Spatial Clustering in the Presence of Obstacles *

Anthony K. H. Tung Jean Hou Jiawei Han

School of Computing Science
Simon Fraser University
British Columbia
Canada V5A 1S6
Email: {khtung, jhou, han}@cs.sfu.ca}

Abstract

Clustering in spatial data mining is to group similar objects based on their distance, connectivity, or their relative density in space. In the real world, there exist many physical obstacles such as rivers, lakes and highways, and their presence may affect the result of clustering substantially. In this paper, we study the problem of clustering in the presence of obstacles and define it as a COD *(Clustering with Obstructed Distance) problem. As a solution to this problem, we propose a scalable clustering algorithm, called* COD-CLARANS *. We discuss various forms of pre-processed information that could enhance the efficiency of* COD-CLARANS *. In the strictest sense, the* COD *problem can be treated as a change in distance function and thus could be handled by current clustering algorithms by changing the distance function. However, we show that by pushing the task of handling obstacles into* COD-CLARANS *instead of abstracting it at the distance function level, more optimization can be done in the form of a pruning function E'. We conduct various performance studies to show that* COD-CLARANS *is both efficient and effective.*

1 Introduction

Cluster analysis, which groups data for finding overall distribution patterns and interesting correlations among data sets, has numerous applications in pattern recognition, spatial data analysis, image processing, market research, etc. Cluster analysis has been an active area of research in computational statistics and data mining, with many effective and scalable clustering methods developed recently. These methods can be categorized into partitioning methods [KR90, NH94, BFR98], hierarchical methods [KR90, ZRL96, GRS98, KHK99], density-based methods [EKSX96, ABKS99, HK98], grid-based methods [WYM97, SCZ98, AGGR98], and model-based methods [SD90, Koh82].

Typically, a clustering task consists of separating a set of objects into different groups according to some *measures of goodness* that differ according to application. A common measure of goodness will be the sum of square of the **direct** Euclidean distance between the customers and the center of the cluster they belong to. However, in many real applications, the use of direct Euclidean distance has its weakness as illustrated by the following example.

Example 1.1 A bank planner wishes to locate 4 ATMs in the area shown in Figure 1(a) to serve the customers who are represented by points in the figure. In such a situation, however, natural obstacles exist in the area and they should not be ignored. This is because ignoring these obstacles will result in clusters like those in Figure 1(b) which are obviously inappropriate. For example, Cluster Cl_1 is, as a result of clustering, split by a river, and some customers on one side of the river will have to travel a long way to the ATM located at the other side. □

Example 1.1 shows a simple but a serious fact which has not been addressed so far: most clustering algorithms assume direct Euclidean distance among the objects to be clustered without obstacles in the way, however, most applications do have obstacles in presence, and the omission of such obstacles may lead to distorted and often useless clustering results.

In this study, we examine the problem of clustering spatial objects with the presence of obstacles. The definition of the problem that we are solving is as follows.

Definition 1.1 The Clustering with Obstructed Distance (COD) Problem
Given (1) a set P of n points $\{p_1, p_2, ..., p_n\}$, and (2) a set O of m **non-intersecting** *obstacles $\{o_1, ..., o_m\}$ in a two-dimensional region, R, with each obstacle o_i represented by a simple polygon, the* **direct Euclidean distance** *between two points p_j and p_k, denoted as $\mathbf{d(p_j, p_k)}$, is the Euclidean distance between*

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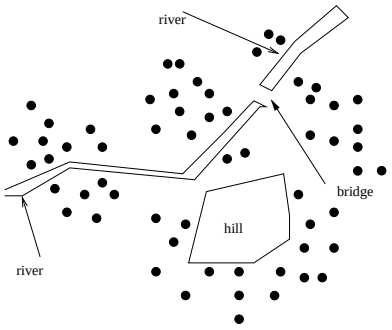
the two points by ignoring the obstacles; whereas the **obstructed distance**, *between the two points, denoted as* $\mathbf{d'(p_j, p_k)}$, *is defined as the length of the shortest Euclidean path from* p_j *to* p_k *without cutting through any obstacles.*

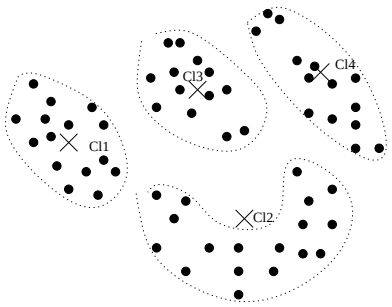
The problem of **clustering with obstacle distance** *(*COD*) is to partition* P *into* k *clusters,* Cl_1, ..., Cl_k, *such that the following square-error function,* E, *is minimized.*

$$E = \sum_{i=1}^{k} \sum_{p \in C_i} (d'(p, c_i))^2$$

where c_i *is the center of cluster* Cl_i *that is determined by the clustering.* □



(a) Customers' locations and obstacles.



