between two points in the road network. The above procedure, which is utilized in the case of static query points, is slightly modified in order to support the case of moving query points.

Acknowledging the advantages of the above fundamental techniques, in this paper we present the first complete treatment of historical NN queries over moving object trajectories, handling both stationary and moving query objects.

3 Problem Statements and Metrics

We first define the NN queries that are considered in this paper. Subsequently, we present the heuristics utilized by our algorithms to implement the metrics needed to formulate our ordering and pruning strategy.

3.1 Problem Statement

Let D be a database of N moving objects with objects ids $\{O_1, O_2, \ldots, O_N\}$. The trajectory T_i of a moving object O_i consists of M_i 3D-line segments $\{ L_{i1}, L_{i2}, \ldots, L_{iM_i} \}$. Each 3D line segment L_j is of the form $((x_{j\text{-}start}, y_{j\text{-}start}, t_{j\text{-}start}), (x_{j\text{-}end}, y_{j\text{-}end}, t_{j\text{-}end}))$, where $t_0 \le t_{j\text{-}start} < t_{j\text{-}end} \le now$. Obviously, as we treat only historical moving object trajectories, each partial linear movement is temporally restricted between t_0, the beginning of the calendar, and *now*, the current time point.

We have already stated that NN queries search for the closest trajectories to a query object Q. In our case, we distinguish two types of query objects: Q_p, a point (x,y) that remains stationary during the time period of the query $Q_{per}[t_{start}, t_{end}]$, and Q_T, a moving object with trajectory T. Furthermore, the MOD is indexed by an R-tree like structure such as the 3D R-tree [16], the STR-tree or the TB-tree [7]. Having in mind the previous discussion, we define the following two types of NN queries:

- NN_Q_p (D, Q_p, Q_{per}) query searches database D for the NN over a point Q_p that remains stationary during a time period Q_{per}, and returns the closest to Q_p point p_c from which a moving object O_i passed during the time period Q_{per}, as well as the implied minimum distance.
- NN_Q_T (D, Q_T, Q_{per}) query is similar to the previous with the difference being upon the query object Q which in the current case is a moving object with trajectory T.

The extensions of the above queries to their continuous counterparts vary in the output of the algorithms. In the continuous case, each query returns a time-varying real number, as the nearest distance depends on time. We introduce the following two types of CNN queries:

- CNN_Q_p (D, Q_p, Q_{per}) query over a point Q_p that remains stationary during a time period Q_{per} returns a list of triplets consisting of the time-varying real value R_i along with a moving object O_i (belonging in database D) and the corresponding time period $[t_{i\text{-}start}, t_{i\text{-}end})$ for which the nearest distance between Q_p and O_i stands. These time-varying real values R_i are, in any time instance of their lifetime, smaller or equal to the distance between any moving object O_j in D and the query point Q_p. The time periods $[t_{i\text{-}start}, t_{i\text{-}end})$ are mutually disjoint and their union forms Q_{per}.
- Similarly, CNN_Q_T (D, Q_T, Q_{per}) differs, compared to the previous, upon the query object Q which in the current case is a moving object with trajectory T. These time-varying real values R_i are, in any time instance of their lifetime, smaller or equal to the distance between any moving object O_j and the query trajectory Q_T. The time periods $[t_{i\text{-}start}, t_{i\text{-}end})$ are mutually disjoint and their union forms Q_{per}.

The above four queries are generalized to produce the corresponding k-NN queries. The generalization of the first two queries is straightforward by simply requesting the 1-st, 2-nd, …, k-th nearest point – with respect to a query point or a query trajectory – from which a moving object O_i passed during the time period Q_{per}, excluding at the same time points belonging to a moving object already marked as the j-th nearest $(1 \leq j < k)$. The continuous queries are generalized to produce k-CNN requesting to provide with k lists of $\{R_i, [t_{i\text{-}start}, t_{i\text{-}end}), O_i\}$ triplets. Then, for any time during the time period Q_{per}, the i-th list $(1 \leq i \leq k)$ will contain the i-order NN moving object (with respect to the query point or the query trajectory) at this time instance.

To exemplify the proposed k-NN extensions, let us recall Fig. 1. Searching for the 2-NN versions of the four queries (Query 1, 2, 3 and 4) presented in Section 1, we will have the following results:

- Query 1 (non-continuous): O_1 (1st NN) and O_2 (2nd NN)

- Query 2 (continuous): 1-NN list includes O_2 for the interval $[t_1,t_3)$ and O_1 for the interval $[t_3,t_4]$; 2-NN list includes O_1 for the interval $[t_1,t_3)$ and O_2 for the interval $[t_3,t_4]$
- Query 3 (non-continuous): O_2 (1st NN) and O_4 (2nd NN)
- Query 4 (continuous): 1-NN list includes O_5 for the interval $[t_2,t_5)$ and O_4 for the interval $[t_5,t_6]$; 2-NN list includes O_4 for the interval $[t_2,t_5)$ and O_5 for the interval $[t_5,t_6]$.

