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Geomancy culture embedded in sustainable green design in modern interior design

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Abstract. As the important content of virtual scene design, furniture layout has been applied in virtual reality, 3d game and interior design. The existing automatic layout of furniture is constrained and shall trigger local optimum readily, and the real-time requirement fails to be satisfied arising from the slow convergence rate of global optimization. Given these, the optimization for hierarchy is proposed to mitigate constraint, and the Intelligent water drop algorithm is adopted to optimize the Geomancy Culture. Firstly, the hierarchical tree is introduced to structurally organize the constrained relationship among furniture and to avoid the constraint. Secondly, the Intelligent water drop algorithm is introduced to optimize the solution of Geomancy Culture. The prominent parallel structure taken on by Intelligent water drop algorithm can be conducive to expediting GPU, thus the algorithm is more efficient. This algorithm is effectively verified through adopting various and diverse instances, and the operating efficiency of this algorithm is anatomized. As the results indicate, the method proposed in this paper improves the quality and increases the efficiency of furniture layout.

Key words. Interior design, Geomancy culture, Intelligent water drop algorithm, green design.

1. Introduction

Scene design is one of the most important parts of computer graphics application, which involves a wide range of fields, from urban planning to personal style. As part of the scene design, the furniture layout has been the focus of graphic research and related applications in recent years. The construction of scene in virtual reality environment and 3d game involves a large number of problems for furniture layout. Generating interior layout through the interaction of handwork shall be arduous but fruitless. It is not only inefficient, but often difficult to obtain satisfactory re-

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sults. Moreover, with the improvement of living standards, people have made higher demands on the quality of furniture. For people who have no experience in home design, they usually move the furniture in the wrong way until they are satisfied. But this limits the free choice and combination of the user to furniture, and the arrangements often cannot satisfy function and requirement from the aesthetic aspect. An automatic display system can assist ordinary users to design and customize the home environment more effectively.

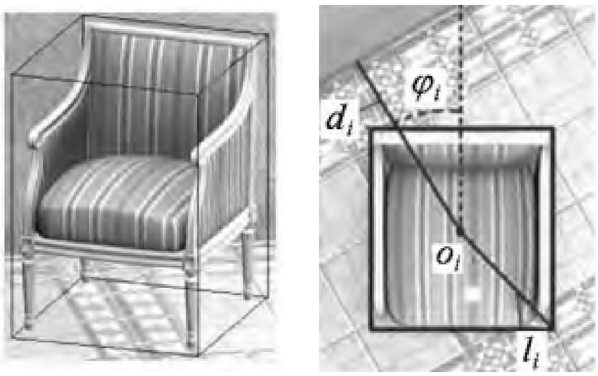
In the early stage, the automatic layout method of 3D scene is mainly based on pseudo-physical constraints, constrained object support relation or semantic database constraints to define effective scenarios. These tasks consider only simple relationships between objects, such as support relationships and contact relationships. Although objects can be neatly placed in the scene through adopting the early-stage 3D automatic scene layout, the human engineering is factored out, inclusive of function and application of scene, and the aesthetic requirement of the entire layout. In recent years, the work began to highlight the functions and aesthetic principles of life experience and interior design, and to convert them into energy constraints. If these regulations are met, the energy shall be minimized. Because these methods are optimized in the uniform energy function, it is easy to result in the constraint conflict and thus get into the local extremum, resulting in the unsatisfactory result. Furthermore, both tasks adopt the intelligent water drop algorithm for solution. Accordingly, the iteration shall be conducted repeatedly, the rate of convergence is low, and the real-time requirements cannot be met in medium and small-sized scenes.

