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QUANTITATIVE EVALUATION OF VIEWPOINT QUALITY FOR 3D VISUALIZATION BASED ON MULTI-ATTRIBUTE FUSION

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Abstract. *Aiming at the fundamental issue of optimal viewpoint selection for the 3D visualization, this paper presents an intelligent optimal viewpoint selection algorithm based on multi-attribute fusion. Through analyzing the influence of several digital image factors (luminance, chrominance, texture details and spatial location, etc.) on human visual characteristics, the mathematical models are established. Combined with intrinsic geometry information, a novel viewpoint quality metric in line with visual characteristic named Viewpoint Potency is built. Evolution algorithm is utilized to select the optimal viewpoint automatically and intelligently. Experimental results demonstrate that the optimal viewpoint selected by the proposed algorithm shares more in common with the sensory choice of human beings. In comparison with existing methods, the proposed method has high efficiency, and requires no user interaction and semantic computation.*
Keywords: Viewpoint selection, Visual perception, Multi-attribute fusion, Viewpoint Potency, Particle swarm optimization

1. **Introduction.** With the rapid growing 3D digital content, the effective display and retrieval of the data become very urgent. Selecting an appropriate observation viewpoint by viewpoint evaluation is an important approach to solve this problem. The metric used for viewpoint quality evaluation in existing literature can be classified into two categories: geometric information based and semantic information based. Geometric information based metric uses the geometric features, such as geometric area [1,2], curvature [3,4], relief saliency [5] and skeleton-based [6,7]. These algorithms are simple and can select the optimal viewpoint automatically, but not conducive to process models with simple geometric feature but important semantic information. Semantic information based metric can be found in [8,9]. Viewpoint selected by this metric is generally consistent with human observation habits, but the operation is more complex and cumbersome. Meanwhile, with restrictions on the semantic understanding and extracting level, these methods have not yet been widely used. In recent years, researchers explored artificial intelligent (AI) techniques in viewpoint selection for 3D visualization [10,11]. These algorithms remarkably eliminate the reluctant viewpoint evaluations, and thus improve the efficiency of the searching process.

With respect to the problem that existing viewpoint selection methods either require complex computation or fail to provide results that conform to human visual habits, in this paper, several digital image factors that influence on human visual perception are analyzed. Combined with intrinsic geometry information, a viewpoint quality metric in line with human visual characteristics named Viewpoint Potency is built. The problem between the size of viewpoints set and the efficiency of algorithm is balanced by utilizing random weight particle swarm optimization (PSO) algorithm in the process of viewpoint optimization. The computation for viewpoint quality which is determined by Viewpoint Potency is accelerated based on graphics processing unit (GPU).

The article continues with the mathematical models of several visual perception influencing factors. The novel viewpoint quality evaluation method: Viewpoint Potency is proposed in detail in Section 3. In Section 4, intelligent viewpoint selection framework is presented. Experimental results and comparison studies are shown in Section 5. Conclusions and future work are given in Section 6.

2. **Visual Perception Characteristic.**

The YIQ method reconstructs three primitive color spectrum information (RGB) that human can recognize into luminance and chrominance information. YIQ consists of the luminance (Y), the warm color chrominance (I), and cold color chrominance (Q). The following expression is used to convert RGB into YIQ.

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.275 & -0.321 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Assume that the image X contains N pixels ($N = m \times n$). The four visual perception influencing factors are given below.

2.1. **Luminance influence factor.**

A scene with low luminance (dark) provides difficult recognition of objects and with high luminance (bright) is hard to extract the edges of object. Therefore, a scene with wide range of luminance values, namely, with high contrast is considered as a good view. Luminance influence factor is defined as:

$$L = K \times \log \frac{l^{\max}}{l^{avg}} = K \times \log \frac{\max\{Y_1, Y_2, Y_3, \dots, Y_N\}}{\frac{1}{N}\sum_{i=1}^{N} Y_i} \tag{2}$$

where $l^{\max}$ is the maximum luminance value of image X. l^{avg} is average luminance value, $l^{\max}/l^{avg}$ approximately expresses the image light stimulation intensity. K usually sets 1.