(b) Clusters formed when ignoring obstacles.

Figure 1. Planning the locations of ATMs

Since our given problem is to ensure a minimized overall travel distances of all the customers in the city, the partitioning-based algorithms will be a good choice as a solution. This is because most of the other categories of clustering algorithm focus on finding natural clusters which do not guarantee minimization of the distances to the cluster centers.

Of the two typical types of partitioning-based algorithms, k-means and k-medoids, the k-medoids method is selected due to the fact that the mean of a set of points is not well defined when obstacles are involved. For example, in Figure 2, the mean of the points is inside an obstacle and thus by definition is unreachable by all the points in the cluster. On the other hand, the k-medoids method chooses an object within the cluster as a center and thus ensures that such a problem does not exist. In view of this, we derived an efficient k-medoids algorithm called COD **algorithm** for solving this problem.

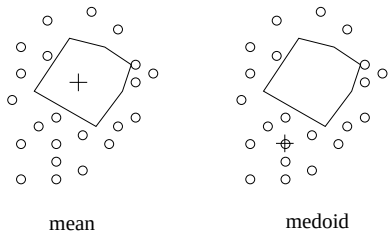


Figure 2. Mean vs Medoid.

The COD-CLARANS algorithm is developed in the spirit of CLARANS [NH94] and is designed for handling obstacles. While CLARANS algorithm can be made to handle obstacles by changing its distance function, COD-CLARANS further optimized this function by "pushing" the task of handling obstacles into the algorithm.

Figure 3 shows the overall structure of COD-CLARANS. To facilitate the running of COD-CLARANS, we pre-process the data and store certain information which will be needed by COD-CLARANS during its run. Pre-processing will be discussed in Section 2. The COD-CLARANS algorithm consists of three main parts, the main algorithm, the computation of the squared-error E and a pruning function E'. The pruning function E' has two purposes. First, it can help to prune off search and avoid the computation of E. Second, in the event when the computation of E cannot be avoided, the pruning function can provide **focusing information** to make the computation of E more efficient. Section 3 will describe them in more detail. In Section 4, we will do a performance study on the COD-CLARANS algorithm. We will discuss some possible future work in Section 5. Our study is concluded in Section 6.

2 Pre-processing

During the course of clustering,the COD-CLARANS often needs to compute the obstructed distance between a point and a temporary cluster center. Our aim of pre-processing here is to materialize information which will facilitate such a computation.

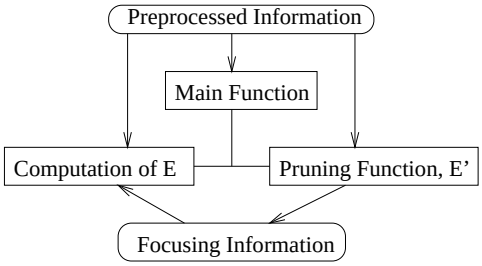


Figure 3. Overview of COD-CLARANS.

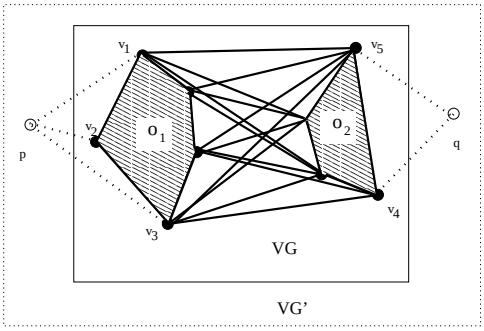


Figure 4. A visibility graph.

