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PSO-BASED DBSCAN WITH OBSTACLE CONSTRAINTS

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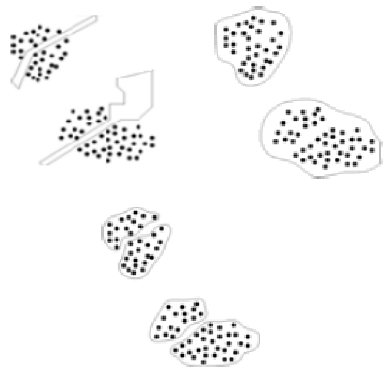
ABSTRACT

This paper presents a new PSO-based optimization DBSCAN space clustering algorithm with obstacle constraints. The algorithm introduces obstacle model and simplifies two-dimensional coordinates of the cluster object coding to one-dimensional, then uses the PSO algorithm to obtain the shortest path and minimum obstacle distance. At the last stage, this paper fulfills spatial clustering based on obstacle distance. Theoretical analysis and experimental results show that the algorithm can get high-quality clustering result of space constraints with more reasonable and accurate quality.

Keywords: *Space Clustering, Obstacle Constraints , Particle Swarm Optimization Algorithm, DBSCAN*

1. INTRODUCTION

Spatial clustering has been an important data mining field of research. At present, the current clustering methods are dividing methods, hierarchical methods, density-based methods, grid-based methods, genetic algorithm, fuzzy method, rough set, and some clustering algorithms also integrate with a variety of methods. However, these clustering algorithms ignore the existence of many constraints in the real world, and constraints will affect reasonability of clustering results, such as rivers, roads, etc., as shown in Figure 1. Due to the obstacle, the two spatial points close to each other may not belong to the same cluster. In previous work, only a few algorithms in the clustering process considered the impact of the obstacles. However, there are many shortcomings in the aspect of efficiency and quality. Therefore, in order to improve the practicality of clustering, it is not only very important to study the space clustering in constraint environment but also practical in the real world environment.



(A)The Distribution Of Points And Obstacles (B) Clustering Regardless Of Obstacles (C) Clustering According To Obstacles

Figure 1: Space Clustering With Obstacle Constraints

To solve the above problem, this paper proposes a new spatial clustering algorithm with obstacles constraints (PSODBSCAN). This method integrates PSO (Particle swarm optimization) global optimization ability with local search features of DBSCAN algorithm, and uses particle swarm to optimize the shortest obstacle distance iteratively, not only taking into account of shortcomings of DBSCAN clustering algorithm, but also taking full account of the real obstacles, thus makes the results of clustering more meaningful.

2. DBSCAN CLUSTERING WITH OBSTACLE CONSTRAINTS

2.1 Classic DBSCAN Clustering Algorithm

DBSCAN algorithm is a density-based clustering method with high-quality, and applicable to geometry clustering of any shape and size, which can automatically determine the number of clusters, and separate clusters with environmental noise effectively. At first we need to introduce the related concepts of DBSCAN algorithm:

Definition 1: (Core Point) Point has at least $MinPts$ objects in Eps neighborhood.

Definition 2: (Boundary Point) Point in the core object's Eps neighborhood, but not meets the requirements of core object.

Definition 3: (Directly Density-reachable) A point p is directly density-reachable from a point q if

$$p \in NEps(q) \text{and} \quad (1)$$

$$| NEps(q)| \geq MinPts \quad (2)$$

Definition 4: (Density-reachable) A point p is density-reachable from a point q if there is a chain of points $P_1 P_2, \ldots, P_n$, $P_1 = Q$, $P_n = P$ such that p_{i+1} is directly density-reachable from p_i.

DBSCAN algorithm efficiency depends on neighbor query and requires inspect each point in data set by checking the neighborhood of each point to find cluster. If a point is a core point, then DBSCAN creates a cluster centered by this point and find directly density-reachable points. The algorithm's time complexity is $O(n^2)$, where n is the number of points in data sets. If using spatial index, DBSCAN algorithm's time complexity is $O(n \log n)$.

