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Research on Mine GIS Index Optimization Based on Voronoi Diagram and Artificial Fish Swarm Clustering

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Abstract

In the study of mine GIS index optimization of mining decision support system, in order to reduce the overlap between the index nodes, in this paper we propose the intensity of polygon to ensure the index nodes have good geometry. In this paper, we also put forward artificial fish swarm clustering based on Voronoi diagram (AFSCV) and apply the AFSCV to mine GIS index splitting algorithm. In the end, we give the optimization rules of AFSCV. In order to verify the effectiveness of our algorithm we compare our method with traditional methods, the experimental results show that our method can improve the query performance of mine GIS database and greatly reduce the overlap which generates from reinsert after the index node split.

Keywords*: mine GIS, Voronoi diagram, artificial fish swarm clustering, splitting algorithm*

1. Introduction

Mine GIS has provided a favorable guarantee for safety production in mine. Through analytic processing of all kinds of geology, surveying, ventilation and prevention, design and other technical parameters, mining enterprise managers can timely and intuitively query related technical data, thus providing decision-making for enterprise decision-makers [1]. With the development of information technology, mine GIS will be continuous improved and its function will be more powerful. The mine GIS is inevitable trend for the development of coal industry, at the same time it must also promote the development processing of mining area digital information [2-3]. The mining area environment sustainable development decision support system appears in such environment.

In order to improve the performance of mining area environment decision support system, in this paper, we optimize the mine GIS index. We implement the optimization of mine GIS index through the combining of Voronoi diagram [4] pretreatment technology and artificial fish swarm clustering. Our method makes the query and analyzes performance greatly improved, thus greatly saving human, material and financial resources in the evaluation of the mining area environment. At the same time, our method can quickly and effectively evaluate the quality of the mining area environment, so our method can provide decision support service for the development and utilization of resources, environmental governance, *etc*. This paper is organized as follows. Artificial fish swarm clustering based on Voronoi diagram (AFSCV) is put forward in Section 2. Optimization rules based on the AFSCV are given in Section 3. Experimental results and analyses are given in Section 4. The paper is concluded by Section 5.

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2. Artificial Fish Swarm Clustering Based on Voronoi Diagram

2.1. Related Definition

In order to optimize the splitting algorithm of mine GIS index we should put forward an index $\Im$ in theory, this index is used to measure whether the splitted graphic geometry meets the requirement of the problem.

Definition 2.1 (Intensity of Polygon) Assuming that a polygon is of n sides, intensity of polygon is measured by $\Im$ ($\Im \geq 0$), the smaller the value of $\Im$, the higher the intensity of polygon, and vice versa. $\Im$ is defined as formula(1).

$$\Im = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(d_i - \bar{d})^2} \qquad (1)$$

In formula(1), d_i is the distance from centre of gravity of polygon to the ith side, $\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i$ is the average distance of the centre of gravity to n sides.

Definition 2.2 (Voronoi Diagram) Given a set generic points $P = \{p_1, \cdots, p_n\} \subset R^2$, $2<n<\infty$ and when $i \neq j$, $p_i \neq p_j$, i、 $j \in I_n = \{1, \ldots, n\}$. Voronoi region is given in formula (2).

$$VP(p_i) = \{p \,|\, d(p, p_i) \leq d(p, p_j)\} \qquad (2)$$

In formula(2), $j \neq i, j \in I_n, d(p, p_i)$ is minimum Euclidean distance between p and p_i. The area determined by p_i calls Voronoi polygon. The graphic defined as $VD(P) = \{VP(p_1), VP(p_n)\}$ is called the Voronoi diagram. Part of the Voronoi diagram is shown in Figure 1.

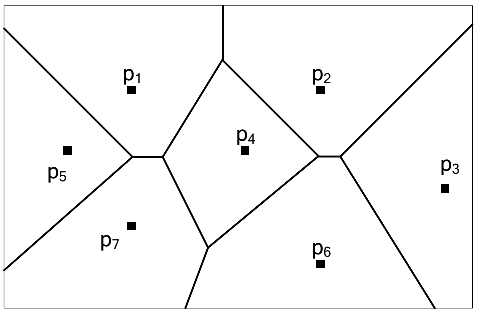

Figure 1. Voronoi Diagram

2.2. Artificial Fish Swarm Clustering Based on Voronoi Diagram (AFSCV)

The main idea of the artificial fish swarm clustering based on Voronoi diagram (AFSCV) is: first generate dual triangle mesh based on Voronoi diagram, dual triangle mesh executes grid division, there are several triangle centers within each grid, we define center point numbers in each grid as food concentration of this region. AFSCV performs optimization operations according to the differences in the concentration of food, eventually Voronoi dual triangulation will generate a number of clusters, each cluster will serve as the division standard of splitting algorithm.

