GeoInformatica 7:3, 255–273, 2003

A Road Network Embedding Technique for K-Nearest Neighbor Search in Moving Object Databases

CYRUS SHAHABI, MOHAMMAD R. KOLAHDOUZAN AND MEHDI SHARIFZADEH
Department of Computer Science, University of Southern California, Los Angeles, California 90089
E-mail: {shahabi, kolahdoz, sharifza}@usc.edu

Abstract

A very important class of queries in GIS applications is the class of K-nearest neighbor queries. Most of the current studies on the K-nearest neighbor queries utilize spatial index structures and hence are based on the Euclidean distances between the points. In real-world road networks, however, the shortest distance between two points depends on the actual path connecting the points and cannot be computed accurately using one of the Minkowski metrics. Thus, the Euclidean distance may not properly approximate the real distance. In this paper, we apply an embedding technique to transform a road network to a high dimensional space in order to utilize computationally simple Minkowski metrics for distance measurement. Subsequently, we extend our approach to dynamically transform new points into the embedding space. Finally, we propose an efficient technique that can find the actual shortest path between two points in the original road network using only the embedding space. Our empirical experiments indicate that the Chessboard distance metric (L_∞) in the embedding space preserves the ordering of the distances between a point and its neighbors more precisely as compared to the Euclidean distance in the original road network.

Keywords: GIS, spatial databases, road networks, moving objects, K nearest neighbors, shortest path, metric space, space embedding, Minkowski metrics, Chessboard metric

1. Introduction

The K-nearest neighbor (KNN) queries are frequently issued in multidimensional spaces. These queries ask for the K closest points to a query point with respect to some distance function. The complexity of the selected distance function has direct impact on the complexity of these queries. These distance functions are often computationally complex because of either the nature of the function and/or the large number of dimensions. A road network is a special case of 2-D spaces where the objects are points that are interconnected by roads and the dimensions specify the geographical coordinates (i.e., latitude and longitude) of the points. An example KNN query for such networks is to find the K closest gas stations to a specific location. Evaluating KNN queries for such networks is computationally expensive because the distance is a function of the network paths connecting the points (e.g., shortest path between two points). Now consider an application where the query point q is moving (e.g., it is a car). In this case, the distance function D from q to the points of interest is to be computed very often and in real-time. This renders the computation of complex distance functions impractical for real-time KNN queries for moving objects.

The majority of the current research on different aspects of KNN queries are based on utilizing different spatial index structures such as R-Tree or Quad-Tree. The use of index structures for distance measurements implicitly implies the use of Euclidean distance between the points. The first contribution of this paper is that it demonstrates that the Euclidean metric is not a good distance approximation for road networks. Our experiments with real-world data show approximately 40% false hits when Euclidean metric is used and 100% recall is achieved. The experiments also show that even for lower percentages of recall, in which Euclidean metric provides a perfect 100% precision, the results are highly out of order.

Therefore, we propose a new approach for KNN queries in road networks that can address both static and moving query points. Our approach, termed road network embedding (RNE), is based on transforming a road network into a higher dimensional space in which simpler distance functions can be utilized. In addition, we show that the Chessboard distance metric in RNE provides a proper approximation of the actual distances between the points. One drawback of RNE is that the embedding technique requires an off-line pre-computation of the shortest paths between all the points in the network. However, we show that for a high percentage of the points, the Chessboard distance can be computed using only a subset of the dimensions. Hence, we introduce the notion of truncated RNE, where the shortest paths from only a small percentage of the points are computed off-line. Our experiments verify that while truncated RNE provides an acceptable accuracy, it extensively reduces the space and computation complexity of RNE.

Our proposed RNE approach is aimed for the KNN queries when the query points are static. For moving query points, RNE must re-compute the embedding of all the original points whenever the object moves (i.e., a new point is added to the original space). To address this problem, we propose an extension to RNE, termed D-RNE, to dynamically embed moving or new query points. Moreover, while RNE can find the nearest neighbor, it cannot determine the actual path between that neighbor and the query point. Hence, we propose a greedy-heuristic algorithm, termed SP-RNE, to find the actual path between the points using only their transformations in RNE.

The remainder of this paper is organized as follows. In Section 2, we review the current research on KNN problem. Section 3 discusses the problem of KNN in road networks and briefly describes a naive solution based on pre-computation of all the distances off-line. Section 4 provides a background on the embedding techniques. We describe our approach for KNN queries by embedding the road networks into higher dimensional spaces, and compare it with the naive pre-computation approach in Section 5. In Section 6, we propose two techniques for dynamic embedding of moving objects and finding the shortest path using the embedding space. We discuss our experimental results and future work in Sections 7 and 8, respectively.

2. Related work

Recently, many new techniques have been proposed for the KNN and range queries in two and multi-dimensional spaces that can be adapted to road networks. They can be categorized into two groups. The first group partitions the space by utilizing different spatial or conventional index structures such as R-Tree [5] and its variants [2]. The second group, graph-based, are based on pre-computation of the nearest neighbors, and then use of index structures and/or Voronoi diagrams [6].

As examples of the first group, Roussopoulos et al. [9] propose branch-and-bound R-tree traversal algorithm to find the nearest neighbor objects to a point, and then generalize it to find the KNN. The main drawback of their algorithm is the depth-first traversal of the index tree that incurs unnecessary disk accesses. Hjaltason and Samet [7] propose a general incremental nearest neighbor algorithm that uses a priority queue on the index tree to reduce disk accesses. Their algorithm is adapted to R-Tree and is suitable for distance browsing queries but does not provide a substantial improvement in performance over the current R-Tree based KNN algorithms. Tao et al. [11] propose query processing methods that use R-Tree as the underlying data structure to address nearest neighbors for a query point that is moving on a straight line segment. Song and Roussopoulos [10] propose utilizing the information contained in the result sets of the previous sampled positions to answer the new queries for KNN. By caching the results of the previous queries, their algorithm provides a more efficient approach when the query points are moving. Their algorithm also provides a better start point for traversing the R-Tree index as compared to the pure static branch-and-bound algorithms. Ferhatosmanoglu et al. [4], introduce the notion of constraint nearest neighbor queries, that are the NN queries with range constraints. They propose an I/O optimized algorithm that is based on integration of the constraints with the tree traversal NN technique discussed in Hjaltason and Samet [7]. The use of index structures (e.g., R-Tree, Quad-Tree) for distance measurement implicitly implies use of Euclidean distance between the objects. This may not necessarily be a good approximation of the actual distance between objects in a road network where the distance between two points depends on the actual path connecting the points and cannot be computed accurately using one of the Minkowski metrics.

