Viewpoint Scoring Approach and Its Application to Locating Canonical Viewpoint for 3D Visualization

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Abstract. In this paper, a novel viewpoint scoring method based on multi-attribute fusion is proposed. The perceptual model of viewpoint preference is explored from geometry and visual perception aspects. Modified mesh saliency entropy is presented as the crucial intrinsic geometric attribute. Several digital image factors which have influence on human visual perception form the viewpoint perception attributes. Evolution algorithm is utilized to select the canonical viewpoint automatically and intelligently. Experimental results demonstrate that the canonical viewpoint obtained by the proposed method contains more visible salient features and better conforms to human visual perception characteristic. Moreover, the method has high efficiency and requires no user interaction.

Keywords: 3D visualization · Canonical viewpoint · Viewpoint attribute · Visual perception · Particle swarm optimization

1 Introduction

The criteria for viewpoint quality estimation in existing literature can be classified into two categories: geometric information based criteria and visual information based criteria. Geometric information based viewpoint quality estimation criteria use geometric information, such as project area of surface [1], geometric area [2], distance-histogram entropy [3]. etc. to measure the goodness of the viewpoint. These algorithms are simple and have high efficiency. The main drawback is that the best viewpoint depends on the polygonal discretization. The attention of the measure will be heavily attracted by a high discretized region. Visual information based optimal viewpoint selection algorithm emerged in recent years. Evaluation factors mainly used in the current literature are curvature [4], mesh saliency [5], shape/detail view descriptor [6], relief saliency [7] and Skeleton-Based [8]. These evaluation factors can extract visual features of the objects in the scene and better conform to human visual habit. The disadvantage is that ignoring geometric information and the calculation is more complicated. During the last few years, researchers explored artificial intelligent (AI) techniques in visualization to accelerate the computing efficiency. Particle Swarm

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Optimizer (PSO) [9] was used to select the optimal viewpoint intelligently. The modified PSO algorithm GA-PSO [10] was used to select the optimal combination of resolution levels of objects for 3D scene. Other algorithms such as shuffled frog leaping [11] and ant colony [12] were integrated into the process of best viewpoint selection.

In this paper, we explore the viewpoint attribute from not only geometry information perspective, but also visual perception perspective. The combination of the viewpoint attributes form a novel viewpoint scoring approach named viewpoint pertinence with the aim of finding the canonical viewpoint. Such a combination inherits the strengths of each attribute while compensating for their individual disadvantages. We place the viewpoints on the viewpoint sphere, the problem between the size of viewpoints set and the efficiency of algorithm is balance by utilizing evolution algorithm in the process of viewpoint optimization. By graphics processing unit (GPU) acceleration, algorithm efficiency is greatly improved.

The rest of the paper is structured as follows: Viewpoint attribute and mathematical models are given in Sect. 2. The novel viewpoint scoring method is given in detail in Sect. 3. In Sect. 4, intelligent viewpoint selection framework is presented. Experimental results and comparison studies to verify the capability of the proposed method are shown in Sect. 5. Conclusion and future work are given in Sect. 6.

2 Viewpoint Attribute

In this section we describe a set of viewpoint attributes from visual perception and computer graphics perspective, and we combine these attributes to form a more effective and accurate viewpoint quality evaluation metric than any one or a few measures taken alone. In Table 1, we enumerate the viewpoint attribute, each attribute is selected from the previous literature which is generally recognized by most scholars or inspired by former presented one.

Table 1. Viewpoint attribute

A_1	**Surface curvature attribute**	*Mesh saliency entropy*
A_2	**surface area attribute**	*Viewpoint entropy*
A_3	**Visual perception attribute**	*Luminance*
A_4		*Chrominance*
A_5		*Texture Details*
A_6		*Spatial Location*
A_7	**Scene information attribute**	*Image information entropy*
A_8	**Object weight attribute**	*Object Visible Priority*

2.1 Surface Curvature Attribute

A1: *Mesh saliency entropy*. Local structural features information of 3D model depends on the mean curvature, because the mean curvature tensor field can express the visual characteristic of 3D model. We combine the information entropy theory and face curvature to build a novel viewpoint quality metric named mesh saliency entropy.

We use the Gaussian-weighted mean curvature of vertices proposed by Lee [13] to calculate mean curvature.