3.2 Metrics

We exploit on the definition of the minimum distance metric (MINDIST) presented in [8] between points and rectangles, in order to calculate, on the one hand, the minimum distance between line segments and rectangles and, on the other hand, the minimum distance between trajectories and rectangles that are needed to implement the above discussed algorithms.

Initially, in [8], Roussopoulos et al. defined the Minimum Distance (MINDIST) between a point *P* in the n-dimensional space and a rectangle *R* in the same space as the square of the Euclidean distance between *P* and the nearest edge of *R*, if *P* is outside *R* (or zero, if *P* is inside *R*).

In the sequel, Tao et al. [13] proposed a method to calculate the MINDIST between a 2D line segment *L* and a rectangle *M*. They initially determine whether *L* intersects *M*; if so, MINDIST is set to zero. Otherwise, they choose the shortest among six distances, namely the four distances between each corner point of *M* and *L* and the two minimum distances from the start and end point of *L* to *M*. Therefore, the calculation of MINDIST between a line segment and a rectangle involves an intersection check, four segment-to-point MINDIST calculations and two point-to-rectangle MINDIST calculations.

In this paper, we propose a more efficient method to calculate MINDIST between a line segment *L* and a rectangle *M* (Fig. 2). As before, if *L* intersects *M*, then MINDIST is obviously zero. Otherwise, we decompose the space in four quadrants using the two axes passing through the center of *M* and we determine the quadrants Q_s and Q_e in which the start (*L.start*) and the end (*L.end*) point of *L* lie in, respectively.

Then, MINDIST is the minimum among:

- Case 1 (*L.start* and *L.end* belong to the same quadrant ($Q_s = Q_e$)): (i) MINDIST between the corner of *M* in Q_s and *L*, (ii) MINDIST between *L.start* and *M* or (iii) MINDIST between *L.end* and *M*.
- Case 2 (*L.start* and *L.end* belong to adjacent quadrants Q_s and Q_e, respectively): (i) MINDIST between the corner of *M* in Q_s and *L*, (ii) MINDIST between the corner of *M* in Q_e and *L*, (iii) MINDIST between *L.start* and *M* or (iv) MINDIST between *L.end* and *M*.
- Case 3 (*L.start* and *L.end* belong to non adjacent quadrants Q_s and Q_e, respectively): two MINDIST between the two corners of *M*, that do not belong in either Q_s or Q_e, and *L*.

This method utilizes a smaller number of (point-to-segment and point-to-rectangle) distance calculations compared to the corresponding algorithm in [13]. Finally, we extend the above method in order to calculate the MINDIST metric between the projection of a trajectory *T* on the plane (usually called route) and a rectangle *M*. Since a route can be viewed as a collection of 2D line segments, the MINDIST between a route of a trajectory and a rectangle can be computed as the minimum of all MINDIST between the rectangle and each line segment composing the route. The efficiency of this calculation can be enhanced by simply not computing twice, with respect to the query rectangle, the quadrant and the MINDIST of the end and the start of adjacent line segments.

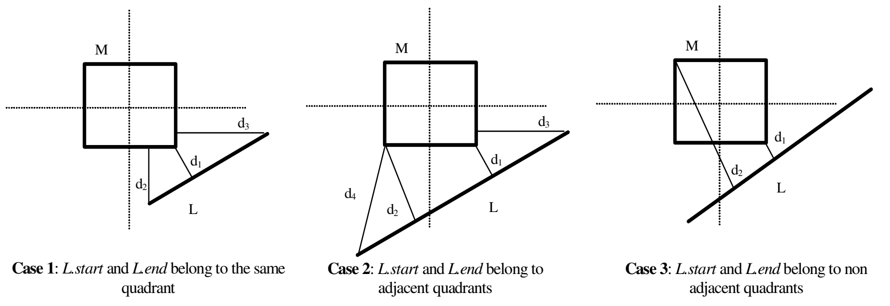

M
d3
d1
d2
L
M
d3
d1
d4
d2
L
M
d1
d2
L
Case 1: *L.start* and *L.end* belong to the same quadrant
Case 2: *L.start* and *L.end* belong to adjacent quadrants
Case 3: *L.start* and *L.end* belong to non adjacent quadrants

Fig. 2. The proposed calculation method of MINDIST between a line segment and a rectangle

4 NN Algorithms over trajectories

In this section we describe in details the algorithms answering the four types of NN queries presented in Section 3.1 and, then, we generalize them in order to support the respective *k*-NN queries.