2.1 The BSP-tree

The Binary-Space-Partition (BSP) tree [SG97] is a data structure which can efficiently determine whether two points p and q are **visible** to each other within the region R. We define p to be **visible** from q in the region R if the straight line joining p and q does not intersect any obstacles. In our algorithm, the BSP-tree is used to determine the set of all visible obstacle vertices from a point p. Henceforth, we will use the notation $vis(p)$ to denote such a set of vertices. More details of the BSP-tree can be found in [SG97].

2.2 The Visibility Graph

Definition 2.1 Visibility Graph
Given a set of m obstacles, $O = \{o_1, ..., o_m\}$, the visibility graph is a graph $VG = (V, E)$ such that each vertex of the obstacles has a corresponding node in V, and two nodes v_1 and v_2 in V are joined by an edge in E if and only if the corresponding vertices they represent are visible to each other. □

To generate VG, we make use of the BSP-tree computed previously and search all other visible vertices from each vertex of the obstacles. The visibility graph is pre-computed because it is useful for finding the obstructed distance between any two points in the region. The following lemma is proven in [O'R98].

Lemma 2.1 *Let p and q be two points in the region R and $VG = (V, E)$ be the visibility graph of R. Let $VG' = (V', E')$ be a visibility graph created from VG by adding two additional nodes p' and q' in V' representing p and q. Similar to earlier definition, E' contains an edge joining two nodes in V' if the points represented by the two nodes are mutually visible. The shortest path between the two points p and q will be a sub-path of VG'.* □

In Figure 4 , we show how the visibility graph VG' can be derived from the visibility graph VG of a region with two obstacles o_1 and o_2. From Lemma 2.1, we can see that the shortest path from p to q will begin with an edge from p to either v_1, v_2 or v_3, go through some path in VG and then end with an edge from either v_4 or v_5 to q.

2.3 Micro-clustering

In order for COD-CLARANS to handle a large number of data points, we use the concept of pre-clustering which is similar to those used in BIRCH [ZRL96], ScaleKM [BFR98] and CHAMELEON [KHK99]. A **micro-cluster** is a compressed representation of a group of points which are so close together that they are likely to belong to the same cluster. As such, instead of representating each point in the micro-cluster individually, we represent them using their center and a count of the number of points in the micro-clusters. Using this summarized information, the COD-CLARANS algorithm can approximate the square-error function E by assuming that all the points in the micro-clusters are located at the center of the micro-cluster.

To ensure that not too much accuracy is sacrificed by using micro-cluster, we limit the radius of each micro-cluster to be below a user-specified threshold, max_radius. With the presence of obstacles, one key complication is to avoid having a micro-cluster that is split by an obstacle. To do so, we first triangulate the region R into triangles [O'R98] and group the data points according to the triangle that they are in. Figure 5 illustrates a triangulation of the region and the forming of micro-clusters within each triangle. Since all the points within a triangle are always mutually visible, it is guaranteered that no micro-cluster will be split by an obstacle.

2.4 Spatial Join Index

While the information described earlier is sufficient for computing the obstructed distance efficiently, improvements can be achieved by the additional computation of a **spatial join index** [Val87, Rot91, LH92]. In such an index, each entry is a 3-tuple $(p, q, d'(p, q))$ where p and q are two points in the region R and $d'(p, q)$ is the obstructed distance between p and q. There are three spatial join indexes which can be materialized:

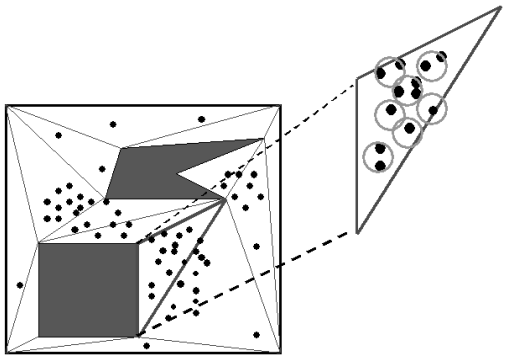


Figure 5. Forming micro-clusters.

1. **VV Index: Compute an index entry for any pair of obstacles vertices**
   The materialization of this index is equivalent to finding the all-pairs shortest paths in the visibility graph VG. We make use of the Johnson's algorithm [CLR90] for this purpose. From Lemma 2.1, we can see that the computation of shortest path between two points in R will often require the calculation of obstructed distance between the vertices. As such materializing the VV index will help avoid the redundant computation of these distances.

