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Intelligent Combination of Discrete LOD Model for 3D Visualization Based on Visual Perception and Information Entropy Fusion

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Abstract: With respect to the problem that single-index evaluation of visual quality in the process of intelligent combination of discrete Level-of-Detail (LoD) model for three-dimensional (3D) visualization can easily result in low reliability. *Human visual perception and information entropy based multi-index fusion intelligent combination of discrete LoD model algorithm was proposed. Through analyzing the visual perception based image quality evaluation index, multi-index fusion evaluation intelligent combination of discrete LoD model framework was built. Comparative experiment with single index model combination bases on PSO method was designed. Model combination optimizing process utilized modified Particle Swarm Optimization (PSO) method which was strengthened by Genetic Algorithm (GA) to avoid falling into local optimum.* Experimental results demonstrate that the proposed method can design high reliability 3D visualization effect which is adapted to human visual perception characteristics, and outperforms other matching methods in designing efficiency and requires no user interaction.

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基于感知与信息熵融合的离散LOD模型智能组合

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摘要：针对图像信息熵单指标评价在三维场景离散 LOD 模型智能组合优化过程中容易造成可信度低的问题，*提出了一种基于视觉感知与信息熵融合的离散 LOD 模型智能组合方法。分析了基于视觉感知的图像质量评价指标，构建了多指标融合的离散 LOD 模型智能组合框架，设计了与基于 PSO 的单指标离散 LOD 模型组合寻优对比实验。结合遗传算法的思想对粒子群算法进行改进，克服了在模型组合寻优过程中粒子群算法易于陷入局部最优的缺点。*实验结果表明，本文方法能够设计出符合人类视觉感知特征的高可信度三维场景，与其他方法相比具有模型组合寻优效率高、无需人工交互的优点。

关键词：三维可视化；智能组合；LOD；视觉感知；多指标融合；GA-PSO
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Introduction

Interactive display and visualization of large data is becoming a basic requirement and mainly used in scientific visualization, virtual prototyping, CAD, movies and other fields [1]. With the rapid development of 3D modeling and data capture technology, the complexity of 3D mesh model seems to grow faster than the ability of graphics hardware to render them interactively. Polygonal Level-of-Detail (LoD)

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technique offers one solution, for which either a series of discrete models or a progressive model is determined during prepossessing.

The technique for choosing the LoD of polygonal objects have used static metrics such as visibility and distance[2], the span of level changed[3] and projection area[4]. These simple metrics improve the frame rate in many cases, but cannot guarantee a regulated or bounded execution time. To guarantee a bounded frame rate, Funkhouser and Sequin[5] have presented a predictive technique that use an estimate of the execution time for the correct choice of the LoD to use. However, the greedy solution only guarantees to be half as good as the optimal solution. Therefore, many improved algorithms appeared in [6-8], the advantage of these methods is considering the relationship of rendering quality and the rendering speed, but the shortcoming is obviously as the process of calculating is quite complicated. In recent years, image-based [9] rendering have received a lot of interest because of its ability to represent complex models in a compact way. Researchers pay more attention on perceptual quality based rendering strategy [10]. The algorithms can generate the best visual quality scene while meeting timing constraints. In [11] the relational table model of sight distance was built, LOD hierarchy and number of interpolating points and applied in terrain generation. In [12] using hybrid projected area and viewpoint distance as a LOD selector is used for visually lossless urban scenes visualization. A new 3D scene rendering approach which utilized the visual information of image scene, natural language and sketch to retrieval 3D models from database was proposed in [13]. Experiments show the proposed approach performs quite well and can effectively build 3D virtual scene rapidly.

Artificial intelligence algorithms, such as PSO, support vector machines, random search algorithm, are applied in 3D visualization [14-16]. In [15], the transfer function is designed automatically by an improved PSO method which is strengthened by genetic algorithm. In [16], PSO algorithm is introduced to solve the multi-resolution model combination problem, different resolution model combination can be considered as a particle, the search for optimal combination is reformulated as a global optimization problem.