In AFSCV, we assume that there are N individuals in fish swarm(N is center point numbers of Voronoi triangulation network), the representation of an artificial fish is $F = (f_1, f_2, \ldots\ldots, f_N)$, $Step$ expresses the longest step of artificial fish, $Visual$ represents the vision field of artificial fish, Try_number expresses the biggest number of foraging,

δ expresses crowded degree factor, the current food concentration of an artificial fish is expressed as $Y = f(F)$. Behaviors of artificial fish swarm are defined as follows.

Definition 2.3 (Foraging Behavior) Assuming the current state of the ith artificial fish is F_i, according to formula(3) randomly select a state F_j in the field of view. In the solving process, if $Y_i < Y_j$, then the ith artificial fish moves one step towards the direction of F_j according to formula(4); else, randomly select state F_j again and estimate whether meet the forward conditions, perform Try_number times repeatedly, if still does not meet the forward conditions, the ith artificial fish moves one step randomly according to formula(5).

$$F_j = F_i + Visual \bullet Rand() \qquad (3)$$

$$F_i^{k+1} = F_i^k + \frac{F_j - F_i^k}{\left\| F_j - F_i^k \right\|} \bullet Step \bullet Rand() \qquad (4)$$

$$F_i^{k+1} = F_i^k + Visual \bullet Rand() \qquad (5)$$

Definition 2.4 (Swarm Behavior) Assuming the current state of artificial fish is F_i and the food concentration of this state is Y_i, in the $Visual$-distance neighborhood, if central location F_c has higher food concentration Y_c, if Y_c is higher and the position of F_c is not too crowded, the artificial fish moves one step towards F_c according to formula(6), otherwise, performs foraging behavior.

$$F_i^{k+1} = F_i^k + \frac{F_c - F_i^k}{\left\| F_c - F_i^k \right\|} \bullet Step \bullet Rand() \qquad (6)$$

Definition 2.5 (Rear-End Behavior) Assuming the current state of artificial fish is F_i and the food concentration is Y_i, in the $Visual$-distance neighborhood, the state of the optimal artificial fish is F_j and the food concentration is Y_j, if Y_j is higher and the position of F_j is not too crowded, the artificial fish moves one step towards F_j according to formula(4), otherwise performs foraging behavior.

Definition 2.6 (Food Concentration) Food concentration function is defined based on the principle of group similarity, as shown in formula(7).

$$Y = f(F_i) = \frac{1}{2}\left(\frac{1}{k}\sum_{j=1, j\neq i}^{k} \left|F_{ci} - F_{cj}\right| + \frac{1}{\frac{1}{n}\sum_{i=1}^{n} D(F_{ci}, F_{cj})}\right) \qquad (7)$$

In formula(7), $D(F_{ci}, F_{cj})$ indicates the distance between artificial fish individual F_{ci} and F_{cj}, $\frac{1}{n}\sum_{i=1}^{n} D(F_{ci}, F_{cj})$ is swarm similarity, k is the number of cluster centers formed during fish clustering, F_{ci} and F_{cj} are clustering center position.

AFSCV algorithm steps are as follows:

Step 1 Assume BN central points of Voronoi triangulation are the initial solution set x_{ij} ($i = 1, 2, ..., BN, j = 1, 2, ..., D$), the initial solution set is a collection of artificial fish populations, initialize vision field $Visual$, moving step $Step$, two-dimensional plane size $(m \times n)$, the maximum number of iterations $G_{\max}$, $G = 0$;

Step 2 The data object (m_i, n_j) randomly places on two-dimensional plane $(m \times n)$;

Step 3 $G{+}{+}$;

Step 4 A group of artificial fish individuals begin to clustering cycle;

Step 5 Use formula (7) to calculate the community similarity of each individual fish in $Visual$ field;

Step 6 Search clustering center position F_c in current fish's $Visual$ field and measure the community similarity.

Step 7 The algorithm performs swarm behavior and rear-end behavior according to community similarity of current artificial fish and clustering center positions; if they do not meet conditions of swarm behavior and rear-end behavior execute foraging behavior.

Step 8 If all the artificial fish individuals in the group end mobile, turn to step 9, else turn to step 4;

Step 9 If the number of iterations G is less than the maximum number $G_{\max}$, turn to step 3, otherwise output the result, terminate the algorithm.

3. Optimization Rules Based on the AFSCV

In the optimization scheme we mainly optimize splitting algorithm and the optimized splitting algorithm makes the splitted nodes have high density (see definition 1), so that we can reduce the overlap between nodes. The optimization scheme mainly adopts the Voronoi diagram and artificial fish swarm clustering to make the splitted nodes have high density.