Yu et al. [12] propose partitioning the data in a high-dimensional space and selecting a reference point for each partition. The data in each partition are transformed into a single dimensional space based on their similarity with respect to a reference point, and KNN queries are performed using 1-D range search on a B^+-Tree index. The effectiveness of this approach depends on how the data are partitioned. Berchtold et al. [1] propose algorithm for similarity search in multimedia databases with large set of high-dimensional points. They suggest precomputing the result of any nearest-neighbor search, that corresponds to a computation of the Voronoi cell of each data point and storing the Voronoi cells into an index structure. The nearest neighbor query is then equivalent to finding the Voronoi diagram that contains the query point. Even though the Voronoi diagram techniques are efficient for first nearest neighbor queries, their extension for the KNN queries requires *a priori* knowledge of the value of K. The main drawback of the techniques based on pre-computation of the shortest paths is that they lack efficient support for KNN queries when the distances corresponding to some of the data points varies.

The proposed approach in this paper can be categorized in the second group and is based on transforming the road networks into a higher dimensional space. The transformation requires a pre-computation of the distances from all or a group of points to all other points.

3. Problem definition

Consider a set of n multidimensional objects $S = (o_1, o_2, \ldots, o_n)$ and a function D that specifies the distance between the objects. The KNN problem with respect to a query point, q, is to find a set $S' \subseteq S$ of K objects with smallest distances to q, that is for any object $o' \in S'$ and $o \in S - S', D(o', q) \preceq D(o, q)$. The distance function D usually requires expensive operations. For example, in a biological database that contain information about protein molecules, a distance function performs complicated quadratic-time structural comparisons to find the similar molecules.

In the context of road networks and moving objects, the original space contains 2-D objects: intersections (original nodes) connected by some streets. The query points in such spaces are usually moving objects (e.g., cars) traveling through the streets from a source to a destination and the KNN problem is defined as finding the closest points of interest (e.g., hospitals, gas stations) to the moving objects. Some of the challenges in such scenarios are:

- The distance function D between two original nodes in the road networks is usually specified as the length of the path between the nodes with some minimum weight (e.g., time to travel along the path). These weights result in complex algorithms for computation of distance functions (e.g., Dijkstra algorithm to find the minimum weighted path in a network with complexity $O(e + n \log n)$, where e and n are number of edges and nodes in the network respectively).
- When the query point q is a moving object, the distance function D from q to the points of interest is to be computed very often and in real-time. This renders the computation of complex distance functions impractical for real-time KNN queries for moving objects.

There are three different ways to address these challenges:

1. One approach is to approximate the complex distance function D with a simpler distance function D' in the same original space. For example, the shortest path between two intersections in a road network can be approximated by their Euclidean distance. The advantage of this approach is that the well studied spatial index structures that are based on the Euclidean distance can be utilized to address regular and constraint KNN queries. The disadvantage, however, is that the Euclidean distance does not properly approximate the actual distance function in the road networks.

2. Another naive approach is the pre-computation of all shortest distance pairs during an off-line process. Consider a road network S with n intersections and e roads. In this approach, we pre-compute the shortest distances between all intersections of S and store the distances into a database. Hence, this approach addresses the challenge of real-time KNN queries by retrieving the distance between two points from the database rather than computing it real-time. The space complexity of this approach is $O(n^2)$ while the computation complexity is $O(n(e + n \log n))$.
3. We propose a third approach as to introduce a new multi-dimensional space with simple distance functions D's (e.g., Minkowski distance metrics) that can either precisely approximate the distances between the original nodes (i.e., $D'(o', p') = D(o, p)$), or at least preserve the ordering of the distances between the original nodes (i.e., $D(p, o) \preceq D(p, q) \Rightarrow D'(p', o') \preceq D'(p', q')$).

In Section 5, we discuss our proposed approach to transform the road network into an embedding space. We compare the pros and cons of approaches 2 and 3 in Section 5.2.

4. Background on embedding

In this section, we provide an overview of the space embedding techniques. Let (S, D) be a finite metric space where S is a finite set of n objects and $D : S * S \rightarrow \Re^+$ is a distance metric over S. The embedding, or transformation, of a finite metric space (S, D) into a vector space $(\Re^k, D')$ is a mapping $E : S \rightarrow \Re^k$ where k is the dimensionality of the vector space and D' is one of Minkowski L_p metrics in $\Re^k$:

$$L_p(x, y) = \left[\sum_{i=1}^{k} |x_i - y_i|^p \right]^{1/p}, \tag{1}$$

in which x_i and y_i are the ith coordinates of two points x, y in space respectively, and p is the order of the Minkowski metric. The first order of the Minkowski metric, L_1, is known as Manhattan distance, the second order L_2 as Euclidian distance, and the infinite order $L_\infty = \max_i |x_i - y_i|$ as Chessboard distance. The objective of embedding is to have a fast and computationally simple D' function such that $D(x, y) \cong D'(E(x), E(y))$. In other words, the distance between two objects in the original metric space should be close enough to the distance between their corresponding embedded points in the embedding space. The quality of an embedding technique E is measured by distortion and stress. Distortion specifies the maximum difference between distance functions D and D' and is equal to $c_1 \times c_2 (c_1, c_2 \geq 1)$ when it is guaranteed that for an embedding technique E:

$$\frac{D(x, y)}{c_1} \leq D'(E(x), E(y)) \leq D(x, y) \cdot c_2, \tag{2}$$

for all pairs of objects $x, y \in S$. Stress represents the overall deviation in the distance and is defined as:

$$\text{Stress} = \frac{\Sigma_{x,y \in S}(D'(E(x), E(y)) - D(x,y))^2}{\Sigma_{x,y \in S} D(x,y)^2}. \tag{3}$$

The optimum D' function generates zero stress, equivalent to no distortion (i.e., $c_1 = c_2 = 1$). An embedding technique E is contractive when $D'(E(x), E(y)) \leq D(x,y)$ and proximity preserved when for all x, y and z in the original space, $D(x,y) \leq D(x,z)$ can be concluded from $D'(E(x), E(y)) \leq D'(E(x), E(z))$.

