Efficient k-Nearest Neighbor Search on Moving Object Trajectories

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Abstract

With the growing number of mobile applications, data analysis on large sets of historical moving objects trajectories becomes increasingly important. Nearest neighbor search is a fundamental problem in spatial and spatio-temporal databases. In this paper we consider the following problem: Given a set of moving object trajectories D and a query trajectory mq, find the k nearest neighbors to mq within D for any instant of time within the life time of mq. We assume D is indexed in a 3D-R-tree and employ a filter-and-refine strategy. The filter step traverses the index and creates a stream of so-called units (linear pieces of a trajectory) as a superset of the units required to build the result of the query. The refinement step processes an ordered stream of units and determines the pieces of units forming the precise result.

To support the filter step, for each node p of the index, in preprocessing a time dependent coverage function $C_p(t)$ is computed which is the number of trajectories represented in p present at time t. Within the filter step, sophisticated data structures are used to keep track of the aggregated coverages of the nodes seen so far in the index traversal to enable pruning. Moreover, the R-tree index is built in a special way to obtain coverage functions that are effective for pruning. As a result, one obtains a highly efficient k-NN algorithm for moving data and query points that outperforms the two competing algorithms by a wide margin.

Implementations of the new algorithms and of the competing techniques are made available as well. Algorithms can be used in a system context including, for example, visualization and animation of results. Experiments of the paper can be easily checked or repeated, and new experiments be performed.

1 Introduction

Moving objects databases have been the subject of intensive research for more than a decade. They allow one to model in a database the movements of entities and to ask queries about such movements. For some applications only the time-dependent location is of interest; in other cases also the time dependent extent is relevant. Corresponding abstractions are a *moving point* or a *moving region*, respectively. Examples of moving points are cars, air planes, ships, mobile phone users, or animals; examples of moving regions are forest fires, the spread of epidemic diseases and so forth.

Some of the interest in this field is due to the wide-spread use of cheap devices that capture positions, e.g. by GPS, mobile phone tracking, or RFID technology. Nowadays not only car navigation systems, but also many mobile phones are equipped with GPS receivers, for example. Vast amounts of trajectory data, i.e., the result of tracking moving points, are accumulated daily and stored in database systems [14, 41, 31].

There are two kinds of such databases. The first kind, sometimes called a *tracking* database, represents a set of currently moving objects. One is interested in continuously maintaining the current

positions and to be able to ask queries about the positions as well as the expected positions in the near future. This approach was pioneered by the Wolfson group [43, 48]. With this approach, a cab company can find the nearest taxi to a passenger requesting transportation.

The other kind of moving objects database represents entire histories of movement [25, 17], e.g. the entire set of trips of the vehicles of a logistics company in the last day or even month or year. For moving points such historical databases are also called *trajectory* databases. The main interest is in performing complex queries and analyses of such past movements. For the logistics company this might result in improvements for the future scheduling of deliveries. For zoologists, the collected movement information of animals (equipped with a radio transmitter) can be used to analyse their behavior.

There has been a lot of interest in research to support such analyses, for example in data mining on large sets of trajectories [23], on discovering movement patterns such as flocks or convoys traveling together [24, 31], on finding similar trajectories to a given one [20], to name but a few. Of course, indexing and query processing techniques (see [35]) play a fundamental role in supporting such analyses.

In this paper we consider the problem of computing continuous nearest neighbor relationships on a historical trajectory database. Nearest neighbor queries are, besides range queries, the most fundamental query type in spatial databases. With the advent of moving objects databases, also time dependent versions have been studied. One can distinguish four types of queries:

- static query vs. static data objects (i.e., the classical nearest neighbor query)
- moving query vs. static data objects (e.g. maintain the five closest hotels for a traveller)
- static query vs. moving data objects (e.g. observe the closest ambulances to the site of an accident)
- moving query vs. moving data objects (e.g. which vehicles accompanied president Obama on his trip through Berlin)

Furthermore, one can consider these query types in a tracking database which leads to the notion of a continuous query, maintaining the result online while entities are moving. This is most interesting for consumer applications. But one can also consider these queries in the context of analysing historical trajectories which is the case studied in this paper.

Note that the last of the four query types is the most difficult and general one. It includes all other cases, as a static object can be represented as a moving object that stays in one place. We will handle this case.

The precise problem considered is the following. We call the data type representing a complete trajectory *moving point* or $\underline{mpoint}$, for short [25, 17]. Let $d(p, q)$ denote the Euclidean distance between points p and q. Let $mp(i)$ denote the position of moving point mp at instant i.

Definition 1 [TCkNN-query] A *trajectory-based continuous k-nearest neighbor query* is defined as follows: Given a query $\underline{mpoint}$ mq and a relation D with an attribute $mloc$ of type $\underline{mpoint}$, return a subset D' of D where each tuple has an additional attribute $mloc'$ such that the three conditions hold:

1. For each tuple $t \in D'$, there exists an instant of time i such that $d(t.mloc(i), mq(i))$ is among the k smallest distances from the set $\{d(u.mloc(i), mq(i)) | u \in D\}$.
2. $mloc'$ is defined only at the times condition (1) holds.
3. $mloc'(i) = mloc(i)$ whenever it is defined.

□

In other words, the query selects a subset of tuples whose moving point belongs at some time to the k closest to the query point and it extends these by a restriction of the moving point to the times when it was one of the k closest.

This query type has been considered in the literature [19, 22] with a further parameter, a query time interval. However, our definition covers this case as well, since one can easily compute the restriction of the query trajectory to this time interval first.

An example of a TCkNN query is shown in Figure 1. To enable easy interpretation of the figure, we assume that all objects only change their x-coordinate and the y-coordinate is fixed to y_0.

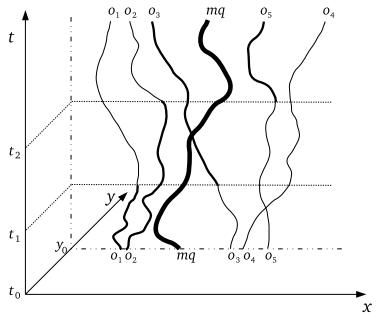


Figure 1: Example of a TCkNN query

Besides the query object mq, there are five moving data objects $\{o_1, \ldots, o_5\}$. We set $k = 2$, that means, we search for the two nearest neighbors. As shown in the figure, the result changes with time. For example, between t_0 and t_1, the result is the set $\{o_1, o_2\}$ and between t_1 and t_2, the result changes to $\{o_2, o_3\}$.

TCkNN queries on the one hand are natural from a systematic point of view as they are the dynamic version of a fundamental problem in spatial databases. They also have many applications, especially in discovering groups of entities traveling together with a query object. Some examples are mentioned in [19, 21]. Further, an efficient solution to this problem might be used as a stepping stone for solving data mining problems such as discovering flock or convoy patterns. Traffic jams are another example of groups of vehicles staying close to each other for extended periods of time.

So far, there exist two approaches for handling TCkNN queries [19, 21]. Both use R-tree like structures for indexing the data trajectories, i.e. in [19] a 3D-R-tree is used and in [21] a TB-tree [39] is utilized. They are discussed in more detail in Section 2.

Our contributions are the following:

- We offer the first filter-and-refine solution, in the form of two different algorithms and query processing operators, called $knearestfilter$ and $knearest$. The first traverses an index to produce an ordered stream of candidate units (pieces of movement), the second consumes such an ordered stream. Both together offer a complete solution. However, $knearest$ can also be used independently. This is important for queries that restrict candidate nearest neighbors by other conditions so that the index cannot be used.

- We offer a solution that employs novel and highly sophisticated pruning strategies in the filter step. A fundamental idea is to preprocess coverage functions for each node of the index that describe how many moving objects are present in the nodes subtree for any instant of time. This is supported by special techniques to build an R-tree and by efficient data structures and algorithms to keep track of pruning conditions.

- We provide a thorough experimental comparison which demonstrates that our algorithm is orders of magnitude faster than the two competing algorithms for larger databases and larger values of k.

- For the first time, such algorithms are made publicly available in a system context and so can be used for real applications. The SECONDOsystem is freely available for download. A new plugin

technology exists that makes it easy for readers of this paper to add a nearest neighbor module (plugin) to an existing SECONDOinstallation. All algorithms can then be used in the form of query processing operators; they can be applied to any data sets that are available in the system or that users provide; the results can easily be visualized and animated.

- We also provide scripts for test data generation and for the execution of experiments. In this way easy experimental repeatability is provided. Besides repeating the experiments shown in the paper, readers can change parameters, explore other data sets, build indexes in other ways, and hence study the behaviour of these algorithms in any way desired, with relatively little effort. Indeed, we would like to promote such a methodology for experimental research and view this paper and implementation as a demonstration of it.

The remainder of this paper is structured as follows. Section 2 surveys related work, especially the two algorithms solving the same problem as this paper. In Section 3.1 we briefly describe the representation of trajectories. Section 3.2 outlines the filter-and-refine strategy. After that, the filter step is described in detail in Section 4. First, we give an overview of the basic idea and expose arising subproblems. The next subsections show how these problems can be solved. Then, the refine step is presented in Section 5. The results of an experimental evaluation comparing our approach with both existing approaches are shown in Section 6. Section 7 explains how the algorithms can be used in the context of the SECONDOsystem and how experiments can be repeated. Finally, Section 8 concludes the paper and gives directions for future work.

2 Related Work

There are several types of kNN queries. The most simple case is that both the query point and the data points are static. The first algorithm for efficient nearest neighbor search on an R-tree was proposed by [42] using depth-first traversal and a branch-and-bound technique. An incremental algorithm was developed in [27]. Again, an R-tree is traversed. Here a priority queue of visited nodes ordered by distance to the query point is maintained. The incremental technique is essential if the number of objects needed is not known in advance, e.g. if candidates are to be filtered by further conditions. Because in this case all involved objects are static, also the result is a fixed set of objects.

The first algorithm for CNN (Continuous Nearest Neighbor) queries was proposed in [44]. It handles the case that only the query object is moving, while the data objects remain static. Here the basic idea is to issue a query at each sampled or observed position of a query point, trying to exploit some coherency between the location of the previous and the current query. This algorithm suffers from the usual problems of sampling. If there are too few sample points, the result may be inaccurate. On the other hand, many sampling points lead to an increase in computation time without any guarantee for a correct result.

An improved algorithm was proposed by [47]. Here an algorithm searches the R-tree only once to find the k nearest neighbors for all positions along a line segment, without the need of sampling points.

There exists a lot of work related to Continuous k Nearest Neighbor queries [45, 29, 40, 37, 50, 49, 9, 28]. In all these approaches tracking databases are assumed and the task is online maintenance of nearest neighbors for a moving query point, in some cases also for moving data points. For each of these objects only the current and near future position is known. Index structures like the TPR-tree are used [40, 9] which indexes current and near future positions; in some cases simple grid structures are employed to support high update rates [49, 50]. In [9] also reverse nearest neighbor queries are addressed. Iwerks et al. [29] also support updates of motion vectors.

Note that all this work is fundamentally different from the problem addressed in this paper because only the current motion vector is known. In contrast, we are considering historical trajectory databases. In this case, the data set is not only a vector for each moving object, but a complete trajectory, and there

is no need to process pieces of a trajectory in a particular order (e.g. in temporal update order). Instead, the set of trajectories can be organized and traversed in any way that is suitable.

A few works have considered the case of historical trajectory databases and we consider these next in some detail.

In [22], Gao et al. propose two algorithms for a query point and for a query trajectory, respectively, on a set of stored trajectories. In contrast to our algorithm, the result is static, i.e. they return the ids of the k trajectories which ever come closest to the query object during the whole query time interval. In contrast, our approach will report the k nearest neighbors at any instant for the lifetime of the query object.

In [19] several types of NN-queries on historical data are addressed. The types depend on whether the query object is moving or not and whether the query itself is continuous or not. One of the types corresponds to the TCkNN query defined in Section 1. The authors represent trajectories as a set of line segments in 3D space (2D + time). The segments are indexed by an R-tree like structure (e.g. 3D R-Tree, TB-tree or STR-tree). The algorithm is formulated for the special case $k = 1$ and then extended to arbitrary values of k. The nodes of the tree are traversed in depth first manner. If a leaf is reached, the contained line segments are inserted into a structure named $nearest$ containing the distance curves between the already inserted segments and the segments coming from the query point. Entries whose minimal distance to the query object is greater than the maximal distance stored in $nearest$ are ignored. Other segments are inserted extending existing entries if applicable. For a non-leaf node, all children are checked whether they can be pruned (minimal distance is larger than the maximal distance stored in $nearest$ during the time interval covered by the node). For an arbitrary k, a buffer of k $nearest$ structures is used.

In this paper we traverse the tree in breadth first manner. Besides the tree, we determine in preprocessing and store the time dependent number of data objects present in a node's subtree[1]. This allows pruning nodes using only information of nodes at the same level of the tree reducing the number of nodes to be considered.

