

Clustering objects for spatial data mining: a comparative study

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Abstract

Spatial data mining (SDM) is searching important relationships and characteristics that can clearly exist in spatial databases. This content aims to compare object clustering algorithms for spatial data mining, before identifying the most efficient algorithm. To this end, this paper compare k-means, Partitioning Around Medoids (PAM) and Clustering Large Applications based on RANdomized Search (CLARANS) algorithms based on computing time. Experimental results indicate that, CLARANS is very efficient and effective.

Introduction

Spatial data mining is the discovery of interesting characteristics and patterns that may exist in large spatial databases. It can be used in many applications such as seismology, minefield detection and astronomy. Clustering, in spatial data mining, is a useful technique for grouping a set of objects into classes or clusters such that objects within a cluster have high similarity among each other, but are dissimilar to objects in other clusters. In the last few years , many effective and scalable clustering methods have been developed. These methods can be categorized into partitioning methods, hierarchal methods, density based methods, grid-based methods, model-based methods and constrained-based methods [1]. Spatial data mining aims to automate such a knowledge discovery process. Spatial data

mining has several objectives, it has an important role in:

- Drawing interesting spatial features and patterns
- Capturing the intrinsic relationships between spatial and non spatial data,
- Presenting data compilance concisely and at higher conceptual levels, and helping reorganized spatial databases to accommodate data semantics, as well as to achieve better good results.

Data analysis used cluster analysis, which generates a set of data elements into groups (or clusters) so in the same group the elements are similar to each other and

different from those in other groups [1,2,3]. Different clustering methods have been developed in several research areas such as statistics, pattern recognition, data mining, and spatial analysis.

Methods of clustering can be broadly classified into groups, there are two clustering groups: partitioning clustering and hierarchical clustering. The first group presents several methods, such as K-means and self-organizing map (SOM) [4], divide a set of elements to a given cluster number. The attribution of a data element is done according to a measure of proximity or dissimilarity. The second group, on the other hand, organizes data items into a hierarchy with a sequence of nested partitions or groupings [2]. Commonly-used hierarchical clustering methods include the Ward’s method [5], single-linkage clustering, average-linkage clustering, and complete-linkage clustering [1,2,6].

In this paper, we are working on a comparative analysis of k-mean, Partitioning Around Medoids (PAM) and Clustering Large Applications based on Randomized Search (CLARANS) algorithm and for that, we are using Flame and Spiral datasets.

The paper is organized as follows: section 2 introduces clustering Algorithms Based On Partitioning. Section 3 present the CLARANS algorithm. Experimental results are presented in section 4. Section 5 concludes the paper with a discussion on ongoing works.

Clustering Algorithms Based on Partitioning

There are two basic types of clustering algorithms [7], partitioning and hierarchical algorithms. In this part, we are interested in the first type which builds a partition dataset of objects n in a database D into clusters k. For this algorithm, k is an input parameter that is, some domain knowledge is required, which unfortunately is not Available for many applications. The partitioning algorithm starts with the initialization of D then uses an optimization strategy of the objective function by an iterative control.

K-means

The K-Means algorithm [8], is one of the simplest algorithms that address the well-known clustering problem. The procedure follows a simple method to classify a given dataset through a certain number of clusters k static a priori. The K-Means algorithm run multiple times to decrease the complexity of grouping data. The K-Means is a simple algorithm used in many areas and it is a noble candidate to work for a randomly generated data points. The assignment process repeated and updated until no point changes clusters, or equivalently, until the centroids remain the same.

K-means algorithm is as follows:

Algorithm: K-means

	Input
	n: total number of clusters
	D: Data set
	Output: n clusters.
a	for initial cluster center randomly choose n objects from data set D;
b	do;
c	based on the mean value of the objects in the cluster, (re) assign each similar object to the cluster;
d	update each cluster means by calculating the mean value of objects for each cluster;
e	until no change found;

Partitioning Around Medoids (PAM)

PAM is similar to K-means algorithm. Like k-means algorithm, PAM divides data sets into groups but based on medoids whereas k-means is based on centroids. By using medoids we can reduce the dissimilarity of objects within a cluster. In PAM, first calculate the medoid, then assign the object to the nearest medoid, which forms a cluster.