In this regard, a hierarchical tree is proposed in this paper to organize the hierarchical optimization method of indoor furniture. On the one hand, the problem of constraint conflict is solved and the constraints are decoupled. On the other hand, the quality of furniture furnishing is increased indirectly. For the given furniture combination and its constraints, the hierarchical tree and root node are first proposed to represent the room to be arranged. The combination of furniture shall be extracted from the scene. For instance, the paired relation between tables and chairs as they show up simultaneously is defined as a furniture group. Such grouping method is similar to the classification method of context propose din literature [8] and the structural group concept proposed in literature [9]. The furniture not combined can be deemed as the furniture group with one piece of furniture. These furniture pieces are constrained by the distance and angle. According to this idea, this paper can establish a hierarchical optimization tree through first optimizing the furnishings in each group, and then allowing the group to meet the constraints of the wall. The constraints can be solved through hierarchical tree. Additionally, a parallel solution algorithm is proposed on the basis of the intelligent water-drop algorithm. Through these efforts, this paper seeks to enable furniture layout system to respond to the users' operation in real time.

2. Hierarchically optimized furniture layout based on Geomancy Culture

2.1. Automatic furniture layout and optimization model

Each piece of furniture is represented by its smallest hexahedral surround box, which marks the corresponding relationship between the box and the front, rear, left and right side of the furniture. Virtually, merely the rear side of the furniture shall be recorded as the reference plane. The bounding box of each object is confirmed by the central point and the rear orientation (o_i, φ_i). As indicated in Fig. 1, o_i refers to the projection of central point of bound box on the plane of xy. Its 2D coordinate is recorded as (x_i, y_i), virtually denoting the included angle between the rear side of object and the nearest wall to the object. d_i indicates the distance between o_i and the nearest wall. l_i is the distance between o_i and any vertex of the underside of bounding box.



(a) Expression of bounding box (b) Definition of myriabit

Fig. 1. Expression of furniture

Based on the observation of domestic scene, the main relationship between objects is summarized as follows:

(1) The relationship between an object and a wall. It mainly represents the distance d_i between the object and the nearest wall and the Angle φ_i between the back and the wall. Its prior value can be obtained by means of actual examples.

(2) The relationship between an object and an object. Pair relationships and hierarchical relation. The furniture scene often takes a certain relative distance and the direction come in pairs, such as table and dining chair, tea table and sofa, etc. While implementing the system, this pair of relationships can be set up through the simple interaction of the user interface. In daily life, an object is supported by other objects because of its gravitational pull, which in turn supports the object placed on it. This support and supported relationships are represented as parent child hierarchies. For instance, In a living room scene, the room can be treated as a root node. All objects that are directly supported by the floor of the room or supported by the wall are the direct child of the root, which is the "first layer objects". Other

objects supported by the first layer objects are the "second layer objects". In this case, the second hierarchical relation is established. Such hierarchical relation differs from the hierarchical tree established in this paper for hierarchical optimization. The hierarchical tree in this paper is established on the basis of the primary and secondary relationship of furniture group that is composed by the paired relationship.

Standard examples of interior design have found that pairs of objects usually have special angles, such as face to face, facing rear, facing left, facing right, left aligned, and right aligned. The paired can be established at any angle. The reason why angle of facing rear is defined is because each object defined in this paper has a rear side. For four chairs around the square table, there shall always be one chair facing the rear side of the table.

2.2. Energy function (Functional and visual standards)

This paper aims to provide the user with a beautiful interior furnishing suitable for living. In order to achieve this goal, the main principles of interior design are applied to computer automatic furniture layout. The television and cabinet shall be better lean against the wall. The sofa is normally placed next to the tea table. A preferable furniture layout shall meet the requirement of function and ne comfortable, and further bring people the sense of job from the higher level of art. The work conducted in literature [6-7] is referenced and improved. Some energy density functions are defined to characterize these principles, e.g. the functional quantifier of accessible room and providing the activity space for using furniture. The objective of this paper is to minimize the sum of energy density function of the sample. The energy density function shall be defined as follow. Property of accessible room. Define a accessible space for each object, allowing people to pass or use it freely. As indicated in Fig. 2, the dimensions of accessible space are determined by prior examples and human dimensions. The energy density function of accessible space overlapped between each object I and object j is defined as:

$$C_\alpha(\Phi) = \sum_{i}^{n} \sum_{j \neq i}^{n} \sum_{k}^{4} \max\left[0, 1 - \frac{\|0_i - c_{jk}\|}{l_i + t_{jk}}\right]. \tag{1}$$