2. **MV Index: Compute an index entry for any pair of micro-cluster and obstacles vertex**
   In such an index, the obstructed distance between any pair of micro-cluster and vertex will be computed. An efficient way to materialize the MV index is to first materialize the BSP-tree and the VV index. For each micro-cluster p, the set of visible obstacle vertices, $vis(p)$ can then be computed by using the BSP-tree and the distance to other non-visible be computed by using the VV Index.

3. **MM Index: Compute an index entry for any pair of micro-clusters**
   By computing this index, the obstructed distance between any two micro-clusters will be materialized. Having the MM index means that COD-CLARANS algorithm will performed like the CLARANS algorithm since a lookup on the index is sufficient to find the obstructed distance between any two micro-clusters. However, the size of such an index will be huge. Thus, we feel that such an alternative will not be feasible.

We will compare the relative performance of the first and second alternatives in Section 4.

3 The COD-CLARANS Algorithm

In this section, we look at the COD-CLARANS algorithm in detail.

3.1 The Main Function

We show the main function of the COD-CLARANS algorithm in Algorithm 3.1. The algorithm first randomly selects k points as the centers of the clusters and then tries to find better solutions by iterating through Step 5 to Step 26. At each iteration, the cluster centers are randomly ordered, and attempts will be made to replace them with a better center in that order. When a center c_j is selected to be replaced, the obstructed distances of the objects to the other $k-1$ centers in *remain* will first be computed in Step 10. This information is computed because they can be repeatedly used in the loop from Step 11 to Step 22 for the computation of E' and E. In Step 12, a random object c_{random} is selected to replace c_j. Using c_{random}, a lower bound for the squared-error E' is computed. If E' is higher than the previous best solution, the actual squared-error E need not be computed since c_{random} is obviously a bad choice. Otherwise, E is computed to determine whether a better solution has been found. If this is so, the best solution will be updated and c_{random} will replace the position of c_j in *current*. For each cluster center, an attempt to replace it will be done max_try times, if no better solution is found for all the centers, the algorithm terminates.

3.2 Computing Obstructed Distance to Nearest Centers in *remain*

In this section, the execution of Step 10 is discussed. We separate this step into two phases:

Algorithm 3.2 *Computing Distances between Objects and Cluster Centres*
Phase I: *For all vertices of the obstacles, find the shortest obstructed distance to the nearest cluster center in remain. Given a vertex v, we denote its nearest cluster center as $N(v)$.*
Phase II: *For each micro-cluster p, let us denote the set of all visible obstacle vertices from p as $vis(p)$. We choose v from $vis(p)$ such that $(d'(v, N(v)) + d(p, v))$ is minimum. The shortest distance between p and its nearest cluster center will be computed as $(d'(v, N(v)) + d(p, v))$ and p 's nearest cluster center in remain will be $N(v)$.*

The execution of Phase I can differ depending on whether the spatial join indexes VV and MV have been materialized. We separate them into three cases.

Algorithm 3.1 Algorithm COD-CLARANS .
Input: A set of n objects, k and clustering parameters, $maxtry$.
Output: A partition of the n objects into k clusters with cluster centers, $c_1, ..., c_k$.
Method:

```
1. Function COD-CLARANS()
2. { randomly select k objects to be current;
3.   compute square-error function E;
4.   let currentE = E;
5.   do
6.   { found_new = FALSE;
7.     randomly reorder current into {c1,...,ck};
8.     for (j=1 ; j≤k ; j++)
9.     { let remain = current − cj ;
       /* remain contain the remaining center */
10.      compute obstructed distance of objects to nearest
         center in remain;
11.      for (try=0; try < max_try; try++)
12.      { replace cj with a randomly selected object crandom ;
13.        compute estimated square-error function E';
14.        if (E' > currentE)
15.          continue; /* Not a good solution */
16.        compute square-error function E;
17.        if (E < currentE) /* Is the new solution better ? */
18.        { found_new = TRUE; /* Found a better solution */
19.          current = {c1,...,crandom,...ck}
             /* replace cj with crandom */
20.          currentE = E;
21.        }
22.      }
23.      if (found_new)
24.        break; /* Reorder cluster centers again */
25.    }
26. } while (found_new)
28. output current ;
27}
```

1. **VV is materialized**
   If VV is computed, then all we have to do is to find the visible vertices from each cluster center c_i and then compute the obstructed distance of each vertex v_j as $d'(c_i, v_j) = min(d(c_i, v_k) + d'(v_j, v_k)), v_k \in vis(c_i)$. The nearest center of each vertex can then be identified.