Face curvature of 3D object is determined by the average curvature of its corresponding vertices. Assuming that the Gaussian-weighted mean curvature of vertices v is $\zeta(v)$, we define the saliency of the triangle T_i as follows:

$$\zeta(T_i) = \frac{1}{3}\sum_{v \in T_i} \zeta(v) \tag{1}$$

To reflect the change in projected area of the triangle due to perspective projection, we use the angle between surface normal vector and the line of sight as adjustable parameters, the modified saliency is defined as follows:

$$\zeta'(T_i) = \zeta(T_i) \cdot P_f \tag{2}$$

Where $P_f = abs(V_d \cdot N_f)$, it represents the projection weight of triangle face f in the visual plane. V_d is the view vector and N_f is the normal vector of triangle face f.

The saliency entropy for a given viewpoint is defined as follows:

$$S(T,p) = -\sum_{i=1}^{N_T} \frac{\zeta'(T_i)}{\sum_{T \in S} \zeta'(T_i)} \log \frac{\zeta'(T_i)}{\sum_{T \in S} \zeta'(T_i)} \tag{3}$$

2.2 Surface Area Attribute

A2: *Viewpoint entropy*. Introduced by Vazquez [1], this attribute combines probability distribution of projected areas of mesh faces and Shannon entropy to qualify the information of a viewpoint. Among the metrics that have been introduced for measuring the object visibility in the 3D scene from a camera position, the viewpoint entropy is the most valid metric up to now.

2.3 Visual Perception Attribute

A3 ~ A6: From the perspective of visual psychology, the vision is a kind of positive feelings behavior, not only relates with the physiological factors, but also depends on psychological factors. The research on human visual system shows that several digital image factors (luminance, chrominance texture details, spatial location factor, etc.) have strong influence on human visual characteristic. So we use these four visual perception factors as the viewpoint attributes and mathematic model of attributes A3 to A6 refer to literature [9].

2.4 Scene Information Attribute

A7: *Image information entropy*. Image information entropy is a statistical form of character, which reflects the average amount of information in the image. Color histogram of image is seen as the probability density function. In [14], image information entropy was used to evaluate viewpoint quality. We use image information to measure the information richness of the corresponding viewpoint.

2.5 Object Weight Attribute

A8: *Object Visible Priority*. This attribute gives the visible priority to each individual model in the 3D scene. In conformity to the weight of objects, the viewpoint position is controllable. Thus attribute A8 is useful to express the detailed part or recognition of a certain object. A8 expresses the importance for each object in the scene, the value is determinate either by user or LOD level of the object in the scene.

3 Viewpoint Scoring Method

In this section, a novel criterion for viewpoint goodness measurement named Viewpoint Pertinence is proposed. The definition of the novel metric contains not only geometric criterion, such as visible projected area, surface curvature, but also non-geometric criteria such as, visual perception, scene information are taken into account. In our precious work, a novel viewpoint quality evaluation metric named Region Weighted Information Entropy (RWIE) [9] was proposed. The novel criterion combines visual perception and information entropy theory which make viewpoint quality evaluation result more conform to human visual habits. So, we use RWIE to represent viewpoint attribute A3 to A7.

We use the attributes enumerated in Table 1 to formalize the Viewpoint Pertinence as expression (4), thus the viewpoint quality can be quantified. An adequate combination of these attributes could give a good measure of viewpoint quality.

$$Vp(S,p) = w_1 \sum_{i=1}^{N} S_i(T,p) + w_2 \sum_{i=1}^{N} V_i(S,p) + w_3 \sum_{i=1}^{N} p_i + w_4 \sum_{j=1}^{M} W_j \times E(R_j) \quad (4)$$

Where w_i is the weight of each attribute of Viewpoint Pertinence which is determined by Analytic Hierarchy Process (AHP) algorithm. N presents the number of models

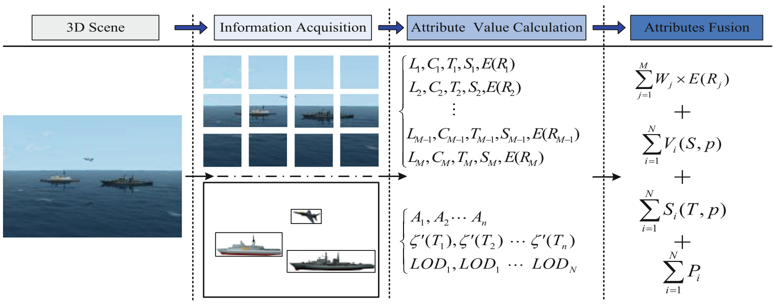


Fig. 1. Implementation process of Viewpoint Pertinence

contain in a scene, M presents the number of equal sized regions that the viewpoint image is divided. Figure 1 presents the implementation process of Viewpoint Pertinence.