Visibility. For some objects (such as TV) that cannot be blocked by other objects, a cone can be defined as a visual range for these objects. As shown in Fig. 3, the visible range is approached by three rectangles. r_{jk} denotes the center of rectangle, s_{jk} refers to the radius diagonal of rectangle. The visibility energy density function of each object i and the object with a visual range $j \in V$ (V refers to the set of furniture with visual range) is defined as:

$$C_v(\Phi) = \sum_{i}^{n} \sum_{j \neq i, j \in V}^{n} \sum_{k}^{3} \max\left[0, 1 - \frac{\|0_i - r_{jk}\|}{l_i + s_{jk}}\right]. \tag{2}$$

The aisle of the door corridor or door corridor should not be occupied by other objects, or people cannot walk in the room. Of course, the doorway of the door can be

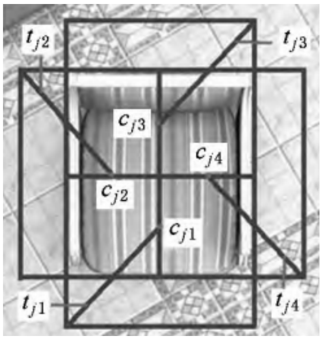


Fig. 2. Center of each accessible space

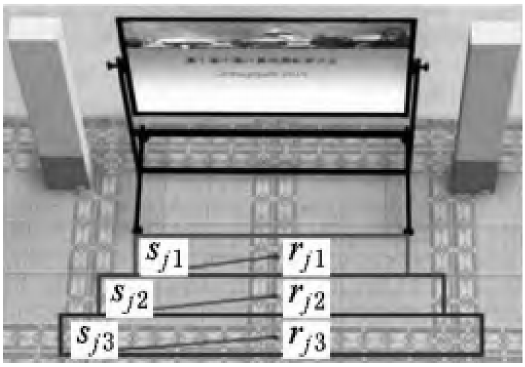


Fig. 3. Center of three rectangles

circuitous, whereas the ideal situation is a smooth curve, which can be approximated by the Bessel curve. The corridor space is represented using a simple rectangle on the curve. The energy function of each object i occupying the corridor (each rectangle is regarded as an object) is defined as $C_h(\Phi)$. The energy density function similar to $C_h(\Phi)$ is defined as:

$$C_p^d(\Phi) = \sum_i \|d_i - d_j\|. \tag{3}$$

$$C_p^{\varphi}(\Phi) = \sum_i \|\varphi_i - \varphi_j\|. \tag{4}$$

Virtually, the visualized energy function $C_p^d(\Phi)$ refers to a V-shape function. The energy goes to 0 at d_i. The energy shall be linearly increased as away from d_i. In the experiment, $C_p^d(\Phi)$ is adequately revised, and the new function u_i is attained as:

$$u_i = \begin{cases} \log_{1/2}\left(\dfrac{d_i}{d_j}\right), \; if \; d_i < d_j \\ 0, \; if \; d_i = d_j \\ \left(\dfrac{d_i - d_j}{d_i}\right)^2, \; if \; d_i > d_j \end{cases} \tag{5}$$

$$C_p^{\varphi}(\Phi) = \sum_i u_i\,. \tag{6}$$

Similarly, the energy of u_i shall go to 0 at d_i. Yet when $d_i < d_j$, u_i shall be a function shaped as log with the radix between $(0, 1)$. When $d_i > d_j$, u_i shall be a conic function. The nearest distance to wall is expected as d_i. As the distance between object and wall d_i decreases, the energy shall decrease. As the distance between object and wall d_i rises, the energy shall increase. In addition to the contrast between furniture and room (primarily referring to wall space), the paired relation constraint furniture can also be defined. For instance, there are also relative distances and Angle constraints between tables and chairs, being similar to the relationship between objects and walls $C_p^d(\Phi)$ and $C_p^{\varphi}(\Phi)$. Assume that the relative distance and angle between 2 objects with paired relation are d_i' and φ_i' that are the prior distance and angle of paired relation, the paired constraint between furniture can be defined respectively as:

$$C_w^d(\Phi) = \sum_i \left\| d_i' - d_j' \right\|. \tag{7}$$

$$C_w^{\varphi}(\Phi) = \sum_i \left\| \varphi_i' - \varphi_j' \right\|. \tag{8}$$

As found in the realization process, the definition of $C_w^{\varphi}(\Phi)$ shall not always satisfy the paired angle constraint of 2 objects, as it only considers the relative angles between two objects. In this regard, This article has redefined the furniture pair relations of Angle constraint energy density function, and 7 kinds of special relationship in pairs are considered: face to face, facing rear, facing left, facing right, left aligned, right aligned and around. The density function of face to face angle constraint is defined as:

$$C_w^{\varphi}(\Phi) = \|\varphi_{gf}\| + \|\varphi_{fg}\| + \|\varphi_{nn} - \pi\|\,. \tag{9}$$

Where φ_{gf} refers to the included angle between the front normal of object g and the direction from g to object f; φ_{fg} refers to the included angle between the front normal of f and the direction of f to g; φ_{nn} refers to the included angle between the front normal of two objects. As indicated in Fig. 4:

Similarly, through rotating the front normal of the object to a certain angle, the energy of angle constraint of other special paired relations can be attained. For instance, the paired relation constraint of facing rear angle can be attained through rotating the front normal of object φ_{fg} for 180°. To sum up, the total energy density function is defined as a linear combination of the foregoing energy types:

$$C(\Phi) = \sum_{x\in\{a,v\}} W_x C_x(\Phi) + \sum_{y\in\{p,w\},z\in\{d,\varphi\}} W_y^z C_y^z(\Phi) + W_h C_h(\Phi)\,. \tag{10}$$

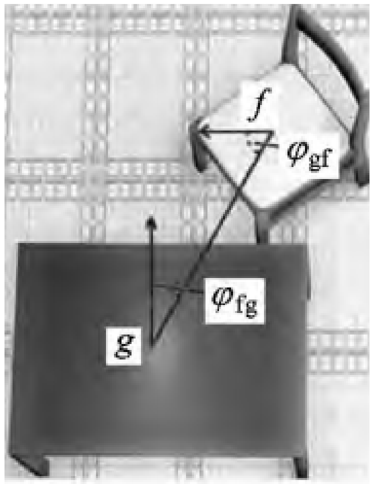


Fig. 4. Paired angle constraint

3. Improvement of intelligent water-drop algorithm

3.1. IWD algorithm

The proposed IWD algorithm is based on two important parameters: forward velocity $velocity\,(IWD)$ and volume of carried solid $soil\,(IWD)$. These two parameters are being continuously changed as river moves forward. As the intelligent water drop moves from position i to position j, the increment of velocity refers to $\Delta velocity\,(IWD)$. Such increment shall be nonlinearly inversely related to the $soil\,(i,j)$ from the position i to position j in the water course:

$$\Delta velocity\,(IWD) = \frac{a_v}{b_v + c_v\,(soil\,(i,j))^2}\,. \tag{11}$$

Where a_v, b_v and c_v are deemed as the parameters that have been given in advance. As intelligent water-drop moves, the varied solid content in the water course is consistent with the solid content varied in the intelligent water-drop.

$$\Delta soil\,(IWD) = \Delta soil\,(i,j)\ . \tag{12}$$

Given that the $soil\,(i,j)$ exerts the $\Delta velocity\,(IWD)$, the varied content of solid shall be nonlinearly inversely related to the time of intelligent water-drop moving from position i to j, i.e. $time\,(i,j)$.