2. **MV is materialized**
   If MV is available, the obstructed distance between any cluster center and any obstacles vertex will be materialized. As such, a search in MV will be sufficient to find the obstructed distance of a node v to the $k-1$ centers. The nearest center of the vertex can then be determined.

3. **No spatial join index is materialized**
   If no spatial join index is available, then the precomputed visibility graph $VG = (V, E)$ will be utilized. We make use of the Dijkstra's algorithm [CLR90] for this purpose. We insert $k-1$ additional nodes representing the $k-1$ cluster centers into V. An edge is created between a cluster center c and a vertex v if v is visible from c. In addition, a **virtual node** s is also inserted and linked by an edge of weight zero to each of the $k-1$ cluster centers. The Dijkstra's algorithm is then ran with the virtual node s as the source point. To identify the closest cluster center for a vertex v, the shortest path from s to v is traced during the run of Dijkstra's algorithm to monitor which cluster center is in the path. This cluster center will be the cluster center that is closest to v.

Once Phase I is completed, the execution of Phase II is trivial except for forming of $vis(p)$ with respect to a point p. We make use of the BSP-tree for this purpose.

3.3 Computing the Lower Bound E'

After c_{random} is generated at line 13 of Algorithm 3.1, we first underestimate the distance between c_{random} and the micro-clusters by using direct Euclidean distance. Note that in Step 10, we have already computed the nearest cluster centers from $remain$ for each object p. Let us denote this center as $N(p)$. If the direct Euclidean distance between a micro-cluster p and c_{random} is shorter than $d'(p, N(p))$ (which is also computed with the $k-1$ unchanged cluster centers), then p is assigned to c_{random} and the direct Euclidean distance between them will be used when computing the estimated square-error function E'. We have the following lemma.

Lemma 3.1 *E' is a lower bound for the actual square-error function E.*

The proof of the Lemma 3.1 is omitted for lack of apace. Since E' is a lower bound of E, we can choose to abandon c_{random} if E' is already higher than the square-error function of the best solution found so far. However, if E' is lower than the best solution, then E must be computed. Since the obstructed distance of each micro-cluster p to $N(p)$ is already calculated, what we need to find is the obstructed distance between the new center c_{random} and the micro-clusters that will be assigned to c_{random}. For this purpose, we can use of the **focusing information** provided by the computation of E' to limit the set of micro-clusters which will have c_{random} as the nearest center. This is done by observing the following lemma.

Lemma 3.2 *If a micro-cluster p is not assigned to c_{random} when computing E', then it can never be assigned to c_{random} when computing E.*

Using Lemma 3.2, we can limit our computation of obstructed distance to c_{random} to a subset of micro-clusters instead of all micro-clusters.

3.4 Computing the Squared-error E

As mentioned earlier, since the obstructed distance of each micro-cluster to its nearest center in *remain* is already computed in Step 10, what we only need to find when computing E is the obstructed distance between the new center c_{random} and the micro-clusters that will be assigned to c_{random}. This process is similar to Step 10 except that we can use the focusing information provided by E' to limit the computation.

4 Performance Study

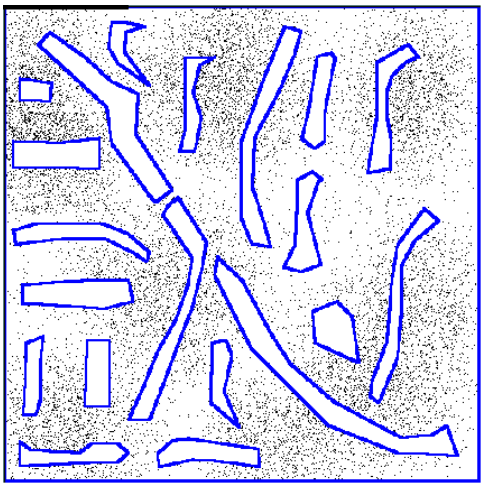
In this section, we will have a look at the performance of the COD-CLARANS algorithm by performing experiments on a PC with a Pentium 600Mhz processor and a IBM 7200rpm hard disk. For these experiments, we use two synthetic datasets, DS1 and DS2, which are shown in Figure 6. DS1 consists of 63350 points randomly distributed in the region. We simulate major "obstacles" like rivers, highways, and industrial parks in the region by adding in 20 obstacles. These polygons have a total of 194 edges. DS2 dataset consists of five clusters that are cut through by "stick" obstacles. There are altogether 60000 points and 10 obstacles in DS2. Each obstacle has 4 edges.