The embedding techniques are classified based on the properties of the original space that they utilize [3]. Two main classes of embedding techniques are *feature* and *distance* classes. For high dimensional original spaces that contain objects with N $(N \gg 1)$ attributes (i.e., N dimensional vector space) with one of the L_ps as their distance function, feature class techniques are used for dimension reduction to generate embedding spaces with $N' \ll N$ dimensions. When the distance function D between the objects in the original space is not one of the L_p metrics (e.g., similarity between protein molecules stored in a database that requires complicated structural comparison or quadratic time sequence matching techniques), distance class techniques that only utilize $D(x,y)$ are used.

In Section 5, we describe how we transform a road network to an embedding space using Lipschitz embedding technique.

5. Road network embedding (RNE)

A road network can be modeled as a weighted graph $G = (V, E)$. Let $|V| = n$ be the number of nodes in G (i.e., road intersections), $|E| = m$ be the number of edges in G (i.e., roads), and $W(e)$ be the weight of an edge $e \in E$ (e.g., length of a road). The distance $d(u,v)$ from node u to v is defined as the length of the minimum weighted path from u to v. We assume that for arbitrary nodes u, v and w, G is undirected: $d(u,v) = d(v,u)$, and $W(e)$ is defined such that the triangular inequality holds: $d(u,v) \leq d(u,w) + d(w,v)$. Therefore, the set of nodes in G with the distance function d generates a metric space (V, d). In this space, d is symmetric, non-negative and obeys triangular inequality.

We propose to utilize Linial, London and Robinovich (LLR) [8] embedding technique on road networks. LLR embedding technique is a contractive specialization of Lipschitz embedding, in which an object in the original space is mapped to a point in a k-D vector space. Consider space (S, D) in which $D(x,y)$ is a distance function between the objects x and y in S. Distance D is extended as follows: let S_i be a subset of S and $D(x, S_i) = \min_{y \in S_i}\{D(x,y)\}$, that is, $D(x, S_i)$ is the distance from x to its closest neighbor in S_i. Let $R = \{S_1, S_2, \ldots, S_k\}$ be a set of subsets of S. Lipschitz embedding with respect to R is then defined as: $E(x) = [D(x,S_1), D(x,S_2), \ldots, D(x,S_k)]$, which is a k-D point in a vector space with each axis corresponding to a reference set in R. LLR embedding defines R as a set of $O(\log^2 n)$ subsets of S: $R = \{S_{1,1}, \ldots, S_{1,\kappa}, \ldots, S_{\beta,1}, \ldots, S_{\beta,\kappa}\}$ where

$\kappa = O(\log n)$ and $\beta = O(\log n)$. Thus the original space is embedded into a $O(\log^2 n)$ dimensional space. Each subset $S_{i,j}$ is defined as a random subset of S with size 2^i. This means that the first κ reference sets have two objects, the second κ reference sets have four, etc., until the last κ reference sets that have approximately $n/2$ objects. The embedding $E(x)$ defined above for LLR has a distortion of $O(\log n)$ (i.e., $c_1 = 1$ and $c_2 = O(\log n)$). By using LLR technique, metric space (V, d) which represents the road network is embedded into $(\Re^k, d')$ in which $k = O(\log^2 n)$ and d' distance function is one of the L_p distance metrics over $\Re^k$ as defined in equation 1. Hence each node v in the original network is mapped to the point $E(v)$ in $O(\log^2 n)$ dimensional embedding space:

$$E(v) = (E_{S_{1,1}}(v), \ldots, E_{S_{1,\kappa}}(v), \ldots, E_{S_{\beta,1}}(v), \ldots, E_{S_{\beta,\kappa}}(v)), \tag{4}$$

in which $E_{S_{i,j}}(v) = d(v, S_{i,j})$.

5.1. RNE: Making LLR practical

Although LLR is a good start for transformation of road networks, it needs some tweaking to convert it to a practical approach.

- To reduce the computation complexity of RNE, we introduce the notion of truncated embedding space as an embedding space where only the distance between the original nodes and the first few reference sets are computed and considered as the attributes of the embedded points. The intuition is as follows. As discussed in Section 5, the value of the (i, j)th attribute of the embedded point $E(x)$ is defined as the minimum distance between the original node x and the (i, j)th reference set in R. We define A and B as sets of subsets of S:

$$A = (S_{1,1}, \ldots, S_{1,\kappa}, \ldots, S_{p,q}), \tag{5}$$

$$B = (S_{p',q'}, \ldots, S_{p',\kappa}, \ldots, S_{\beta,1}, \ldots, S_{\beta,\kappa}), \tag{6}$$

  in which $1 \leq p \ll \beta$ and $1 \ll p' \leq \beta$. The sets A and B contain the first and last few reference sets of R. Since the number of nodes in the reference sets of A are far less than the number of nodes in the reference sets of B (e.g., sets with $p = 1$ contain 2 nodes while the sets with $p' = \beta$ contain $n/2$ nodes), the distances between original nodes x and y to the sets in A are probably greater than the distances to the sets in B. Hence, the values of $|E_{i,j}(x) - E_{i,j}(y)|$ that correspond to the reference sets in A are probably greater than the values corresponding to the sets in B. This means that the first attributes of the embedded points, and hence the first reference sets of R, are more effective than the last attributes when the Chessboard metric is used. The results of our experiments confirm this intuition.

- The Chessboard metric can precisely approximate the actual distance between some nodes (i.e., $d' = d$). Consider the contractive property of the LLR approach that implies when (V, d) is embedded into $(\Re^{\log^2 n},\ L_\infty)$:

  $$d'(E(x), E(y)) = \max_{i,j} |d(x, S_{i,j}) - d(y, S_{i,j})| \leq d(x, y). \tag{7}$$

  This means that when the Chessboard metric is used for distance measurement, d' is always less than or equal to d. The equality of d' and d holds in the following two cases:

  1. When for some $i, j, S_{i,j} \in R, x \in S_{i,j}$ and x is the nearest node to y in $S_{i,j}$. Therefore $d(y, S_{i,j}) = d(y, x)$ and $d(x, S_{i,j}) = 0$. Hence $|d(x, S_{i,j}) - d(y, S_{i,j})| = d(x, y)$.
  2. When for some $i, j, S_{i,j} \in R$, the shortest path from x to its nearest node in $S_{i,j}$, say z, passes through y. In this case z is also the nearest node to y in $S_{i,j}$. Therefore $d(x, S_{i,j}) - d(y, S_{i,j}) = d(x, z) - d(y, z) = d(x, y)$.