[21] extends the approach of [22] to continuous queries, hence, also to the TCkNN problem. The entries stored in a TB-tree are inserted into a set of k lists $l_1 \dots l_k$. These lists contain distance functions with links to the corresponding units. For each instant the distance value in list l_i is smaller or equal to the distance value in list l_{i+1}. Thus, for each instant the list l_i contains the distance to the current i-th neighbor or ∞ if no distance is stored for this instant. The maximum distance stored in a list l_i is called $Prunedist(i)$. Thereby all objects whose minimum distance is greater than $Prunedist(k)$ can be pruned. The main algorithm traverses a TB-tree in best first manner. A priority queue sorted by minimum distance contains non-processed nodes of the tree. The queue is initialized with the root of the tree. If the top element of the queue is a node, it is removed and its entries are inserted into the queue ignoring those non overlapping the query time interval and those with $minDist > Prunedist(k)$. Unit entries are inserted into the set of lists. The process is finished when the minimum distance of the top entry of the queue is greater than $PruneDist(k)$ or the queue is exhausted. So, pruning is based on disjoint time intervals or information from the trajectory entries. A more detailed description is given in Section 6.3.

In contrast, our approach allows pruning using also information of nodes on higher levels of the tree. Because the refinement step of our algorithm can be used separately, it is possible to combine it with other filter steps, for example if a query contains additional filter conditions.

As already mentioned, we maintain for each node of the R-tree index used some derived information. Some previous work has augmented R-trees and other structures by storing such auxiliary information in each node [32, 38, 34, 46]. For example, the aggregate R-tree (aR-tree) [32, 38] stores numerical measures associated with regions in its leaves, and aggregations over such values for each subtree in internal nodes (the root of the subtree). Aggregation functions can be *count*, *sum*, or *max*, for example. It supports efficient aggregate range queries, i.e., computing the aggregate over a query region.

[1] Actually, we use a simplified version of this moving integer.

3 Preliminaries

3.1 Representation of Trajectories

Figure 2 shows the trajectories of two moving points in 3D space. We use the sliced representation [17] to represent the trajectory of a moving object. A trajectory $T =< u_1, u_2, \ldots, u_n >$ is a sequence of so-called *units*. Each unit consists of a time interval and a description of a linear movement during this time interval. The linear movement is defined by storing the positions at the start time and the end time of the unit. We denote a unit as $u = (p_1, p_2, t_1, t_2)$, where $p_1, p_2 \in \mathbb{R}^2$ and $t_1, t_2 \in \underline{instant}$. Within a trajectory, time intervals of distinct units are disjoint. The sequence of units is ordered by time.

This is a well established definition of trajectory in the literature [26]. Another common representation is a temporally ordered sequence of triples (t_i, x_i, y_i). Both representations can be easily converted into the other one. The definition based on units emphasizes that a trajectory is an approximation of a continuous movement curve that can be evaluated at any instant of time. The second definition is often interpreted to represent a sequence of observations.

How trajectories are derived from observations is a complex issue that is beyond the scope of this paper. A simple possibility is that a GPS receiver captures positions every two seconds, which may be typical for car navigation systems. But there may be other steps involved such as map matching or compression [33, 13], and the frequeny of transmitting positions may depend on update policies.

In the data model of [25, 17], a trajectory corresponds to a data type *moving(point)*, or $\underline{mpoint}$. There is also a data type corresponding to a unit called $\underline{upoint}$.

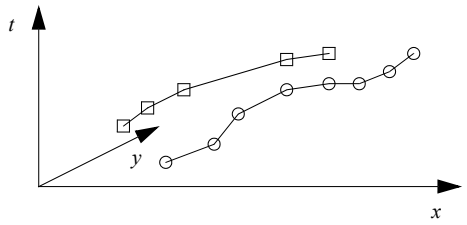


Figure 2: Two trajectories in space

A set of trajectories can be represented in a database in two ways. The first is to use a relation with an attribute of type $\underline{mpoint}$. Hence each moving object is represented in a single tuple consisting of the trajectory together with other information about the object. This is called the *compact representation*.

Second, one can use a relation with an attribute of type $\underline{upoint}$. In this case, a moving object is represented by a set of tuples, each containing one unit of the trajectory. The object is identified by a common identifier. This is called the *unit representation*.

In the following we assume that the set D of data trajectories is stored in unit representation, and the query trajectory is given as a value of the $\underline{mpoint}$ data type, i.e., a sequence of units.

3.2 Filter-and-Refine Strategy

We now describe our approach to evaluate a spatio-temporal k-nearest neighbor query. We assume a set of data moving points in unit representation, i.e., a relation R with an attribute $mloc$ of type $\underline{upoint}$. This relation is indexed by a spatio-temporal (3D) R-tree R_mloc containing one entry for each unit. Further parameters are the query moving point mq of type $\underline{mpoint}$, and the number k of nearest neighbors to be found. We use the well-known filter-and-refine strategy with the two steps:

Filter Traverse the R-tree index R_mloc to determine a set of candidate units containing at least all parts of the moving points of R that may contribute to the k nearest neighbors of mq. Return these as a stream of units ordered by unit start time.

Refine Process a stream of units ordered by start time to determine the precise set of units forming the k nearest neighbors of mq.

These two steps are explained in detail in the following two sections.

Whereas the complete algorithm uses the two steps together, it is possible to use the refinement step independently. For example, think of a scenario where a criminal has taken a hostage and is trying to escape by car. The database contains information about all vehicles moving in the area. Suppose vehicles in the database have an attribute "type" distinguishing types of cars such as {private, truck, police, ambulance}. A query "Find the closest 20 cars in the neighborhood of the hostage car" should be evaluated as expected, by filter-and-refine. However, since ambulances and police cars are relatively rare, a query such as "Determine the five closest police cars" would be more efficiently determined by retrieving police cars (using an index on *type*), sorting their units by start time and then applying the refinement step directly.

4 The Filter Step: Searching for Candidate Units

4.1 Basic Idea: Pruning by Nodes with Large Coverage

Obviously the goal of the filter step must be to access as few nodes as possible in the traversal of the index R_mloc.

We proceed as follows. Starting from the root, the index is traversed in a breadth-first manner. Whenever a node is accessed, each of its entries (node of the next level or unit entry in a leaf) is added to a queue Q and to a data structure $Cover$ explained below. The $Cover$ structure is used to decide whether a node or unit entry can be pruned. The entries in $Cover$ and Q are linked so that an entry found to be prunable can be efficiently removed from Q. The question is by what criterion a node can be pruned. Consider a node N that is accessed and the query trajectory mq. See the illustration in Figure 3.

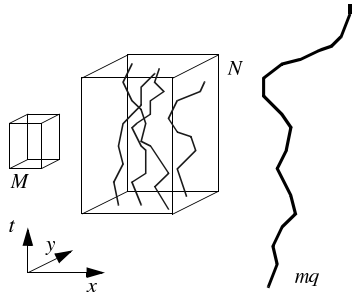


Figure 3: Nodes and query trajectory mq

Node N contains a set of unit entries representing trajectories. In fact, each segment of a trajectory is represented as a small 3D box, but we have nevertheless drawn the trajectories directly. Furthermore, node N looks like a leaf node. However, if it is an inner node of the R-tree, we may still consider the set of units or trajectories represented in the entire subtree rooted in N in the same way.

Suppose that at any instant of time within node Ns time interval $[N.t_1, N.t_2]$ at least n trajectories are present in N and $n \geq k$. Let M be a further node and Ms time interval be included in Ns time interval. Furthermore let the minimal distance between the xy-projection of M and the xy-projection of mq (restricted to $[M.t_1, M.t_2]$) be larger than the maximal distance between the xy-projection of N and the xy-projection of mq (restricted to $[N.t1, N.t2]$). Then node M and its contents can be pruned as they cannot contribute to the k nearest neighbors of mq. This is illustrated in Figure 4.

More formally, for a node K let $box(K)$ denote its spatiotemporal bounding box, i.e., the rectangle $[K.x_1, K.x_2, K.y_1, K.y_2, K.t_1, K.t_2]$. For a trajectory u let $box(u)$ denote its spatiotemporal bounding

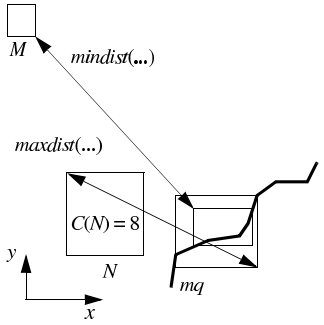


Figure 4: Pruning criterion of Lemma 1, k = 5

box and let $u[t_1, t_2]$ denote its restriction to the time interval $[t_1, t_2]$. For a 3D rectangle $B = [x_1, x_2, y_1, y_2, t_1, t_2]$ let B_{xy} denote its spatial projection $[x_1, x_2, y_1, y_2]$ and B_t denote its temporal projection $[t_1, t_2]$, respectively. For a node K, let $C_K(t)$ denote the number of trajectories represented in the subtree rooted at K present at instant t. $C_K(t)$ is a function from time into integer values, called the *coverage function*. Let $C(K) = \min_{t \in [K.t_1, K.t_2]} C_K(t)$ be called the (minimal) *coverage number* of K. For a (hyper-) rectangle r in a d-dimensional space $\mathbb{R}^d$ let $points(r)$ denote all enclosed points of $\mathbb{R}^d$, i.e,

$$points(r) = \{(x_1, \ldots, x_d) \mid r.b_1 \leq x_1 \leq r.t_1, \ldots, r.b_d \leq x_d \leq r.t_d\}$$

where $r.b_i$ and $r.t_i$ denote the bottom and top coordinates of r in dimension i, respectively. For two rectangles r and s their minimal and maximal distances are defined as

$$mindist(r, s) = min\{d(p, q) | p \in points(r), q \in points(s)\}$$

$$maxdist(r, s) = max\{d(p, q) | p \in points(r), q \in points(s)\}$$

where $d(p, q)$ denotes the Euclidean distance between two points p and q. Then we can formulate the pruning condition as follows.

Lemma 1 *Let M and N be nodes of the R-tree R_mloc, mq the query trajectory, and k the number of nearest neighbors desired. Then*

$$\begin{array}{ll} & C(N) \geq k \\ \wedge & box_t(M) \subseteq box_t(N) \\ \wedge & mindist(box_{xy}(M), box_{xy}(mq[box_t(M)]) > \\ & maxdist(box_{xy}(N), box_{xy}(mq[box_t(N)]) \\ \Rightarrow & M \textit{can be pruned}. \end{array}$$

More generally, several nodes together may serve to prune another node M if for any instant of time within Ms time interval the sum of their coverages exceeds k and they are all closer to the query trajectory.

Lemma 2 *Let S be a set of nodes of the R-tree R_mloc, $S(t) = \{s \in S | t \in box_t(s)\}$ the nodes of S present at time t, and $M \notin S$ another node. Let mq be the query trajectory, and k the number of nearest neighbors desired.*

$$\begin{array}{ll} & \forall t \in box_t(M) : \sum_{s \in S(t)} C(s) \geq k \\ & (\forall s \in S : mindist(box_{xy}(M), box_{xy}(mq[box_t(M)]) > \\ \wedge & \qquad maxdist(box_{xy}(s), box_{xy}(mq[box_t(s)])) \\ \Rightarrow & M \textit{ can be pruned.} \end{array}$$

To realize this pruning strategy, the following subproblems need to be solved:

- Efficiently determine the xy-projection bounding box of a restriction of the query trajectory to a time interval.
- Determine coverage numbers for the nodes of the R-tree index.
- Define the Cover data structure needed for pruning and provide an efficient implementation.

These subproblems are addressed in the following subsections. After that, the complete filter algorithm is described.

4.2 Determining the Spatial Bounding Box for a Partial Query Trajectory

As mentioned in Section 3.1, the query trajectory is represented basically as an array of units with distinct time intervals, ordered by time. A simple approach to compute the bounding box for the restriction to some time interval (called the restriction bounding box) is to search the unit containing the start time of the interval using a binary search. For the (sub-) unit the bounding box is computed. Then the sequence of units is scanned until the end of the interval is reached. The union of the bounding boxes of all visited units yields the final result. Here the union of two rectangles is defined as the smallest enclosing rectangle of the two arguments. If the interval is long, a lot of units must be processed. For example, if the time interval covers the lifetime of the query trajectory, all units have to be visited.

Whether query or data trajectories are long or short depends on the application. In the experiments of Section 6 typical short trajectories have about 100 units. Trajectories in the BerlinMOD benchmark [16] where vehicles are observed over a period of one month (at scale factor 1.0 of the benchmark) have an average number of 26963 units. The longer query trajectories are, the more important is an efficient computation of restriction bounding boxes as this has to be done for each node of the R-tree accessed in the search.

To enable efficient computation of a restriction bounding box we compute at the beginning of the filter step an alternative representation of the query trajectory, called a *BB-tree* (*bounding box tree*). Essentially it is a binary tree over the sequence of units of the trajectory such that the units are the leaves of the tree. Each node has an associated time interval. For a leaf this is the unit time interval, for an internal node it is the concatenation of the time intervals of the two children. Furthermore, each node p has an associated rectangle which is the spatial projection bounding box of the set of units represented in the subtree rooted in p. An example of a BB-tree is shown in Figure 5.

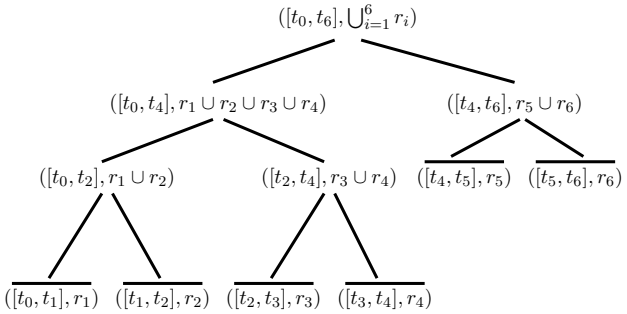


Figure 5: BB-tree

For computing the bounding box for a given time interval, we apply the following algorithm to the root of the tree:

We use the notations $n.t_1$, $n.t_2$, $n.r$, and $n.u$ to access the start instant, the end instant, the rectangle, and the unit, repectively. Furthermore, we use *n.left* and *n.right* to get the sons of n.

