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Collision Detection Algorithm based on Quantum Ant Colony

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Abstract

For today's traditional collision detection algorithms in the complex three-dimensional scene with the problems of slow detection rate and low detection accuracy, a fast collision detection algorithm based on quantum ant colony is proposed. Firstly, the hierarchical bounding box technique is used to quickly eliminate disjoint objects, and the random collision detection technology is used to transform the problem into the feature-to-distance optimization problem of the object to be detected in two-dimensional space. Combining quantum computing technology and ant colony algorithm, quantum ant colony algorithm is used to solve the collision detection problem. Experimental verification proves that the real-time and accuracy of the algorithm can be satisfied if the number of polygons to be detected is large.

Keywords:*Virtual Reality, Collision Detection, Bounding Volumes, Quantum Ant Colony Algorithm*

I. INTRODUCTION

Collision detection technology is a hot issue in the fields of computer graphics and virtual reality. The main task of collision detection is to detect whether two or more objects occupy the same space in a virtual scene, and when they occupy the same space, a collision is generated [1]. In recent years, with the development of computer graphics technology, real-time simulation of large-scale complex scenes has received extensive attention. The model interaction in complex scenes consumes a lot of computer resources, and the requirements for collision detection algorithms are getting higher and higher. Many researchers have proposed different theoretical methods based on collision detection, including GPU-based collision detection methods [2], Hierarchical Bounding Volumes Trees [3], distance fields [4]. Wait. However, these traditional methods have certain limitations and shortcomings in the current complex virtual environment. It is not efficient in the face of collision detection in complex scenes[5][6][7].

In this paper, quantum ant colonies are introduced into collision detection, and a fast collision based on quantum ant colonies is proposed.In the precise detection stage, the collision detection problem in complex three-dimensional space is transformed into a two-dimensional discrete space optimization problem, and the quantum ant colony algorithm is introduced to solve it. Optimization problems can flexibly control the accuracy and efficiency of the detection algorithm.

II. RANDOM COLLISION DETECTION ALGORITHM

Random collision detection is a geometric space-based collision detection algorithm, which is characterized by a certain precision in exchange for the efficiency of collision detection. The algorithm randomly samples the object and combines the sampled feature pairs into the search space. The collision detection process searches for the feature pairs in the search space in a certain way. The only condition for feature pair selection is that the distance between them is computable. For a three-dimensional model, the feature pair can be any combination of points, edges, and triangles. However, in terms of the computational efficiency of the fitness function, the combination efficiency of points and points is the highest and the calculation speed is the fastest[8]. The accuracy of collision detection is related to the sampling rate of feature points. When the sampling rate of feature points is large, the accuracy of the algorithm will increase and the efficiency of the algorithm will decrease[9]. When the sampling rate of feature points is small, the accuracy of the algorithm will be relatively reduced, and the efficiency of the algorithm will be improved. By dynamically adjusting the sampling rate, the accuracy and efficiency of the algorithm can be controlled and the best collision detection effect can be obtained[10].

III. QUANTUM ANT COLONY ALGORITHM FOR SOLVING COLLISION DETECTION PROBLEMS

The ant colony algorithm is a bionic generalized stochastic optimization algorithm based on real ant colony behavior, which is used to solve the combinatorial optimization problem[11]. The traditional ant colony algorithm will have a certain degree of premature aging and stagnation in the process of optimization, and it is less efficient in solving the optimization problem in two-dimensional discrete space.

The Quantum Ant Colony Algorithm (QACA) is a probabilistic optimization method combining quantum computing with ant colony algorithm. In the 1990s, foreign scholars A. Narayanan & M. Moor first proposed the concept of quantum ant colony[12]. After that, many scholars in China also began to study the quantum ant colony algorithm. The ant colony algorithm combined with quantum computing technology is different from the traditional ant colony algorithm in that: 1 the probability amplitude of the introduced qubit can double the search space and improve the convergence speed; 2 control the ant movement through the quantum revolving gate, using quantum non- The door is used to implement the mutation operation to prevent the ant colony from falling into the local optimal solution; 3 the pheromone released by the ant during the movement is scattered at the position where the ant is currently passing.

Spatial Quantization Coding Method

Qubit is a unit of information storage with two quantum states, a unit vector defined in the search space[13].