  For the original nodes that are close to each other, the Chessboard metric provides a better approximation for the actual distance ($d' \simeq d$). The intuition is as follows. Consider two original nodes x, y that are very close to each other. Also suppose that the Chessboard distance between x and y is computed using reference set $S_{i,j} \in S$ which as stated above, is probably one of the first few reference sets of S with only a few nodes. These assumptions imply that: (a) one node, z, in $S_{i,j}$ is probably the closest node to both x and y, and (b) z is far from x and y. These resemble a triangle $\triangle xzy$ where the $\widehat{xzy}$ angle is close to $0°$ and $|d(x, z) - d(y, z)| \simeq d(x, y)$.

  Note that in the computation of the Chessboard distance, different $S_{i,j}$s are evaluated. The combination of x, y and each $S_{i,j}$ resembles a different triangle, but the one that has the minimum value for angle $\widehat{xzy}$, and hence leads to the maximum value for d', is picked by the Chessboard metric. Also note that for the points that are far from each other, the closest points from each $S_{i,j}$ to x and y are probably different, and hence, the distances from x and y to those points are independent from each other.
- LLR is not proximity preserved and cannot be used directly for nearest neighbor search. However, our experiments with real-world road network show that in practice, the distortion introduced by LLR is usually, smaller than the worst case $O(\log n)$. Hence, when the small values of distortion are tolerable, LLR with Chessboard metric L_∞ for RNE can be used as a selective filter in a filter/refine search strategy.

5.2. *Analysis*

In this section, we compare RNE with the naive pre-computation approach discussed in Section 3 in terms of precision, storage requirement, computation complexity and functionality.

5.2.1. Precision. As discussed in Section 3, the naive approach is based on pre-computing the shortest path between all pairs of the original nodes. Hence this approach provides a 100% precision when the distance between two original nodes are requested. In contrast, RNE provides an approximation of the actual distance which in the worst case is distorted by a factor of $O(\log n)$. Our experiments, however, show that for real world road networks, distortion is usually far less than the worst case and hence RNE also provides acceptable precision in practice.

5.2.2. Storage requirement. The space complexity of the pre-computation approach is $O(n^2)$ since the shortest path between all pairs of n original nodes generate a symmetric matrix with n^2 elements, equivalent to $n^2/2$ tuples in a database. In contrast, each node in RNE is mapped to only one point (i.e., n tuples in the database) with $\log^2 n$ dimensions, requiring space complexity of $O(n \log^2 n)$. The space complexity for truncated RNE is $O(n\sqrt{n})$.

5.2.3. Computation complexity. RNE uses the original distance function d (e.g., shortest traveling time in a road network) to compute the transformations of the original nodes. This means that RNE is even more computationally complex than the pre-computation approach. However, truncated RNE that only requires the shortest path computation to a fraction of subsets of R, and hence to a fraction $(O(\sqrt{n}))$ of the original nodes, provides a better computation complexity: $O(n^2\sqrt{n})$ as compared to $O(n^3)$ for the pre-computation approach (when the Dijkstra's algorithm is used).

5.2.4. Functionality. RNE is complementary to the current research on different aspects of the KNN problem and embedding techniques. For example, caching techniques for querying KNN of moving objects that are based on Euclidean distance and R-Tree index structure can be adapted to be used in the embedding space by using Chessboard distance and X-Tree [2] index structure. In contrast, the pre-computation approach only keeps the distances between all pairs of the original nodes and hence no index structure can be utilized to explore the geometry feature of the nodes.

6. RNE extensions

The RNE approach discussed in Section 5 is not aimed to address the points that dynamically change location and hence their distances to other points varies (e.g., moving query points or new points of interest), nor can it identify the actual path between the points. In this section, we propose two extensions to RNE in order to: (a) dynamically embed moving objects, and (b) find the actual path between two points in the original space using their transformations in the embedding space.

6.1 Dynamic RNE (D-RNE)

In the road network embedding approach discussed so far, we assumed that the query points and the points of interest are subsets of the original points (i.e., intersections) and are embedded off-line. This is not a realistic assumption since the query points are often moving objects and the location of the points of interest are usually between intersections and may not even be predetermined. With the current embedding techniques, insertion of a new set of points into the original space leads to the recomputation of the transformations of all original points in the initial original space. This renders these techniques impractical for the problem of finding KNN in a road network when the query points and the points of interest have dynamic locations. Hence an online embedding technique is required to embed these points as their locations change.

We propose an extension to the transformation technique discussed in Section 5 to embed the query points real-time. Our technique utilizes two features:

1. The query points and points of interest in a road network are always on the paths between the original nodes, meaning that insertion of these points into the original space does not introduce new edges into the original graph and does not change the distances between the original nodes.
2. The probability of using those subsets of S that have fewer number of nodes is higher with the Chessboard metric L_∞ as the distance measure (as discussed in Section 5.1).

