Fast Obstacle Spatial Query on Navigation Mesh

by

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Contents

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Abstract

Obstacle k-Nearest Neighbours problem is the k-Nearest Neighbour problem in a two-dimensional Euclidean plane with obstacles (*OkNN*). Existing and state of the art algorithms for OkNN are based on incremental visibility graphs and as such suffer from a well known disadvantage: costly and online visibility checking with quadratic worst-case running times. In this research we develop a new OkNN algorithm which avoids these disadvantages by representing the traversable space as a collection of convex polygons; i.e. a Navigation Mesh. We then adapt an recent and optimal navigation mesh algorithm, *Polyanya*, from the single-source single-target setting to the the multi-target case. We also give two new and online heuristics for OkNN. In a range of empirical comparisons we show that our approach can be orders of magnitude faster than competing methods that rely on visibility graphs.

Keywords: Obstacle Nearest Neighbor, kNN, Navigation Mesh, Spatial Search, Obstacle Distance, Obstacle Navigation

Chapter 1

Introduction

1.1 Overview

Obstacle k-Nearest Neighbor (OkNN) is a common type of spatial analysis query which can be described as follows: given a set of target points and a collection of polygonal obstacles, all in two dimensions, find the k closest targets to an a priori unknown query point q. Such problems appear in a myriad of practical contexts. For example, in an industrial warehouse setting a machine operator may be interested to know the k closest storage locations where a specific inventory item can be found. OkNN also appears in AI path planning field, for example, in competitive computer games, agent AIs often rely on nearest-neighbour information to make strategic decisions such as during navigation, combat or resource gathering.

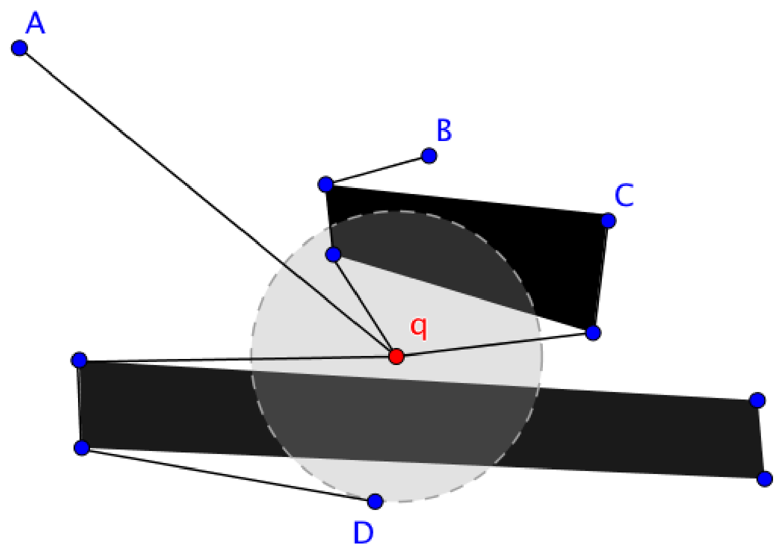


Figure 1.1: We aim to find the nearest neighbour of point q from among the set of target points A, B, C, D. Black lines indicate the Euclidean shortest paths from q. Notice D is the nearest neighbor of q under the Euclidean metric but also the furthest neighbor of q when obstacles are considered.

Tradional kNN queries in the plane (i.e. no obstacles) is a well studied problem that can be handled by algorithms based on spatial index. A key ingredient to the success of these algorithms is the Euclidean metric which provides perfect distance information between any pair of points. When obstacles are introduced however the Euclidean metric becomes an often misleading lower-bound. Figure 1.1 shows such an example.

1.2 Major Challenges

Two popular algorithms for OkNN, which can deal with obstacles, are *local visibility graphs* [13] and *fast filter* [12]. Though different in details, both of these methods are similar in that they depend on the incremental and online construction of a graph of co-visible points, and use *Dijkstra* to compute shortest path. Algorithms of this type are simple to understand, provide optimality guarantees and the promise of fast performance. Such advantages make incremental visibility graphs attractive to researchers and, despite more than a decade since their introduction, they continue to appear as ingredients in a variety of kNN studies from the literature; e.g. [4–6]. However, incremental visibility graphs also suffer from a number of notable disadvantages including:

1. online visibility checks;
2. an incremental construction process that has up to quadratic space and time complexity for the worst case;
3. duplicated effort, since the graph is discarded each time the query point changes.