2.2. **Chrominance influence factor.**

When visualizing multi-dimensional data, we often focus on a specific element of the array data by representing with color change. A higher chrominance total or its abrupt change seems to provide better views. Thus we use chrominance variance to represent the impact on the human visual perception. Chrominance influence factor is defined as:

$$C = \lambda \times C_I + (1 - \lambda) \times C_Q \tag{3}$$

where C_I, C_Q are the chrominance variances of I and Q, and λ usually sets $0 \sim 0.5$.

$$C_I = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(I_i - \frac{1}{N}\sum_{i=1}^{N} I_i\right)} \qquad C_Q = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(Q_i - \frac{1}{N}\sum_{i=1}^{N} Q_i\right)} \tag{4}$$

2.3. **Texture details influence factor.**

Spatial frequency indicates the clarity of image detail. The higher spatial frequency is, the more texture details a region contains, and the more attention human visual will be paid to. Texture detail influence factor is defined as:

$$T(F) = \sqrt{RF^2 + CF^2} \tag{5}$$

where RF and CF are the row and column frequencies of the image pixels, and $F(i, j)$ is the gray value of the pixel (i, j). Expressions are as follows:

$$\begin{aligned} RF &= \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (F(i,j) - F(i,j+1))^2} \\ CF &= \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (F(i,j) - F(i+1,j))^2} \end{aligned} \tag{6}$$

2.4. **Spatial location influence factor.** When people observe a picture, the first note is the central part, and then turn around. Namely the importance of the image is generally decreasing from the center to the surrounding. Assuming that the 2D projected image of a 3D scene contains n objects, the spatial location sensitivity of the object i is defined as:

$$S_i = 1 - (1 - \beta) \times \frac{\sqrt{(x_{ic} - x_c)^2 - (y_{ic} - y_c)^2}}{d} \tag{7}$$

where x_c and y_c are the center coordinates of image X. x_{ic} and y_{ic} are the coordinates of object i. d represents the distance from the farthest object to the image center coordinates. β is the basis weight and usually sets $0 \sim 0.5$.

3. **Viewpoint Potency.** In this section we present a novel metric for viewpoint quality evaluation named Viewpoint Potency. The definition of Viewpoint Potency contains several properties of chrominance and luminance, and simultaneously the number of visible faces and projection areas are also taken into account. We enumerate the attributes in Table 1 that are useful for the measure of viewpoint quality.

Table 1. Viewpoint Potency attributes

$\mathbf{A_1}$	Viewpoint Entropy
$\mathbf{A_2}$	Luminance
$\mathbf{A_3}$	Chrominance
$\mathbf{A_4}$	Texture Details
$\mathbf{A_5}$	Object Spatial Location
$\mathbf{A_6}$	Object Visible Priority

We formalize the Viewpoint Potency as Equation (8) with the attributes enumerated in Table 1 so that the optimal viewpoint can be quantified. Assume that the 3D scene contains n objects.

$$\begin{aligned} Vp(S,p) &= \sum_{i=1}^{n} Vp_i(S,p) \\ &= \sum_{i=1}^{n} (w_1 \times V_i + w_2 \times L_i + w_3 \times C_i + w_4 \times T_i + w_5 \times S_i + w_6 \times P_i) \end{aligned} \tag{8}$$

where w_i is the weight of each attribute of Viewpoint Potency, which is determined by analytic hierarchy process (AHP) algorithm. V_i, L_i, C_i, T_i, S_i, P_i represent the value of attributes $A_1 \sim A_6$.

The values of $A_1 \sim A_5$ are calculated for each object. A_1 is calculated by the algorithm in [2]. $A_2 \sim A_5$ are calculated according to Equation (2) to Equation (7), and the pixel number is determined by the bounding box of the object in the scene. A_6 is given as the level of importance for each object, and is determinate by current levels of detail (LOD) value of the object. Figure 1 presents the implementation process of Viewpoint Potency.