Consider figure 1 where the query point Q is on the path between the directly connected original nodes P_i and P_j. From feature 1, we can conclude that if the query point Q was initially in the original space, the distance between Q and $S_{a,b}$, the (a, b)th dimension of $E(Q)$, would be calculated as:

$$E_{S_{a,b}}(Q) = D(Q, S_{a,b}) = \min(D(Q, P_i) + D(P_i, S_{a,b}), D(Q, P_j) + D(P_j, S_{a,b})). \qquad (8)$$

Insertion of Q after the original nodes are embedded may change some of the subsets of $S_{a,b}$ with a probability of $2^a/n$. This probability is negligible for the road networks with large number of original nodes $(n \gg 1)$ and the subsets $S_{a,b}$ with a very few nodes $(a \not\gg 1)$. This means that inclusion of Q into the original space would not have changed the subsets

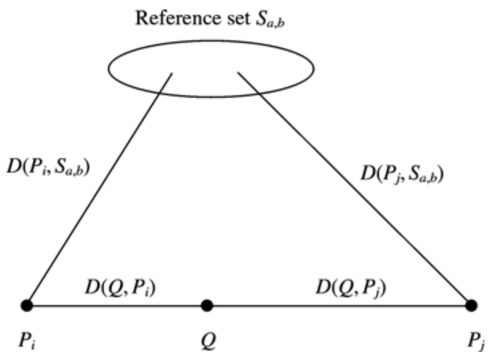


Figure 1. Dynamic embedding of moving query point Q with D-RNE.

of S that have a few nodes, but may have changed the subsets that contain large number of nodes (i.e., $a \gg 1$), which in turn may lead to changes in the values of (a, b)th dimensions of the embedded points. But feature 2 indicates that these dimensions are not effective when the Chessboard metric is used for distance measurements. We conclude that despite possible changes in the embedding of the original nodes when a new node is inserted into the original space, the Chessboard distances between the embedded points still remain the same. Hence we generalize equation 8 to calculate all dimensions of $E(Q)$. The results of our experiments confirm that even more than one point can be dynamically and precisely embedded using our technique.

6.2. *Shortest path in RNE (SP-RNE)*

While the embedding techniques are intended to approximate the actual complex distance functions with simpler functions, they are not aimed to find the shortest path between the nodes in a road network. In this section, we propose a greedy-heuristic algorithm to find the shortest path between two points in the original space using only the distances between their transformations in the embedding space. Consider the query point Q and point of interest I in figure 2 and suppose that Q is only connected to points $P_1, P_2, \ldots, P_i$. The intuition of our algorithm is that for a perfect embedding function E that $D(x, y) = D'(E(x), E(y))$ for all $x, y \in S$, if the shortest path from Q to I passes through points $\rho_1, \rho_2, \ldots, \rho_i$, then the shortest path from $E(Q)$ to $E(I)$ passes through $E(\rho_1), E(\rho_2), \ldots, E(\rho_i)$ and vice versa. We assume that for an embedding function with distortion, the probability that the shortest path from $E(Q)$ to $E(I)$ does not pass through $E(\rho_1), E(\rho_2), \ldots, E(\rho_i)$ is proportional to the distortion: the higher the distortion, the higher the possibility that the shortest path from $E(Q)$ to $E(I)$ goes through different points

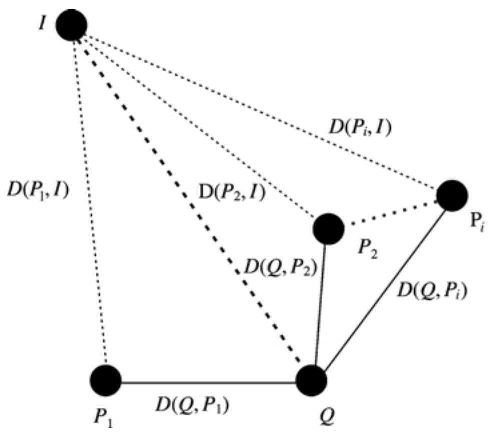


Figure 2. Shortest path estimation with SP-RNE.

```
FindPath ( Node $Q$, Node $I$) {
  $Path = \{Q\}$
  While($Q \neq I$) {
    $Q = FindNextNode(Q, I, Path)$
    $Path = Path \cup \{Q\}$ }
  $Path = Path \cup \{I\}$
  Return Path }

FindNextNode( Node $Q$, Node $I$, Nodes Already Visited) {
  Find $P_j$, $P_j \in$ Neighbors($Q$) such that:
    For (All $P_i$, $P_i \in$ Neighbors($Q$)
          and $P_i \notin$ Already Visited)
      $D'(E(Q), E(P_j)) + D'(E(P_j), E(I)) \leq$
      $D'(E(Q), E(P_i)) + D'(E(P_i), E(I))$
  Return $P_j$ }
```

Figure 3. Algorithm for shortest path computation in RNE.

than the shortest path from Q to I. Our proposed algorithm for finding the shortest path from Q to I is shown in figure 3.

The algorithm tries to find the global optimum solution by searching through the local optimums. In the first step, a point P_j among all directly connected neighbors of the query point Q is found such that the length of the path from the transformations of Q to P_j to I is minimum among all P_is. This point is selected as the next point in the shortest path from Q to I, and is then considered as the next query point. The algorithm continues on the next query points until it reaches a point that is directly connected to I. In order to avoid cycles, in each step of the algorithm we disregard the neighbors that are already selected as part of the shortest path.

The complexity of the algorithm is related to the length of the diameter of the network: the longest path between any two points in the network when $W(e) = 1$ for all e. The upper-bound of the complexity is $O(n)$, when the shortest path from Q to I contains all other points in the network (e.g., when Q and I are two ends of a line with other points in between). In a real world road network that nodes have a degree of 4 or less, the complexity of the algorithm is far less. For example, the average complexity of the algorithm for a Manhattan network is $O(\sqrt{n})$.

7. Performance evaluation

We conducted several experiments to: (1) compare the precision of different Minkowski metrics for distance measurement in the embedding space discussed in Section 4, (2) study the impact of K and density of the points of interest on the performance of the RNE approach, and (3) study the accuracy of D-RNE approach and SP-RNE technique discussed in Section 6.

For our experiments, we used a real data set for Kuwait obtained from NavTech Company. The data covers a rectangular area with corner points latitude and longitude (47.51,29.06) and (48.44,29.60) and contains 117,000 road segments, that constitute a graph with approximately 50,000 nodes. Different features in that area were also used as points of interest with different densities (density of the points of interest is defined as the number of points of interest over the number of original nodes). For example, parks, educational institutes, restaurants and signs represented different sets of points of interest with density = 0.5%, 1.5%, 2.5% and 10% respectively. In our experiments, we randomly selected 5% of the original nodes as the query points, performed the KNN query for each point using different approaches/distance metrics, measured the results by precision-recall and longest common subsequence metrics as compared to the correct result, and reported the average numbers. The precision-recall was used to measure the accuracy while the longest common subsequence was used to measure how precisely each approach/metric preserves the ordering in the result sets.