4.1 NN algorithm for stationary query objects (points)

The NN algorithm for stationary query objects (`PointNNSearch` algorithm, illustrated in Fig. 3, provides the ability to answer NN queries for a static query object Q_p, during a certain query time period $Q_{per}[t_{start}, t_{end}]$. The algorithm uses the same heuristics as in [8] and [2], pruning the search space according to Q_{per}.

The algorithm accesses the tree structure (which indexes the trajectories of the moving objects) in a depth-first way pruning the tree nodes according to Q_{per} rejecting those being fully outside it. At leaf level, the algorithm iterates through the leaf entries checking whether the lifetime of an entry overlaps Q_{per} (Line 4); if the temporal component of the entry is fully inside Q_{per}, the algorithm calculates the actual Euclidean distance between *Q* and the (spatial component of the) entry; otherwise, if the temporal component of the entry is only partially inside Q_{per}, a linear interpolation is applied so as to compute the entry's portion being inside Q_{per} (Line 5) and calculate the Euclidean distance between *Q* and the portion of that entry. When a candidate nearest is selected, the algorithm, backtracking to the upper level, prunes the nodes in the active branch list (Line 20) applying the MINDIST heuristic [8] [2].

```
Algorithm PointNNSearch(node N, 2D point Q, time period Qper, struct
Nearest)
 1.  IF N Is Leaf
// Iterate by computing actual Euclidean distance from point Q
 2.    FOR i = 1 to N.EntriesCount
 3.      E = N.Entry(i)
// If entry is (fully or partially) inside the period
 4.      IF $Q_{per}$ Overlaps (E.$T_S$, E.$T_E$)
// Compute entry’s spatial extent inside the period
 5.        nE = Interpolate(E, Max($Q_{per}$.$T_S$, E.$T_S$), Min($Q_{per}$.$T_E$, E.$T_E$))
// Compute actual distance from Q. Update Nearest if necessary
 6.        Dist = Euclidean_Dist_2D(Q, nE)
 7.        IF Dist < Nearest.Dist
 8.          Nearest.Entry = nE
 9.          Nearest.Dist = Dist
10.        END IF
11.      END IF
12.    NEXT
13.  ELSE
// Generate branch list with entries overlapping the query period
14.    BranchList = GenBranchList(Q, N, $Q_{per}$)
// Sort active branch List by MinDist
15.    SortBranchList(BranchList)
// Iterate through active branch List
16.    FOR i = 1 TO BranchList.Count
17.      E = N.Entry(i)
// Visit Child Nodes
18.      NN = E.ChildNode
19.      PointNNSearch(NN, Q, $Q_{per}$, Nearest)
// Apply MinDist heuristic to do pruning
20.      PruneBranchList(BranchList)
21.    NEXT
22.  END IF
```

Fig. 3. Historical NN search algorithm for stationary query points (PointNNSearch)

4.2 NN algorithm for moving query objects (trajectories)

PointNNSearch algorithm can be modified in order to support the second type of NN query where the query object is a trajectory of a moving point (`TrajectoryNN-Search` algorithm, illustrated in Fig. 5). At the leaf level, the algorithm calculates the minimum horizontal Euclidean Distance between each leaf entry and each query trajectory segment using the `Min_Horizontal_Dist` function (Line 10) which computes the minimum horizontal Euclidean Distance between two 3D line segments. In addition, for each segment of trajectory Q and before calculating its distance from the current entry we first check whether its temporal extent overlaps the temporal extent of the bounding rectangle of node *N*.

```
Algorithm genTrajectoryBranchList(node N, trajectory Q)
 1.  FOR i = 1 TO N.EntriesCount
 2.    E = N.Entry(i)
// If entry is (fully or partially) inside the trajectory lifetime
 3.    IF (Q.$T_S$, Q.$T_E$) Overlaps (E.$T_S$, E.$T_E$)
// Compute trajectory's spatial extent inside E's lifetime
 4.      nQ = Interpolate(Q, Max(Q.$T_S$, E.$T_S$), Min(Q.$T_E$, E.$T_E$))
// Compute MinDist between the resulted trajectory and the rectangle
 5.      Dist=MinDist_Trajectory_Rectangle(nQ, E)
// Add the rectangle along with its calculated distance in the list
 6.      List.Add(nQ, Dist)
 7.    END IF
 8.  NEXT
 9.  RETURN List
```