Algorithm 1: *get_box(n, t_1, t_2)*

Input: *n* - node of a bbox-tree;
$[t_1, t_2]$ - a time interval.
Output: the bounding box of the query trajectory, restricted to $[t_1, t_2]$

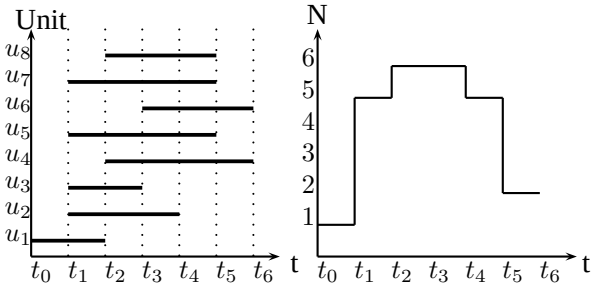
```
1 if t1 > n.t2 ∨ t2 < n.t1 then return an empty box;
2 if t1 ≤ n.t1 ∧ t2 ≥ n.t2 then return n.r ;
3 if n is an inner node then
4     return get_box(n.left) ∪ get_box(n.right) ;
5 else
6     let u be a copy of n.u;
7     restrict u to [t1, t2];
8     return bbox(u);
```

The structure is closely related to a segment tree [15] that we will also use in Section 4.4. The algorithm *get_box* is quite similar to the algorithm for inserting an interval into a segment tree. It is well known that the time complexity is $O(\log n)$ where n is the number of leaves of the tree (units of the query trajectory). The BB-tree can be built in linear time.

4.3 3D R-tree and Coverage Number

4.3.1 Coverage Numbers

If all units of the data trajectories are stored within a 3D R-tree, we can compute for each node n of the tree its coverage function $C_n(t)$, a time dependent integer. Recall that $C_n(t)$ is the number of units present at instant t within the subtree rooted in n. An example of the distribution of units within a node and the resulting coverage curve are shown in Figure 6.



(a) units on time (b) coverage function

Figure 6: Coverage Function

In Section 4.1 we have seen that for pruning only one number $C(n)$, the minimal coverage number, is used. This would be 1 in Figure 6. Now it is easy to see that due to boundary effects only a small number of units will be present at the beginning or end of a node's time interval.[2] Hence if we use simply the

[2]To see this, consider the following simple experiment: n intervals of length k (k an integer) are placed randomly on integer coordinates within an interval B of length $n+k-1$. With a random distribution, one interval starts on each of the coordinates $0, ..., n-1$ of B. If we consider the number of intervals $c(u)$ present at each coordinate u, it first increases as $c(u) = u+1$ in the range $[0, k-1]$, then remains constant at $c(u) = k$ in the range $[k, n]$ (because on each coordinate, one interval starts and one ends), and then decreases as $c(u) = k-(u-n)$ in the range $[n+1, n+k-1]$. Hence we have the maximum value k within a long middle part, but at the boundaries only a minimum of 1.

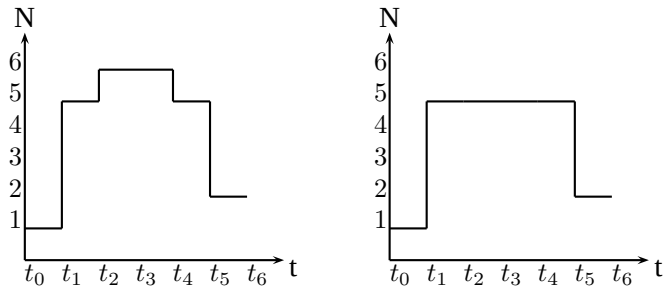
minimum of the coverage function, no good pruning effect can be achieved. On the other hand, within a reduced time interval, e.g. from t_1 to t_5, a large minimal coverage could be observed.

The idea is therefore to use instead of one coverage number three of them, by splitting a node's time interval into three parts, namely two small parts at the beginning and end with small coverage numbers, and a large part in the middle with a large coverage number. In Figure 6 we could use $([t_0, t_1], 1), ([t_1, t_5], 5), ([t_5, t_6], 2)$.

We introduce an operator to compute from the coverage function the three numbers, called the *hat* operator (because the shape of the curve reminds of a hat). Technically it takes an argument c of type moving integer or $\underline{mint}$, describing the coverage function, and returns an $\underline{mint}$ r with the following properties:

- $deftime(r) = deftime(c)$
- $\forall t \in deftime(r) : r(t) \leq c(t)$
- r consists of three units at most
- the area under curve r is the maximum of all possible areas fulfilling the first three conditions

An application of the hat operator is shown in Figure 7.



(a) coverage curve (b) result of hat

Figure 7: Application of the hat operator

Intuitively it is good for pruning if a large coverage number is obtained over a long time interval. The goal is therefore to maximize the area of the "middle" unit of the result which is the product of these quantities. Using a stack, the simplification of the curve can be done in linear time with respect to the number of units of the original moving integer. This is shown in Algorithm 2. Here $c.t_1$ and $c.t_2$ denote the start and end of the definition time of moving int c.

The idea of this algorithm is to process the units of the given coverage curve in temporal order and to maintain on a stack a sequence of units with monotonically increasing coverage values. When a unit is encountered that reduces the current coverage, then the potential candidates for middle units ending at this point are examined by taking them from the stack. The largest rectangle seen so far is maintained. This is illustrated in Figure 8.

In Figure 8, when unit u is encountered, the last three stack entries a, b, and c with higher coverage values than that of u are popped from the stack, and for each of them the size of the respective rectangle is computed. Start time, end time, and coverage of the largest rectangle so far are kept.

4.3.2 Building the R-tree

This section describes how an R-tree over the data point units can be built, which will support k-NN queries in an efficient way. A node of the R-tree can be pruned if

Algorithm 2: *hat(c)*

Input: *c* - an mint (moving integer) describing a coverage function
Output: a reduced mint with only three units

```
1  let s be a stack of pairs < t, n >, initially empty;
2  let int area = 0;
3  extend c by a pseudo unit <[c.t2, c.t2 + 1], 0]>;
   /* ensures that all entries are popped from stack at the end   */
4  for each unit u in c do
5      if s is empty then s.push(< u.t1, u.n >) else
6          if s.top().n < u.n then s.push(< u.t1, u.n >) else
7              t_end = u.t1;
8              while s.top().n > u.n do
9                  < t_start, cn >= s.top(); s.pop();
10                 if area == 0 then
11                     area = (t_end − t_start) × cn;
12                     < t1, t2, n >=< t_start, t_end, cn >;
13                 else
14                     newarea = (t_end − t_start) × cn;
15                     if newarea > area then
16                         area = newarea;
17                         < t1, t2, n >=< t_start, t_end, cn >;
18             s.push(< t_start, u.n >)
19 Now the middle unit is < t1, t2, n >. Scan the units before t1 and after t2 to compute the minimal
   coverages first and last for the time intervals [c.t1, t1] and [t2, c.t2], respectively;
20 return the mint consisting of the three units ([c.t1, t1], first), ([t1, t2], n), and ([t2, c.t2], last);
```

- there are enough candidates available in other nodes, and
- the minimum distance of the node to the query point is higher than the maximum distance of the query point to each node in the current candidate set.

The first condition can be achieved with a small set of candidate nodes if the coverage numbers are high. The second condition requires a good spatial distribution of the nodes of the R-tree.

Experiments have shown that if we fill the R-tree either by the standard insertion algorithm or by a bulkload [11, 12] using z-order [36], for example, only the spatial distribution of the nodes will be good. But the coverage numbers will be very small and a large candidate set is required.

However, by using a customized bulkload algorithm for filling the R-tree, we can achieve some control over the distribution of the R-tree nodes. The bulkload works as follows: It receives a stream of entries (bounding box and a tuple id) and puts them into a leaf of the R-tree until either the leaf is full or the distance between the new box and the current bounding box of the leaf exceeds a threshold. When this happens, the leaf is inserted into a current node at the next higher level and a new leaf is started. In this way, the tree is built bottom-up.

This bulkload algorithm itself does not care about the order of the stream. So by changing the order, the structure of the R-tree is affected. For example, if we sort the units by their starting time, temporally overlapping units are inserted into the same node and the coverage number is very high. But this order ignores spatial properties and so the nodes will have many and large overlappings in the xy-space.

To get both, high coverage numbers and good spatial distribution, we do the following. We partition the 3D space occupied by the units into cells, using a regular grid. The spatial partition (or cell size) is

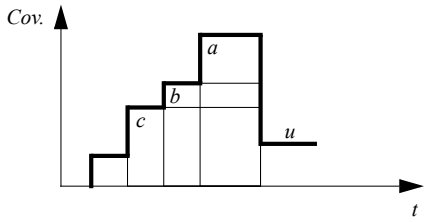


Figure 8: Stack maintained in Algorithm 2

chosen in such a way that within a cell, at each instant of time, on the average about p units are present. Then the temporal partition is chosen such that within a cell enough units are present to fill on the average about r nodes of the R-tree. A stream of units to be indexed is extended by three integer indices x, y, t representing a spatiotemporal cell containing the unit[3], hence has the form $< unit, tupleid, x, y, t >$. The stream is then sorted lexicographically by the four attributes $< t, x, y, unit >$ where the order implied by the fourth attribute is unit start time. In this way, a subsequence of units belonging into one cell is formed and these are ordered by start time. Such subsequences are packed by the bulkload into about r nodes of the R-tree, resulting in nice hat shapes as desired in Section 4.3.1.

In our experiments, we have chosen $p = 15$ and $r = 6$ with good results. Some motivation for such a choice of values for p and r is the following. The goal of the design is to obtain within each cell of the partition a "vertical" stack of nodes of the R-tree. This is so that units with similar time intervals are usually within the same node, leading to good coverage curves. A node of the R-tree can take in our implementation about 60 unit entries. The average number of moving objects present in a cell at any instant of time, p, should be clearly below 60 so that divisions between R-tree nodes introduced by the bulkload occur on the temporal dimension only. p is an average, so it should not be too close to 60 to keep the property also in places where objects get more dense.

Regarding the number of nodes r in a cell, observe that from the last unit (in temporal order) within a cell to the first unit of the next cell a "jump" occurs (a larger distance within the 3d space) which causes the bulkload to terminate the current node even if it is not full. Only this last one of the r nodes can be underfilled. If r is not too small, e.g. $r = 6$, this unfilled space is compensated by the other $r - 1$ full nodes.

4.3.3 The Combined Data Structure

One may consider to extend the R-tree structure by fields in each node for the three pairs of time interval and coverage number. The computation of coverage numbers should then be integrated into R-tree construction and update algorithms.

Whereas such a strategy is often used in the literature when specific algorithms are proposed (e.g. [38]), in our view it is not a good choice within a system context. The R-tree is a fundamental structure for spatial and spatio-temporal indexing and it should not be modified to support particular query types whenever it can be avoided. In particular, adding fields to each node will decrease the number of entries per node and the fanout and hence increase running times for all other types of queries.

Therefore in our implementation we use a standard R-tree. This index is denoted *R_mloc*. Coverage numbers are computed by traversing *R_mloc* and storing for each node three tuples in a relation *Cov*. Tuples have the form (nid, u) where nid is the node identifier and u an integer unit, a value of type $\underline{uint}$. Such a unit consists of a time interval and an integer and hence can nicely represent one of the three coverage numbers. The relation *Cov* is furthermore indexed by a B-tree index on node identifiers, *Cov_nid*.

[3] containing one of its corner points, for example

4.3.4 Maintenance of R-tree and Coverage Numbers under Updates

The problem considered in this paper is efficient continuous k nearest neighbor search on historical trajectory databases. For this purpose, a static construction of the R-tree index and a one-time computation of the coverage numbers is sufficient.

Nevertheless, a trajectory database might be used to keep track of currently moving vehicles, continuously adding recent pieces of movement. An interesting question is therefore whether the data structure used by our algorithm permits updates or always needs to be recomputed from scratch.

Since the R-tree was built in a special way by bulkload to obtain good coverage curves, using the standard R-tree insertion is not feasible as it would destroy such properties. However, we can offer an efficient bulk update technique for the combined data structure consisting of *R_mloc*, *Cov*, and *Cov_nid*.

The key observation is that on the one hand, online updates arrive in temporal order, and on the other hand, our bulkload technique builds the R-tree as a sequence of temporal slices, as the major sorting criterion for the bulkload is the temporal slice number t. This means that entries are added to the root node, and more generally the top levels of the tree, in temporal order.

We can therefore proceed as follows. We denote the existing structure as R_1 = *R_mloc*, C_1 = *Cov*, and B_1 = *Cov_nid*.