2.2 Improved DBSCAN Clustering Algorithm With Obstacle Constraints

When traditional DBSCAN algorithm measures the distance of point P and point Q, it uses the Euclidean distance to calculate straight-line distance between two points, which will be unreasonable in the case of obstacles. The existing of obstacles usually makes point P and point Q not visible to each other, that is the connection line of point P and point Q could intersect with obstacles. This paper uses particle swarm algorithm to optimize the obstacles path, and defines the minimum obstacle distance between point P and point Q is the shortest path value of point P and point Q bypass all the obstacles.

Meanwhile, due to the shortcoming of difficulty in discovering clusters with large density difference, this paper uses partition-based DBSCAN clustering method, that is to cluster based on the spatial density distribution of points. Thus, when facing the problem of uneven distribution of data density and cluster density, it will select a smaller value which results in a more dilute Eps cluster divided into multiple similar clusters, and at the same time selecting a larger Eps value will not ignore the differences of larger density.

3. PSO-BASED DBSCAN ALGORITHM WITH OBSTACLE CONSTRAINTS

3.1 Particle Swarm Optimization Algorithm

PSO (Particle swarm optimization) is an evolutionary computation technique, and firstly introduced by Kennedy and Eberhart in 1995. Similar to genetic algorithm, the study of birds prey behavior is an iteration-based optimization tool. In the PSO algorithm, each optimization problem solution is a bird in the search space, and is abstracted as particles in the N-dimensional space. Particle i in the position of N-dimensional space represents a vector, and the flight speed of each particle is also a vector. Currently, PSO algorithm has been widely used in function optimization, neural network training, fuzzy system control and other applications of genetic algorithms.

PSO initializes to be a group of random particles (random solutions), and then finds the optimal solution iteratively. Assuming in d-dimensional search space the position and velocity of i particle is $X^i = (x_{i,1}\ x_{i,2} \cdots x_{i,d})$ and $V^i = (v_{i,1}\ v_{i,2} \cdots v_{i,d})$ respectively, and during each iteration, particles update themselves by tracking the two "extreme value". One extreme is the best particle solution of itself, which is the individual extreme $pbest$, and the other extreme is the optimal solution of the current group, which is the global minimum $gbest$. When PSO finds out these two optimal values, each particle updates its own pace and the new location according to the following formula:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1 r_1 [p_{i,j} - x_{i,j}(t)] + c_2 r_2 [p_{g,j} - x_{i,j}(t)] \quad (3)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), j = 1, 2, \cdots, d \quad (4)$$

In the formula c_1 and c_2 are positive learning factors, generally being equal to 2, at the same time r_1 and r_2 are uniformly distributed random numbers between 0 and 1. This paper uses random weight factor method, setting w to a random number with random distribution, which can overcome the shortcomings caused by the linear decrease, that is:

$$\begin{cases} w = \mu + \sigma * N(0,1) \\ \mu = \mu\min + (\mu\max - \mu\min) * rand(0,1) \end{cases} \quad (5)$$

In the above formula, $N(0,1)$ is standard random number with normal distribution, and $rand(0,1)$ is random number between 0 and 1. $\mu\max$ is the maximum value of random weighted w's average value. σ is the variance of w's random weight, setting to be

$\mu\max = 0.8$, $\mu\min = 0.5$ and $\sigma = 0.2$.

3.2 Obstacle path optimization based on PSO

Obstacles will inevitably affect the spatial distance between objects, which directly affects the clustering results. When it comes to obstacles, the main solution methods are: view method, grid method, neural networks, artificial potential field, etc. However, these methods all have the defects of search path complexity and inefficiency. This paper combined the theory of mobile robot obstacle avoidance path planning in the dynamic process with particle swarm optimization algorithm to calculate the obstacle distance in the clustering process, which achieved good results and high performance.