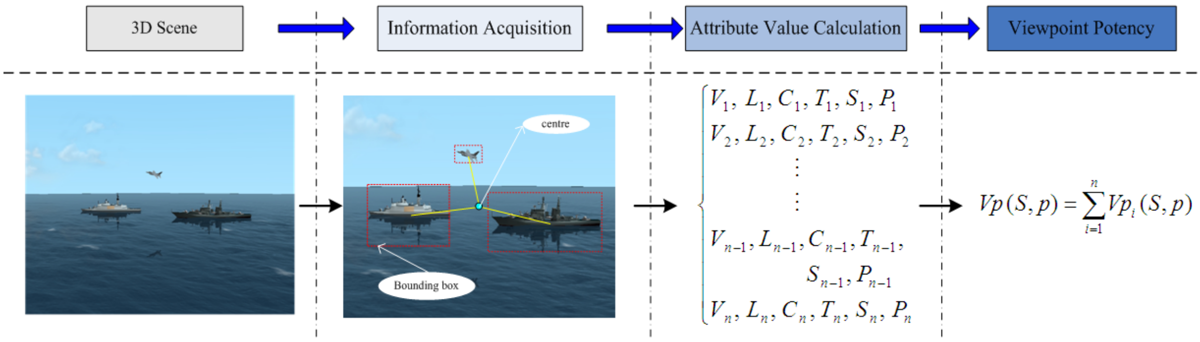

FIGURE 1. Implementation process of Viewpoint Potency

According to Figure 1, the overall computational process of Viewpoint Potency for the given viewpoint (S, p) is shown by Algorithm 1.

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

ROW_pixel, COL_pixel: Pixel width and height of object bounding box
$[w_1, w_2, w_3, w_4, w_5, w_6] \leftarrow$ Attribute weight determination using AHP
$Vp_i(S, p) \leftarrow 0$, $Vp(S, p) \leftarrow 0$, $n \leftarrow$ The number of object in scene
  For $(i = 0;\ i < n;\ i{+}{+})$
    Compute the visual perception attributes (L_i, C_i, T_i);
      Compute the geometric attributes (V_i, S_i);
        Compute the visible priority P_i;
  End for
      Compute the Viewpoint Potency of object i $Vp_i(Sp)$;
  For $(i = 0;\ i < n;\ i{+}{+})$
    Accumulate $Vp(S, p)$;
  End for

4. **Intelligent Optimal Viewpoint Selection Framework.** The basic idea of the algorithm is converting the searching for the optimal viewpoint into a parameters optimization problem, the set of all possible viewpoints which have a fixed distance from objects as the searching area. Through coding, particle evaluation and updating, after several times of iteration, the optimal viewpoint can be obtained. Intelligent viewpoint selection algorithm framework is shown in Figure 2.

4.1. **Encoder and initialization.** Viewpoints are encoded into particles to solve the problem of finding the optimal viewpoint by PSO. As shown in Figure 3, viewpoints are positioned on the enclosed sphere of 3D scene. A population $P(t)$ of particles at time t is $P(t) = \{p_1(t), p_2(t), \cdots, p_N(t)\}$, and N represents the population size. Therefore, a particle at time t is encoded as $p_i(t) = V_i = (R, \delta_i, \theta_i)$.

The initial population $P(0)$ might be selected randomly or by users. However, the representative particles could direct the iterations more effectively. So we define several typical view directions which cover the top, front, back, left and right parts of the viewpoint sphere in the initialization of the PSO.

4.2. **Viewpoint evaluation and searching process.** Assume the new generated population is $P(t')$, and particle i in $P(t')$ is $P_i(t')$. We compute the fitness value $Fit(P_i(t'))$ for $P_i(t')$ according to Algorithm 1, and then compare the $Fit(P_i(t'))$ with $Fit(pBest)$ and $Fit(gBest)$ to achieve particle evolution, where *pBest* is the best solution of each particle achieved so far, and *gBest* is the global best value obtained by all particles in the population so far. The evolutionary process should meet the following rules.