The probability amplitude of ant i with n qubits is expressed as:

$$q_i = \left[\begin{vmatrix}\cos(t_{i1})\\ \sin(t_{i1})\end{vmatrix}\begin{vmatrix}\cos(t_{i2})\\ \sin(t_{i2})\end{vmatrix}\begin{vmatrix}\cdots\\ \cdots\end{vmatrix}\begin{vmatrix}\cos(t_{in})\\ \sin(t_{in})\end{vmatrix}\right] \quad (1)$$

The search space M is a discrete space composed of two model feature pairs. When two objects collide in three-dimensional space, there may be multiple collision points. In the search space, there are multiple extreme values, and the position of the object will follow. The change of time changes, so the space is a multi-peak dynamic search space. The solution space we construct is a complex environment with dynamic changes and multiple targets.

Transfer of Ant Position in Space

The quantum ant colony mainly encodes the pheromone on each path in the ant colony algorithm[14]. The essence is to fuse quantum technology in the ant colony algorithm, and select the ant's forward target according to the intensity and visibility of the pheromone. The ant colony is updated according to the position of the ants after

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the movement. Let the number of ant colonies be m, and each ant qubit is n.

In the ant colony algorithm, the ant calculates the path transition probability based on the pheromone strength and path heuristic information in the ant motion process, determines the next position of the ant by the motion probability, and applies the same method to solve the ant movement in the quantum ant colony. The path transfer probability of the ant k transferred from the location i to j is as follows:

$$p_{ij}^{k} = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{s\in allow_k}[\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}}, & s \in allow_k \\ 0 \quad , & s \notin allow_k \end{cases} \quad (2)$$

In Quantum Ant Colony Optimization Algorithm (QACO), the ant position is represented by its own qubit, and the update of the ant position is usually achieved by updating the quantum bit probability amplitude. In quantum algorithms, quantum revolving gates are commonly used to update qubits. Quantum revolving gates are defined as follows:

$$R(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \quad (3)$$

The x_r is approximated by x_s by the quantum revolving door to complete the update of the ant position. The size and sign of the rotation angle $\Delta\theta$ are determined according to the set adjustment strategy. The size of $\Delta\theta$ determines the convergence speed. If the $\Delta\theta$ is too large, the algorithm may not converge to the global optimum,but the $\Delta\theta$ is too small will affect the convergence speed of the algorithm. Therefore, the setting of the magnitude and direction of the rotation angle $\Delta\theta$ is crucial. The rotation angle of this paper is as follows:

$$\Delta\theta = 0.5\pi * \exp(-gen/MAXgen) \quad (4)$$

In many cases, ACO tends to fall into local optimum due to the loss of population location diversity in the search space. The introduction of mutation operator can realize the variation of individual position of the population, improve the diversity of the population, and reduce the possibility of local convergence of the population. QACO uses quantum non-gates to achieve population variation[15].

The implementation process is as follows:

$$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \cos\theta_{ij} \\ \sin\theta_{ij} \end{bmatrix} = \begin{bmatrix} \cos(\theta_{ij} + \frac{\pi}{4} - 2\theta_{ij}) \\ \sin(\theta_{ij} + \frac{\pi}{4} - 2\theta_{ij}) \end{bmatrix} \quad (5)$$

Compared with the methods provided in other literature, this method effectively enhances population diversity.

Pheromone Update Rules

The next position of the ant is determined by the intensity and visibility of the pheromone[16][17]. The pheromone represents the degree of the current spatial optimal position, and the fitness function is combined with the pheromone.The pheromone update rules are as follows:

$$\tau(x_n) = \tau(x_o) + sgn(\Delta f) * |\Delta f|^{\alpha} \quad (6)$$

$$\eta(x_n) = \eta(x_o) + sgn(\Delta\partial f) * |\Delta\partial f|^{\beta} \quad (7)$$

x_o:Initial position, x_n:Changed position.

When all ants in the population update the position, the pheromone intensity in the space is updated according to following formula :

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} \quad (8)$$

ρ :pheromone polatility , an artificial parameter. In general, $\rho \in (0,1)$.