In the process of intelligent combination of 3D discrete LoD model, visualization effect evaluation results directly affect the model level selection. In [16], using only image information entropy to evaluate visual effects still has a certain deviation from people's subjective judgment. In this paper, we propose an objective image evaluation method based on visual perception and information entropy which makes evaluation result more in line with human visual perception characteristics. Meanwhile, GA-PSO hybrid algorithm which is strengthened by Genetic Algorithm to overcome the problem that basic PSO algorithm can easily falls into local optimum, the results of tests show that this modified PSO algorithm has a better global searching ability and efficiency in the application of 3D visualization.

The rest of this paper is organized as follows. Section 1 describes the intelligent combination framework. In section 2, we introduce the multi-index fusion evaluation method based on visual perception and information entropy. Section 3 gives the modified PSO algorithm. Experiment results are analyzed in Section 4. Finally, we come to a conclusion in section 5.

1 Intelligent Combination Framework

The basic idea of intelligent combination algorithm is transferring the abstract evaluation of discrete LoD model combination into the explicit evaluation of its rendering image, and transfers the searching for optimal models combination into a multiple parameters optimization problem. Intelligent combination algorithm framework is shown in Fig.1.

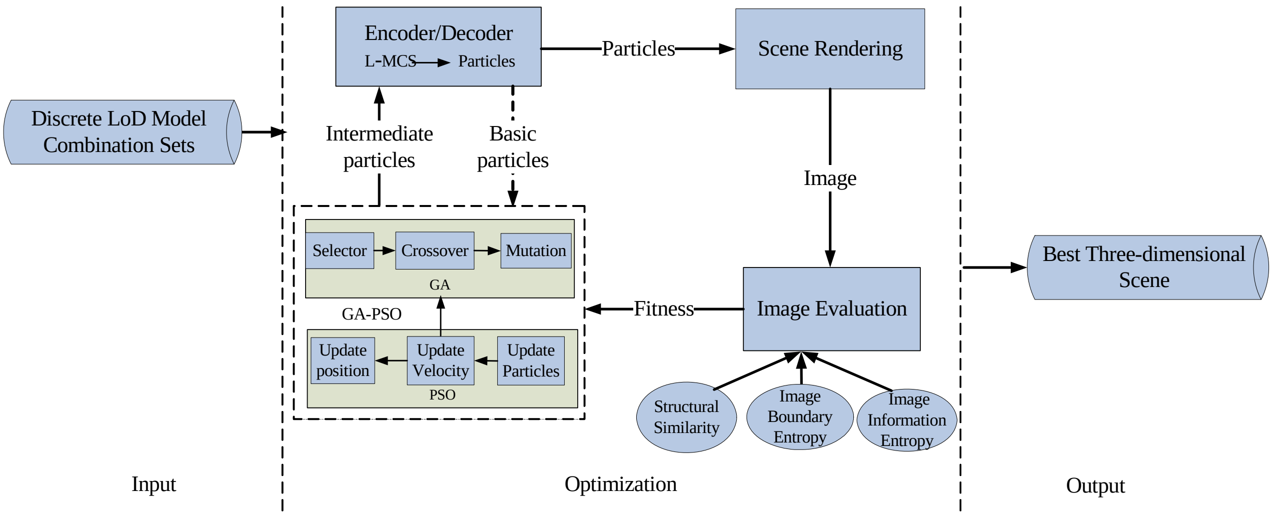


Fig.1 Intelligent combination algorithm framework

Optimization part is the core of the algorithm, mainly includes four modules: Encoder/Decoder, Scene rendering, Image evaluation and GA-PSO. The function of each module is described below:

Encoder/Decoder: This module has two functions, one is encoding the input initial discrete LoD model combination sets (L-MCS), the other is decoding the intermediate particles as model combination, and passes them to the Scene Rendering module.