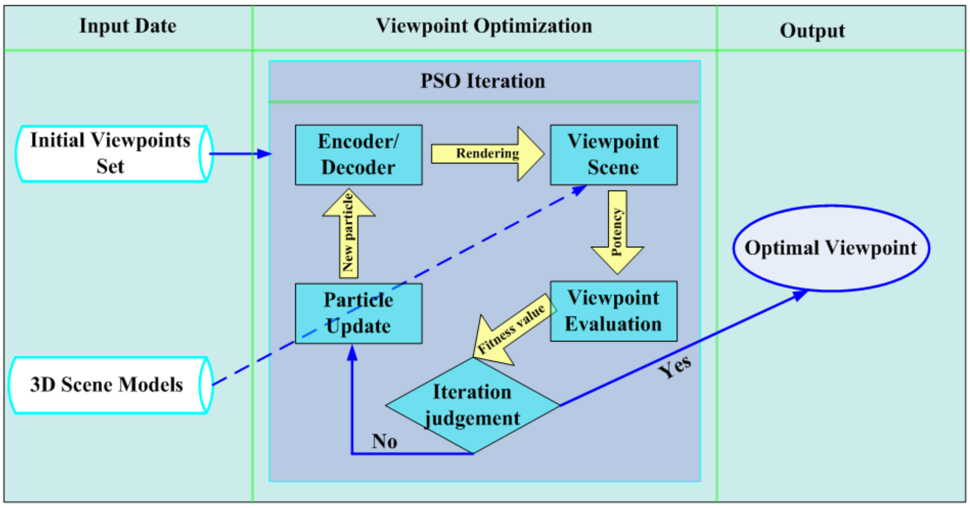

Figure 2. Intelligent optimal viewpoint selection algorithm framework

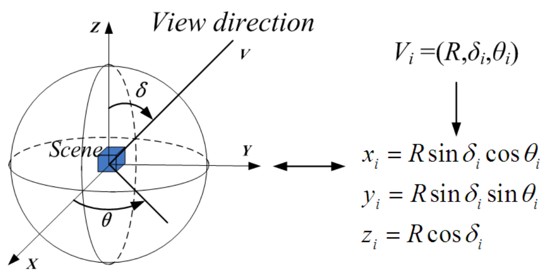

Figure 3. Viewpoint sphere and coordinate transformation

• If the fitness value of particle $P_i(t')$ is larger than $P_i(t)$, then $Fit(P_i(t')) > Fit(P_i(t))$; If $Fit(P_i(t')) > Fit(pBest)$, then update $pBest$ with $P_i(t')$.

• If the fitness value of particle $P_i(t')$ is larger than $P_j(t')$, then $Fit(P_i(t')) > Fit(P_j(t'))$; If $Fit(P_i(t')) > Fit(gBest)$, then update $gBest$ with $P_i(t')$.

In each iteration step, each particle updates its velocity and position with the $pBest$ and $gBest$ and generates the new population $P(t'')$ to begin a new iteration. The iteration is terminated only when the two following conditions are met:

• The number of the iterations reaches the predefined maximum Max;

• $|gBest(P(t')) - gBest(P(t))| \leq$ Min, where Min is the predefined minimum Min.