In our experiments, we set the parameter *max_try* to be 40. Micro-clusters are formed by applying the BIRCH algorithm described in [ZRL96].

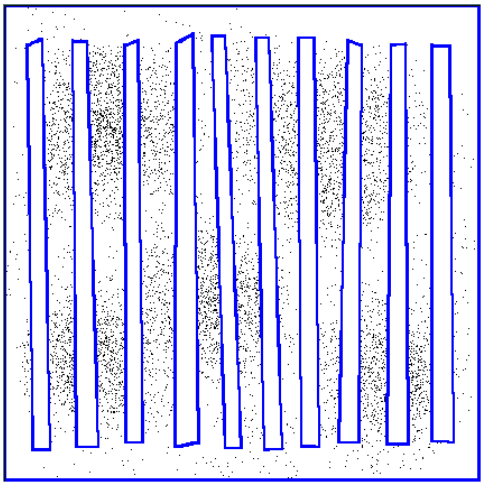
The experiments proceed as follows. First, we assess the efficiency and effectiveness of the various flavor of COD-CLARANS by running our algorithms on DS1. COD-CLARANS can be separated into three categories in term of materialized index: 1) non materialized, 2) VV materialized and 3) MV materialized. We denote them as COD-CLARANS-N, COD-CLARANS-VV, and COD-CLARANS-MV, respectively. In addition, a symbol "%" will be appended to the end of these algorithms to denote a version in which the pruning function is **not** used. We assess these algorithms by adjusting the parameter *max_radius* that control the number of micro-clusters being formed. Next, we look at the clustering result of COD-CLARANS on DS2 and compare it to those of CLARANS which ignore obstacles in its clustering.

4.1 Varying *max_radius*

In this experiment, we vary the number of micro-clusters that are generated from DS1 by tuning the parameter *max_radius* that bound the radius of the micro-clusters being formed. There are two purposes in doing this. First, since more accuracy will be lost when



(a) DS1.



(b) DS2.

Figure 6. Two datasets.

max_radius is increased, we like to investigate how the quality of the clusters is affected by the use of micro-clustering. Second, since the number of micro-clusters varies according to *max_radius*, we can investigate how the various algorithms scale up as the number of micro-clusters increases. Performing this as a scalability test is preferable over arbitrarily adding points which may affect the distribution of the data and subsequently the execution time of the algorithms.

The various values of *max_radius* and the number of micro-clusters which are formed for DS1 shown in Table 1 together with the average squared-error of the clusters. As can be seen, the increase in the quality of the

Table 1. Effect of Varying max_radius.

max_radius	No. of Micro-Clusters	Average E
0.00	63350	1.48
0.01	8178	1.49
0.02	3133	1.51
0.03	1546	1.55
0.04	965	1.56
0.05	520	1.59

clusters due to micro-clustering is not significant comparing to the decrease in the number of micro-clusters for DS1. The drop in cluster quality by performing micro-clustering is at most 8%.

Let us now look at the pre-processing time that is required for DS1 in Figure 7. The pre-processing time for COD-CLARANS-N and COD-CLARANS-VV are only minorly affected by max_radius. This is because the only pre-processing operation that max_radius has an effect on is the forming of micro-clusters. We can also see that COD-CLARANS-VV has a higher pre-processing time due to the materialization of the VV index which is equivalent to an all-pair shortest path search on the visibility graph. COD-CLARANS-MV, on the other hand, will decrease with as max_radius increases. This is because increasing max_radius will result in less micro-clusters and corresponding the amount of computation that much be done to calculate the obstructed distance between each micro-clusters and the obstacles vertices.

Next, let us look at the actual running time of our algorithm for DS1 in Figure 8. From the graph, we have the following observations.