1. We collect enough update units to fill m temporal slices, $m \geq 1$.[4]
2. For these a separate R-tree R_2 is built by bulkload using the procedure described in Section 4.3.2. In our implementation, the new R-tree R_2 is constructed within the file of the storage manager also used by R_1 which ensures that its node (= record) identifiers are distinct from those of R_1.
3. C_2 is computed as the coverage number relation of R_2.
4. A B-tree index B_2 on node identifiers is computed for C_2. This index is used in step 7 below.
5. R_2 is inserted into R_1. This is done in constant time as only an entry with a pointer to the root of R_2 is added to one of the top level nodes of R_1. As both R-trees have been constructed within the same storage manager file, they now form a uniform structure.
6. All entries of C_2 are inserted into C_1. This is possible because node identifiers are distinct. These insertions into C_1 are also propagated into the index B_1.
7. Let q be the node of R_1 to which the entry pointing to the root of R_2 was added. The coverage numbers for a small set of nodes Q, consisting of q and its ancestors, if any, are recomputed and corrected in relation C_1. Observe that all other coverage numbers of the previous trees R_1 and R_2 are not affected by the merge of the two trees and are therefore correct already. Also the index B_1 on C_1 is not affected since node identifiers of the updated tuples are the same.
8. Structures R_2, C_2, and B_2 are discarded.

The resulting tree has almost the same shape as one built by bulkload in a single step. Small differences are: (i) there is one possibly underfilled node for each bulk update – the previous root node, and (ii) the computation of coverage numbers in step 7 is now based on looking up coverage numbers of entries of the nodes in Q in C_1 and C_2, whereas in a single bulkload, the precise coverage functions are used in the aggregation. These small differences do not affect the query performance as shown in the experiments in Section 6.4.5.

To support the bulk update technique we had to slightly modify the R-tree code, adding methods to create a new R-tree within the same storage manager file as another one, and to insert one tree into another. However, these changes do not affect the efficiency of other queries as the node structure is unchanged.

[4] A typical duration of a slice for a large data set is 5 minutes, see Section 6.

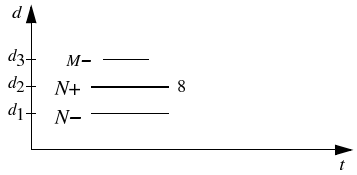


Figure 9: Representing node coverages, one node

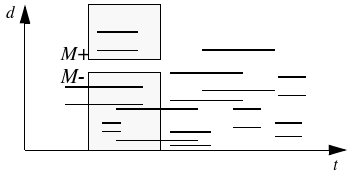


Figure 10: Representing node coverages, many nodes

4.4 Keeping Track of Node Covers

In this section we describe the data structure $Cover$ used to control the pruning of nodes or unit entries. Suppose a node N of the R-tree is accessed, its coverage number[5] is n = 8, and its minimal and maximal distance to the query trajectory, restricted by N's time interval, are d_1 and d_2, respectively. Assume a further node M is accessed whose minimal distance is d_3. This can be represented in a 2D diagram as shown in Figure 9. The edge for the minimal distance of node N is called the lower bound, denoted $N-$ and drawn thin, the edge for the maximal distance is called the upper bound, denoted $N+$ and drawn fat. As discussed before, if $k \leq 8$, M can be pruned.

The idea is to maintain a data structure $Cover$ representing this diagram during the traversal of the R-tree. Whenever a node is accessed, its lower bound is used as a query to check whether this node can be pruned. If it cannot be pruned, its lower and upper bounds are entered into $Cover$, and its upper bound is also used to prune other entries from $Cover$.

An upper or lower bound is represented as a tuple $b = ([t_1, t_2], d, c, lower)$ where $[t_1, t_2]$ is the time interval, d the distance, c the coverage, and lower a boolean flag indicating whether this is the lower bound. We also denote the coverage as $C(b) = b.c$.

Whereas Figure 9 represents the pruning criterion of Lemma 1, the general situation of Lemma 2 is shown in Figure 10.

When node M is accessed, first a query with the rectangle below its lower bound $M-$ is executed on $Cover$ to retrieve the upper bounds intersected by it. The set of upper bounds U found is scanned in temporal order, keeping track of aggregated coverage numbers, to determine whether M can be pruned. Let C_{min} be the minimal aggregate coverage of bounds in U. If $k \leq C_{min}$, M can be pruned. If M cannot be pruned, it is inserted into $Cover$. If $k \leq C(M) + C_{min}$, a second query with the rectangle above the upper bound $M+$ is executed, retrieving the lower bounds contained in it. All nodes to which these lower bounds belong, are pruned.

From this analysis, we extract the following requirements for an efficient implementation of the data structure *Cover*:

1. It represents a set of horizontal line segments in two-dimensional space.
2. It supports insertions and deletions of line segments.
3. It supports a query with a point *p* to find all segments below *p*.

[5]In this section, for simplicity we assume a node has a single coverage number instead of the three coverages computed by the hat operator. The modification to deal with three numbers is straightforward.

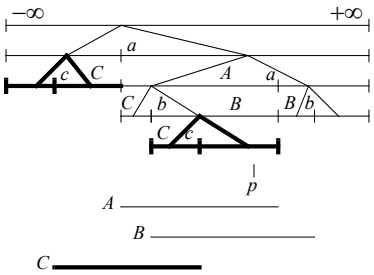


Figure 11: The *Cover* structure, a modified segment tree

4. It supports a query with a line segment *l* to find all left or right end points of segments below *l* or above *l* (pruning lower bounds above *M*+).

Two available main memory data structures that fulfill related requirements are a segment tree [15] and a standard binary search tree. The segment tree

- represents a set of intervals
- supports insertion and deletion of an interval
- supports a query with a coordinate [6] *p* to find all intervals containing *p*.

The binary search tree

- represents a set of coordinates (start and end instants of time intervals, in this case).
- supports insertion and deletion of coordinates.
- supports range queries, i.e., queries with an interval to find all enclosed coordinates.

We might use these two data structures separately to implement *Cover*, but instead we employ a slightly modified version of the segment tree that merges both structures into one. Such a structure is shown in Figure 11.

The segment tree is a hierarchical partitioning of the one-dimensional space. Each node has an associated node interval (drawn in Figure 11); for an internal node this is equal to the concatenation of the node intervals of its two children. A segment tree represents a set of (data) intervals. An interval is stored in a segment tree by *marking* all nodes whose node intervals it covers completely, in such a way that only the highest level nodes are marked (i.e., if both children of a node could be marked then instead the father is marked). Marking is done by entering an identifier of (pointer to) the interval into a node list. For example, in Figure 11 interval *B* is stored by marking two nodes. It is well-known that an interval can only create up to two entries per level of the tree, hence a balanced tree with *N* leaves storing *n* intervals requires O($N + n \log N$) space. A coordinate query to find the enclosing intervals follows a path from the root to the leaf containing the coordinate and reports the intervals in the node lists encountered. This takes O($\log N + t$) time where *t* is the number of answers. For example, in Figure 11 a query with coordinate *p* follows the path to *p* and reports *A* and *B*.

The segment tree is usually described as a semi-dynamic structure where the hierarchical partitioning is created in advance and then intervals are inserted or deleted just by changing node lists. We use it here as a fully dynamic structure by first modifying the structure to accomodate new end points and then marking nodes. When new end points are added, they are also stored in further node lists *node.startlist* and *node.endlist* (besides the standard list for marking, *node.list*). In Figure 11 entries for end points are shown as lower case letters. The thin lines in Figure 11 show the structure after insertion of intervals *A*

[6] We call a single value from a one-dimensional domain a coordinate.

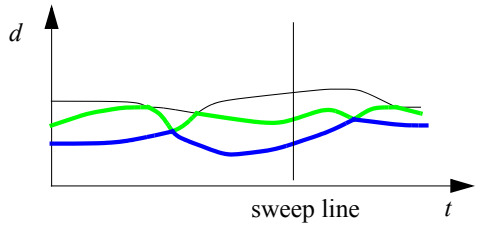


Figure 12: Computing the lowest k distance curves

and *B*. The fat lines show the modification due to the subsequent insertion of interval *C*. The structure now also supports range queries for end points, like a binary search tree. If the tree is balanced, the time required for a range query is O(*log N* + *t*) for *t* answers.

In our implementation we use an unbalanced tree which is very easy to implement. The unbalanced structure does not offer worst case guarantees but behaves quite well in practice, as will be shown in the experiments.

The interface to the *Cover* structure is provided by the four methods:

- *insert_entry(ce)*. *ce* is a cover entry, defined below. Inserts it by its time interval.
- *delete_entry(ce)*. Deletes entry *ce* from the node lists (but does not shrink the structure).
- *point_query(n, t)*, *n* a node, *t* an instant of time. Returns all entries whose time interval contains *t*.
- *range_query(n,* t_1, t_2*)*. *n* is a node, [t_1, t_2] - a time interval. Returns a list of pairs of the form <*which, ce*> where *which* $\in$ {*bottom*, *top*}, *ce* a cover entry (bottom indicates a start time, top an end time). The list contains only entries whose start or end time lies within [t_1, t_2], in temporal order w.r.t their start or end time.

The algorithms for these operations can be found in Appendix A.

4.5 The Filter Algorithm

We are now able to describe the filter algorithm, called *knearestfilter*, precisely. It uses subalgorithms *node_entry* and *unit_entry* to create entries for the $Cover$ structure. It further employs a method *insert_and_prune* of the $Cover$ structure with its subalgorithms *mincover* and *prune_above*. These algorithms are shown on the next pages (Algorithms 3 through 8).

5 Refinement

The problem to be solved in the refinement step is to compute for a sequence of units, arriving temporally ordered by start time, a sequence of units (that may be equal to an input unit or a part of it) that together form the k nearest neighbors over time. For each arriving unit, its time dependent distance function to the query trajectory is computed. Depending on whether the unit overlaps one or more units of the query trajectory, the distance function may consist of several pieces with different definition. It is well-known (see e.g. [17]) that the distance between two moving point units with the same time interval is in general the square root of a quadratic polynomial.

The problem is to compute the intersections of a set of distance curves to determine the lowest k curves, and to return the parts of units corresponding to these pieces. This is illustrated in Figure 12 where the units corresponding to the two lowest of three distance curves are to be returned.

The intersections of the distance curves can be found efficiently by slightly modifying the standard plane sweep algorithm for finding intersections of line segments by Bentley and Ottmann [10]. The

Algorithm 3: *knearestfilter(R, R_mloc, Cov, Cov_nid, mq, k)*

Input: *R* - a relation with moving points in unit representation, i.e., with an attribute *mloc* of type *upoint* ; *R_mloc* - a 3D R-tree index on attribute *mloc* of *R*; *Cov* - a relation containing coverage numbers for each node of the R-tree *R_mloc*; *Cov_nid* - a B-tree index on the *nid* attribute of *Cov* representing the node identifier of the R-tree; *mq* - a query trajectory of type *mpoint*; *k* - the number of nearest neighbors to be found.

Output: an ordered set of candidate units, ordered by unit start time, containing all parts of the *k* moving points of *R* closest to *mq*;

```
1  let Q be a queue of nodes of the R-tree, initially empty; (To be precise, Q contains pairs of the
   form <node, coverptr> where node is a node of the R-tree and coverptr is a pointer into the
   Cover data structure.
2  let Cover be the Cover structure, initialized with node(-∞,+∞);
3  let mqbb be a BB-tree representing mq;
4  node r = R_mloc.root();
5  Q.enqueue(<r, null>);
6  while Q is not empty do
7      <r, coverptr> = Q.dequeue();
8      if coverptr ≠ null then Cover.delete_entry(coverptr);
9      for each entry c of r do
10         if r is an inner node then ce=node_entry(c, mqbb, Cov, Cov_nid);
11         else ce = unit_entry(u, mqbb);
12         Cover.insert_and_prune(ce, k, Q, c);
13 S = Cover.range_query(Cover.root(), -∞,+∞);
14 Cand = ∅;
15 for each < which, s >∈ S do
16     if which = bottom then Cand.append(s);
17 return Cand;
```

basic idea of that algorithm is to maintain the sequence of line segments (curves in our case) intersecting the sweep line. Encountering the left end of a curve (within the sweep event structure ordered by t-coordinates), it is inserted into the sweep status structure, checking the two neighboring curves for possible intersections. Any intersections found are entered into the event queue of the sweep for further processing. Encountering the right end of a curve, it is removed from the sweep status structure, checking the two curves above and below for intersection. Encountering an intersection found previously, the two intersecting curves are swapped, and the two new pairs of curves becoming neighbors are checked for intersections. For the sweep status structure, a balanced tree can be used. Whereas computing the intersections of two quadratic polynomials (which can be used directly instead of the square roots) is slightly more difficult than finding the intersection of two line segments, the basic strategy of the algorithm [10] works equally well here.

Because units arrive in temporal order, one can scan in parallel the sequence of incoming units, the priority queue of upcoming events, and the query trajectory mq. The time interval of an incoming unit u is either enclosed in the time interval of the current unit mu of mq or extends beyond it. If it is enclosed, an event for deleting this distance curve from the sweep status structure at the end time $u.t_2$ is created. If the time interval extends beyond that of mu, the distance curve is computed until $mu.t_2$ and two events for deleting the curve at time $mu.t_2$ and for handling the remaining part of u are created.

Since the focus of this paper is on the filter step, and the refinement step is relatively straightforward, we omit further details here.

Algorithm 4: *node_entry(n, mqbb, Cov, Cov_nid)*

Input: *n* - a node of the R-tree; *mqbb* - the query trajectory represented as a BB-tree; *Cov* - a relation containing coverage numbers for nodes of the R-tree; *Cov_nid* - a B-tree index on node identifiers of *Cov*.