Fig. 4. Generating Branch List of Node N against Trajectory Q

```
Algorithm TrajectoryNNSearch(node N, trajectory Q, time period $Q_{per}$,
struct Nearest)
 1.  Q = Interpolate(Q, Max(Q.$T_S$, $Q_{per}$.$T_S$), Min(Q.$T_E$, $Q_{per}$.$T_E$))
 2.  IF N Is Leaf
 3.    FOR j = 1 to Q.Entries
 4.      QE=Q.Entry(j)
 5.      IF (QE.$T_S$, QE.$T_e$) Overlaps (N.$T_S$, N.$T_E$)
 6.        FOR i = 1 to N.EntriesCount
 7.          E = N.Entry(i)
 8.          IF (QE.$T_s$, QE.$T_e$) Overlaps (E.$T_S$, E.$T_E$)
 9.            nE = Interpolate(E, Max(QE.$T_S$, E.$T_S$), Min(QE.$T_E$, E.$T_E$))
10.            Dist = Min_Horizontal_Dist(QE, nE)
11.            IF Dist < Nearest.Dist
12.              Nearest.Entry = nE
13.              Nearest.Dist = Dist
14.            END IF
15.          END IF
16.        NEXT
17.      END IF
18.    NEXT
19.  ELSE
20.    BranchList = GenTrajectoryBranchList(Q, N)
21.    SortBranchList(BranchList)
22.    FOR i = 1 TO BranchList.Count
23.      E = N.Entry(i)
24.      NN = E.ChildNode
25.      nQ = Interpolate(Q, Max(Q.$T_S$ NN.$T_S$), Min(Q.$T_E$ NN.$T_E$))
26.      TrajectoryNNSearch(NN, nQ, Nearest)
27.      PruneBranchList(BranchList)
28.    NEXT
29.  END IF
```

Fig. 5. Historical NN search algorithm for moving query points (TrajectoryNNSearch)

At the non-leaf levels, the algorithm utilizes `GenTrajectoryBranchList` function (pseudo-code in Fig. 4) instead of `GenBranchList`. `GenTrajectory-BranchList`(*node N*, *Trajectory Q*) utilizes the `MinDist_Trajectory_ Rectangle` metric introduced in Section 3.2 in order to calculate the MINDIST between the query trajectory and the rectangle of each entry of the node. Here, we have to point out that we do not calculate MinDist_Trajectory_Rectangle against the original query trajectory *Q*, but against the part of *Q* being inside the temporal extent of the bounding rectangle of *N*, and therefore (if necessary) we have to interpolate to produce the new query trajectory *nQ*.

4.3 Extending to *k*-NN algorithms

In the same fashion as in [8], we generalize the above two algorithms to searching the k-nearest neighbors by considering the following:

- Using a buffer of at most k (current) nearest objects sorted by their actual distance from the query object (point or trajectory).
- Pruning according to the distance of the (currently) furthest object in the buffer.
- Updating the distance of each moving object inside the buffer when visiting a node that contains an entry of the same object closer to the query object.

5 CNN Algorithms over trajectories

The continuous counterparts of the previously described algorithms are also of branch-and-bound type.

5.1 CNN algorithm for stationary query objects (points)

We first discuss the query that searches for the nearest moving objects to a stationary query point at any time during a given time period. ContPointNNSearch algorithm used to process this type of query is illustrated in Fig. 6.

All the continuous algorithms use a MovingDist structure (Fig. 6, Line 6), storing the parameters of the distance function, along with the entry's temporal extent and the associated minimum and maximum (D_{min} and D_{max} respectively) of the function during its lifetime. We also store the actual entry inside the structure in order to be able to return it as the query result. ConstructMovingDistance simply calculates this structure.

In Line 8, the Nearests structure is introduced. Nearests is a list of adjacent "*Moving Distances*" temporally covering the period Q_{Per}. Roof is the maximum of all moving distances stored inside the Nearests list and is used to quickly reject those entries (and prune those branches at the non-leaf level) having their minimum distance greater than Roof (consequently, greater than all moving distances stored inside the *Nearests* list). More details on the maintenance of the Nearests structure can be found in [3].