The basic idea of PAM algorithm is choosing an initial representative object (center) for each cluster at random. The remaining objects are assigned to the nearest cluster [9], according to its dissimilarity with the representative object. In order to improve the quality of clustering, it is necessary for the iterative process to replace the non-representative objects with the representative object repeatedly. Cost function is used to measure whether this non-representative object instead of the current representative object or not. If so, then replace; else, not replace. The correct classification is given.

In the remainder, we use:

- I_m : current medoid that is to be replaced,
- I_p : the new medoid to replace I_m ,
- I_j : other non-medoid objects that may or may not need to be moved
- $I_{j,2}$: current medoid that is nearest to I_j .

Now, to formalize the effect of a swap between I_m and I_p , PAM computes costs C_i for all non-medoid objects I_j .

Case 1. suppose I_j currently belongs to the cluster represented by I_m . Furthermore, let I_j be more similar to $I_{j,2}$ than to I_p , i.e., $d(I_j, I_p) \geq d(I_j, I_{j,2})$, where $I_{j,2}$ is the second most similar medoid to I_j . Thus, if I_m is replaced by I_p as a medoid, I_j would belong to the cluster represented by $I_{j,2}$. Hence, the cost of the swap as far as I_j is concerned is:

$$C_i = d(I_j, I_{j,2}) - d(I_j, I_m) \tag{1}$$

This equation always gives a nonnegative C_i , indicating that there is a nonnegative cost incurred in replacing I_m with I_p .

Case 2. I_j currently belongs to the cluster represented by I_m . But, this time, I_j is less similar to $I_{j,2}$ than to I_p , i.e., $d(I_j, I_p) < d(I_j, I_{j,2})$. Then, if I_m is replaced by I_p , I_j would belong to the cluster represented by I_p . Thus, the cost for I_j is given by:

$$C_i = d(I_j, I_p) - d(I_j, I_m) \tag{2}$$

Unlike in (1), C_i here can be positive or negative, depending on whether I_j is more similar to I_m or to I_p .

Case 3. suppose that I_j currently belongs to a cluster other than the one represented by I_m . Let $I_{j,2}$ be the representative object of that cluster. Furthermore, let I_j be more similar to $I_{j,2}$ than to I_p . Then, even if I_m is replaced by I_p , I_j would stay in the cluster represented by $I_{j,2}$. Thus, the cost is:

$$C_i = 0 \tag{3}$$

Case 4. I_j currently belongs to the cluster represented by $I_{j,2}$. But, I_j is less similar to $I_{j,2}$ than to I_p .

Then, replacing I_m with I_p would cause I_j to jump to the cluster of I_p from that of $I_j, 2$. Thus, the cost is:

$$C_i = \underline{d(I_j, I_p)} - d(I_j, I_j, 2) \tag{4}$$

and is always negative. Combining the four cases above, the total cost of replacing I_m with I_p is given by:

$$DCmp = \sum C_i \tag{5}$$

We now present PAM algorithm

Algorithm PAM

1	Select k representative objects arbitrarily.
2	Compute $DCmp$ for all pairs of objects I_m, I_p where I_m is currently selected, and I_p is not.
3	Select the pair I_m, I_p which corresponds to $\min(I_m, I_p) DCmp$. If the minimum $DCmp$ is negative, replace I_m with I_p , and go back to step 2.
4	Otherwise, for each nonselected object, find the most similar representative object. Halt

The experimental study show that PAM is efficient for small data sets, (e.g., 100 objects in 5 clusters) but isnot sufficient to process medium and large data sets. For this reason a complexity analysis on PAM is necessary. This analysis motivates the development of CLARANS.

Clustering algorithms based on randomized search

In this section we will show our clustering algorithm CLARANS. Compared to the revealed clustering methods, CLARANS is very effective and efficient (experimental results). CLARANS is a variant of PAM [10,11,12], that uses the same neighbourhood operation but takes the form of a stochastic first-found hill climber. In each iteration, a medoid object, i , and non-medoid object, j , are selected at random until the clustering produced when their rules are switched is better than the current clustering. The algorithm begins with a random choice of k -medoids, and no construction phase is required. Basing on the study [10] two parameters are used in this algorithm, *numlocal* and *maxneighbour*. *numlocal* indicates how many runs of the local search algorithm are performed. At the end of each run, the algorithm restarts at a randomly selected solution. The second parameter, *maxneighbour*, indicates the maximum number of neighbours the algorithm examines at each step.