In our first set of experiments, we investigated how precisely different metrics for distance (i.e., Chessboard, Euclidean and Manhattan) in the embedding space approximate the real distance in the original space, by finding the KNN of the query points when the density of the points of interest varies. Figure 4 depicts the precision of these metrics when $K = 5$ and 100% recall is achieved (i.e., when all the correct nearest neighbors are found). Our experiments for other values of K show similar trends. As shown in the figure, precision of the Chessboard metric in the embedding space increases up to 98% as the density grows. In contrast, Euclidean metric in the original space behaves independent from the density and provides an almost constant precision of 60% to 70%. This means that when the Euclidean distance is used in the original space to find the KNN of a query point, 40% of the result set are false hits. The figure suggests a threshold value for the density of the points of interest, 0.5% for our data set, that can be used in a query optimizer to utilize either the Euclidean metric in the original space or the Chessboard metric in the embedding space for distance measurement. The figure also shows that the Chessboard metric always outperforms Manhattan and Euclidean metrics in the embedding space. Hence, from now on, we focus on comparison between the Chessboard metric in the embedding space and the Euclidean metric in the original space.

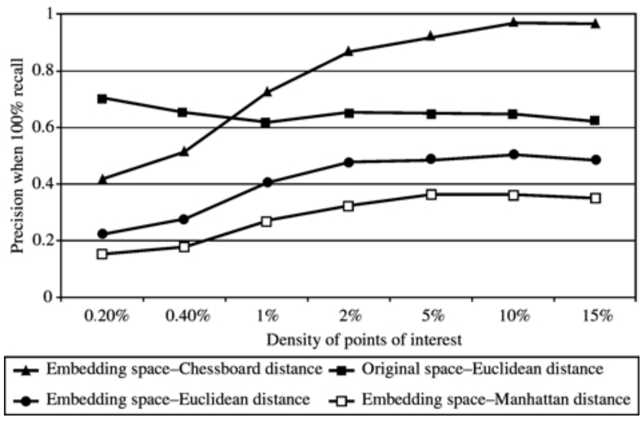
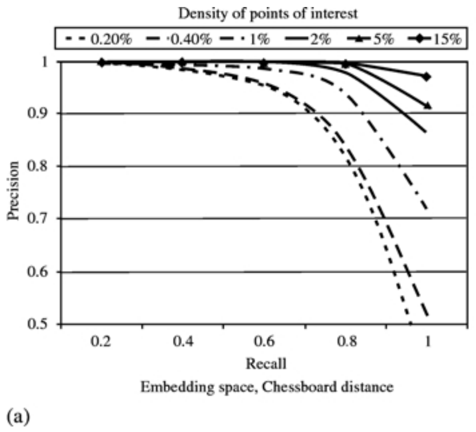


Figure 4. Precision comparison of different distance metrics with $K = 5$.



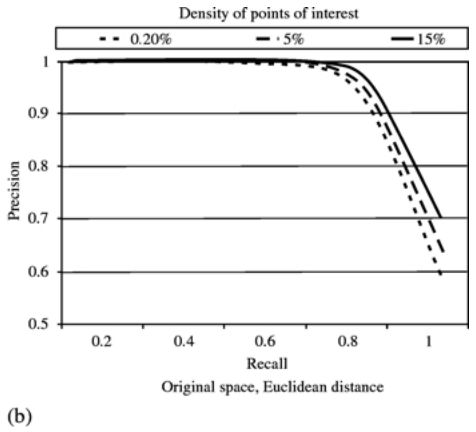
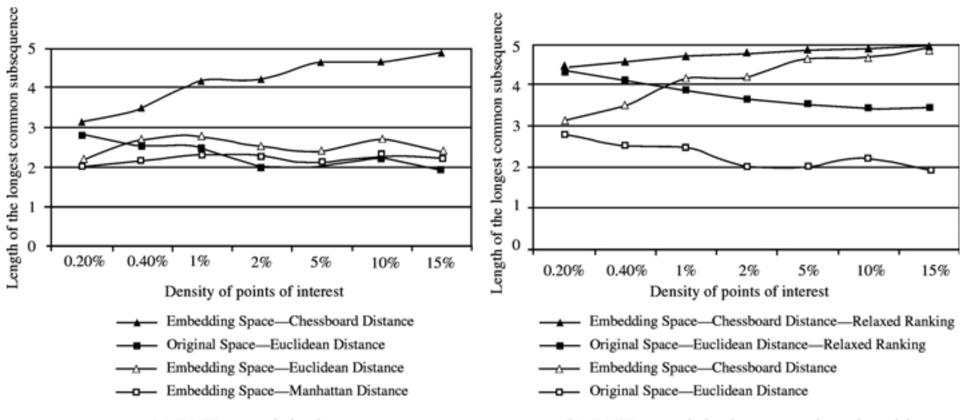


Figure 5. Precision-recall with $K = 5$.

Figure 5 depicts the precision-recall graph of the Chessboard metric in the embedding space and the Euclidean metric in the original space. As shown in figure 5(a), Chessboard metric provides a better performance as the density of the points of interest increases. This is because the higher the density of the points of interest, the higher the possibility of the first K of those points being closer to the query point, and hence less distortion (as discussed in Section 5.1). In contrast, figure 5(b) shows that the performance of the Euclidean metric in the original space slightly degrades as the density increases. The intuition here is that when the points of interest are sparse, the neighbors are far enough from the query point that even the Euclidean metric can preserve the ordering of the distances. Comparison between figure 5(a) and 5(b) also shows that the Euclidean distance in the original space provides a better precision as compared to the Chessboard metric in the embedding space only when the points of interest are very sparse.

Figure 6(a) depicts how different approaches preserve order in the result set when $K = 5$ (results for other values of K have similar trends). The Y axis in the figure is the length of the longest subset of the result set that has the same order as the actual result set. As shown in the figure, the Chessboard metric in the embedding space always outperforms other metrics/approaches and provides better ordering in the result set as the density of the points of interest increases. In contrast, the ordering in only 40% to 60% of the results are preserved when the Euclidean metric in the original space is used. This means that even for lower percentage values of recall in which Euclidean metric provides a 100% precision (figure 5(b)), the results are highly out of order. Since in certain applications, the mis-ordering of some points in the result set (i.e., the neighbors with close distances from the query point) may be tolerable, a relaxed measure can be used to compute the longest common subsequence in the result sets. Figure 6(b) shows the results when we relaxed the longest common subsequence measure by 10% (i.e., we neglected the mis-orderings between the neighbors that have less than 10% difference in their distances from the query point). As shown in the figure, this small relaxation of our measure leads to much better order preservation in the result set of both Chessboard metric in the embedding space and



(a) RNE vs. original space (b) RNE vs. original space, relaxed ranking

Figure 6. Comparison of order preservation by different approaches with $K = 5$.