When backtracking at non-leaf levels, ContPointNNSearch applies PruneContBranchList, which prunes the branch list using the MINDIST heuristic: First, it compares the MINDIST of each entry with Roof, then it calculates the maximum distance inside the *Nearests* list during the entry's lifetime and prunes all entries having MINDIST greater than the calculated one.

```
Algorithm ContPointNNSearch(node N, 2D point Q, Period $Q_{per}$, List
Nearests, Roof)
 1.  IF N Is Leaf
 2.    FOR i = 1 to N.EntriesCount
 3.      E = N.Entry(i)
 4.      IF $Q_{per}$ Overlaps (E.$T_S$, E.$T_E$)
 5.        nE = Interpolate(E, Max($Q_{per}$.$T_S$, E.$T_S$), Min($Q_{per}$.$T_E$, E.$T_E$))
 6.        MovingDist = ConstructMovingDistance(nE, Q)
 7.        IF MovingDist.$D_{min}$ < Roof
 8.          UpdateNearests(Nearests, MovingDist, Roof)
 9.        END IF
10.      END IF
11.    NEXT
12.  ELSE
13.    BranchList = GenBranchList(Q, N, $Q_{per}$)
14.    SortBranchList(BranchList)
15.    PruneContBranchList(BranchList, Nearests, Roof)
16.    FOR i = 1 TO BranchList.Count
17.      E = N.Entry(i)
18.      NN = E.ChildNode
19.      ContPointNNSearch(NN, Q, $Q_{per}$, Nearests, Roof)
20.      PruneContBranchList(BranchList, Nearests, Roof)
21.    NEXT
22.  END IF
```

Fig. 6. Historical CNN search algorithm for stationary query points (ContPointNNSearch)

5.2 CNN algorithm for moving query objects (trajectories)

The fourth type of NN query is the continuous version of the NN query where the query object is the trajectory of a moving point. The algorithm `ContTrajectoryNNSearch`, used to process this type of query is illustrated in Fig. 7.

`ContTrajectoryNNSearch` differs from `ContPointNNSearch` at two points only: Firstly, at leaf level, `ConstructMovingDistance` calculates the "Moving distance" between two moving points, instead of one moving and one stationary in the non-continuous case (Line 10). As in `TrajectoryNNSearch`, we perform a loop through all the 3D line segments of the query trajectory *Q* and, for each segment of *Q* and before processing the leaf entries, we first check whether the lifetime of *Q* overlaps the temporal extent of the bounding rectangle of *N* (Line 8). Secondly, at the non-leaf level, `GenBranchList` is replaced by `GenTrajectoryBranchList` introduced in the description of `TrajectoryNNSearch` algorithm (Line 19).

```
Algorithm ContTrajectoryNNSearch (node N, Trajectory Q, time period
$Q_{per}$, List Nearests, Roof)
  Q = Interpolate(Q, Max(Q.$T_S$, $Q_{per}$.$T_S$), Min(Q.$T_E$, $Q_{per}$.$T_E$))
  IF N Is Leaf
    FOR j = 1 to Q.Entries
      QE=Q.Entry(j)
      IF (QE.$T_s$, QE.$T_e$) Overlaps (N.$T_S$, N.$T_E$)
        FOR i = 1 to N.EntriesCount
          E = N.Entry(i)
          IF (QE.$T_s$, QE.$T_e$) Overlaps (E.$T_S$, E.$T_E$)
            nE = Interpolate(E, Max(QE.$T_S$, E.$T_S$), Min(QE.$T_E$,E.$T_E$))
            MovingDist = ConstructMovingDistance(nE, QE)
            IF MovingDist.$D_{min}$ < Roof
              UpdateNearests(Nearests, MovingDist, Roof)
            END IF
          END IF
        NEXT
      END IF
    NEXT
  ELSE
    BranchList = GenTrajectoryBranchList(Q, N)
    SortBranchList(BranchList)
    PruneContBranchList(BranchList, Nearests, Roof)
    FOR i = 1 TO BranchList.Count
      E = N.Entry(i)
      NN = E.ChildNode
      nQ = Interpolate(Q, Max(Q.$T_S$, NN.$T_S$), Min(Q.$T_E$, NN.$T_E$))
      ContTrajectoryNNSearch(NN, nQ, Nearests, Roof)
      PruneContBranchList(BranchList, Nearests, Roof)
    NEXT
  END IF
```

Fig. 7. Historical CNN search algorithm for moving query points (ContTrajectoryNNSearch algorithm)

5.3 Extending to *k*-CNN algorithms

The two continuous algorithms can be also generalized to searching the *k*- nearest neighbors by considering the following:

- Using a buffer of at most *k* current `Nearests` Lists
- Pruning according to the distance of the furthest `Nearests` Lists in the buffer – therefore `Roof` is calculated as the maximum distance of the furthest `Nearests` List
- Processing each entry against the *i*-th list (with *i* increasing, from 1 to *k*) checking whether it qualifies to be in a list
- Testing each moving distance, replaced by a new entry in the *i*-th list, against the (*i*+1)-th list to find whether it qualifies to be in a list.