Output: an entry for the Cover data structure, of the form $<[t_1, t_2]$, *mindist, maxdist, cn,nodeid, tid, queueptr, refs*$>$.

```
1 [t1, t2] = box_t(n);
2 let box = mqbb.getBox(mqbb.root(), t1, t2);
3 mindist = mindist(box_xy(n), box);
4 maxdist = maxdist(box_xy(n), box);
5 cn = getcover(n.id, Cov, Cov_nid);
6 return new entry <[t1, t2], mindist, maxdist, cn, n.id, ⊥, null, ∅ >;
```

Algorithm 5: *unit_entry(n, mqbb)*

Input: *u* - a unit entry from a leaf of the R-tree; *mqbb* - the query trajectory represented as a BB-tree.

Output: an entry for the Cover data structure, of the form $<[t_1, t_2]$, *mindist, maxdist, cn,nodeid, tid, queueptr, refs*$>$.

```
1 [t1, t2] = box_t(n);
2 let box = mqbb.getBox(mqbb.root(), t1, t2);
3 mindist = mindist(box_xy(n), box);
4 maxdist = maxdist(box_xy(n), box);
5 return new entry <[t1, t2], mindist, maxdist, 1,⊥, u.tid, null, ∅ >;
```

6 Experimental Evaluation

In this section, we first describe the data sets used for an experimental evaluation of our approach. We then consider some properties of the proposed algorithm, namely selection of grid sizes, the time required to compute coverage numbers in preprocessing, and the effectiveness of the filter step. We explain the implementation of the algorithms HCNN and HCTkNN [19, 21]. The three algorithms are then compared varying the size of the data set, the parameter k, and the query time interval. An evaluation on very long trajectories follows. Finally, an investigation of the bulk update technique completes the experiments.

For the experiments a standard PC (AMD Athlon XP 2800+CPU, 1GB memory, 60GB disk) running SUSE Linux (kernel version 2.6.18) is used. All algorithms were implemented within the extensible database system SECONDO [8].

Algorithm 6: *insert_and_prune(ce, k, Q, c)*

Input: *ce* - a cover entry of the form $<[t_1, t_2]$, *mindist, maxdist, cn, nodeid, tid, queueptr,refs*$>$; *k* - the number of nearest neighbors to be found; *Q* - a queue of nodes; *c* - a node or unit entry.

Output: none

```
1 int mc = mincover(ce);
2 if mc < k then
3 |   insert_entry(ce);
4 |   if c is a node then ce.queueptr = Q.enqueue(<c, ce>);
5 |   if mc + ce.cn ≥ k then prune_above(ce, Q);
```

Algorithm 7: *mincover(ce)*

Input: *ce* - a cover entry
Output: C_{min}, the minimal aggregate coverage below the lower bound of *ce*.

```
1  let root = this.root();
2  let S_1 = point_query(root, ce.t_1);
3  int c = 0;
4  for each s ∈ S_1 do
5      if s.maxdist < ce.mindist then c = c + s.cn;
6  C_min = c;
7  let S_2 = range_query(root, ce.t_1, ce.t_2);
8  for each <which, s> ∈ S_2 do
9      if s.maxdist < ce.mindist then
10         if which = bottom then c = c + s.cn;
11         else
12             c = c - s.cn ;
13             if c < C_min then C_min = c;
14 return C_min;
```

6.1 Data Sets

In the performance study, we use three different data sets. One of them contains real data obtained from the R-tree Portal [3]. Here, 276 trucks in the Athens metropolitan area are observed. We call this data set *Trucks*. It was also used in earlier experiments in [19, 21].

The second data set simulates underground trains in Berlin. In the basic version it contains 562 trips of trains, moving according to schedule on a certain day between 6:00 am and 10:17 am. We will enlarge this data set by a scale factor n^2 by making n^2 copies of each trip, translating the geometry n times in x and n times in y-direction. We call the original data set *Trains* and derived data sets *Trains* n^2.

The third data set – called *Cars* – is a simulation of 2,000 cars moving on one day in Berlin. This was obtained from the BerlinMOD Benchmark [1, 16].

From each data set, 10 query objects are selected. In later experiments, the running time and number of page accesses of a query is measured as the average over 10 queries using these different objects.

Table 1 lists detailed information about the data sets.

6.2 Properties of Our Approach

6.2.1 Grid Sizes

Grid sizes for our approach are determined as described in Section 4.3.2. For the original *Trains* data set this results in a 3 x 3 spatial grid (of which in fact only 3 x 2 cells contain data) and a temporal partition of size 5 minutes. Using the same cell size everywhere, the scaled versions *Trains* n^2 in fact employ grids of size $(3n)^2$. A detailed calculation is given in Appendix C.

For the *Cars* data set by similar considerations a spatial grid of size 12 x 12 is determined and a temporal partition of 30 minutes.

The *Trucks* data set is small in comparison. In this case we have not bothered to impose a grid but simply built the R-tree by bulkload on a temporally ordered stream of units. This is good enough. The temporal ordering in any case creates good coverage curves.

Algorithm 8: *prune_above(ce, Q)*

Input: *ce* - a cover entry;
Q - a queue of nodes.
Output: none

```
1  let root = this.root();
2  let S = range_query(root, ce.t_1, ce.t_2);
3  let ht be a hashtable, initially empty;
4  for each <which, s> ∈ S do
5      if s.mindist > ce.maxdist then
6          if which = bottom then ht.insert(s);
7          else
8              if ht.lookup(s) then
9                  delete_entry(s);
10                 if s.queueptr ≠ null then Q.dequeue(s.queueptr);
```

6.2.2 Computing the Coverage Number

This section investigates the time needed to compute the coverage numbers depending on the number of nodes of the R-tree. For this experiment, we have used scaled versions of the *Trains* data set. Table 2 shows the numbers of nodes for the different data sets.

Because the computation of the coverage number requires many additions of moving integer values, we can expect that this computation is expensive. Figure 13 shows the times required to compute the coverage numbers including the hat simplification. Because this computation is required only once in the preprocessing phase, the long running times are acceptable.

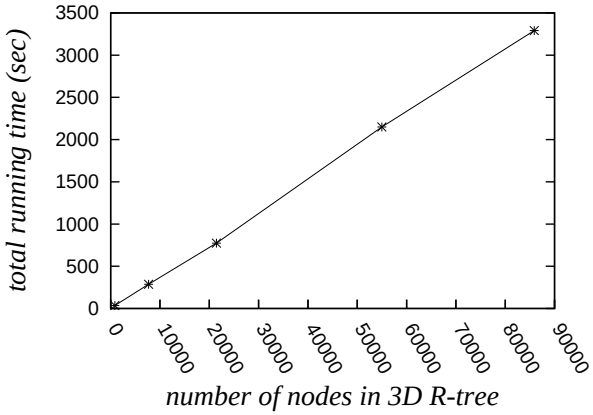


Figure 13: Time to Compute the *Coverage Numbers*

6.2.3 Effectiveness of the Filter Step

In this section we measure how many candidate units are created by the filter step. This number reflects the pruning ability of the filtering algorithm which has great influence on the query efficiency because the units passing the filter step must be processed in the cost intensive refinement step.

For the first experiment, we have varied the data size. As data sets we have used scaled versions of *Trains*. The number of requested nearest neighbors was set to $k = 5$, the query time to $Q_t = 1$. The query was performed with a query object available in all data sets, *train111*. The result is shown in

Name	No. of Objects	No. of Units	X-Range Y Range	average lifetime of an object
Trucks	276	111,922	[0, 44541.6] [0, 53956.7]	10 hours
Cars	2,000	2,274,218	[-10836, 32842] [-6686, 28054]	24 hours
Trains	562	51,444	[-3560, 25965] [1252, 21018]	1 hour
Trains9	5,058	462,996	[26440, 115965] [31252, 111018]	1 hour
Trains25	14,050	1,286,100	[26440, 175965] [31252, 171018]	1 hour
Trains64	35,968	3,292,416	[26440, 265965] [31252, 261018]	1 hour
Trains100	56,200	5,144,400	[26440, 325965] [31252, 321018]	1 hour

Table 1: Statistics of Data Sets

data set	**no. of units**	**no. of nodes**
Trains	51,444	847
Trains9	462,996	7,701
Trains25	1,286,100	21,437
Trains64	3,292,416	54,986
Trains100	5,144,400	85,895

Table 2: Numbers of R-tree Nodes

Figure 14(a). Also the number of units of the final result is part of this figure. One can see that the filter step returns roughly the same number of candidates for all data sizes.

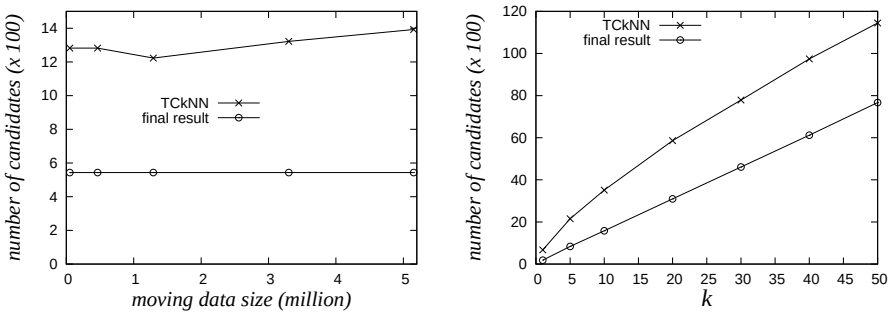
Second, we have varied the number k of requested neighbors for the data set *Trains25*. Here a query object *train742* was used in all queries. Figure 14(b) depicts the behaviour of our algorithm. When k increases, the number of candidates returned by the filter algorithm increases proportional to the final result.

6.3 Competitors' Implementation

To be able to compare our solution with the two existing algorithms, we have implemented both the HCNN [19] algorithm and the HCTkNN [21] algorithm within the SECONDO-framework. Because HCTkNN uses a TB-tree [39] for indexing the moving data, the TB-tree was also implemented as an index structure in SECONDO. HCNN applies the depth first-first method to traverse the index structure where both a TB-tree and a 3D R-tree can be used. From the experimental results in [19] we know that the 3D R-tree has a better performance than the TB-tree for the HCNN algorithm. Therefore we compare our approach with this faster implementation. HCTkNN traverses the TB-tree in best first manner.

Both algorithms use a set of data structures, whose elements are so-called $nearest\_lists$, to store the result found so far when traversing the index. The size of this set corresponds to k, the number of neighbors searched.

Figure 15 depicts the structure of a single $nearest\_list$. The entries of the list are ordered by starting



(a) Parameter Datasize (b) Parameter *k* (*Trains25*)

Figure 14: The number of units returned by the filter step

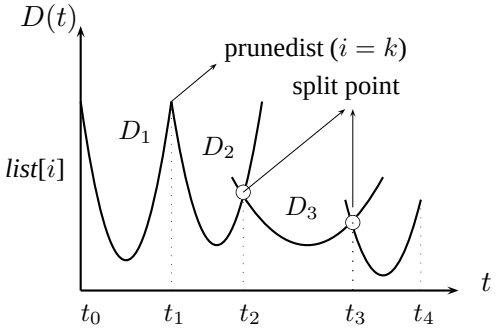


Figure 15: Nearest List Structure

time. An entry has the form $e =< tid, D, t_1, t_2, mind, maxd >$, where *tid* corresponds to an entry in the leaf node of the index, D is a function depending on time, $D(t) = a \cdot t^2 + b \cdot t + c$, denoting the moving distance between the entry and the query object during the time interval $[t_1, t_2]$, $mind$ and $maxd$ is the maximum or the minimum value of that function, respectively. The time intervals of the entries stored in a single list are pairwise quasi disjoint, meaning that they can share only a common start or end point.

When considering the set of k lists $list[1], \ldots, list[k]$, for each instant t, $list[i].D(t) \leq list[i+1].D(t)$, $1 \leq i < k$, holds. The maximum value stored in $list[i]$ is called $prunedist(i)$. If the union of the time intervals of the entries in $list[i]$ does not cover the complete query time interval then $prunedist(i) = \infty$ holds. Thus $prunedist(k)$ is the maximum distance of the k nearest neighbors found so far. All entries whose minimum distance is greater than $prunedist(k)$ can be pruned. When inserting a new entry e, we start at $list[1]$. If the time interval of e is already covered by another entry, we split the entries if necessary and try to insert the entries having a greater distance function into $list[2]$. So high values move up within the set of lists until $list[k]$ is reached or their time interval is not any more covered.

Besides using $prunedist$, HCNN applies a further pruning strategy to filter impossible non-leaf nodes. For each entry in non-leaf node, it checks the maximum distance of already stored tuples in the list restricted to the entry's life time. If the minimum distance of an entry is larger than the maximum, it can be pruned. Compared with the pruning strategy with only a global maximum distance, it can prune more nodes whose time interval is disjoint with that covered by $prunedist$.

6.4 Evaluation Results

In this section we compare the performance of the three algorithms.

6.4.1 Varying Data Size

In the first experiment, we vary the data size N where all other parameters remain unchanged. We set k to five, so that each query object asks for its five nearest neighbors. Regarding the query time interval, the default is to use the entire life time of the query object, i.e., $Q_t = 1$.