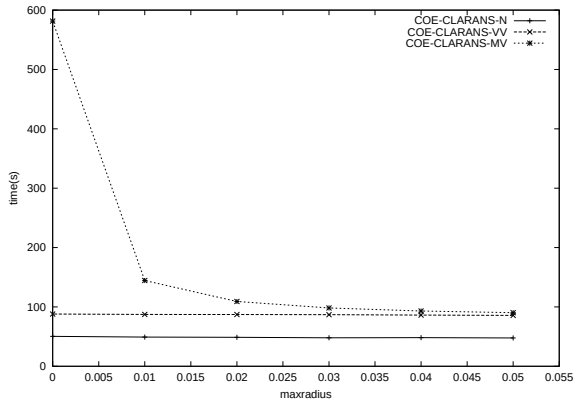


Figure 7. Pre-processing Time of DS1.

First, algorithms which does not use the pruning function will have a longer execution time than those with pruning function. This is especially true for COD-CLARANS-N% when the number of micro-clusters is high. The execution time of COD-CLARANS-N% on DS1 reach as high as 66392 seconds and 3119 seconds when max_radius is set to 0.00 and 0.01 respectively. When spatial join indexes are available, the differences between the pruning and non-pruning versions are narrower. This is because the computation of obstructed distance is more efficient with the use of spatial join indexes and thus the reduction of processing time through the pruning function becomes less significant.

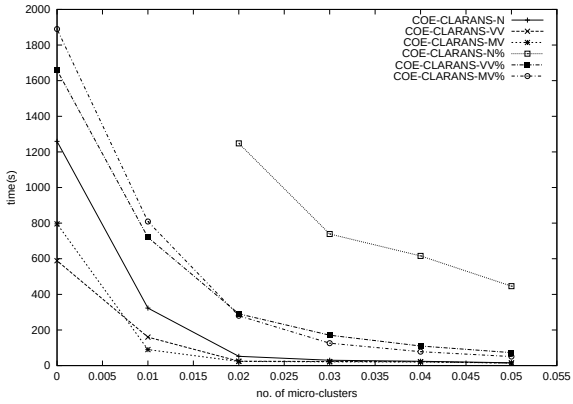


Figure 8. Algorithms Running Time of DS1.

Second, the spatial join indexes are useful in reducing the execution time of the algorithms. This is true even when the pre-processing times are taken into consideration. For the pruning versions of the COD-CLARANS algorithm, having spatial indexes will improve the execution times of the algorithms marginally. Having spatial join indexes in the non-pruning versions of the algorithm however, has significant advantages over one that does not have spatial join indexes. Between the two spatial join indexes, VV and MV, having the MV index generally gives better performance than having the VV index. The only exception is observed for DS1 when the number of micro-clusters is high. In such a case, the size of MV is much higher than the size of VV and the time taken to access MV will offset the advantage that it has by storing more information.

As a whole, we found that the COD-CLARANS algorithm scales well for large number of points. We recommend the use of spatial join index MV if the number of edges is small. However, the use of spatial join index VV will be more space efficient since the obstructed distance between any two obstacle vertices is sufficient to avoid running the Dijkstra algorithm on the visibility graph.

4.2 Clustering Results

To ascertain that clustering with consideration of obstacles is in fact useful, we will compare the cluster quality of COD-CLARANS with the clusters that is discovered by the CLARANS algorithm. For the

CLARANS algorithm, we first cluster the data points by ignoring the obstacles. At the end of the algorithm, the cluster centers are fixed. Data points are then allocated to the nearest centers **by obstructed distance** and the squared-error will be computed. Note that in this case, points which are earlier assigned to a cluster center may be reassigned to a different one when obstacles are taken into consideration. The results of the two algorithms for DS2 are shown in Figure 9.

When $k = 5$, the average squared-error found by the COD-CLARANS algorithm on DS2 is 1.24 while CLARANS gives an average squared-error of 1.68. The clustering result of DS2 illustrates why COD-CLARANS performs better than CLARANS in both cases. Let us refer to the space between any two obstacles as a corridor. As we can see, the cluster centers that are discovered by the COD-CLARANS algorithm are mostly placed at the "entrance" of the corridor so that they are accessible by points from other corridors. On the other hand, CLARANS which has no knowledge of the obstacles will place the centers into the corridors, which means that points from other corridors will be very far from the nearest center.