4.3. **Random weight PSO.** The standard PSO algorithm can easily drop into local optimum and has low convergence speed, and we use random weight PSO algorithm to overcome these shortcomings. In modified PSO, velocity and position of each particle are updated by Equation (9) and Equation (10).

$$v_{im}^{k+1} = w * v_{im}^k + c_1 * Rand() * \left(p_{im}^k - x_{im}^k\right) + c_2 * Rand() * \left(p_{gm}^k - x_{im}^k\right) \tag{9}$$

$$x_{im}^{k+1} = x_{im}^k + v_{im}^k \tag{10}$$

where c_1 and c_2 are the learning factor. w is weight coefficient, which can improve global and local search ability of the algorithm. The random weight w is defined as:

$$\begin{cases} w = \mu + \sigma \times N(0,1) \\ \mu = \mu_{\min} + (\mu_{\max} - \mu_{\min}) \times rand(0,1) \end{cases} \tag{11}$$

where $N(0,1)$ represents a random number of standard normal distribution, and $rand(0,1)$ is random number from 0 to 1. $\mu_{\max}$ is the maximum value of the mean value of the random weight, and $\mu_{\min}$ is the minimum value. σ is the variance of the mean value of the random weight. Parameters value setting refers to Section 5.

Algorithm 2 shows the overall procedure of intelligent viewpoint selection.

Algorithm 2: Viewpoint selection using random weight PSO algorithm

$t \leftarrow 0$, $Npartical \leftarrow N$, $gBest \leftarrow p_1(0)$, $Niteration \leftarrow 0$, $Maxiteration \leftarrow M$
$pBest(p_i(0)) \leftarrow 0$, $i = 1, 2, \ldots,$ $Npartical$
$R \in [d_1, d_2]$, $\theta_i \in [0, 2\pi]$, $\delta_i \in [0, \pi/2]$
Select several typical view directions (R, θ_i, δ_i), $i = 1, 2, \ldots,$ $Npartical$
Initialize $p_i(Niteration)$, $i = 1, 2, \ldots,$ $Npartical$
$P(Niteration) \leftarrow \{p_1(Niteration), p_2(Niteration), \ldots, p_N(Niteration)\}$
While $Niteration < Maxiteration$ Do
For each particle $p_i(Niteration)$ *in* $p(Niteration)$ *Do*
Compute the Viewpoint Potency $Vp(S, p)$ for $E(p_i(Niteration))$
If $E(p_i(Niteration)) > pBest(p_i(Niteration))$ Do
$pBest(p_i(Niteration)) \leftarrow E(p_i(Niteration))$
If $pBest(p_i(Niteration)) > E(gBest)$ Do
$gBest \leftarrow p_i(Niteration)$
End For
Update P $(Niteration)$
Selecting the optimal viewpoint according to the particle *gBest*

5. **Experimental Results and Analysis.** The proposed algorithm is carried on Intel Core i7 with 4GB RAM and 2048MB graphic card. Software configuration: Window 7 system, OpenGL 3.2, OSG 2.8.2, Visual studio 2012.

We use three models to form the test 3D scene. According to AHP algorithm, the weight of Viewpoint Potency attributes is $w = (0.3828, 0.1445, 0.0391, 0.2358, 0.0789, 0.1189)$. Initial viewpoint set V_0 is $\{(R, 0°, 0°), (R, 0°, 90°), (R, 90°, 90°), (R, 180°, 90°), (R, 270°, 90°)\}$, and viewpoint distance $R = 300$, $0 < \theta < 2\pi$, $0 < \delta < \pi$. Table 2 shows the parameters setting of random weight PSO.

Figure 4 shows the change of fitness value of each particle in the evolutionary process. The optimal viewpoint is obtained by the second particle in the fifteenth generation. The polar coordinate is $(300, 75°, 310°)$, and spatial coordinate is $(186, -221, 78)$. The rendered image of this viewpoint is shown in Figure 7(c).