Scene rendering: Once new particles are generated, Scene Rendering module renders the corresponding 3D scene one by one, the rendered images are transmitted to the Image Evaluation module.

Image evaluation: By the assessment result of the visualization effect, the fitness value of the corresponding model combination can be obtained.

GA-PSO: Velocity and position of each particle is updated by basic PSO. According to a predetermined selection, crossover probability and arithmetic random variation, the new particle is generated.

In the process of intelligence combination of discrete LoD models, model combination is encoded as particles, From the initial discrete LoD model combination sets, each model combination is the particle position in the search space, the fitness value of each particle is determine by visual quality evaluation. Velocity and position is updated by basic PSO. According to a predetermined selection, crossover probability and arithmetic random variation, the new particle is generated. Through continuously iterative optimization satisfactory models combination will be found.

The basic process of the algorithm is as follows:

Step1.Enter the initial model combination sets and initialization parameters. After scene rendering and image evaluation, pass the results to GA-PSO optimization module;

Step 2.Update particle velocity and position by basic PSO algorithm to achieve particles update;

Step 3.Transmit the particles generated by PSO to genetic operator module, according to the selector, crossover and mutation order, generate a new set of particles;

Step 4.Decoding particles as model combinations, then rendering the scene and evaluate the 2D projected image of 3D scene;

Step 5.If the iteration termination condition is reached, then output scene image of the current model combination, otherwise return to step 2), update the particles, into a new round of iteration.

Iteration termination condition is stable residuals or the maximum number of iterations.

2 Multi-index Evaluation Method

In the application of artificial intelligence algorithm for combination of multi-resolution model, particle evaluation is a very critical link, not only the necessary basis to update position and speed of the particle, but also the reference value of the selection mechanism for GA-PSO. The model combinations are encoded as particles, so the evaluation of the particle can be transformed into the evaluation of its rendering image.

Image quality evaluation should fully comply with the human visual perception characteristics, a large number of studies show that HVS-based approach is better than traditional method. Structural similarity (SSIM) and image boundary entropy are consistent with the characteristics of human visual system, so we combine visual perception based image quality evaluation index and information entropy to build the target evaluation function.

2.1 Image Structural Similarity

When rendering the scene, the selection of model resolution level should be in accordance with the current size of the object's geometric errors or projected size on a screen, making the scene effect under certain viewpoint has exactly same effect or within a certain error range as original scene that using the finest resolution. Hence, evaluation of image quality of a scene can be transformed into seeking the similarity between realistic scene effect and the scene that is rendered by the finest resolution.

The existing image quality evaluation metrics can be classified into three categories: human-visual-system based, statistics-based and information-based classes. Experimental results indicate that human-visual-system based metrics are superior to others. SSIM shows a better consistency with human visual system than other image quality metrics. SSIM compares a reference image (X) with the image (Y) that contains the rendered discrete LoD models. The reference image is obtained by rendering the models at high quality. The mathematical model of SSIM is defined as:

$$SSIM\left(\mathrm{X},\mathrm{Y}\right)=\left[l(\mathrm{X},\mathrm{Y})\right]^{\alpha}\left[\mathrm{c}(\mathrm{X},\mathrm{Y})\right]^{\beta}\left[\mathrm{s}(\mathrm{X},\mathrm{Y})\right]^{\gamma} \quad (1)$$

Where $l(\mathrm{X},\mathrm{Y})$ is the Luminance comparison, $\mathrm{c}(\mathrm{X},\mathrm{Y})$ is the Contrast comparison and $\mathrm{s}(\mathrm{X},\mathrm{Y})$ is the Structure comparison. α , β , γ usually set them 1.

$$\begin{cases} l(\mathrm{X},\mathrm{Y})=\dfrac{2\mu_X\mu_Y+C_1}{\mu_X^2+\mu_Y^2+C_1} \\ \mathrm{c}(\mathrm{X},\mathrm{Y})=\dfrac{2\sigma_X\sigma_Y+C_2}{\sigma_X^2+\sigma_Y^2+C_2} \\ \mathrm{s}(\mathrm{X},\mathrm{Y})=\dfrac{2\sigma_{XY}+C_3}{\sigma_X\sigma_Y+C_3} \end{cases} \quad (2)$$

Where μ_X , μ_Y is the mean sensitivity of luminance, σ_X , σ_Y is the standard deviation of image luminance and σ_{XY} is gray covariance of image X and Y.