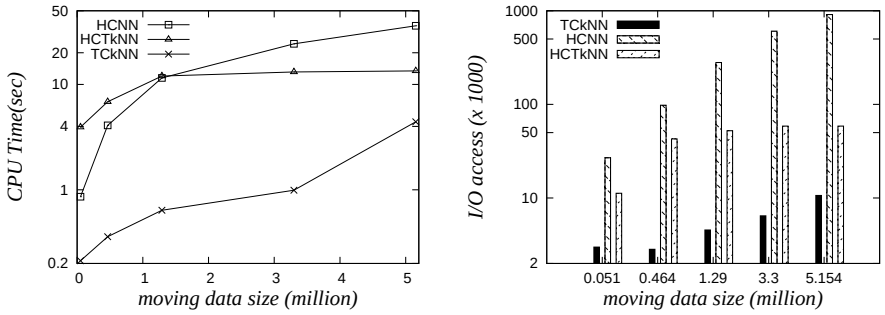
Originally we had built the 3D R-tree for HCNN by applying the regular R-tree insertion algorithm to a stream of units ordered by start time. The authors had informed us that they had used this method to build the R-tree in their experiments [18]. However, in our experiments we found that HCNN behaves quite badly on large data sets with R-trees built in this way. We discovered that it has a much better performance when the R-tree is built by bulkload on a temporally ordered stream of units.

To demonstrate this, in a few experiments we have built the R-tree in both ways and compared the results. We call the two versions HCNN-Standard and HCNN-Bulk, respectively. On the small *Trucks* data set it is feasible to show the results in the same graph; this is done below in Section 6.4.3. Unfortunately, in this first experiment varying the data size, the execution times for HCNN-Standard soon become extremely large. Therefore they have not been included in the graphs. In the following, when results are labeled HCNN, always HCNN-Bulk is meant.

Figure 16 reports the effect of varying the number of moving units on CPU and I/O cost. Note that Figure 16(a) and (b) are plotted using a log scale. The CPU cost of all algorithms increases when N becomes larger, but the curve of TCkNN always remains at a lower level than HCTkNN and HCNN. Algorithms TCkNN and HCNN show a similar behaviour, but because we start at a lower level, the cost is smaller. HCTkNN is worse than HCNN for small data sets, but it becomes better when the data size increases. This is due to its simple pruning strategy where only the global maximum distance is applied to filter impossible nodes whereas HCNN applies one more pruning strategy which takes more time.

For the largest data set (5.154 million units), the CPU response time of our algorithm is 4.419 seconds, while HCTkNN and HCNN require 13.453 seconds and 36.017 seconds, respectively.

Also, the I/O cost of TCkNN is relatively small compared with the other two competitors. There are two main reasons. First, HCNN and HCTkNN don't optimize the index structure for kNN queries as we have done. Second, the TB-tree structure only stores units of a single object within a leaf node. If an object covers large distances, the leaf nodes of the TB-tree will have a large spatial extent.



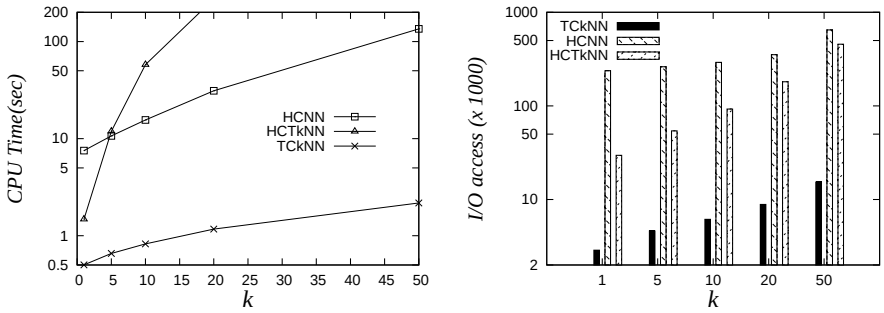
(a) CPU Cost (b) I/O Cost

Figure 16: Performance versus data size

6.4.2 Performance versus k

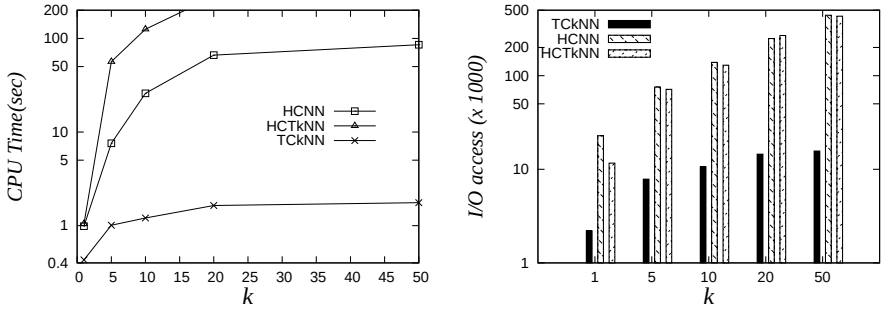
Here, we compare the running times of the algorithms if the number k of requested neighbors is changed. We have set k to one of $\{1, 5, 10, 20, 50\}$. As data sets serve *Trains25* and *Trucks*. Figures 17 and 18 show the CPU cost and the I/O access depending on k. Note that all figures are drawn in a log scale. Our algorithm and HCNN have similar curves but our algorithm is always at a lower level. If k increases, the absolute gap between TCkNN and the competitors enlarges. HCTkNN is better than HCNN for small

values of k, e.g., $k = 1$, but when k enlarges, its cost increases quickly so that it is worse than HCNN, because it only uses the global maximum distance to prune. When some nodes can't be pruned, it is necessary to traverse the entire list structure from the bottom to the top list. If k is large, more levels of the $nearest\_list$ have to be visited.



(a) CPU Cost (b) I/O Cost

Figure 17: Performance versus *k* (*Trains25*)



(a) CPU Cost (b) I/O Cost

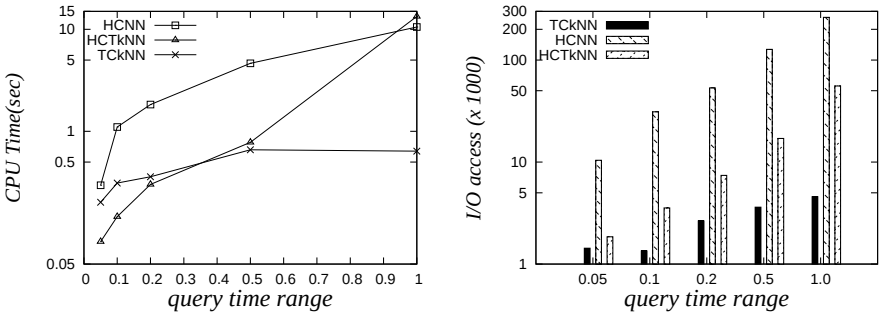
Figure 18: Performance versus *k* (*Trucks*)

6.4.3 Query Time Range

In this experiment, we show the performance of the algorithms in dependence on the duration of definition time of the query object. For varying the time interval, we have cut out a randomly chosen connected part of the original query object in which actually the number of units (and thus the definition time) is varied. In the experiment on *Trucks*, we have included both versions of HCNN, i.e., HCNN-Standard and HCNN-Bulk.

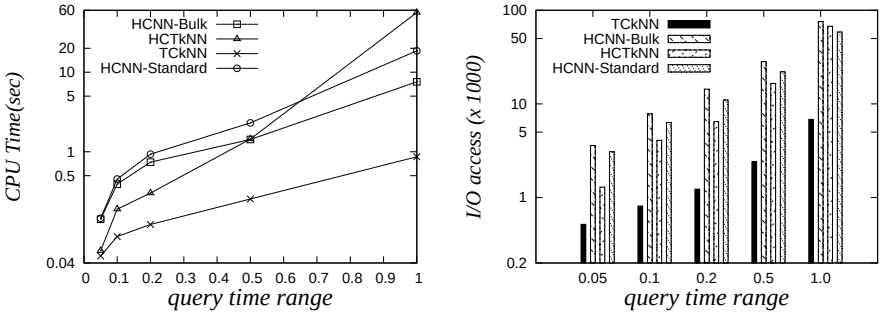
Figures 19 and 20 illustrate the experimental results. For a short query time interval, HCTkNN is better than HCNN-Bulk and HCNN-Standard, and has no big difference with our algorithm. This is because the number of tuples stored in each list is small if the time interval is short so that the linear traversal has no difference with binary search in the segment tree structure. The HCNN (Bulk and Standard) algorithm has one more pruning strategy which takes time to check the minimum and maximum distance. When the query time interval increases, the advantage of our algorithm becomes obvious and it almost stays at the same level whereas the other algorithms take more time than our solution.

As the HCNN algorithm is faster if the index is built by bulkload instead of the standard way, in the other experiments we have only compared with HCNN-Bulk.



(a) CPU Cost (b) I/O Cost

Figure 19: Performance versus query duration (*Trains25*)



(a) CPU Cost (b) I/O Cost

Figure 20: Performance versus query duration (*Trucks*)

6.4.4 Evaluation on Long Trajectories

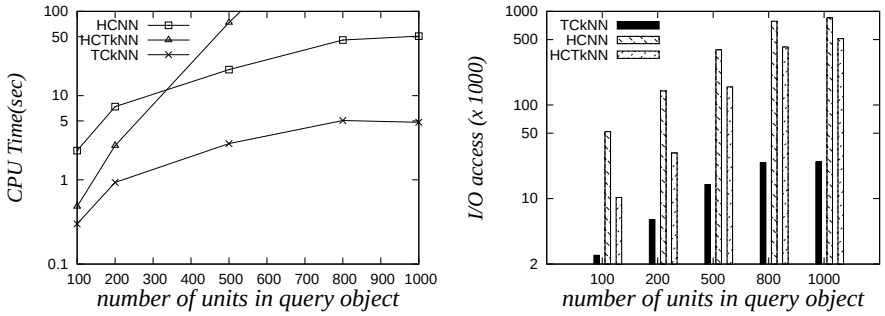
To examine the scalability of the algorithm, we do special experiments on data and query objects with long trajectories. The longest trajectories can be found in the data set *Cars*, thus we use this data set for the experiments. We vary the number of units of the query object using one of the numbers $\{100, 200, 500, 800, 1000\}$ and k is set to five.

Figure 21 reports the experimental result. Our algorithm takes less than 6 seconds CPU time for all cases, while HCNN takes more time, increasing from 2.222 seconds to 50.83 seconds, which is about 8 times more than TCkNN for a query object with 1000 units. HCTkNN is faster than HCNN for the smallest number of units, but it becomes significantly more expensive and the CPU time increases in an even larger slope, e.g., for 500 units, it costs 73.768 seconds already. This is due to the trajectory preservation property of a TB-tree and the linear structure of the $nearest\_list$.

Also especially for leaf entries from the index, our BB-tree structure is helpful because it can compute a bounding box of the query object for a given time interval in logarithmic instead of linear time needed by the other algorithms. Note that during the traversal of the index, for each node/entry the algorithm has to find the subtrajectory of *mq* overlapping the time interval of the node/entry. This step has to be done a lot of times, so when *mq* has a long trajectory (more units), a linear interpolation method takes more time. For the I/O cost, the value of TCkNN is between 3 and 25 ($\times 10^3$), which is also much smaller than HCTkNN and HCNN.

6.4.5 Bulk Updates

Finally, we investigate the behaviour of the bulk update technique described in Section 4.3.4. The first experiment compares the running times of building the data structure in a single step or in a series of updates, respectively. We use the *Trains25* data set. To perform a series of updates, in each step we



(a) CPU Cost (b) I/O Cost

Figure 21: Evaluation on long trajectory (*Cars*)

collect the units belonging to a group of six temporal layers (corresponding to a period of 30 minutes) and update R-tree and coverage numbers for this set.

The results are shown in Figure 22. The curve labeled "Build by Update" shows the accumulated cost after processing each group of layers. In total nine such groups are processed. One can see that the overhead compared to building the data structures in a single step is only about 20%.

The first and the last two groups of updates need less time than the others. This is due to the fact that at the start and end of the time period less trains are around (as trains gradually begin and end their service).

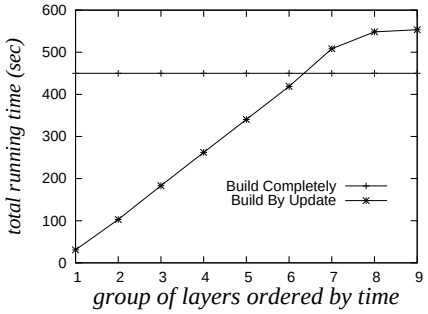


Figure 22: Time Cost for Building Structures(*Trains25*)

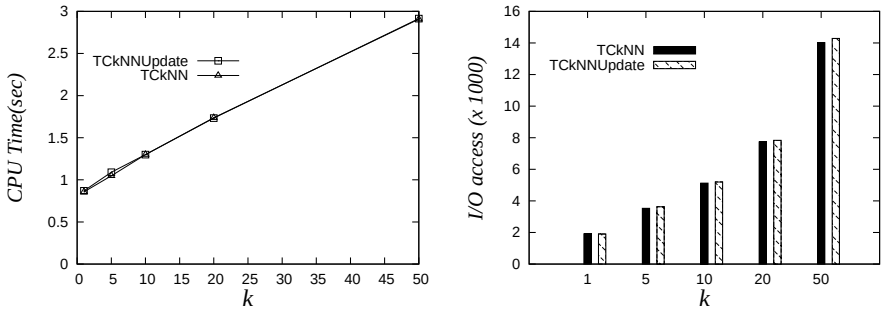
The second experiment compares the query performance on the two data structures representing the complete set *Trains25* built either in a single step or in a series of updates. This is to check whether the structure built by updates perhaps has a degraded performance. We repeat the experiment "Performance vs. k" of Section 6.4.2.