Algorithm CLARANS

1. Enter *numlocal* and *maxneighbor* as input parameters. Initialize i to 1, and *mincost* to a large number
2. Set *current* to an arbitrary node in G_n, k .
3. Set j to 1.
4. Random neighbor S of the *current*, and based on equation 5, calculate the cost differential of the two nodes. If S has a lower cost, set *current* to S , and go to step 3.

5. Otherwise, increment j by 1. If $j > \text{maxneighbor}$, go to step 4.

6. Otherwise, when $j > \text{maxneighbor}$, compare the results if the first is lower than mincost , apply mincost on the cost of the current and apply bestnode on current

7. Increment i by 1. If $i > \text{numlocal}$, output bestnode and halt. Otherwise, go to step 2.

Experimental results

In order to evaluate CLARANS in practice, we compare its performance with that of different k -medoids clustering techniques, using the dataset. The three algorithms were implemented using Python programming language on PC, Intel Core i5 CPU (2.40 GHz) with 8GB RAM, Windows 10.

Results of K-means

We start by implementing the k -means algorithm based on data distribution models using this algorithm, we want to distribute the data to a precise number of clusters. To achieve this task, we have chosen a dataset (of 240 data). In figure 1 we choose the dataset and the number of cluster $k = 3$. We get the execution result after four iterations as shown in Figure 2. Figure 3 illustrates the performance measure of K -means while figure 4 shows the distribution of clusters.

Results of PAM

For the PAM algorithm, we use the same dataset from the previous part of k -means (240 data). Figure 5 illustrates the data initialisation of using PAM. To start the algorithm, we have fixed a number of clusters $k = 3$. In this program we have proposed a TCMP coefficient that can be calculated at each iteration, if TCMP is negative we continue the iterations. The iteration stop in the first positive TCMP value and note the medoid values in order to determine the clusters (Figure 6 & Figure 7). Performance measure is given in Figure 8, and the distribution of clusters is illustrated in figure 9.

Result of CLARANS

The CLARANS algorithm consists in finding the most representative objects in each of the clusters for which these objects cost (for example, the sum of the distance to others belonging to the same cluster) is minimal. These objects are called medoids. After selecting the medoids, each of the grouped objects goes to the cluster whose representative is the medoid closest to that object. CLARANS is based on a random search for medoid candidates, a cost calculation and a comparison with the current best local solution.

This action is repeated until the number of randomly selected objects with a cost greater than the current one the lowest local cost will not exceed 'neighbors'. Then the cost of the best local solution is compared to the best global solution achieved to date and if it is smaller then local solution becomes global. Whether the local solution has become global or not, the counter is incremented by 1, and the algorithm is run again until the number of such passes reaches 'local minimum' values. Then, the current best overall solution is returned to run this algorithm :

- Number of clusters in the data is 3
- Number of objects (points / polygons) to generate, the value is 240.
- Number of clusters / medoids to search, the default is the value of the numlocal parameter, the value is 3.
- Maximal number of neighbors in cluster 15

```

SELECT DATASET
1. Flame, 240 data
2. Spiral, 312 data

input options: 1

DATASET FLAME

Input K: 3

METHODE CLUSTERING
1. K-MEANS
2. PAM

input options: 1

K-MEANS CLUSTERING
-----
>> CENTROID INITIAL:
Centroid 1: [ 7.7 20.05]
Centroid 2: [ 7.9 21.6]
Centroid 3: [ 6.7 21.3]
    
```

Figure 1. Data initialization

```

ITERATION 4
-----
>> CENTROID NOW:
Centroid 1: [ 7.87222222 17.49611111]
Centroid 2: [ 9.46333333 23.6683908 ]
Centroid 3: [ 3.55793651 22.0484127 ]

>> CLUSTER NOW
Cluster Document Numbers1:
47 38 39 40 41 42 43 44 45 46
57 48 49 50 51 52 53 54 55 56
67 58 59 60 61 62 63 64 65 66
77 68 69 70 71 72 73 74 75 76
87 78 79 80 81 82 83 84 85 86
97 88 89 90 91 92 93 94 95 96
107 98 99 100 101 102 103 104 105 106
117 108 109 110 111 112 113 114 115 116
158 118 119 120 121 | 150 151 152 153 156
- - - - -

Cluster Document Numbers2:
131 122 123 124 125 126 127 128 129 130
141 132 133 134 135 136 137 138 139 140
159 142 143 144 145 146 147 148 149 157
177 160 161 162 166 172 173 174 175 176
193 178 179 180 187 188 189 190 191 192
208 194 200 201 202 203 204 205 206 207
218 209 210 211 212 213 214 215 216 217
233 219 220 221 222 228 229 230 231 232
- 234 235 236 237 238 239 240 - -

Cluster Document Numbers3:
10 1 2 3 4 5 6 7 8 9
20 11 12 13 14 15 16 17 18 19
30 21 22 23 24 25 26 27 28 29
163 31 32 33 34 35 36 37 154 155
183 164 165 167 168 169 170 171 181 182
224 184 185 186 195 196 197 198 199 223
- 225 226 227 - - - - -
    
```