2.2 Image boundary entropy

Research on the human visual system shows that image edge information plays a crucial role in image perception process. Compared with the interior region, boundary region has more information. So we use image boundary entropy as a significant reference in image quality assessment.

When calculating the image boundary entropy, we first need to extract the image boundary information. Sobel operator, Prewitt operator and Canny operator are commonly used to extract image boundary. Among three operators, Sobel operator has minimum calculation expense but lower boundary extraction accuracy. The algorithm requires high computational efficiency, while the resolution of the border is relatively not so high, so we use Sobel operator to extract the border information. Image boundary entropy is defined as

$$H(IMG) = -\sum_{i=1}^{width}\sum_{j=1}^{height} g(i,j)\log_2 g(i,j) \tag{3}$$

$$g(i,j) = |\nabla f(i,j)| = \sqrt{(f(i,j)-f(i+1,j+1))^2 + (f(i+1,j)-f(i,j+1))^2} \tag{4}$$

Where $g(i,j)$ represents the grayscale values of the points after treatment $f(i,j)$ indicates pre-treatment grayscale value of point (i,j).

2.3 Image information entropy

The concept of information entropy was introduced to the image processing. Color histogram of image is seen as the probability density function. Image information entropy is a statistical form of character, which reflects the average amount of information in the image, and the expression defines as follows:

$$H(IMG) = -\sum_{i=1}^{width}\sum_{j=1}^{height} p(i,j)\log_2 p(i,j) \tag{5}$$

$$p(i,j) = x(i,j) / \sum_{i=1}^{width}\sum_{j=1}^{height} x(i,j) \tag{6}$$

Where width, height are respectively the width and height of the image, which means the size of the image. $x(i,j)$ is the gray value at the point (i,j).

It is necessary to convert color image to grayscale image firstly. For the usual color image with RGB format, grayscale value is calculated according to the percentage R: G: B = 0.30:0.59:0.11.

2.4 Hybrid evaluation

Three indexes can be used as an objective evaluation of image quality. For the diversity of user's needs and visual expectations, it is difficult to use a single index to determine the final image quality. To this end, we use linear superposition of three indexes with equal proportions as image evaluation method, and user can set different weight to three indexes to meet their needs. Three objective image evaluation indexes are focused on structural similarity, boundary number and gradation uniformity.

For more complex applications, subjective evaluation can be added into the model combination optimization process. This hybrid makes the model combination process from full automatic to semi automatic, but user can control the evolution direction and course of the algorithm, the evaluation process can control the , this not only expresses the specific needs of users, but also help users to better understand the characteristics of the rendering scene.

3 GA-PSO Hybrid Algorithm

The high convergence speed of basic PSO algorithm meets the real-time requirements in visualization process, but it can easily drop into local optimum. In this paper, genetic operators are introduced into PSO algorithm. Compared with the GA and PSO, GA-PSO has better global search capability and high convergence speed.

Initial models combination is encoded as particles, flying according to the basic PSO, velocity and position of each particle is updated by Eq (7) and Eq (8), then according to a predetermined probability of selection, crossover and arithmetic random variation, the new particle swarm is generated. Specific mechanisms of genetic operators are as follows:

$$v_{i+1,d} = v_{i,d} + c_1 r_1 (p_{i,d} - x_{i,d}) + c_2 r_2 (p_{g,d} - x_{i,d}) \quad (7)$$

$$x_{i+1,d} = x_{i,d} + v_{i+1,d} \quad (8)$$

Selection mechanism: Selection mechanism adopts roulette method. The select probability of particle i is defined as

$$p_i = {F_i}/{F_{sum}} \quad i = 1, 2, \cdots n \quad (9)$$

Where n is the number of particles, F_i is the fitness value of particle i, F_{sum} is sum of the fitness of all particles. Select too many particles will reduce the crossover and mutation probability, lost the advantage of GA, while fewer particles enhanced random, but lost the high convergence speed of PSO. Experimental results show that 70% can achieve a better balance.