Euclidean metric in the original space. This means that the mis-orders introduced by both metrics are mostly for the points that have very close values for their distances with the query point.

Our next set of experiments were aimed to investigate the impact of K on the performance of the different metrics. Figure 7 shows the results of the experiments for $K = 5$, 10 and 20 when the density of the points of interest is 1%. As shown in the figure,

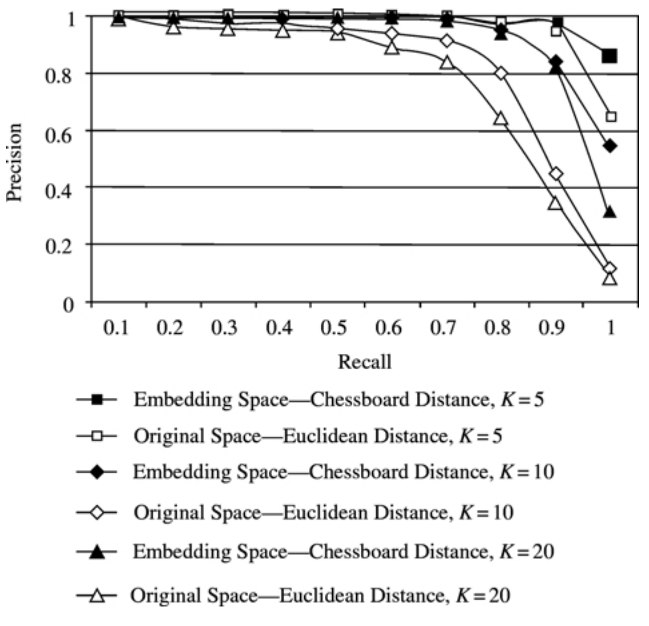


Figure 7. Precision-recall when K varies.

both Chessboard and Euclidean distance metrics perform better for smaller values of *K* and the performance of both decrease as the percentage of the recall increases. The reason is that the higher values of recall are achieved when the points of interest that are further from the query point are found. Higher values of *K* also introduce points of interest that are further from the query point. As we discussed in Section 5.1, the points of interest that are far from the query point contribute to more distortion and hence less precision.

In our next set of experiments, we synthetically generated 3,500 new nodes (7% of the original nodes) in the original space to investigate the performance of D-RNE. Note that the inclusion of the new nodes does not change the distances between the original nodes. The results showed that the difference between the precisions when the synthetic nodes are embedded off-line and when they are dynamically embedded in real-time using D-RNE approach is always less than 0.8%. In our next set of experiments, we studied nodes. Figure 8 shows that the difference between the precisions when the synthetic nodes are embedded off-line and when they are dynamically embedded online using D-RNE approach is negligible. We also studied the accuracy of the SP-RNE technique. Our experiments showed that in 72% of the cases, the path between two nodes calculated by SP-RNE matches the actual shortest path between them, and for the other 28% is on average 11% longer.

Our final set of experiments were aimed to study the space requirements of pre-computation, RNE and truncated RNE approaches. Table 1 shows the observations. As shown in the table, 256 dimensions are required for the RNE, while the Chessboard distance is computed for over 95% and 90% of the embedded points using only the first 70

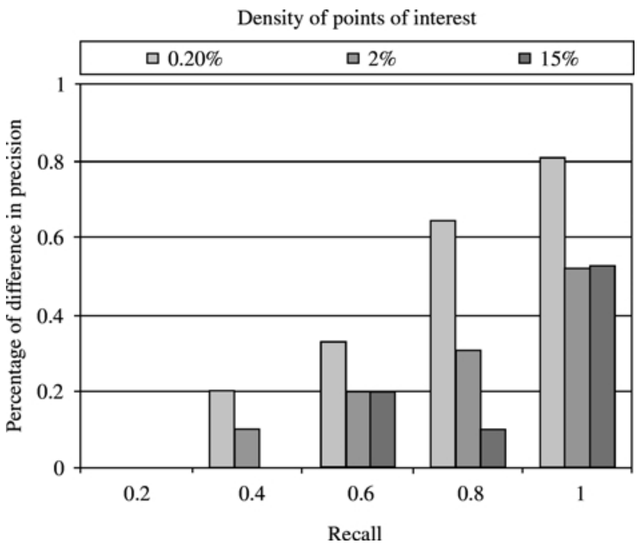


Figure 8. Comparison of RNE and D-RNE.

Table 1. Complexity comparison of pre-computation, RNE and truncated RNE.

Approach	*Dimensions*	*Shortest Paths Computed For*	*Number of Tuples*	*Required Space*
Pre-Computation		50,000 nodes	1.25 billion	30 GB
RNE	256	50,000 nodes	50,000	103 MB
T-RNE, 95% acc.	70	672 nodes	50,000	28 MB
T-RNE, 90% acc.	40	160 nodes	50,000	16 MB

and 40 dimensions, respectively. The table also illustrates that the shortest path computation in truncated RNE approaches are performed for far less number of nodes as compared to the regular RNE and pre-computation approaches: 672 and 160 nodes versus 50,000 nodes. Finally, the number of tuples generated and the total disk space required by the pre-computation approach is extensively larger than those of the RNE approaches.

8. Conclusion and future work

In this paper, we focused on the class of KNN queries for moving objects in road networks. We showed that in road networks the Euclidean distance measure does not properly preserve the order of the actual shortest distances between a query point and its neighbor points, and hence is not an appropriate distance measure for KNN queries. Alternatively, we proposed to apply an embedding technique to a road network (RNE) in order to convert its points to a higher-dimensional space. Subsequently, we showed the effectiveness of the Chessboard metric as the distance measure for the embedded points. Our experiments with real data sets demonstrated that the Chessboard metric always outperforms other Minkowski metrics in the embedding space. We also proposed two extensions to RNE. First, we discussed our D-RNE algorithm to dynamically embed new points (e.g., moving query points and new points of interest) into the embedding space. Second, we presented SP-RNE to find the shortest path between points in the original road network using their transformations in the embedding space.