Figure 2. Result execution

```

Previous Cluster = Current Cluster, Program Stopped
DAVIES BOULDIN INDEX: 0.9103101538064692
SILHOUETTE SCORE : 0.36809144584002623
RUNTIME : 0.5003621578216553 second
    
```

Figure 3. Performance measures

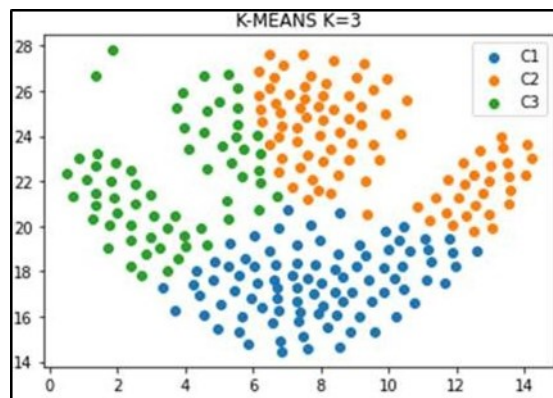


Figure 4. Plot of k-means algorithm

```

SELECT DATASET
1. Flame, 240 data
2. Spiral, 312 data

Input options: 1

DATASET FLAME

Input K: 3

METHODE CLUSTERING
1. K-MEANS
2. PAM

Input options: 2

PAM CLUSTERING
-----
>> INITIAL MEDOID
Medoid 1: 151
Medoid 2: 160
Medoid 3: 162
    
```

Figure 5. Data initialization(PAM)

```

ITERATION 4
-----
>> MIN TCMP: -3.491113430007843
Since MIN TCmp is Negative, Continue to Next Iteration \ n
>> MEDOID NOW
Medoid 1: 109
Medoid 2: 220
Medoid 3: 34

ITERATION 5
-----
>> MIN TCMP: 0.6046744490736465
Because MIN TCmp is positive, the program stops
    
```

Figure 6. Iteration medoids

Cluster Document Numbers1:										
79	64	65	66	67	69	71	73	75	77	
89	80	81	82	83	84	85	86	87	88	
99	90	91	92	93	94	95	96	97	98	
109	100	101	102	103	104	105	106	107	108	
119	110	111	112	113	114	115	116	117	118	
129	120	121	122	123	124	125	126	127	128	
139	130	131	132	133	134	135	136	137	138	
149	140	141	142	143	144	145	146	147	148	
159	150	151	152	157	158	159	160	175	-	
Cluster Document Numbers2:										
169	1	2	161	162	163	165	166	167	168	
180	170	171	172	173	174	176	177	178	179	
190	181	182	183	184	185	186	187	188	189	
200	191	192	193	194	195	196	197	198	199	
210	201	202	203	204	205	206	207	208	209	
220	211	212	213	214	215	216	217	218	219	
230	221	222	223	224	225	226	227	228	229	
240	231	232	233	234	235	236	237	238	239	
	-	-	-	-	-	-	-	-	-	
Cluster Document Numbers3:										
	3	4	5	6	7	8	9	10	11	12
	13	14	15	16	17	18	19	20	21	22
	23	24	25	26	27	28	29	30	31	32
	33	34	35	36	37	38	39	40	41	42
	43	44	45	46	47	48	49	50	51	52
	53	54	55	56	57	58	59	60	61	62
	63	68	70	72	74	76	78	153	154	155
	156	164	-	-	-	-	-	-	-	-

Figure 7. Number of cluster

```

DAVIES BOULDIN INDEX: 0.8465921532603109
SILHOUETTE SCORE : 0.40505082830054445
RUNTIME : 13.82312273979187 second
    
```