According to Fig. 1, the overall computational process of Viewpoint Pertinence Vp for the given viewpoint Vp_i is showed by Algorithm 1.

Algorithm 1: Computing the Viewpoint Pertinence *Vp* for the given viewpoint (*S*,*p*)

M:The number of image segmentation regions with equal size

N:The number of object in scene

$W_j \leftarrow 0,\ E(R_j) \leftarrow 0,\ V_i(S,p) \leftarrow 0,\ S_i(T,p) \leftarrow 0,\ P_i \leftarrow 0$

$[w_1, w_2, w_3, w_4] \leftarrow$Attribute weight determination using AHP

For (i=0; i<N; i++)

Compute mesh saliency entropy $S(T, p)$, viewpoint entropy $V(S, p)$, Visible Priority P;

End for

For (j=0; j<M; j++)

Compute the perception factors (L, C, T, S) and image information entropy $E(R)$;

Compute the weight W_j for each region after normalization;

End for

$Vp(S,p) \leftarrow$Attributes value accumulate;

4 Viewpoint Selection Using PSO Algorithm

In order to eliminate the number of viewpoint quality evaluations, thus improve the efficiency of the optimal viewpoint searching process, we adopt we adopt the random weight PSO to select the canonical viewpoint intelligently and automatically. In the previous literature, viewpoints are located on the viewpoint sphere [9], which have a fixed distance from the center of the sphere. Differ from previous method, we define the view distance R as a variable within a certain range. The viewpoint set contains different view direction and distance, these viewpoints can be represented by multi-resolution hierarchy.

The standard PSO algorithm can easily drop into local optimum and has the low convergence speed, we use random weight PSO to overcome these shortcomings. In modified PSO, velocity and position of each particle is updated by Eqs. (5) and (6).

$$v_{im}^{k+1} = w \times v_{im}^{k} + c_1 \times Rand() \times (p_{im}^{k} - x_{im}^{k}) + c_2 \times Rand() \times (p_{gm}^{k} - x_{im}^{k}) \tag{5}$$

$$x_{im}^{k+1} = x_{im}^{k} + v_{im}^{k} \tag{6}$$

Where c_1 and c_2 are the learning factor. w is weight coefficient. The random weight w is defined as:

$$\begin{cases} w = \mu + \sigma \times N(0, 1) \\ \mu = \mu_{\min} + (\mu_{\max} - \mu_{\min}) \times rand(0, 1) \end{cases} \tag{7}$$

Where $N(0,1)$ represents a random number of standard normal distribution. μ_{max} is the maximum value of the mean value of the random weight, μ_{min} is the minimum value. σ is the variance of the mean value of the random weight.

The basic process of the algorithm is as follows:

***Step*1.** Enter the initial viewpoints candidate set, random weight PSO parameters and the viewpoint sphere parameters, then encoding viewpoints into particles in PSO;

***Step*2.** Update particle velocity and position by random weight PSO algorithm to achieve particle evolution;

***Step*3.** Decoding particles to obtain the corresponding viewpoint coordinate, render the scene for each alternative viewpoint respectively;

***Step*4.** Evaluating the viewpoint image quality by using Algorithm 1 to calculate the fitness value of each particle, then update the *pBest* and *gBest*;

***Step*5.** If the iteration termination condition is reached, then output canonical viewpoint, otherwise return to step 2), update the particles, into a new round of iterations