In section 2.4, we will introduce these two algorithms with detail, and discuss why they have such disadvantages.

1.3 Major Objectives

In this research, we develop a new method for computing *OkNN* which avoids same disadvantages in existing works. Our research extends an existing very fast point-to-point pathfinding algorithm *Polyanya* to multi-target case.

1.4 Thesis Organisation

The rest of the thesis is organised as follows:

- In chapter 2, we review related works in different area, includes: AI searching, spatial index and spatial query processing.
- In chapter 3, we introduce the proposed algorithms and discuss their behaviors, formal proof for correctness will be proveded.
- In chapter 4, we provide experiment results to demonstrate the performance of propsed algorithms.
- In chapter 5, we summarize our contributions and discuss future works.

Chapter 2

Literature Review

2.1 Overview

As we've mentioned in previous chapter, OkNN problem appears in both AI path planning and Spatial query processing. Therefore, this literature review includes related works in these two fields.

In section 2.2, we introduce two classic pathfinding algorithms: *Dijkstra* and *A**, as the historic background. In section 2.3, we introduce a spatial index *R-tree*, and discuss how it solves traditional kNN problem. In section 2.4, we focus on existing works on OkNN, two algorithms based on *Local Visibility Graph* will be discussed. In section 2.5, we introduce a very fast point-to-point algorithm in AI path planning field which shows a new direction to solve OkNN problem. In section 2.6, we briefly discuss other related spatial queries which can be improved by our research.

2.2 Classic pathfinding

The most widely used pathfinding algorithm is *Dijkstra* [3]. The algorithm works on a nonnegative weighted graph, it requires a priority queue and regards the length of shortest path as key, and it visit vertices in the order of lenght of shortest path until requirements be satisfied, e.g. the target has been found. When the target is the furthest vertex to the start vertex, *Dijkstra* has to explore the entire map. Based on such consideration, researchers generalized *Dijkstra* algorithm to *best-first search* which explores a graph by expanding the most promising node chosen acording to a specified rule. *A** [8] is known as a famous *best-first search*, it select the path that minimizes:

$$f(n) = g\text{-}value(n) + h\text{-}value(n)$$

where n is the last node on the path, *g-value* is the length of shortest path from start to n, *h-value* is a estimation of shortest path from n to the goal which is problem-specific. One important propert of *h-value* is admissibility, meaning that it never overestimates the actual cost to the target. For example, in an Euclidean plane with obstacles, *h-value* can be the Euclidean distance.

In following sections and the chapter 3, we will show how *Dijkstra* and *A** algorithms be applied on the OkNN problem.

2.3 Spatial Index

2.3.1 *R-tree*

R-tree has many variations [1,7,9,11], they improve efficiency in different aspects, but they still provide same functionality, so we only introduce the classic *R-tree* in this section.

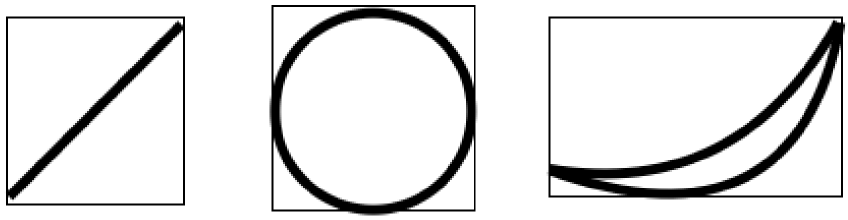
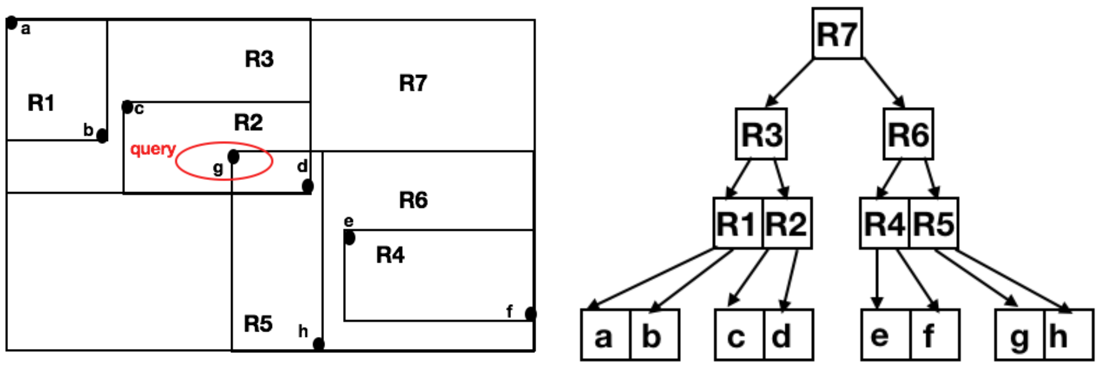