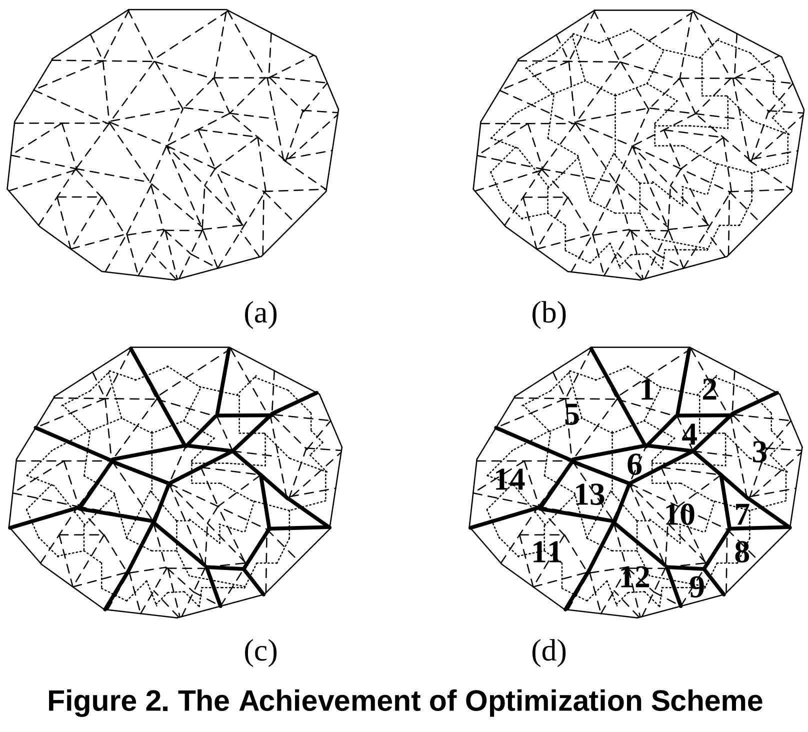

Figure 2. The Achievement of Optimization Scheme

The optimization scheme has the following four execution rules.

Execution rule 3.1 we consider to be divided polygon node as convex hull Y, randomly generate M discrete points in the convex hull Y, on the basis of the convex hull Y and M discrete points we build Voronoi dual triangle mesh G, as shown in Figure 2(a).

Execution rule 3.2 From the execution rule 3.1 we can get Voronoi dual triangle mesh G, take all the centre of gravity of each triangle in the Voronoi dual triangle mesh G, use the C centres to build second-Voronoi dual triangle mesh G^E, as shown in Figure 2(b).

Execution rule 3.3 From the execution rule 3.2 we can get second-Voronoi dual triangle mesh G^E, we consider each centre of gravity of second-Voronoi dual triangle mesh G^E as the initial value, and then start the AFSCV algorithm, perform artificial fish swarm clustering, and finally get R clusters, as shown in Figure 2(c).

Execution rule 3.4 we respectively find convex hull of R clusters which are got by perform execution rule 3.3, so the polygon is divided into R polygons, as shown in Figure 2(d).

4. AFSCV Experiment and Performance Analyses

Experiments are performed on the computer with Intel Core i3, 4 gb of memory, Windows XP Professional operating system and implemented by C++ programming. In order to verify the correctness and efficiency of the proposed algorithm, we use part of ore district surface vector diagram of hubei province in 1995 to test, this area contains 60-56236 vector polygons, and in these vector polygons there are 45 to be divided polygons.

Performance comparison and analyses are from two aspects: on the one hand, the performance comparison and analyses are between using splitting algorithm and unusing splitting algorithm, on the other hand, we use four kind of classic algorithms-Exhaustive splitting algorithm (algorithm A) [6], Linear splitting algorithm (B) [7], Quadratic division algorithm (C) [8] and Binary tree splitting algorithm (D) [9] to compare with the splitting algorithm which is proposed in this paper.

The simulation results are as follows: from Figure 3 we can see using a variety of splitting algorithms to build trees consume higher time than not using splitting algorithm, this is mainly due to that the splitting algorithm increases the time of establishing the tree, we can obviously see that the consuming time of our method is slightly higher than the unusing splitting algorithm. From Figure 4 we can see using a variety of splitting algorithms can obviously improve query performance, at the same time the query performance of using our method is significantly higher than other four classical splitting algorithms. We take setting up a tree and query together, the time cost as shown in Figure 5, algorithm C and D consume too high time in building tree, so the comprehensive efficiency is lower than unused splitting algorithm. Although splitting algorithms themselves of our method, the algorithm A and B increase the building tree time, they get efficient query performance, taken together, the overall time-consuming of these three splitting algorithms decrease significantly than unused splitting algorithm. At the same time, the comprehensive efficiency of our method is much better than other four classical splitting algorithms.