6 Performance Study

The above illustrated algorithms can be implemented in any R-tree-like structure storing historical moving object information such as the 3D R-tree [16], the STR-tree [7] and the TB-tree [7]. Among them, we have chosen to implement the algorithms using the TB-tree due to its proven efficiency regarding historical trajectory information, as demonstrated in [7]. In our implementation, we set a page size of 4096 bytes and a (variable size) buffer fitting the 10% of the index size, thus leading to a maximum of 1000 pages. The experiments were performed in a PC running Microsoft Windows XP with AMD Athlon 64 3GHz processor, 512 MB RAM and several GB of disk size.

6.1 Datasets

While several real spatial datasets are around for experimental purposes, this is not true for the moving object domain. Nevertheless, in this paper, we have exploited on two real-world datasets: a fleet of trucks and a fleet of school buses illustrated in Fig. 8(a) and (b), respectively, and consisting of 276 (112203) and 145 (66096) trajectories (entries in the index), respectively. We have also used synthetic datasets generated by the GSTD data generator [14] in order to achieve a scalability in the volumes of the datasets. A snapshot of the generated data using GSTD is illustrated in Fig. 8(c). The synthetic trajectories generated by GSTD correspond to 20, 50, 100, 250, 500 and 1000 moving objects with the position of each object sampled approximately 1500 times.

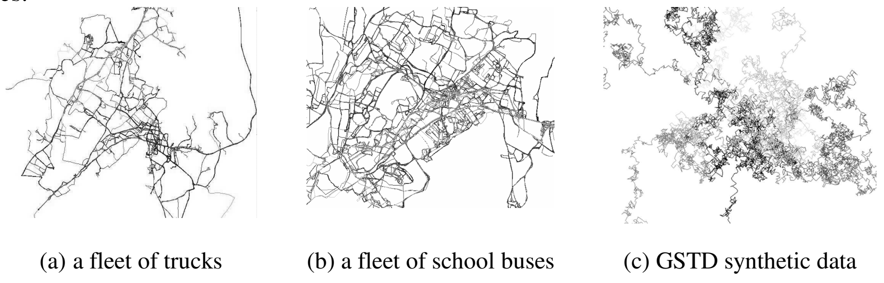

(a) a fleet of trucks (b) a fleet of school buses (c) GSTD synthetic data

Fig. 8. Snapshots of real and synthetic spatiotemporal data

Table 1 illustrates summary information about the datasets used. The number of pages occupied by the index for each dataset will be used for calculating the pruning acheived in the search space.

Table 1. Summary Dataset Information

	Real Data		*GSTD*					
	Trucks	*Buses*	*20*	*50*	*100*	*250*	*500*	*1000*
# trajectories	276	145	20	50	100	250	500	1000
# entries	112203	66096	30277	75717	151482	378803	757360	1514844
index size in pages (of 4kb)	835	466	205	507	1010	2521	5040	10073

6.2 Results on the Search Cost of the non-continuous algorithms

The performance of the proposed algorithms was measured in terms of node accesses. Several queries were used in order to evaluate the performance of the proposed algorithms over the synthetic and real data. In particular, we have used the following query sets:

- Q1, Q2: `PointNNSearch` was evaluated with two sets of 500 NN queries increasing the number of moving objects over the GSTD datasets. The queries used a random point in the 2D space and a time period of 1% (5%) of the temporal dimension for Q1 (Q2).
- Q3, Q4: `TrajectoryNNSearch` was evaluated with two sets of 500 NN queries increasing the number of moving objects over the GSTD datasets. The 500 query objects (trajectories) were produced using GSTD also employing a Gaussian initial distribution and a random movement distribution. Then, in Q3 (Q4) we used a random 1% (5%) part of each trajectory as the query trajectory.
- Q5, Q6: two sets of 500 k-NN queries over the real Trucks dataset increasing the number of *k* with fixed time and increasing the size of the time interval (with fixed *k*=1) respectively. For `PointNNSearch` we used a random point in the 2D space with a 5% of time as query period, while for `TrajectoryNNSearch` we used a random part of a random trajectory belonging to Buses dataset, temporally covering 1% of time.