$$\Delta soil\,(IWD) = \frac{a_s}{b_s + c_s\,(time\,(i,j))^2}\,. \tag{13}$$

Where a_v, b_v and c_v are deemed as the parameters that have been given in advance. The parameter $time\,(i,j)$ can be calculated by the velocity and distance model in the physics.

$$time\,(i,j) \propto \frac{d\,(i,j)}{velocity\,(IWD)}\,. \tag{14}$$

As abstracted in the algorithm, the time for intelligent water-drop moving from i to j can be defined as:

$$time\,(i,j) = \frac{HUD\,(i,j)}{velocity\,(IWD)}\,. \tag{15}$$

Where $HUD\,(i,j)$ refers to the defined reverse heuristic function. The residual solid content in the water course can be defined as:

$$soil\,(i,j) = \rho_0 \times soil\,(i,j) - \rho_n \times \Delta soil\,(i,j)\ . \tag{16}$$

Where ρ_0 and ρ_n are deemed as parameters of weight, meeting the following requirements:

$$\rho_0 + \rho_n = 1\,. \tag{17}$$

The carried volume of solid in water-drop can be defined in the updated formula as:

$$soil\,(IWD) = soil\,(IWD) + \Delta soil\,(i,j)\ . \tag{18}$$

The solid content is the water course is similar to a type of obstruct. Hence the water follow shall be largely possible to select the path with less solid content and comparatively large water follow. Hence, the corresponding probability in IWD algorithm $p\,(i,j)$ can be defined as:

$$\begin{cases} p\,(i,j) = \dfrac{f\,(soil\,(i,j))}{\sum_k f\,(soil\,(i,j))} \\ f\,(soil\,(i,j)) = \dfrac{1}{\varepsilon + g\,(soil\,(i,j))} \end{cases} \tag{19}$$

Where ε refers to positive HIS, g is primarily functionalized to ensure the solid converted to be positive. Thus it can be defined as:

$$\begin{aligned} & g\,(soil\,(i,j)) = \\ & \begin{cases} soil\,(i,j)\,,\ if\ \min\,(soil\,(i,j)) > 0 \\ soil\,(i,j) - \min\,(soil\,(i,j))\,,\ else \end{cases} \end{aligned} \tag{20}$$

Where $\min\,(soil\,(i,j))$ refers to the minimum solid content in water course from i to j.

3.2. ADR-IWD

In the foregoing algorithm update process, the IWD algorithm only updates the soil content on the path, whereas factoring out the change of soil information in the whole channel. In order to increase the probability of other drops reaching the target node, and correct the above problems, as presented in Fig. 5.

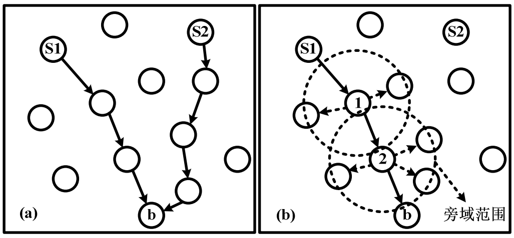


Fig. 5. Algorithm to update the side domain

Fig. 5 (a) and (b) illustrates the IWD algorithm and the IWD algorithm for updating the side domain. As (b) indicates, as the intelligent water-drop moves to node (1) and (2), the side domain of the node shall be broadcasted, and the solid content of node in the side domain shall be updated. Such method is to elevate the optimizing efficiency for interior design.