We performed several experiments with real-world data sets to evaluate our techniques. The major results can be summarized as follow:

- When the density of the points of interest increases, the precision of the Chessboard metric in the embedding space improves, while the precision of the Euclidean metric in the original space degrades. This suggests a threshold value for the density of the points of interest that can be used in a query optimizer to utilize either the Euclidean metric in the original space or the Chessboard metric in the embedding space.
- The Chessboard metric in the embedding space always preserves the ordering in the result sets better than the Euclidean metric in the original space. The result sets of the Euclidean distance are highly out of order even for low values of recall when the precision is 100%.

- The truncated RNE technique provides a much better space and computation complexity as compared to the pre-computation approach.
- The precisions of the proposed D-RNE and SP-RNE techniques provide satisfactory approximations for RNE and shortest path computations, respectively.

We plan to extend this study in three ways. First, we would like to study the impact of utilizing Voronoi diagrams for the original space on the precision of the embedding approach with KNN queries. Voronoi diagrams can be used to prune some of the possible false hits from the result set. Second, we plan to modify the current Euclidean-based caching techniques for KNN queries to work for the Chessboard metric in the embedding space. Finally, we are planning to formalize the trade-offs between the Euclidean metric in the original space and the Chessboard metric in the embedding space in order to utilize these trade-offs within a query optimizer for choosing one approach over the other.

Achnowledgments

This research has been funded in part by NSF grants EEC-9529152 (IMSC ERC), IIS-0238560 (CAREER) and IIS-0082826, NIH-NLM grant nr. R01-LM07061, NASA/JPL contract nr. 961518, DARPA and USAF under agreement nr. F30602-99-1-0524, and unrestricted cash gifts from Microsoft, NCR and Okawa Foundation.

References

1. S. Berchtold, B. Ertl, D.A. Keim, H.-P. Kriegel, and T. Seidl. ''Fast nearest neighbor search in high-dimensional spaces,'' in *Proc. 14th IEEE Conf. Data Engineering, ICDE*, 23–27, 1998.
2. S. Berchtold, D.A. Keim, and H.-P. Kriegel. ''The X-tree: An index structure for high-dimensional data,'' in *Proceedings of the 22nd International Conference on Very Large Databases*, 28–39, Morgan Kaufmann Publishers, San Francisco, U.S.A., 1996.
3. C. Faloutsos and K.-I. Lin. ''Fastmap: A fast algorithm for indexing, data-mining and visualization of traditional and multimedia datasets,'' in *Proceedings of the 1995 ACM SIGMOD International Conference on Management of Data*, San Jose, California, 163–174, ACM Press, May 22–25, 1995.
4. H. Ferhatosmanoglu, I. Stanoi, D. Agrawal, and A.E. Abbadi. ''Constrained nearest neighbor queries,'' in *SSTD, Redondo Beach*, USA, 257–278, July 12–15, 2001.
5. A. Guttman. ''R-trees: A dynamic index structure for spatial searching,'' in *SIGMOD'84, Proceedings of Annual Meeting*, Boston, Massachusetts, 47–57, ACM Press, June 18–21, 1984.
6. S.L. Hakimi, M. Labbe, and E. Schmeichel. ''The voronoi partition of a network and its implications in location theory,'' in *ORSA Journal on Computing*, Vol. 4, 1992.
7. G.R. Hjaltason and H. Samet. ''Distance browsing in spatial databases,'' in *ACM Transactions on Database Systems*, Vol. 24, 265–318, 1999.
8. N. Linial, E. London, and Y. Rabinovich. ''The geometry of graphs and some of its algorithmic applications,'' in *IEEE Symposium on Foundations of Computer Science*, 577–591, 1994.
9. N. Roussopoulos, S. Kelley, and F. Vincent. ''Nearest neighbor queries,'' in *Proceedings of the 1995 ACM SIGMOD International Conference on Management of Data*, San Jose, California, 71–79, ACM Press, May 22–25, 1995.

10. Z. Song and N. Roussopoulos. ‘‘K-nearest neighbor search for moving query point,’’ in *SSTD, Redondo Beach*, USA, July 12–15, 2001.
11. Y. Tao, D. Papadias, and Q. Shen. ‘‘Continuous nearest neighbor search,’’ in *Proceedings of the Very Large Data Bases Conference (VLDB)*, Hong Kong, China, 2002.
12. C. Yu, B.C. Ooi, K.-L. Tan, and H.V. Jagadish. ‘‘Indexing the distance: An efficient method to KNN processing,’’ *The VLDB Journal*, 421–430, 2001.

Cyrus Shahabi is currently an Assistant Professor and the Director of the Information Laboratory (InfoLAB) at the Computer Science Department and also a Research Area Director at the Integrated Media Systems Center (IMSC) at the University of Southern California. He received his Ph.D. degree in Computer Science from the University of Southern California in August 1996. He has two books and more than seventy articles, book chapters, and conference papers in the areas of databases and multimedia. His current research interests include Streaming Architectures and Multidimensional Databases.

Mohammad R. Kolahdouzan received the B.S. degree in Electrical Engineering from the Sharif University of Technology at Tehran in 1991, and the M.S. degree in Electrical Engineering (Computer Networks) from the University of Southern California, Los Angeles, CA, in 1998. He is currently working towards the Ph.D. degree in Computer Science at the University of Southern California. He is currently a research assistant working on Multidimensional and Spatial Databases at the Integrated Media Systems Center (IMSC)—Information Laboratory at the Computer Science Department of the University of Southern California.

Mehdi Sharifzadeh received the B.S. degree in Computer Engineering from the Sharif University of Technology at Tehran in 1995, and the M.S. degree in Computer Engineering (Parallel Processing) from the Sharif University of Technology at Tehran in 1998. He is currently working towards the Ph.D. degree in Computer Science at the University of Southern California. He is currently a research assistant working on Multidimensional and Spatial Databases at the Integrated Media Systems Center (IMSC)—Information Laboratory at the Computer Science Department of the University of Southern California.