Figure 23 shows the results, using labels TCkNN and TCkNNUpdate for the two structures.[7] Obviously the results are quite similar and the bulk update structure is as good as the original one.

7 System Use and Experimental Repeatability

Together with this paper, we also publish the implementations of the three algorithms compared. This is possible using a feature recently available in the SECONDO environment, called a SECONDO *Plugin*. It allows authors of a paper to wrap their implementation into a so-called algebra module and to make data structures and algorithms available as type constructors and operators of such an algebra. Extensions to the query optimizer or the graphical user interface are also supported but are not needed in this paper.

[7] Although for TCkNN this is the same experiment as in Section 6.4.2, the numbers are slightly different. This is because experiments in this section have been made several months later in revising the paper, with the current version of SECONDO.



(a) CPU Cost (b) IO Cost

Figure 23: Performance vs. k for Bulk Update (*Trains25*)

Authors can create a plugin, which is a set of files together with a small XML file describing the extensions, and publish it as a zip-file. Readers of the paper can install the plugin into a standard SECONDO system obtained from the SECONDO web site. More details can be found at [6].

Publishing also the implementations has several benefits. Algorithms can be used in a system context and prove their usefulness in real applications. Experiments reported in the paper can be checked by the reader. Other experiments not provided by the authors can be made, using other parameter settings or other data sets. Details of the experiments not clear from the description can be examined.

Finally, the next proposal of an improved algorithm will find an excellent environment for comparison as it is not any more necessary to reimplement the competing solutions.

7.1 Using the Algorithms in a System

In this section we explain how the algorithm TCkNN proposed in this paper as well as the two competing algorithms HCNN [19] and HCTkNN [21] can be used within the SECONDO system.

7.1.1 Preparations

As far as needed, perform the following steps:

- Set up an environment to compile and run SECONDO.
- Download a SECONDO system of version 2.9.1 or higher.[8]
- Download the NearestNeighbor Plugin from the web site and install it within SECONDO.
- Build the system (make).
- Restore the database `berlintest` that comes with the SECONDO system.

The required software and explanations can be found at the SECONDO web site [8] which includes the plugin web site [6]. More detailed instructions to perform these steps and a short introduction to using SECONDO are also given in Appendix B.

7.1.2 Using knearest

As discussed in Section 6, the main test data we use are derived from the relation *Trains* in the database *berlintest*, containing 562 undergrund trains moving according to schedule on the network *UBahn*. The schema of *Trains* is

[8] Bulk updates are available only with version 2.9.2 and the revised plugin.

```
Trains(Id: int, Line: int, Up: bool, Trip: mpoint)
```

where *Id* is a unique identifier for this train (trip), *Line* is the line number, *Up* indicates which direction the train is going, and *Trip* contains the actual trajectory.

On the small *Trains* relation it is feasible to run a TCkNN query using just the $knearest$ operator which implements the refine step as described in Section 5. We use the unit representation of *Trains*, a relation called *UnitTrains*. It is present in the database, but could also be created using the command:

```
let UnitTrains = Trains feed
  projectextendstream[Id, Line, Up; UTrip: units(.Trip)] consume
```

The $projectextendstream$ operator creates a stream of units from the *Trip* attribute of each input tuple and outputs for each unit a copy of the original tuple restricted to attributes *Id*, *Line*, *Up*, and the new unit attribute *UTrip*.

Start a SECONDO system (kernel and Javagui) and open database *berlintest*. Then type at the prompt:

1. `query UnitTrains count`

   Relation *UnitTrains* is present and has 51544 tuples.

2. We create a version of *UnitTrains* where units are ordered by start time:
   ```
   let UTOrdered = UnitTrains feed
     extend[Mintime: minimum(deftime(.UTrip))]
     sortby[Mintime asc] consume
   ```
   Operator $extend$ adds derived attributes to tuples.

3. `query UBahn`

   Display the *UBahn* network as a background.

4. `query Trains`

   This loads the entire set of trains into the user interface for display. It takes some time. Choose display style *QueryMPoint*.

5. `query train7`

   This loads a SECONDO object of type $\underline{mpoint}$ which we will use as a query object. Display as *QueryPoint*.

6. Find the five continuous nearest neighbors to *train7*.
   ```
   query UTOrdered feed knearest[UTrip, train7, 5] consume
   ```
   Arguments to the $knearest$ operator are the ordered stream of unit tuples, the name of the attribute, the query trajectory, and the number of neighbors. Choose *QueryMPoint2* for display style. In the animation, one can observe that always the five closest trains appear in blue (the result of this query).

7. Find the five continuous nearest neighbors to *train7* belonging to line 5.
   ```
   query UTOrdered feed filter[.Line = 5]
     knearest[UTrip, train7, 5] consume
   ```
   This illustrates that nearest neighbors fulfilling additional conditions can be found.

7.1.3 Creating Test Data

We now show how the test data are generated. Here we restrict attention to the creation of data set *Trains25*. This is done by running the script file `createtrains25` from [4] which needs to be placed in the `secondo/bin` directory. The file is explained in Appendix C.

Close down any running SECONDO system. Open a new shell and type

```
SecondoTTYNT -i createtrains25
```

This creates appropriate versions of relations and indexes for the three algorithms.

7.1.4 Using the Three Algorithms CTkNN, HCNN, and HCkNN

Each of the three main algorithms compared in the experiments is available as an operator. They are called $knearestfilter$ and $knearest$, $greeceknearest$, and $chinaknearest$ for CTkNN, HCNN, and HCTkNN, respectively.

As a query object we use *train742*, which is the first train of line 7 within the field (4, 2) of the 5 x 5 pattern. The dataset considered now can be visualized by translating the underlying *UBahn* network in the same way (see Appendix C for an explanation).

1. Create UBahn25 and visualize it:

   ```
   let UBahn25 = UBahn feed five feed {f1} five feed {f2} product product
     projectextend[Name, Typ;
       geoData: .geoData translate[30000.0 * .no_f1, 30000.0 * .no_f2],
       FieldX: .no_f1,
       FieldY: .no_f2]
     consume;

   query UBahn25
   ```

   As discussed in Section 6, the *Trains25* dataset has about 1.3 million units. It is too large to load it entirely into the viewer. To be able to interpret the answer of the query, we visualize the trains moving in field (4, 2) together with the query object, *train742*.

2. Load trains from field (4, 2) and the query object.

   ```
   query Trains25 feed filter[(.FieldX = 4) and (.FieldY = 2)] consume;
   query train742
   ```

3. Find the 5 closest trains to *train742* within data set *Trains25*, using TCkNN. We proceed in two steps to display first the candidates found in the filter step, using operator $knearestfilter$, and then the complete solution.

   ```
   query UnitTrains25_UTrip UnitTrains25
     UnitTrains25Cover_RecId UnitTrains25Cover
     knearestfilter[UTrip, train742, 5] consume;

   query UnitTrains25_UTrip UnitTrains25
     UnitTrains25Cover_RecId UnitTrains25Cover
     knearestfilter[UTrip, train742, 5]
     knearest[UTrip, train742, 5] consume;
   ```

   The arguments to *knearestfilter* are the R-tree index and the indexed relation, then the B-tree index on the relation with coverage numbers and this relation, finally (in the square brackets) the attribute name, the query trajectory, an the number k.

4. Find the 5 closest trains to *train742* within data set *Trains25*, using HCNN.

   ```
   query UTOrdered_RTreeBulk25 UTOrdered25
     greeceknearest[UTrip, train742, 5] consume;
   ```

   Arguments are the R-tree and the unit relation, clustered in the same way.

5. Find the 5 closest trains to *train742* within data set *Trains25*, using HCkNN.

   ```
   query UnitTrains_UTrip_tbtree25 UnitTrains25C
     chinaknearest[UTrip, train742, 5] consume;
   ```

   Arguments are the TB-tree and the unit relation. Here units are ordered by train objects.

7.2 Repeating the Experiments

Experiments can be repeated using the scripts provided at [4]. As a preparation, extract all the files from this zip-archive and place them into the `secondo/bin` directory. Files for data generation should be called, for example:

```
SecondoTTYNT -i createtrains25
```

Files for performing experiments should be called

```
SecondoTTYBDB -i query-k-trains25
```

As an example, Appendix D shows the script `query-k-trains25` to run the experiment "performance vs. k" of Section 6.4.2. Note that the last queries examine SECONDO relations SEC2COMMANDS and SEC2COUNTERS. These system relations capture information about query execution; each command after starting a SECONDO system is numbered sequentially. Hence after the first command for opening the database, the ten queries for each of the three algorithms are numbered 2 through 11, 12 through 21, and 22 through 31, respectively. The queries aggregate over these executions to get average CPU time and numbers of page accesses.

Results should roughly correspond to those displayed in Figure 17. Of course, only trends should agree; absolute numbers may differ due to the different platforms used.

8 Conclusions

In this paper we have studied continuous k nearest neighbor search on moving objects trajectories when both query and data objects are mobile. We have presented a filter-and-refine approach. The main idea in the filter step was to compute for each node of the index its time dependent coverage function in preprocessing and to store a suitable simplification of this function. Coverage numbers are then essential for pruning during the index traversal. This is further supported by the use of efficient data structures to compute spatial bounding boxes of partial query trajectories and to keep track of node coverages and node distances during traversal. The refinement step can also be used independently to find continuous k nearest neighbors fulfilling further predicates. An experimental comparison shows that the new algorithm outperforms the two competing algorithms in most cases by orders of magnitude.

As a second aspect, we have advocated a methodology of experimental research that makes data structures and algorithms available in a system context and that publishes together with papers also their implementation used in experiments. A platform has been provided that allows authors to publish software in this way. As a benefit, readers can relatively easily repeat or extend the experiments presented in the paper. Furthermore, in the long run, researchers will find existing implementations to compare to instead of always reimplementing competing techniques from scratch. We have used the research contribution of this paper as an example to demonstrate this style of publishing experimental research.

Open questions for future work are whether the pruning techniques of the filter step can be adapted to other cases, for example other query types such as reverse nearest neighbors, network-based movement, or the presence of additional predicates.

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A Implementation of the Cover Structure

A node has the following structure:

type *node* = **record**
time interval $[t_1, t_2]$;
pointer to node *left, right*;
list of *cover_entry list*;
list of pairs <*which*, *cover_entry*> *startlist, endlist*
end record.

The lists *list*, *startlist*, and *endlist* are doubly linked lists with elements of the form <*pred*, *succ*, *pointer to cover_entry*>. Whenever a *cover_entry* is added to such a list, actually a pointer to the *cover_entry* is inserted and at the same time a pointer to this list element is added to the list *refs* in the *cover_entry*. In this way efficient deletion of cover entries is possible.

Update methods are *insert_entry*, *add_coordinate*, *insert_interval*, and *delete_entry*. Query methods are *point_query* and *range_query*.

Algorithm 9: *insert_entry(ce)*

Input: *ce* - a cover entry;
Output: none

```
1  let root = this.root();
2  add_coordinate(root, ce.t1, true, ce);
3  add_coordinate(root, ce.t2, false, ce);
4  insert_interval(root, ce.t1, ce.t2, ce);
```

Algorithm 10: *add_coordinate(n, t, start, ce)*

Input: *n* - a node;
t - an instant of time;
start - a boolean indicating whether a left or right end is added;
ce - a cover entry.
Output: none

```
/* modifies the segment tree to accomodate a possibly new
   coordinate t and adds the entry as either a start or an end
   entry.                                                    */
1  if n is a leaf then
2      if n.t1 < t < n.t2 then
3          n.left = new node(n.t1, t);
4          n.right = new node(t, n.t2);
5          if start then n.right.startlist.append(<bottom, ce>);
6          else n.left.endlist.append(<top, ce>);
7  else // n is an inner node
8      if t = n.left.t2 then
9          if start then n.right.startlist.append(<bottom, ce>);
10         else n.left.endlist.append(<top, ce>);
11     else
12         if t < n.left.t2 then add_coordinate(n.left, t, start, ce);
13         else add_coordinate(n.right, t, start, ce);
14
```

Algorithm 11: *insert_interval(n, t_1, t_2,ce)*

Input: *n* - a node;
$[t_1, t_2]$ - a time interval;
ce - a cover entry;
Output: none

```
1  if [n.t1, n.t2] ⊆ [t1, t2] then n.list.append(ce);
2  if n is an inner node then
3      if t1 < n.left.t2 then insert_interval(n.left, t1, t2, ce);
4      if t2 > n.right.t1 then insert_interval(n.right, t1, t2, ce);
```

Algorithm 12: *delete_entry(ce)*

Input: *ce* - a cover entry
Output: none

```
1  for each s ∈ ce.refs do remove(s);
```

Algorithm 13: *point_query(n, t)*

Input: *n* - a node;
t - an instant of time.

Output: a set of entries whose time intervals contain *t*.

```
1  if n = null then return ∅;
2  else
3      if n.t1 ≤ t ≤ n.t2 then
4          return n.list ∪ point_query(n.left, t) ∪ point_query(n.right, t);
5      else return ∅;
```

Algorithm 14: *range_query(n, t_1, t_2)*

Input: *n* - a node;
$[t_1, t_2]$ - a time interval.