The value of $soil\,(i,j)$ is updated in line with formula (6). For the node k in the j side domain of node, if distance for k reaching to b shall be less than that reaching to j, the solid content in $edge\,(k,j)$ shall not be updated. Otherwise, node k shall generate the new IWD, with the solid content as 0, velocity as $InitVel$. Accordingly, the velocity of IWD shall be defined as:

$$velocity\,(IWD') = InitVel + \frac{a_v}{b_v + c_v\,(soil\,(i,j))^2}\,. \tag{21}$$

The removed solid content in $edge\,(k,j)$ refers to:

$$\Delta soil\,(k,j) = \frac{a_s}{b_s + c_s\,(HUD\,(k,j)/velocity\,(IWD'))^2}\,. \tag{22}$$

The formula for updating solid in $edge\,(k,j)$ is denoted as:

$$\begin{aligned} soil\,(k,j) = {} & (1-\rho_n)\,soil\,(k,j) \\ & - \rho_n\,(1 + hd_k - hd_j)\,\Delta soil\,(k,j) \end{aligned} \tag{23}$$

3.3. ADR-IWD interior design optimization

The interior design coding is the foundation of the ADR-IWD interior design optimization algorithm in the interior design intelligent optimization scheme. Each individual water drop simulates a design plan, and each water drop starts from the initial value of the design. By this time, the design set passed by the water-drop is empty. The smart drop selects the next design from the list of accessible locations. When all available design solutions have been accessed, the smart drop will return to the original design. When the first water drop builds up the route of the accessible location design scheme, the second drop begins to explore, until all the water drops construct a complete design path. The interior design code shall be presented as in Fig. 6.

As indicated in the coding scheme in Fig. 6, this coding method represents three design solutions for the eight design schemes, where the "0" represents the design scheme (except for the last one). The first one is responsible for the design of "2", "1" and "5", and the second is responsible for the design plan "4", "3" and "8", and the third responsible for the design scheme is "6" and "7". Based on the description of the intelligent water drop algorithm updated by the side domain and interior design problem, the pseudo-code of the interior design algorithm based on the ADR-IWD algorithm is shown in table 1.