Crossover mechanism: Arithmetic crossover strategy is applied, arithmetic crossover linear scale fusion two particles, fusion proportion is randomly determined at run-time. Arithmetic crossover linearly fuses two model combinations, searching intermediate region between them. We set 15% default probability of selected particle perform arithmetic crossover.

Mutation mechanism: Mutation can bring greater randomness to the optimization, broaden search area and avoid falling into local optimum. However, higher mutation probability will make the searching over randomized, slow down convergence speed. In this paper, mutation probability is set to 15%.

4 Experimental Results and Analysis

The proposed algorithm is carried on Intel Core i7 2.93GHZ with 4GB RAM and NVIDA GTX graphic card. Software configuration is Window 7 system, OpenGL 3.2, OSG 2.8.2, VS 2012.

Test scene is formed by three models: aircraft, ship and sea. Aircraft and ship both contain five resolution levels. The corresponding vertex number and polygon number are given in Table1 and 2. Sea has six resolution levels. Table 3 shows the resolution level of the sea, ‘Y’ means include and ‘N’ not included, and some numbers represent their respective properties.

Table 1 Resolution levels, vertex number and polygon number of aircraft

Resolution level	5	4	3	2	1
Vertex number	3460	2452	1828	1420	1253
Polygon number	1228	822	600	450	393

Table 2 Resolution levels, vertex number and polygon number of ship

Resolution level	5	4	3	2	1
Vertex number	12330	11198	9901	6605	6051
Polygon number	6578	6013	5317	3341	3071

Table 3 Resolution levels of sea

Resolution level	6	5	4	3	2	1
Reflection effect	Y	Y	Y	Y	Y	N
Illumination	Y	Y	Y	Y	N	N
Wind velocity	12	12	12	12	8	4
Spray	Y	Y	Y	Y	Y	N
Fog density	0.0015	0.0015	0.001	0	0	0
Trail	Y	N	N	N	N	N

In the process of rendering with the proposed algorithm, image quality evaluation method using linear superposition of three indexes with equal proportions. PSO optimization parameters set as: learning factor c1 and c2 set to 2, the inertia weight to 1.There are three particles, maximum number of iteration is 20, selection, crossover and mutation probability is set to 70%, 15%, 15%.

The rendering image sequence in the process of iterative optimization is showed in Fig.2.Using GA-PSO algorithm, after eleven times iteration the optimal model combination is obtained, and image quality evaluation values of the sequence are increasing, we can see that the entire process is toward the better solution program, visualization effect of the rendering scene is getting better and better.

Fig.2 Particle evolution sample

We designed a comparative experiment, three optimization algorithms: PSO, GA and GA-PSO are utilized in model combination optimization. Fig.3 shows the change of fitness value of three optimization algorithms. As Fig 3 shows that GA-PSO has higher convergence speed than both PSO and GA, this is due to the modified algorithm combines the high convergence speed of PSO and the excellent global search capability of GA. GA-PSO can obtain the optimal model combination in about eleven generations, while PSO needs about thirteen generations and GA about nineteen.