Collision Detection Algorithm Based on Quantum Ant Colony

The algorithm is as follows. In the pre-detection phase of collision detection, a tree-shaped layered bounding box is established by dividing the basic primitives by the longest axis in a top-down manner. The geometrical simple AABB bounding box is used to approximate the complex geometric model, and the complex geometric elements in the 3D model are formed into a tree structure through the bounding box, and the object is gradually approached. During the traversal of the hierarchical bounding box, the

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geometric primitive pairs that do not intersect are quickly eliminated by a simple intersection test between the bounding boxes. In the precise detection stage, a quantum ant colony algorithm is introduced to solve the collision detection problem of objects in three-dimensional space into an optimization problem in two-dimensional discrete space. By controlling the degree of the bounding box tree structure tree in the pre-detection phase and the selection of the feature points in the accurate detection, the detection speed and the detection quality of the algorithm can be controlled, which can not only reduce the storage space, simplify the input, but also effectively improve the detection.

The construction method of the hierarchical bounding box splitting plane in this paper is as follows:

(1) taking an object in three-dimensional space, and establishing an AABB bounding box containing all its primitives with its root node, the bounding box containing all the basic geometric primitives of the object;

(2) Applying the longest axis segmentation method to determine the segmentation axes of the left and right subtrees, and determining the projection of all the basic geometric primitives in the root node on the segmentation axis;

(3) Divide the left and right subtrees by dividing points, and find the maximum and minimum points of the projection as two center points. According to the input basic geometric primitive, the mass point projection is divided into two groups from the distance between the two central points;

(4) Recursively call the above process until the discriminant function end condition is satisfied. The condition can be the height of the hierarchical bounding box tree structure, or the maximum number of geometric primitives contained in the leaf node.

When intersecting the hierarchical bounding box, if the box intersect, the geometry surrounded by the bounding box is further tested. If the two levels of bounding boxes A and B do not intersect at the node of a certain A, then it is found that the node does not intersect with all objects of B in A. Unnecessary intersection tests can be quickly eliminated by hierarchical bounding boxes.

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

In order to verify the characteristics and performance of the algorithm, several sets of experiments were conducted.

Experiment 1: In order to verify the feasibility of the quantum ant colony algorithm applied to collision detection and determine the influence of the feature on the sampling rate on the efficiency of the algorithm.

For example, if a collision detection accuracy of about 20% is required, we can select the sampling rate of the first group and the second group; if the collision detection rate of 70% is to be achieved, the sampling rate of the first group is better.

Experiment 2: A random collision detection algorithm based on quantum ant colony algorithm (QACO), a random collision detection algorithm based on ant colony algorithm (ACO), a collision detection algorithm based on hierarchical bounding box (HBV), and a random collision based on particle swarm optimization (PSO) The detection algorithm compares the collision detection rates. as shown in Fig.1:

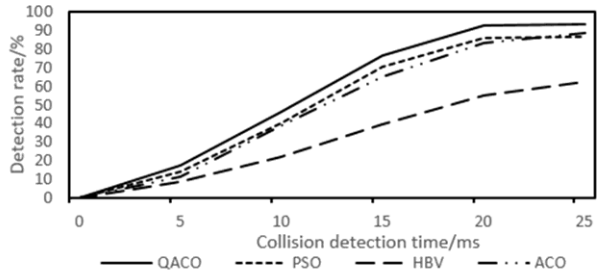

Fig1. Comparison of multiple algorithm detection effects

According to the results, the detection rate of the PSO algorithm and the ACO algorithm can only reach about 80%, which is lower than the QACO algorithm. This is because the introduction of quantum technology in the algorithm increases the number of positions of the population in the search space. The introduction of the mutation operator increases the diversity of the population, thus avoiding local convergence, improving the processing speed of the algorithm and reducing the algorithm time.

V. CONCLUSIONS

Aiming at the problems of low detection accuracy and slow detection rate, this paper proposes a collision detection algorithm based on quantum ant colony. First, the disjoint objects are eliminated by the AABB bounding box preprocessing stage, and the input is optimized to save space. The quantum ant colony algorithm is introduced to solve the optimization problem in random collision detection. The quantum computing technology is used to increase the search position of ant colony in space, and the quantum non-gate is used to avoid local convergence. The experimental results show that the algorithm has certain advantages in collision detection in complex scenes.

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