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

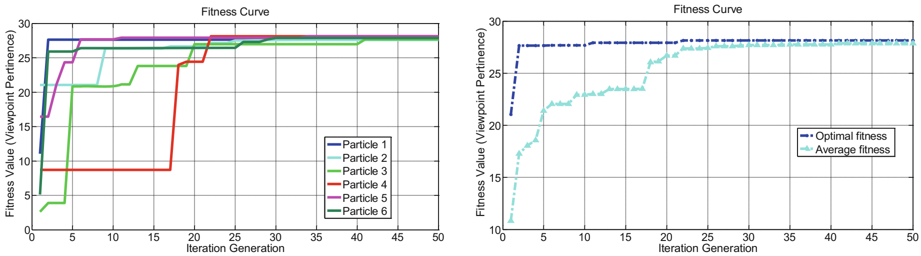
5 Experimental Results and Analysis

We use three models (aircraft, ship and sea) to form the test scene. Through the AHP analysis, the weight of four attributes is w = {0.2053 0.2594 0.1137 0.4216}. Viewpoint distance R has 4 resolution levels, angle θ has 30 resolution levels, δ has 10 resolution levels. So the number of the candidate viewpoints is 4*10*30. The viewpoint image is 800*600, and divided into 48 blocks with equal size of 100*100 pixels. The initial viewpoint location covers the top, front, back, left and right direction of the viewpoint sphere, but the viewpoint distance is randomly selected. Table 2 shows the corresponding parameters setting of adaptive weight PSO in the process of viewpoint selection.

Table 2. Parameters setting of random weight PSO

Population size	Dimension	Maximum iterations number	μ_{max}	μ_{min}	σ	C_1, C_2
6	3	50	0.8	0.5	0.2	2, 2

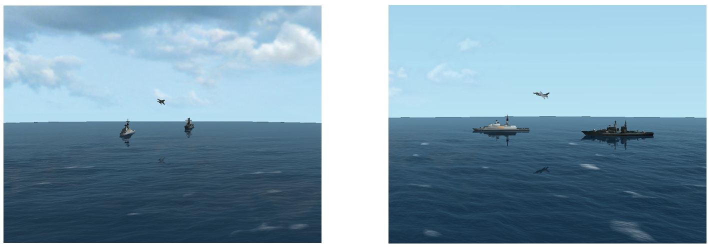
Fig. 2 a shows the change of fitness value of six particles in the iterative process. The average fitness and optimal fitness curve of the six particles is showed in Fig. 2 b. From Fig. 2, we can see each particle gradually close to the optimal solution in the evolutionary process, the entire process is toward the better solution program, and the viewpoint quality is getting better and better. The canonical viewpoint is obtained by the fourth particle in the 22nd generation. The rendered image of obtained canonical viewpoint is showed in Fig. 3 b.



(a) Fitness curves (b) Average fitness and optimal fitness curves

Fig. 2. The fitness curves of six particles

In the same experimental environment condition, we compare the canonical the viewpoint selected by the proposed algorithm with the algorithm in [14]. Fig. 3 a is the optimal viewpoint selected by method in [14] and Fig. 3 b is by our algorithm.



(a) (b)

Fig. 3. Optimal viewpoint selection by algorithm in [14] and proposed algorithm

Image information entropy is used in graphics area to represent the information richness of an image. We can see although viewpoint image contains more information of the scene but it does not conform to human observation habits. The selected viewpoint distance is too far to see the objects of the scene clearly and the small object (aircraft) is submerged in scene background. So the canonical viewpoint obtained by image information entropy can easily affected by scene background.

The proposed algorithm considered not only geometric information, human visual perception characteristics are taken into account. From Fig. 3 b, we can have a more comprehensive understanding of the scene than Fig. 3 a. The canonical viewpoint selected by our algorithm contains enough geometric information to understand what are the objects and the shape. Meanwhile, the definition of Viewpoint Pertinence contains chrominance and luminance information, so we can see the bright part of the aircraft and the left ship. From geometry and visual perception aspects, the canonical viewpoint selected by our algorithm is superior to algorithm in [14].

6 Conclusions and Future Work

In this paper, we present a novel viewpoint scoring method based on multi-attribute fusion. The perceptual model of viewpoint pertinence is formalized as a combination of viewpoint attributes which are believed to be significance for viewpoint selection. Random weight PSO is introduced to eliminate the reluctant viewpoint evaluations, and by GPU acceleration the efficiency and speed of algorithm is improved. The canonical viewpoint obtained by the proposed method contains more visible salient features and better conforms to human visual perception.

There are many potential attributes of viewpoint preference described in the literature, we will explore and enrich the classes of viewpoint attributes. Moreover, we will use this method in a number of applications, such as trackball controls and extensions and camera orbits optimization.

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