Table 2. Parameters setting of random weight PSO

Population size	Dimension	Max iteration number	$\mu_{\max}$	$\mu_{\min}$	σ	c_1, c_2
6	3	30	0.8	0.6	0.2	2

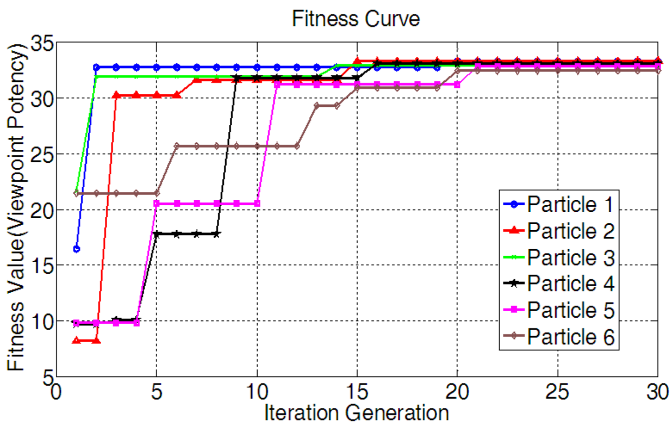

Figure 4. Fitness curves

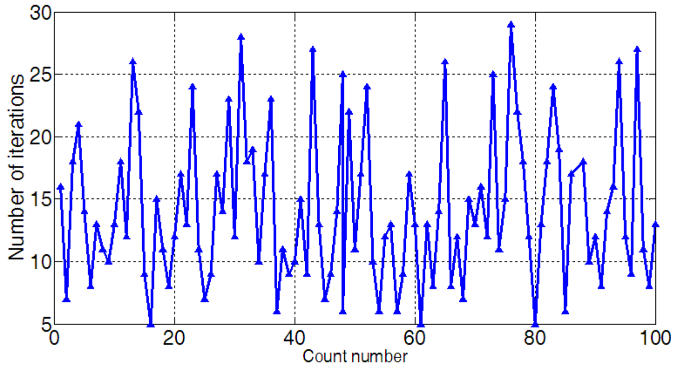

Figure 5. Number of iteration statistics

Figure 6. Viewpoint image sequence based on random weight PSO optimization

In the case of the same experimental environment condition, we designed an experiment which applied 100 times optimal viewpoint selection based on random weight PSO. As shown in Figure 5, there are 83 times the number of iterations is less than 20, and 65 times less than 15. Result indicates that random weight PSO has fast convergence rate and can meet the actual requirement.

From Figure 4, we can see each particle gradually closes to the optimal solution in the iterative process, the entire process is toward the better solution program, and the viewpoint quality is getting better and better. The optimal solution and the rendered images of the iteration process are shown in Figure 6.

We compare our algorithm with algorithms in [1,11]. Figure 7 shows the optimal viewpoint obtained by three algorithms. Figure 7(a) is selected by algorithm in [1], Figure 7(b) is by algorithm in [11] and Figure 7(c) is by the proposed algorithm.

Viewpoint entropy proposed in [1] only considers the size of the projected area and the number of visible faces to determine the viewpoint quality, but does not contain chrominance and luminance information, so we can see Figure 7(a) has more visible faces but with the low luminance. Figure 7(b) is obtained by image information entropy. Image information entropy is used to represent the information richness of an image. Although image Figure 7(b) contains more information of the scene it does not conform to human observation habits, and the small object (aircraft) is submerged in scene background. Therefore, the optimal viewpoint obtained by image information entropy can be easily

Figure 7. Optimal viewpoint selected by algorithms in [1,11] and proposed algorithm

affected by scene background. The proposed algorithm considered both scene geometric information and human visual perception characteristics. We can see the viewpoint selected by our algorithm is superior to algorithms in [1,11].

6. **Conclusions and Future Work.** In this paper, we analyzed the four visual perception influencing factor. Combined with viewpoint entropy and object visible priority, a novel viewpoint quality metric named Viewpoint Potency is proposed and applied to the optimal viewpoint selection for 3D scene. Result shows the optimal viewpoint selected by the proposed algorithm better conforms to human visual habits. Through GPU acceleration, the efficiency and speed of the algorithm is greatly improved.

We only discuss the selection of optimal viewpoint in this paper, how to select a set of viewpoints, and according to the geometric position relationship and user concerned information, automatically planning an optimal browsing route to make the users have a more comprehensive understanding of the scene is future direction of our work.

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