Assume S and G are the two objects within many obstacles in the clustering process. The mission for particle swarm optimization is to search a shortest collision-free path between S and G, and the value of this path is the shortest obstacle distance between S and G, the objective function of which is shown as below:

$$F = \sum_{i=2}^{n_p} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \quad (6)$$

To accelerate the calculation speed, we firstly connect point S and G to be a line SG, and divide it into n equal portions. Make vertical line of SG in each divide point, then get

$$L_1, L_2, \ldots, \text{and} Ln.$$

Secondly starting from point S, we connect each discrete points in all vertical lines, then get a set of discrete obstacle points $\text{Obstacle\_path} = (S, P_1, P_2, ..., Pn, G)$, where $P_j(j = 1, 2, ..., n)$ is non-obstacle point and the line of P_j and its adjacent points has no obstacle point. At last, we set SG as X-axis, and set the line through S but perpendicular to X-axis as Y-axis, then create a new coordinate system X'OY', which will conduct coordinate transformation to deal with all discrete points (x, y) in each vertical line.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x - x_s \\ y - y_s \end{bmatrix} \quad (7)$$

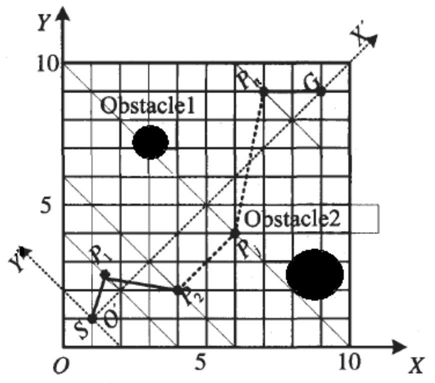


Figure 2: Coordinate Transformation Model

In the above formula, α is the angle value of counterclockwise rotation of original X-axis to line SG, and (x_1, y_1) is starting point S's coordinate in original coordinate system. In the coordinate system X'OY', we define S as the P_0, G as P_{n+1}, then simplify $Obstacle\_path$ encoding to be:

$$Obstacle\_path = [0 \ y_1' \ y_2' \ldots \ y_n' \ 0] \quad (8)$$

For writing convenience, if no special instructions, we use y instead of y'. Obstacles distance *Obstacle_dist* is:

$$Obstacle\_dist = \sum_{j=0}^{n} \sqrt{(\frac{L_{SG}}{n+1})^2 + (y_{j+1} - y_j)^2} \quad (9)$$

In the above formula, L_{SG} is the length of line SG.

The search steps of minimum obstacle distance calculation based on PSO are shown as follows:

We select the obstacle distance of starting point S to G as fitness value. The smaller the fitness value, the more optimal solution obtained. Fitness function is shown below:

$$F_i(y) = \sum_{j=0}^{n} \sqrt{(\frac{L_{SG}}{n+1})^2 + (y_{j+1}^i - y_j^i)^2} \quad (10)$$

In the above formula, y_j^i presents the $j(j=1,2,...,n)$ -dimensional position of particle $i(i=1,2,...,N)$; both ends of the constraints $y_0^i = y_{n+1}^i = 0$.

In this paper, we use circles to represent obstacles. In the process of particle swarm initialization and optimization, we not only have to consider the boundary constraints, but also dynamic obstacle avoidance, so we must verify whether the distance between particles location in each dimension and the center of the obstacle circle is greater than the radius of distance circle. The distance between particles location and the center of the obstacle $dist_{s\_ob}$ is:

$$dist_{s\_ob} = \sqrt{(x_k - \frac{L_{SG}}{n+1} * j)^2 + (y_k - y_j^i)^2} \quad (11)$$

In the above formula, (x_k, y_k) denotes the coordinate of k center of obstacle circle, and y_j^i denotes $j(j=1,2,...,n)$ -dimensional position of particles $i(i=1,2,...,N)$.