Output: a list of pairs of the form $<$*which, ce*$>$ where *which* $\in \{$*bottom, top*$\}$, *ce* a cover entry. The list contains only entries whose start or end time lies within $[t_1, t_2]$, in temporal order w.r.t their start or end time.

```
1  if n = null then return ∅;
2  else
3      if n.t2 < t1 then return ∅;
4      else
5          if t2 < n.t1 then return ∅;
6          else
7              S = ∅;
8              if t1 ≤ n.t1 ≤ t2 then S = concat(S, n.startlist);
9              if n is not a leaf then
10                 S = concat(S, concat(range_query(n.left, t1, t2), range_query(n.right, t1, t2)));
11             if t1 ≤ n.t2 ≤ t2 then S = concat(S, n.endlist);
12             return S;
```

B Installing and Using SECONDO With the Nearest Neighbor Plugin

In the sequel we describe how a SECONDO system and the Nearest Neighbor Plugin can be installed and the `berlintest` database be restored. Then a short example session shows how to use SECONDO.

B.1 Installing a SECONDO System

If you happen to have a running SECONDO installation with a system of version 2.9.1 or higher, this step can be skipped. Otherwise:

1. Go to the SECONDO web site at [8]. Go to the *Downloads* page, section *Secondo Installation Kits*. Select the version for your platform (Mac-OS X, Linux, Windows). Get the installation guide and download the SDK. Follow the instructions to get an environment where you can compile and run SECONDO.

2. Go to the Source Code section of the *Downloads* page and download version 2.9.1. Extract it and replace the SECONDO version from the installation kit by this version.

B.2 Installing the Nearest Neighbor Plugin

From the SECONDO Plugin web site [6] get the two files `Installer.jar` and `secinstall`. The Nearest Neighbor plugin is a file `NN.zip` available at [2]. Follow the instructions in section *Installing Plugins* at [6] to install it. Then recompile the system (i.e., call `make` in directory `secondo`).

B.3 Restoring a Database

We first restore the database *berlintest* that comes within the SECONDO distribution:

1. Start a SECONDO system:

   ```
   cd ~secondo/bin
   SecondoTTYNT
   ```

   After some messages, a prompt should appear:

   ```
   Secondo =>
   ```

2. At the prompt, enter

   ```
   restore database berlintest from berlintest
   close database
   quit
   ```

B.4 Looking at Data

The relation *Trains* in the database *berlintest* contains 562 undergrund trains moving according to schedule on the network *UBahn*. This relation is used in the experiments to create larger test data sets *Trains* n^2. The schema of *Trains* is

```
Trains(Id: int, Line: int, Up: bool, Trip: mpoint)
```

where *Trip* contains the actual trajectory.

We briefly look at these data within the system.

1. Start the SECONDO kernel together with the graphical user interface. Open a shell and type

   ```
   cd ~secondo/bin
   SecondoMonitor -s
   [SecondoMonitor.exe -s on a Windows platform]
   ```

Open a new shell:

```
cd ~secondo/Javagui
sgui
```

2. In the command window (top left), type

   ```
   open database berlintest;
   query UBahn
   ```

   A pop-up window appears asking for a display style for the *geoData* attribute of the *UBahn* relation. Leave the default and click OK. The *UBahn* network appears in the viewer at the bottom.

3. In the *File* menu, select *Load categories* which makes some other display styles available. Choose *BerlinU.cat*.

4. In SECONDO, it is possible to type query plans directly, without the use of an optimizer. This is what we do next. In the command window, type:

   ```
   query Trains count
   ```

   This confirms that relation *Trains* is present and has 562 tuples. Operator $count$ is applied to the *Trains* relation in postfix notation.

5. ```
   query Trains feed filter[.Trip present six30] consume
   ```

   This selects trains whose *Trip* attribute is defined at 6:30 (*six30* is a SECONDO object of type $\underline{instant}$ in the database). Here the $feed$ operator (applied in postfix notation to *Trains*) creates a stream of tuples. The $filter$ operator passes only tuples to its output stream fulfilling a predicate. $Consume$ collects a stream of tuples into a relation which is then displayed at the user interface.

   A pop-up window asks for the display style. From *View Category* select *QueryMPoint*. Standard attributes appear in the text window at the left side of the Hoese viewer (the viewer forms the bottom of the entire window). When you select one of the *Trip attributes*, also geometries appear in the graphics window on the right.

6. Animate the displayed trains using the buttons at the top left of the viewer. The double arrow buttons allow one to double or halve the speed of the animation.

This may suffice as a brief introduction to using SECONDO. To become a bit more acquainted with the user interface and the querying and visualizing of moving objects, we recommend to go through the "Do it yourself demo" ([5], Section 2). More information about using SECONDO can be found at the Web site [8], in particular in the user manual [7].

C Creation of Test Data

This is a commented version of file `createtrains25`.

This script creates the *Trains25* data set for each of the three algorithms TCkNN, HCNN, and HCTkNN. Starting point is the relation *Trains* containing 562 undergrund trains moving according to schedule on the network *UBahn*. We now explain the commands in the script.

```
let five = ten feed filter[.no < 6] consume;

let Trains25 = Trains feed five feed {f1} five feed {f2}
  product product
  projectextend[Id, Line, Up;
    Trip: .Trip translate[[const duration value (0 0)],
      30000.0 * .no_f1, 30000.0 * .no_f2],
    FieldX: .no_f1,
    FieldY: .no_f2]
  consume;
```
```

The first command creates a relation *five* containing the numbers 1 through 5. It is used to make 25 copies of the *Trains* in the next command, using two $product$ operator calls to build the Cartesian product of *Trains* and two instances of relation *five*. Note that operations are often applied in postfix notation. Next the $projectextend$ operator performs a projection on each tuple, keeping attributes *Id*, *Line*, and *Up*. It als adds new attributes to the tuple whose values are computed from existing attributes. Attribute *Trip* is derived from the original *Trip* attribute by translating the geometry in the (x, y, t) space. The temporal shift is 0, hence all copies of the trains move at the same time as their originals. However, spatially, geometries are shifted by distance no_f1 * 30000 in x-direction and by distance no_f2 * 30000 in y-direction. Here no_f1 and no_f2 come from the two instances of the *five* relation. Hence 25 copies are made of each train arranged in a 5 x 5 grid. The field indices in the grid are also kept in the tuple as *FieldX* and *FieldY*. The last operation $consume$ collects the stream of tuples into a relation.

```
let train742 = Trains25 feed
  filter[(.Line = 7) and (.FieldX = 4) and (.FieldY = 2)]
  extract[Trip];

let train123 = Trains25 feed
  filter[(.Line = 1) and (.FieldX = 2) and (.FieldY = 3)] extract[Trip];

...
```

Next ten query trains are selected from the new *Trains25* relation. The $extract$ operation gets the value of attribute *Trip* from the first tuple of its input stream. Hence *train742* is now an object of type $\underline{mpoint}$, i.e., a trajectory.

As explained in Section 4.3, we partition the 3D space into small spatiotemporal cells such that each cell contains on the average enough units to fill about r nodes of an R-tree. The original *Trains* relation fits spatially into a box of size 30000 x 20000, with lower left corner at position (-3600, 1200). Copies are moved by multiples of 30000 as shown above. We now impose a grid with cells of size 10000 x 10000 spatially, and 5 minutes temporally. The calculation leading to these sizes is the following. One can observe that in the original *Trains* relation at any instant of time on the average 90 trains are present. We aim to have about $p = 15$ objects present within each spatial cell, hence form a grid of 6 cells. This defines the cell size of 10000 x 10000 for the original *Trains* relation. The relation has 51444 units. An R-tree node can take about 60 entries in our implementation; hence to fill about $r = 5$ nodes, about 300 units should be in a spatiotemporal cell. Assuming units are uniformly distributed in space and time, 51444 / (6 * 300) = 28.58 means that the temporal extent should be split into roughly 30 parts. As the temporal extent of the trains relation is about 2.5 hours, the duration of each part should be about 5 minutes. The larger relation *Trains25* will use the same temporal partitioning; the spatial grid cells of size 10000 x 10000 are effectively translated in the same way as the *Trains*.

```
let six00 = theInstant(2003,11,20,6);
let minutes5 = [const duration value (0 300000)];
```

To introduce the temporal partition of the 3D space, we define the instant 6am and a duration of 5 minutes (300000 ms).

```
let UnitTrains25 = Trains25 feed
  projectextendstream[Id, Line, Up; UTrip: units(.Trip)]
  addcounter[No, 1]
  extend[
    Temp: (minimum(deftime(.UTrip)) - six00) / minutes5,
    CellX: real2int((minD(bbox2d(.UTrip), 1) + 3600.0) / 10000.0),
    CellY: real2int((minD(bbox2d(.UTrip), 2) - 1200.0) / 10000.0)]
  sortby[Temp asc, CellX asc, CellY asc, UTrip asc]
  remove[Temp, CellX, CellY]
  consume;
```

The $projectextendstream$ operator creates a stream of units from the *Trip* attribute of each input tuple and outputs for each unit a copy of the original tuple restricted to attributes *Id*, *Line*, *Up*, and the new unit attribute *UTrip*. Then $addcounter$ adds an attribute *No* with a running number to the current tuple. The $extend$ operator computes integer indices *Temp*, *CellX*, and *CellY* according to the 3D partition explained above for a given unit, accessing its geometry. The resulting stream of tuples is sorted first by the three indices of a spatiotemporal cell, and finally by *UTrip* (which in effect is the start time of the unit). After sorting, the indices needed for sorting can be removed again before storing the relation.

```
let UnitTrains25_UTrip = UnitTrains25 feed addid bulkloadrtree[UTrip];
```

The R-tree is created by bulkload. The order in the underlying relation is the same as that used in the bulkload; hence a clustering effect is achieved.

```
let UnitTrains25Cover = coverage(UnitTrains25_UTrip) consume;
```

The $coverage$ operator traverses the R-tree, computing the coverage function and from it the three coverage numbers resulting from the hat operation (Section 4.3.1). They are entered into relation *UnitTrains25Cover*.

```
let UnitTrains25Cover_RecId = UnitTrains25Cover createbtree[RecId];
```

The relation with coverage numbers is indexed. This completes data generation for our algorithm TCkNN. Next test data for HCNN are generated.

```
let UTOrdered25 = UnitTrains25 feed sortby[UTrip asc] consume;

let UTOrdered_RTreeBulk25 = UTOrdered25 feed addid
  bulkloadrtree[UTrip];
```

The *UnitTrains25* are ordered by units and stored in this order. This is essentially an order on the start times of units. The index is then built by bulkload on the temporally ordered stream of tuples. Again the index is clustered like the relation. As discussed in Section 6, this version of HCNN is the most efficient one.

```
let UnitTrains25C = Trains25 feed
  projectextendstream[Id, Line, Up;  UTrip: units(.Trip)]
  addcounter[No, 1] consume

let UnitTrains_UTrip_tbtree25 = UnitTrains25C feed addid
  bulkloadtbtree[Id, UTrip, TID];
```

Finally, for HCTkNN the *UnitTrains25* relation must be in the order of *Train* objects. Then the TB-tree index is built by bulkload.

D Queries on *Trains 25*, varying k

This is a shortened version of file `query-k-trains25`.

```
open database berlintest;
#for different number of neighbors requested, change the value of k

#Germany
query
  UnitTrains25_UTrip UnitTrains25 UnitTrains25Cover_RecId UnitTrains25Cover
  knearestfilter[UTrip, train742, 5]  knearest[UTrip,train742, 5] count;
query
```

```
  UnitTrains25_UTrip UnitTrains25 UnitTrains25Cover_RecId UnitTrains25Cover
  knearestfilter[UTrip, train523, 5]  knearest[UTrip,train523, 5] count;
... (10 queries in total)

# Greece Bulk
query UTOrdered_RTreeBulk25 UTOrdered25 greeceknearest[UTrip,train742, 5]
  count;
query  UTOrdered_RTreeBulk25 UTOrdered25 greeceknearest[UTrip,train523, 5]
  count;
... (10 queries in total)

#China
query UnitTrains_UTrip_tbtree25 UnitTrains25 chinaknearest[UTrip,train742,5]
  count;
query UnitTrains_UTrip_tbtree25 UnitTrains25 chinaknearest[UTrip,train523,5]
  count;
... (10 queries in total)

# Results Germany
query SEC2COMMANDS feed filter[(.CmdNr >= 2) and (.CmdNr <= 11)]
  avg[CpuTime];
query SEC2COUNTERS feed filter[.CtrStr = "SmiRecord::Read:Calls"]
  filter[(.CtrNr >= 2) and (.CtrNr <= 11)] avg[Value];

# Results Greece Bulk
query SEC2COMMANDS feed filter[(.CmdNr >= 12) and (.CmdNr <= 21)]
  avg[CpuTime];
query SEC2COUNTERS feed filter[.CtrStr = "SmiRecord::Read:Calls"]
  filter[(.CtrNr >= 12) and (.CtrNr <= 21)] avg[Value];

# Results China
query SEC2COMMANDS feed filter[(.CmdNr >= 22) and (.CmdNr <= 31)]
  avg[CpuTime];
query SEC2COUNTERS feed filter[.CtrStr = "SmiRecord::Read:Calls"]
  filter[(.CtrNr >= 32) and (.CtrNr <= 41)] avg[Value];

close database;
```