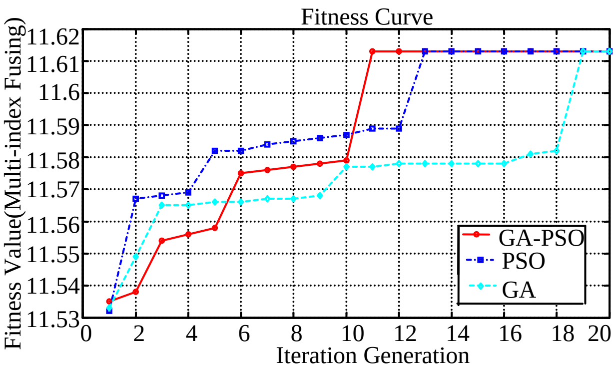
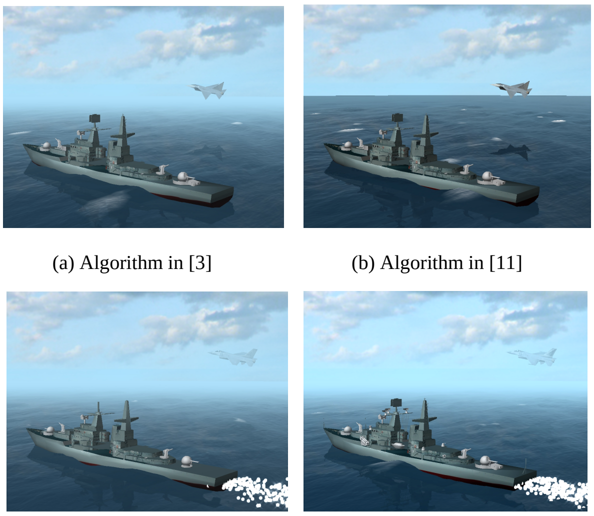


Fig.3 Fitness curve of three optimization algorithms

The obtained optimal model combination and the drawn image by algorithm in [3,11,16] and proposed algorithm are showed in Fig.4.



(a) Algorithm in [3] (b) Algorithm in [11]

(c) Algorithm in [16] (d) Proposed algorithm

Fig.4 Optimal rendering effect by four algorithms

Image 4(a) is drawn by the algorithm in [3], image 4(b) is drawn by the algorithm in [11], 4(c) is by algorithm in [16] and 4(d) is by the proposed algorithm. The resolution level of sea, ship, aircraft, and corresponding image evaluation index values of optimal scene rendered by the four algorithms are showed in Table 4. In [16] only use image information entropy to evaluate the quality of rendered scene, but image boundary information was ignored, this can be reflected by the boundary of ship model in image 4(c). In image 4(b), the resolution level of the models is determined by sight distance model which conform to human visual characteristics. So the ship has the finest resolution level. 4(a) is rendered by the static metric which use the span of level changed to determine the resolution level of each model in the scene.

We can see the three evaluation index values of proposed are super to other three methods. Using the image quality evaluation method proposed in this paper, evaluation results of four images showed in Table 4 indicates that the quality of image (d) is better than other images. The corresponding resolution level selected by our method is more adapted to human visual perception characteristics that we can see the object near our viewpoint more clearly should use high LoD, while far object use low LoD.

Table 4 Resolution Levels and evaluation index values of optimal scene rendered by four algorithms

Method	Resolution Levels	SSIM	Boundary Entropy	Information Entropy
Algorithm in [3]	5.4.1	0.9093	4.0911	6.8907
Algorithm in [11]	3.5.2	0.9036	4.7081	6.8861
Algorithm in [16]	6.2.5	0.9105	4.7529	6.9046
Proposed algorithm	6.5.1	0.9291	4.7675	6.9102

5 Conclusions

In this paper, multi-index fusion intelligent combination of discrete LoD model is proposed. Visualization effect is evaluated by image objective evaluation method based on visual perception and information entropy fusion. GA-PSO hybrid algorithm is introduced to overcome the shortcoming that basic PSO can easily falls into local optimum. The experimental results demonstrate that the proposed approach is able to design high reliability 3D scene which is adapted to human visual perception characteristics.

Human eyes are the ultimate judgers of image and give the most correct result, the human factor should be emphasized, and introducing subjective evaluation to the process of visualization effect assessment will be our future work.

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