In addition, we need to consider whether the line of each particle's adjacent two-dimensional coordinates intersects with obstacles. The distance between the center of obstacle circle and particle's adjacent two-dimensional coordinates $dist_{ss\_ob}$ is:

$$dist_{ss\_ob} = \frac{|Ax_k + By_k + C|}{\sqrt{A^2 + B^2}} \quad (12)$$

In the above formula, (x_k, y_k) denotes k coordinates of the center of obstacle circle, and A, B, C are determined by the lines of each particle's adjacent two-dimensional coordinates as follows:

$$\begin{cases} A * \frac{L_{SG}}{n+1} * j + By_j^i + C = 0 \\ A * \frac{L_{SG}}{n+1} * (j+1) + By_{j+1}^i + C = 0 \end{cases} \quad (13)$$

In the above formula, y_j^i denotes the $j(j=1,2,...,n)$ -dimensional position of particle $i(i=1,2,...,N)$.

Obstacle path optimization based on PSO steps are shown as below:

Step 1 Initialize particle dimension n , particle number N . Randomly initialize the position and velocity of each particle. In initialization process of $y_{i,j}^0$, not only consider boundary constraints, but also consider dynamic obstacle avoidance, which uses formula (11) and (12) to judge obstacle avoidance.

Step 2 Calculate the fitness of each particle by fitness function (10), store particle's current position and fitness value in *pbest*, store in the position of best individual position and fitness value of each *pbest* in *gbest*;

Step 3 Update particle velocity by formula(3).

Step 4 Update particle position by formula (4), and consider boundary constraints and dynamic obstacle avoidance.

Step 5 Update weights by formula (5).

Step 6 As for each particle, and compare its fitness value with its best position *pbest*, if better, then set it current best position.

Step 7 Compare all current *pbest* and *gbest* value, and update *gbest*.

Step 8 Return to step 3, 4 and 5 to iterate until the algorithm reaches the maximum number of iterations or meets the accuracy requirements then when search stops to obtain the shortest path $Obstacle\_path_{best}$ and minimum obstacle distance $Obstacle\_dist_{best}$.

3.3 PSODBSCAN Algorithm with Obstacle Constraints

PSODBSCAN algorithm based on particle swarm optimization with obstacle constraints not only overcomes the shortcoming of classic DBSCAN algorithm, but also can realize dynamic obstacle avoidance which can calculate obstacle distance efficiently. The pseudo code of the PSODBSCAN algorithm is shown as below:

```
Input: SetObject, Eps, MinPts
Output: Clutering result
Algorithm:
PSODBSCAN(SetObject，Eps，MinPts)
{
 ObstaclePrint;
For(i=1；i<=SetObject.size；i++)
{Object=SetObjeet．get(i)；
IF(Object．ID= =UNCLASSFIED)
{Seed=AcquireNeighbor(SetObject，Object，Eps)
；
IF(! IsCoreObject(Object，MinPts，Seed))
ChangeID(Object，NOISE);
ELSE
Cluster(SetObject，Object，Eps，MinPts，Seed)
;
}
}
PrintClusteringResult;
}
```

Function ObstaclePrint draws obstacles in the coordinate system, and function AcquireNeighbor (SetObject, Object, Eps) returns all the neighboring objects of Object within Eps, and function IsCoreObject (Object, MinPts, Seed) determines whether Object is a core object, and function Cluster (SetObjeet, Objeet , Eps, Minpts, Seed) returns a set of connected density points. Mealwhile function AcquireNeighbor (SetObject, Object, Eps) needs invoke particle swarm optimization algorithm to determine the minimum obstacle distance, and its pseudo-code is shown as follows:

```
Input: SetObject, Eps, MinPts
Output: all the neighboring objects of Object
within Eps
Algorithm:
Seed=AcquireNeighbor(SetObject，Object，Eps)
{
For(j=1;j<=DensitySet(Object).size;j++)
  {CheckObject=DensitySet.get(i)
   ChangeXOY(CheckObject,Object)
   Obstacle_distbest= PSO(fitness,N,c1,c2,w,M,D)
   IF(Obstacle_distbest<=Eps)
     Seed.add(CheckObject)
  }
}
```