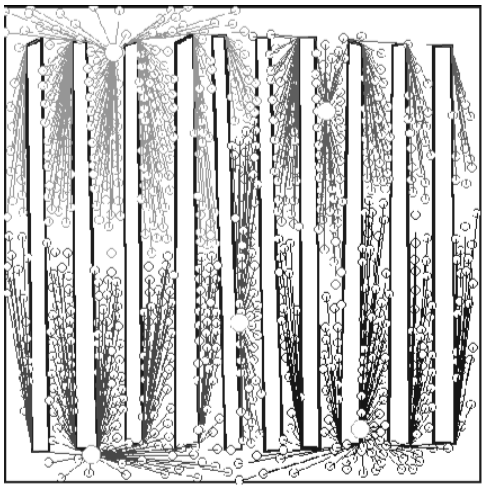
While the performance of COD-CLARANS is better than CLARANS for low value of k, this performance gap is found to decrease as we increase k. The reason behind this is that as k increases, most points will be directly visible to the nearest center. As such, the effect of the obstacles will diminish. We thus conclude that COD-CLARANS will be effective for value of k in which most point will not be directly visible from any of the k centers.

5 Future Work

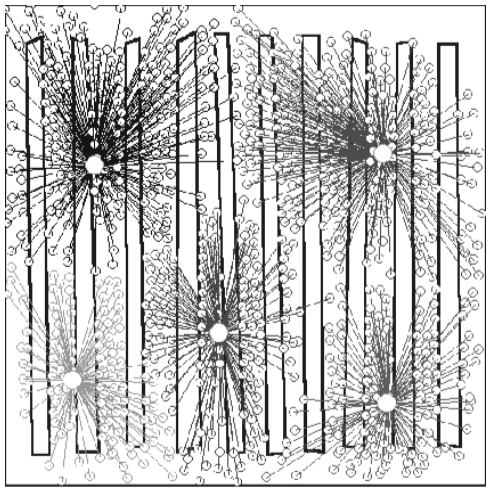
While the work presented here is sufficient for many applications of clustering with obstructed distance, there are still a lot of future work to be considered.

Although the model of discussion in this paper is in a two-dimensional region with obstacles represented as simple polygons, it can be generalized to other models as well. For example, consider clustering objects around a network structure. We can still perform micro-clustering although there is no requirement for other pre-processing information. To speed up the process, a spatial join index can still be materialized. A pruning function E' can also be used to prune the search space.

In our work, one implicit assumption is that the number of obstacles is smaller than the number of data points. This is true for many applications like ATM locations planning where we only need to take major obstacles into consideration. However, in cases where there are a lot of obstacles between any two data points,



(a) Result of COD-CLARANS.



(b) Result of CLARANS.

Figure 9. Clustering Result for DS2.

techniques like micro-clustering will not be applicable since a triangulation of the region will result in few or no points in each triangular region. Further study is required to handle such cases.

Besides this, a look at how obstacles will affect other clustering paradigms will be interesting as well. For example, it will be challenging to see how density-based algorithms like DBSCAN [EKSX96] can be enhanced to cluster under obstructed distance. Since DBSCAN makes uses of the k-nearest-neighbors operation to perform clustering, an immediate subproblem is to find the k nearest neighbors with consideration of obstacles. This subproblem is a challenge by itself as most

k-nearest-neighbors implementation are relying on spatial index structures like the R-tree to speed up the operation and no consideration of obstacles are taken in such a spatial data structure [BBKK97].

6 Conclusion

In this paper, we have studied on the problem of Clustering with Obstructed Distance (COD) which we believe is a very has many practical applications. We formalize the definition of this problem and derive an algorithm COD-CLARANS for solving it. We discuss various types of pre-processed information that could enhance the efficiency of COD-CLARANS . By pushing the handling of obstacles into the COD-CLARANS algorithm instead of abstracting it at the distance function level, we are able to provide a pruning function E' that greatly enhance the efficiency of COD-CLARANS . We perform various experiments on COD-CLARANS to ascertain its usefulness and scalability. Finally, we discuss some potential enhancements to the COD-CLARANS algorithm. We believe that there is still a lot of room for research in the problem of COD and hope that our work could motivate more people to look into this area.

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