Figure 8. Performance measure

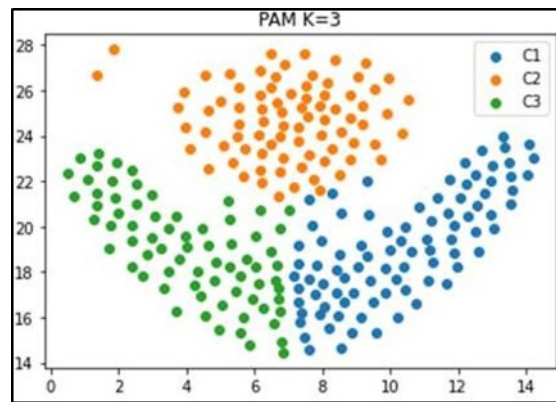


Figure 9. Plot of PAM algorithm

Points in two-dimensional space with x and y coordinates implemented as a class with x and y attributes were adopted as a data model. The second spatial data model used for analysis are polygons also defined in two-dimensional space, implemented as a class with the vertices attribute being a list containing the point objects belonging to the polygon.

The cost has been implemented:

- for points as the sum of the distances between all the points in the individual clusters and the medoids in these clusters.
- for polygons, as the sum of the smallest distance between the vertices of all polygons in the individual groups and the medoid polygons in these groups.

Figure 10 and Figure 11 shows the result obtained by CLARANS algorithm.

Runtime

Execution time has been measured by the required time for forming clusters by the clustering algorithms k-means, PAM and CLARANS. Time required for each algorithm has been recorded and results have been drawn. Computing time (in seconds) are shown in table 1 and table 2. For this work we choose two spatial datasets (312 data) and flame (240 data). A graphical representation of results has been created in Figure 12 and Figure 13, which is a chart used for comparison with clustering algorithms.

Comparing computing time of the clustering algorithms shows that the CLARANS algorithm takes less time than others, that means this work indicates CLARANS performance is better than others according to time chart.

All the proposed algorithms has been implemented using programming language python. From the experimental results, the graphical representation shows that CLARANS has a low execution time value compared to other algorithms for ($k = 3$ [0.21; 0.36]), ($k = 10$ [0.60; 0.68]) even if we have to change the value of k, and also the size of dataset but PAM has a longer execution time.

- for the execution time of Kmeans has an intermediate value between the two algorithms.
- the number of k clusters has an influence on the execution time.
- the size of dataset has an effect on the variation of the execution time. Clarans is the best clustering algorithm compared to PAM and K-MEANS.


```

80% |██████████| 4/5 [00:00<00:00, 29.20it/s]
New minimum cost: 54425.96110199471

New minimum cost: 47485.10849150339
100% |██████████| 5/5 [00:00<00:00, 17.73it/s]

Algorithm execution time: --- 0.2800159454345703 seconds ---
Minimum cost: 47485.10849150339

Success!
Medoids found:
Point: X=1740 Y=1403
Point: X=836 Y=1607
Point: X=1324 Y=1932
    
```

Figure 10. Execution result

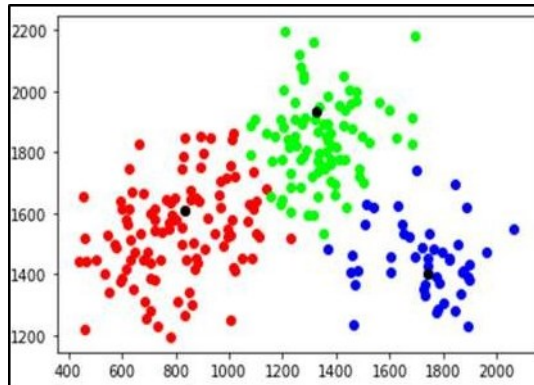


Figure 11. Plot of CLARANS algorithm

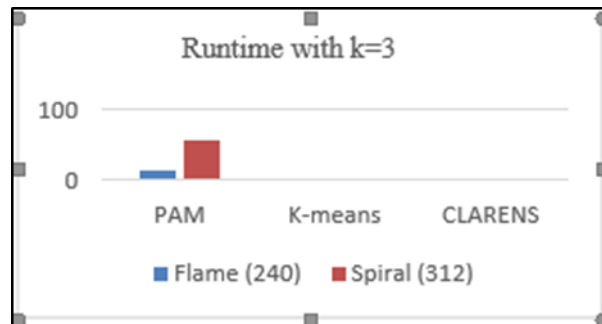


Figure 12. Time chart of k-means, PAM and CLARANS algorithms to form three clusters of different dataset.