Function DensitySet(Object) returns all the neighboring objects of Object within Eps, and ChangeXOY(CheckObject,Object) transforms coordinates of CheckObject and Object according to formula (5), that is the point S and G denote CheckObject and Object in the coordinate. When PSO optimization function PSO(fitness,N,c1,c2,w,M,D) initializes and updates particle position, it needs to verify whether the current position is inside the obstacle or not. Its pseudo-code is shown as follows:

```
Input: Particle Location，Particle Dimension
Index，Obstacle Circle X coordinate CircleX，
Obstacle Circle Y coordinate CircleY，Obstacle
Circle Radius
Output: 0 or 1
Algorithm:
Ob=CheckObstacle(Location,Index,CircleX,Circle
Y,Radius)
{
For(k=1;k<=CircleX.size;k++)
{Dist1= AcquireDist1(CircleX.get(k),
CircleY.get(k), Radius.get(k),Location,Index);
 Dist2= AcquireDist2(CircleX.get(k),
CircleY.get(k), Radius.get(k),Location,Index);
 IF(Dist1<Radius.get(k)| Dist2<Radius.get(k))
   {Ob=1;
    break;
   }
 ELSE
   Ob=0;
}
}
```

Function AcquireDist1(CircleX.get(k), CircleY.get(k), Radius.get(k), Location,Index) calculates the distance between the current position and the center of obstacle circle, that is dists_ob, and function AcquireDist2(CircleX.get(k), CircleY.get(k), Radius.get(k),Location,Index) calculates the distance between the center of obstacle circle and the value of adjacent two position line, that is distss_ob. If either Dist1 or Dist2 exceeds the radius value of obstacle circle, then we set Ob equal to be 1 and break a loop and re-allocate position.

4. EXPERIMENTS

Experiment1 Assumed that work space is 100 * 100, and obstacles are circles of different size. After the coordinate transformation, S(0,50) becomes the starting point and G(100,50) becomes the target point. Let's divide line SG into 20 equal portions, so we have 19 particle swarm dimensions and 40 particles. Let's make learning factor C1 and C2 equal to 2 and the maximum number of iterations 1000. Now we repeat experiment many times, and we can see Figure 3 shows two experiments results of the optimum collision-free paths, which have the shortest obstacle distances 103.9572 and 108.4472 respectively; Figure 4 shows the curves of two tests' global optimal fitness Pbest calculated by the fitness function, changing with the iteration times. We can see from Figure 4 that algorithm convergence speed is very fast at the first stage, and it achieves before reaching the maximum number of iterations. Table 1 shows each dimension of the vertical coordinates of all the shortest paths obtained by random weight PSO algorithm, where the 0-dimensional and 20-dimensional both have vertical coordinate value of 50.

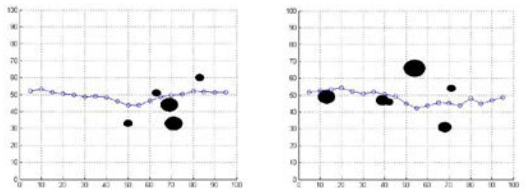


Figure 3:The Shortest Obstacle Paths Obtained In Two Experiments

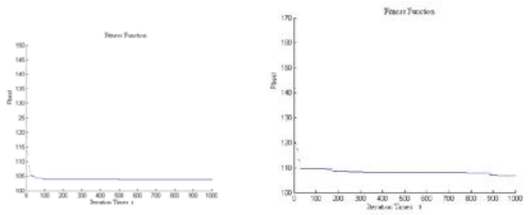


Figure 4: The Relation Curves Of Global Optimum Fitness And Iteration Times In Two Experiments

Table 1. Each Dimension Of The Vertical Coordinates Of Shortest Paths In Two Experiments

NO.	1	2	3	4
Experiment1	52.1932	53.0893	51.4093	50.3336
Experiment2	51.5499	52.4902	53.2507	54.2206
NO.	5	6	7	5
Experiment1	49.7808	48.6230	49.0342	48.3477
Experiment2	52.1577	50.8536	51.7714	50.4668
NO.	9	10	11	12
Experiment1	46.0816	43.6644	43.6157	46.2131
Experiment2	49.3712	44.9194	42.1973	43.6519
NO.	13	14	15	16
Experiment1	48.6356	49.4453	50.2560	51.8427
Experiment2	45.5313	45.2874	43.6198	48.2376
NO.	17	18	19	20
Experiment1	51.5004	51.4360	51.3508	50
Experiment2	44.7523	46.7864	48.6647	50

Table 2 shows two experimental results of view method, traditional PSO algorithm and PSO algorithm with random weights, from which we can see that the optimum values of these three algorithms are obtained in two different environments, with average obstacle distance obtained from two experiments to be average value.