Table 1. Pseudocode of ADR-IWD interior design

```
parameters for initialization algorithm: , set the initial solid content as , the initial velocity of water drop as;
while the terminal condition is not satisfied do;
  for each IWD do;
    set the taboo and candidate list as;
      while a complete path is not established do;
         IWD: =empty vehicle;
         current node i:=depot;
         while with the scheme having not been designed or without the scheme having not been designed;
            calculating the probability of selecting all feasible paths;
              select the next node;
              update the water-drop velocity;
            update the varied solid content;
            update the solid content in water course;
            update the content of solid in water drop;
            current node i:=next node j;
            update the designing method;
            update the information of designing path;
         endwhile
      endwhile
      evaluate the solution;
       endfor
       update the optimal solution;
      update the overall optimal solution,
       while each individual of elite population do;
       update the solid of side domain;
      endfor
      endwhile
return the optimal design scheme
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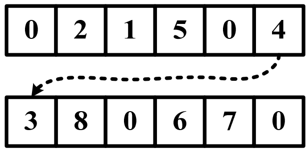

Fig. 6. Coding scheme

4. Experimental analysis

In this paper, a large number of (to be counted) furniture models are downloaded from the 3d model website(Resources.blogscopia,K1icker,Archive3D,Trimble 3D Warehouse), and the basic classification is carried out according to the label, inclusive of cabinet, chair, table, tea table, shelf, table, TV, etc. additionally, the models of all furniture pieces are made consistent with each other in size and direction manually.

In order to verify the effect and time performance of the algorithm in this paper, we carried out a large number of instance tests on 3.2 GHz Intel@CoreTM i5 3470 CPU,8 GB RAM,and NVIDIA GeForceGTX 650 Ti the PC of the graphics card. In this paper, five scene examples are selected for comparison and analysis, which are the living room, the study, the bedroom, the writing room and the dining room. Because the random algorithm is used, the results of each run are not necessarily the same. Therefore, in this paper, we run three times for each example, and get the results of 3 decorations. In this paper, an aisle is added for the two rows of furniture in the middle and the front of the door for constraint. However, as the irregular room and number of tables are relatively large, the weights of the energy items used in the experiment are as follows, $W_a = 3.0$, $W_v = 0.1$, $W_h = 5.0$, $W_p^d = 10.0$, $W_p^{\varphi} = 10.0$, $W_p^d = 10.0$ and $W_w^{\varphi} = [10, 15]$.

Yu et al. use the smart drop algorithm to optimize all the objects in the scene. To easily conduct comparison, such method is also implemented in this paper, referred to as MakeItHome. In MakeItHome, the maximum iteration number $I_{\max}$ of this paper is 45000 (larger than the maximum iteration used in the literature [6]). The initial temperature of the water drops is determined after many experiments $T_0 = 20000$. Besides, the attenuation factor of temperature $\lambda = 0.999$, and the withdrawal condition is the times of energy being no longer changed less than $I_{\max}/5$. As Fig. 7 indicates, even if the initial temperature is increased, the maximum number of iterations (45,000) will not change, and the energy will not change after a certain number of iterations, i.e. quality of solution shall not be perfected.

Because of the problem of constraint conflict in MakeItHome method, the problem solution space is more complex, which leads to the difficulty in getting the optimal solution in the limited time. Although the advantage of the intelligent water drop algorithm is that it can get rid of the local optimal, the result of the complex problem is not ideal. And even if it converges to the global optimal solution, the rate of convergence shall be small. The complexity of arranging furnishings is not only related to the number of furniture, but also the logarithm of the pairs of fur-

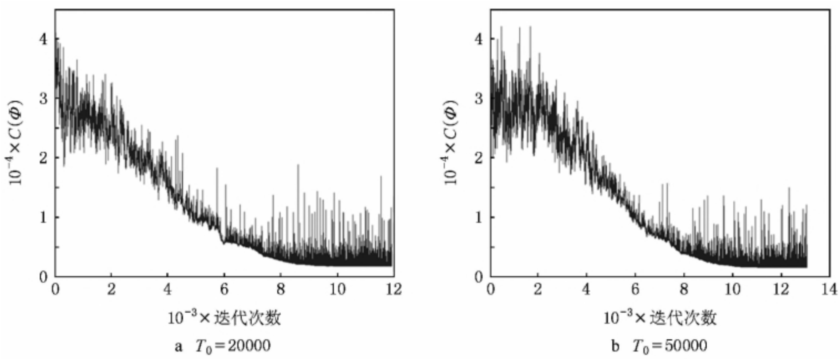

Fig. 7. Relationship between energy and iterations

niture. Additionally, it is closely related to the paired relationship between objects having been already in pairs. In this case, the problem shall be more complicated. Therefore, for more furniture, more crowded rooms, more complicated pairs, it will be difficult to solve. The idea of hierarchical optimization proposed in this paper decomposes the constraint conflict of the paired relationship, which makes the pairs of furniture distinct. The local optimization is conducted, and secondly the overall optimization is carried out, which shall simplify the complex problems, and embody the idea of divide-and-conquer.

5. Conclusion

In this paper, the problem of constraint conflict is easy to be found in the existing method, and the hierarchical tree is established to degrade the constraint conflict based on the priori paired relationship between furniture, i.e. the solution space of the higher dimensional solution is decomposed into a relatively low solution space. Accordingly, it also reduces the search complexity and improves the speed of search. In addition, in order to further improve the solution efficiency, this paper introduces the intelligent water drop algorithm to optimize the solution. Compared with the intelligent water drop algorithm, the intelligent water drop has a faster convergence speed, since it also starts searching from multiple initial values, thus improving the quality of the search. Eventually, the experiment was carried out with five scenarios, and the results showed that the effectiveness of the method in this paper, the setting of the scene satisfied the functional and aesthetic requirements, and the time was also faster than the existing methods. How to automatically define the constraint relationship between furniture and generate reasonable hierarchical tree through semantic analysis is worth delving into. It is also possible to consider using local intelligent water droplet reversible jumps, and automatically adding and deleting furniture in the process of optimization. This paper only considers the furnishings in the room, which can be extended to one floor or even the whole building in the future. In addition, furniture style and lighting and color collocation are also worthy delving into.

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