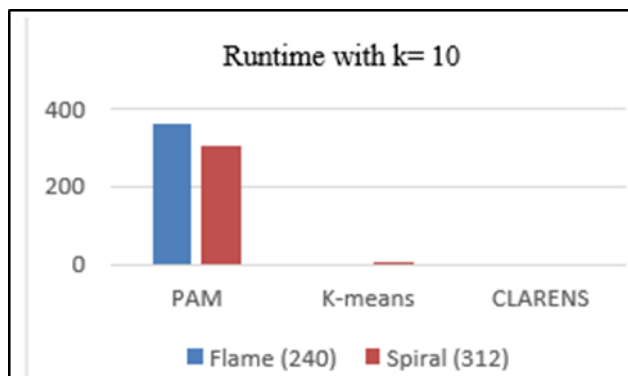


Figure 13. Time chart of k-means, PAM and CLARANS algorithms to form ten clusters of different dataset.

Table 1. Time referency (k=3)

Dataset	PAM	Kmeans	CLARANS
Flame (240)	13.8	0.5	0.21
Spiral (312)	56.4	1.69	0.36

Table 2. Time referency (k=10)

Dataset	PAM	Kmeans	CLARANS
Flame (240)	363.63	3.34	0.6
Spiral (312)	304.53	6.11	0.68

Conclusion

Clustering is an unsupervised method aimed at grouping and creating a collection of similar objects within the same group . . This work is about algorithms of clustering and their effectiveness for spatial data mining. The experimental result indicates that CLARANS algorithm reduces the execution time and gives better clusters when compared with other algorithms. But it's not always the case. CLARANS doesn't give better cluster. So future research work will be first focused on developing an algorithm, which will increase the performance of segmentation process. Further work also lies in this area. A result line can be drawn from this experimental work and is it is that CLARANS algorithm has better efficiency than PAM and K-MEANS algorithm.

References

1. Ch.N.Santhosh Kumar et al, Spatial Data Mining using Cluster Analysis, *International Journal of Computer Science & Information Technology (IJCSIT)* Vol 4, No 4, August 2012
2. Alper Aksac, Tansel Ozyer and Reda Alhaji, Data on cut-edge for spatial clustering based on proximity graphs, *Elsevier Data in brief* 28 (2020).
3. Yaohui Liu, Dong Liu, Fang Yu and Zhengming Ma, A Double-Density Clustering Method Based on "Nearest to Firstin" Strategy, *Symmetry* 2020, 12, 747; doi:10.3390/sym12050747.
4. Kohonen, T. (2001). Self-organizing maps. Berlin; New York: Springer.
5. Mark J. Embrechts, Christopher J. Gatti, Jonathan Linton, and Badrinath Roysam, Hierarchical Clustering for Large DataSets, in book: *Advances in Intelligent Signal Processing and Data Mining*, 2013
6. Ward, J. H. (1963). Hierarchical grouping to optimise an objective function. *Journal of the American Statistic Association*, 58, 236–244
7. Han, J., & Kamber, M. (2001). Data mining: Concepts and techniques. *Morgan Kaufmann Publishers*.

8. Youssef Fakir, Jihane Elklil, Clustering Techniques for Big Data Mining, Lecture Notes in Business Information Processing book series (LNBIP, volume 416), 2021
9. MacQueen, J. B.: Some methods for classification and analysis of multivariate observations, in *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, Vol. 1, 1967, pp. 281–297.
10. Reynolds, A. P., Richards, G. and Rayward-Smith, V. J.: The application of K-medoids and PAM to the clustering of rules, in Z. R. Yang, H. Yin, and R. Everson (eds.), in *Proceedings of the Fifth International Conference on Intelligent Data Engineering and Automated Learning (IDEAL '04)*, 2004, pp. 173–178.
11. Ng, R. T. and Han, J.: CLARANS: A method for clustering objects for spatial data mining, *IEEE Trans. Knowl. Data Eng.* 14(5) (2002), 1003–1016.
12. Raymond T. Ng and Jiawei Han, CLARANS: A Method for Clustering Objects for Spatial Data Mining, *IEEE transactions on knowledge and data engineering*, vol. 14, no. 5, september/october 2002