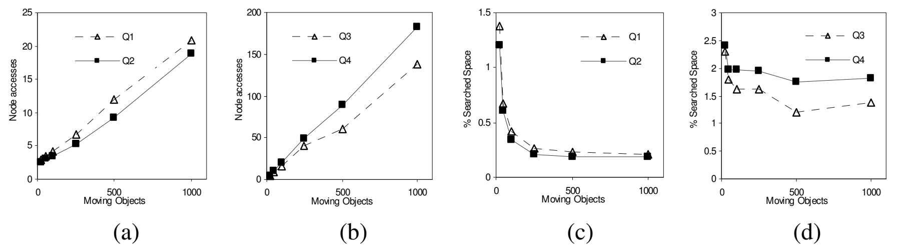


Fig. 9. Node Accesses and searched space in queries Q1-Q4 with the number of moving objects

Fig. 9 illustrates the average number of node accesses per query for the query sets Q1-Q4 evaluating `PointNNSearch` and `TrajectoryNNSearch`. In particular, Fig. 9(a) shows the average number of node accesses per query using the point query sets Q1 and Q2, while Fig. 9(b) shows the average number of node accesses per query using the trajectory query sets Q3 and Q4. As it is clearly illustrated, the performance of the algorithm depends linearly on the dataset cardinality and degrades (more pages are accessed) as the cardinality grows. It is worth to point out that comparing query sets Q1 and Q2, the algorithm accesses more pages in query set Q1, although the lifetime of Q2 is longer than that of Q1 (5% against 1% of the total time). This observation can be explained bearing in mind that decreasing the query temporal extent, the expected nearest distance increases, resulting in fewer pruned nodes in the backtracking procedure of the algorithm. As expected, `TrajectoryNNSearch` tends to be much more expensive than `PointNNSearch`.

The results in Fig. 9(c) and (d) demonstrate the percentage of the indexed space actually used for searching. As illustrated, in all cases, increasing the index size, the percentage of the space to be searched decreases, resulting (for over 1000 moving objects) in a 0.20% of the whole index space for point NN queries and in a 1.2% - 2% for trajectory NN queries. So as to make the results more readable, we have to point out that a range search over the index with zero spatial and 1% temporal extent would lead to a searching among the 10% of the whole indexed space – showing that the pruning performed by our algorithms is much more efficient than a sequential search. The conclusion gathered from the previous observations is that the algorithms presented show high pruning ability, well bounding the space to be searched in order to answer NN queries.

The performance of the two non-continuous NN algorithms increasing the number of k is shown in Fig. 10(a) against Buses dataset.

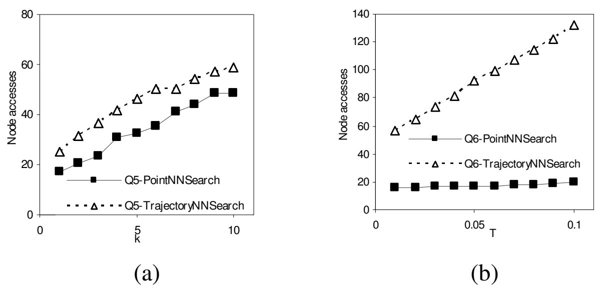


Fig. 10. Node Accesses in queries (a) Q5 increasing the number of k and (b) Q6 increasing the query temporal extent

Clearly, the number of node accesses needed for the processing of a *k*-NN query increases linearly with *k*. Fig. 10(b) illustrates the average number of node accesses per non-continuous point and trajectory query increasing the temporal extent against the real "trucks" dataset. It is clear that the cost of `TrajectoryNNSearch` tends to increase with greater rate than the increase of `PointNNSearch`. This observation can be easily explained since when increasing the temporal interval, the spatial extent of the query trajectory also increases leading to a greater spatial space to be searched.

6.3 Results on the Search Cost of the continuous algorithms

In coincidence with the experiments conducted for the non-continuous algorithms, the continuous NN search algorithms were evaluated with the following query sets:

- Q7, Q8: `ContPointNNSearch` was evaluated with two sets of 500 NN queries increasing the number of moving objects over the GSTD datasets like what was done for query sets Q1 and Q2.
- Q9, Q10: `ContTrajectoryNNSearch` was evaluated with two sets of 500 NN queries increasing the number of moving objects over the GSTD datasets like what was done for query sets Q3 and Q4.

- Q11, Q12: two sets of 500 *k*-CNN queries over the real dataset of buses increasing the number of k with fixed time and increasing the size of the time interval (with fixed *k*=1) respectively. For `ContPointNNSearch` we used a random point in 2D space with a 5% of time as query period, while for `ContTrajectoryNN-Search` we used a random part of a random trajectory belonging to the buses dataset, temporally covering 1% of time.