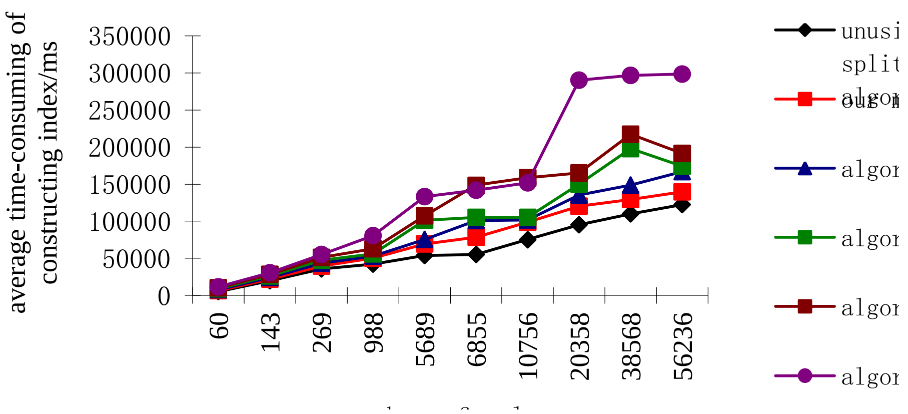

Figure 3. Contrast of the Efficiency of Building Index

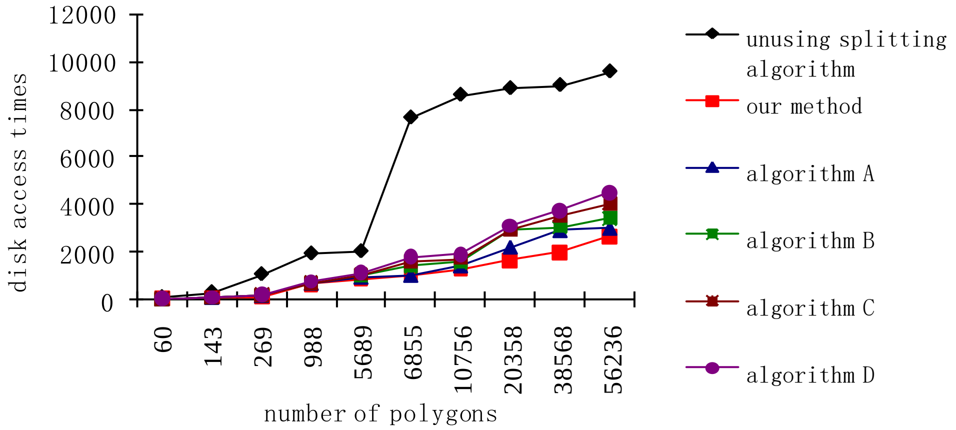

Figure 4. Contrast of I/O Times of Visiting Disk Page

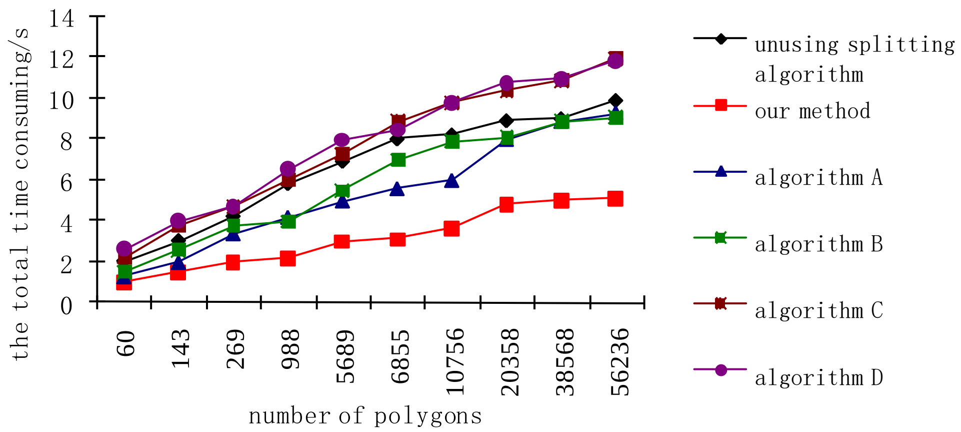

Figure 5. Contrast of Overall Efficiency

5. Conclusions

In this paper, we optimize the mine GIS index of mining decision support system to eliminate the overlap between nodes in the index structure, thereby improving the query efficiency. In order to ensure that the splitted node has compact geometry and reduce the overlap between the brother nodes, we put forward intensity to measure the compact degree of splitted nodes. In this paper, we use the Voronoi diagram and artificial fish swarm clustering to optimize splitting algorithm, all the splitted nodes have compact geometry, thereby improving the query performance of the mine GIS.

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