Figure 2.1: Both segments, circle and irregular shape can be represented by their MBR

R-tree is a heighb-balanced tree [7], all objects are stored in leaf node. In leaf node, if an object is not a point, it would be represented by its *Minimal Bounding Rectangle* (MBR), figure 2.1 shows example of MBRs. Each interior node is also represented by a MBR which contains either leaf nodes or descendant interior nodes. To guarantee efficiency, each non-root node of *R-tree* can contain at least m entries and at most M entries, where m, M are specified constant when *R-tree* is built, and *R-tree*'s root alway has two entries. Usually, objects retrieval start from the root, then narrow down to children nodes based on spatial information in their MBRs, and finally retrieve objects from leaf nodes. Figure 2.2 shows how to store and retrieve objects.



(a) Hierachy of MBRs

(b) Corresponding tree structure

Figure 2.2: $\{a, b, c, d, e, f, g, h\}$ is the object set, $R1, R2, R4, R5$ are leaf nodes, $R3, R6$ are interior nodes, and $R7$ is the root. The red oval is a range query, starting with $R7$, since $R6$'s MBR overlapped with query area, we narrow down to $R6$, then to $R5$, and finally retrieve g. Notice that $R3, R2$ also overlap with the query, so they will also be visited, but nothing retrieved.

From the example in figure 2.2, we can see that overlapping area will be explored multiplel times in retrieval progress, which duplicated efforts. So there is a variant doesn't allow overlapping in interior node, called R^+*-tree* [11].

2.3.2 Nearest Neighbor Query

In the *R-tree*, all nodes are organized by their spatial information, so that the nearest neighbor of a point can be retrieved by exploring tree nodes in some order. To introduce the algorithm, we need to discuss two metrics: given query point q and the MBR of a tree node

- ***mindist*** is the minimal distance from q to the MBR, it estimates the distance from q to inside object, so this metric is the priority of the tree node;
- ***minmaxdist*** is the uppber bound of the NN distance of any object inside the MBR, if the *mindist* of any MBR large than this value, then such MBR cannot contains the nearest object, so this metric is for pruning.

The algorithm starts with root node and proceeds down the tree. When it visits a leaf node, current nearest neighbor will be updated; When it visits a non-leaf node, the children of such node is sorted by *mindist*, and pruned by *minmaxdist*, then algorithm does *depth-first-search* on ordered and pruned children nodes; when algorithm finished, the updated nearest neighbor is the answer.

This kind of algorithm is called *branch-and-bound* traversal, which has been well studied and widely used in other artifical intelligence areas [11], and existing NN queries are based on it with different ordering and pruning strategies, more details are in [2, 10].

2.4 Obstacle k-Nearest Neighbor

2.5 Pathfinding on Navigation Mesh

2.6 Related Spatial Queries

Chapter 3

Proposed Algorithms

3.1 Overview

3.2 Interval Heuristic

3.3 Target Heuristic

3.4 Summary

Chapter 4

Empirical Analysis

4.1 Overview

4.2 Benchmark

4.3 Competitors

4.4 Experiment 1: lower bounds on performance

4.5 Experiment 2: computing more nearest neighbor

4.6 Experiment 3: changing number of targets

Chapter 5

Conclusion and Future Work

5.1 Research Contributions

5.2 Future Works

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