Fig. 11 illustrates similar results as in Fig. 9, regarding the continuous counterpart of the NN algorithms, thus, illustrating the average number of node accesses per query for the queries sets Q7- Q10. In particular, Fig. 11(a) presents the average number of node accesses per query using `ContPointNNSearch` against query sets Q7 and Q8 while Fig. 11(b) presents the average number of node accesses per query using `ContTrajectoryNNSearch` against query sets Q9 and Q10.

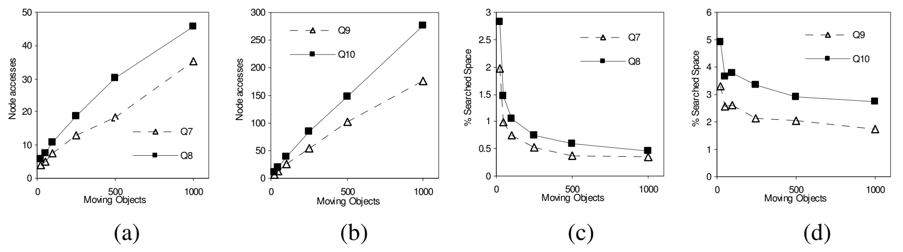
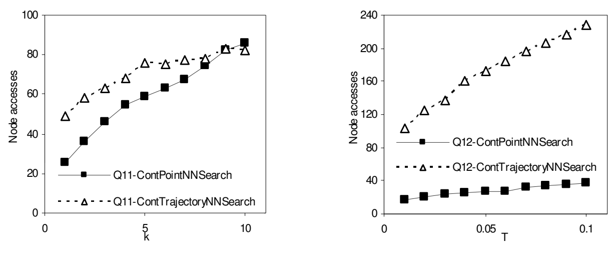


Fig. 11. Node Accesses and searched space in queries Q7-Q10 increasing the number of moving objects

Again, the performance of the algorithms linearly depends on the dataset cardinality and degrades (more pages are accessed) as the cardinality grows. Fig. 11(c) and (d) show the accessed index part as a percentage of the indexed space, illustrating that in all cases, increasing the index size the percentage of the space to be searched decreases, resulting (for over 1000 moving objects) in a 0.50% of the whole index space for point CNN search and in a 2.5% - 3 % for trajectory CNN search.

A comparison between the non-continuous NN algorithms with their continuous counterparts (e.g. Fig. 9 vs. Fig. 11), shows that the continuous algorithms are much more expensive than the non-continuous ones, which is expected since the continuous algorithms prune the search space by using a list of moving distances instead of a single distance.

The performance of the continuous NN algorithms increasing the number of *k* is illustrated in Figure 12(a) for the real Buses dataset. The number of node accesses required for the processing of a *k*-NN query increases linearly with *k*. Figure 12(b) illustrates the average number of node accesses per continuous point and trajectory query increasing the temporal extent for Trucks dataset. Presenting the same behavior as with the non-continuous queries, the performance of `ContTrajectoryNNSearch` tends to degrade with greater rate than that of `ContPointNNSearch`, having the same explanation (by increasing the temporal interval, the spatial extent of the query trajectory also increases leading to a greater spatial space to be searched).



(a) (b)

Fig. 12. Node Accesses in queries (a) Q11 increasing the number of k and (b) Q12 increasing the query temporal extent

7 Conclusions and Future Work

NN queries have been in the core of the spatial and spatiotemporal database research during the last decade. The majority of the algorithms processing such queries so far mainly deals with either stationary or moving query points over static datasets or future (predicted) locations over a set of continuously moving points. In this work, acknowledging the contribution of related work, we presented the first complete treatment of historical NN queries over moving object trajectories stored on R-tree like structures. Based on our proposed novel metrics, which support our searching and pruning strategies, we presented algorithms answering the NN and CNN queries for stationary query points or trajectories and generalized them to search for the k nearest neighbors. The algorithms are applicable to R-tree variations for trajectory data, among which, we used the TB-tree for our performance study due to its proven efficiency regarding historical trajectory information. Under various synthetic datasets (generated by GSTD) and two real trajectory datasets, we illustrated that our algorithms show high pruning ability, well bounding the space to be searched in order to answer NN and CNN queries. The pruning power of our algorithms is also verified in the case of the *k*-NN and *k*-CNN queries (for various values of *k*).

As such, future work includes the development of algorithms to support distance join queries ("*find pairs of objects passed nearest to each other (or within distance d from each other) during a certain time interval and/or under a certain space constraint*"). A second research direction includes the development of selectivity estimation formulae for query optimization purposes investing on the work presented in [15] for predictive spatiotemporal queries.

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