Table 2. Results Comparison Of Three Algorithms

	View Method	Traditional PSO Method		PSO Method with Random Weight	
	Calculated Value	Optimum Value	Average Value	Optimum Value	Average Value
Experiment 1	103.9286	104.2538	105.1547	103.9572	104.4587
Experiment 2	108.3785	109.1532	109.9726	108.4472	108.8359

The experimental results show that PSO algorithm with random weight has better performance than traditional PSO algorithm with higher path searching capability and closer value calculated by view method. In both experiments, the optimum values calculated PSO algorithm have minimum gap, and PSO algorithm with random weight and traditional PSO algorithm are superior to view method in time efficiency. In order to verify whether the experiments have general results, we create many obstacle path problems randomly, and use the same parameters with above three algorithms, similar results obtained.

Experiment2 We analyze the clustering of 100 sample objects with no obstacle constraint and many obstacle constraints respectively, and select sample objects including obstacle circles. Figure 5(a) shows the results of PSODBSCAN clustering algorithm. We can see that object points in the same cluster are marked as same color, and object points in the different clusters are marked as different colors, with noise objects marked as dark blue color and ID number equal to -1. Figure 5 (a) shows spatial clustering algorithm result with no obstacle, and Figure 5 (b) shows PSODBSCAN algorithm space clustering results with same sample objects.

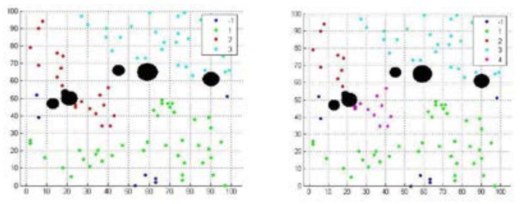


Figure 5: The Clustering Results Of PSODBSCAN Algorithm With Obstacle Constraints

The experimental results show that the existence of obstacles affects the continuity of data space, so directly affect the results of space clustering distribution. Contrast Figure 5 (a) and Figure 5 (b), we can see that PSODBSCAN algorithm reflects the impact of spatial obstacles, which divides objects of No.2 category into No.2 and No.4 clusters located at both sides of obstacle circle, and get a more ideal clustering result.

In summary, when at the initial stage particles distribute in the whole solution space, PSODBSCAN has more random character than other algorithm. Meanwhile in each iteration process all the particles share their own "information" and improve their "self-Quality", so that each candidate solution has dual advantages of self-learning and others-learning with fast convergence. At the same time, in the implementation process, as a result of coordinate transformation, PSODBSCAN algorithm reduces computational amount to a large extent, thereby improving execution speed of the algorithm.

5. SUMMARY

Space clustering with obstacle constraints has a strong practical value, and becomes a research focus in field of spatial data mining in recent years. This paper presents a new DBSCAN clustering method based on the PSO optimization, aiming at enriching obstacle path computation method and providing an effective choice for DBSCAN clustering algorithm in obstacle space. The innovation of PSODBSCAN algorithm lies in the reference of mobile robot path planning method, and the simplification of two-dimensional coordinates into one-dimension, then the usage of particle swarm optimization to calculate the minimum obstacle distance between objects, at last the basis of minimum obstacle distance to spatial clustering. Experimental results show that, PSODBSCAN clustering algorithm has not only the advantages of density clustering, but also more reasonability, accuracy in the field of dealing with spatial constraints, which has important theoretical value and significance to achieve accurate clustering in constrained environment.

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