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Architecture Plane Layout Simulation Model Based on Probability Optimization Genetic Algorithm

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Abstract
In light of the existing problems of standard genetic algorithm in the application of architecture plane layout optimization, this paper proposes a layout optimization model based on genetic algorithm with probability optimization. Firstly, it introduces the ant colony algorithm reconstructed with the combination of some characteristics of genetic algorithm, randomly distributing a series of binary code for each ant as the initial pheromone intensity. Then roulette selection strategy is adopted to replace current individuals. The fitness sharing function is optimized by a combined method of Hamming distance measure and fitness distance. Finally, mutation and crossover operator is adjusted adaptively. The simulation results show that the proposed genetic algorithm has better optimizing performance than standard genetic algorithm and improves the space utilization rate in the architecture plane layout.
Key words: ARCHITECURE LAYOUT, PHEROMONE MODEL, ROULETTE, FITNESS SHARING FUNCTION, ADAPTIVE OPERATOR, MIXED DISTANCE

Introduction

High-rise building which is a space form and has its own aesthetic design, really influences the city, but it is worth paying more attention to the relationship between the high-rise buildings and the urban space, namely how to lay out in the city. There are great differences in the layout of high-rise buildings in different cities [1]. We cannot measure the advantages and disadvantages of the city model only by building height or the city economic efficiency and so on, because the height and appearance can easily be exceeded. In particular, it is necessary to put the high-rise buildings in the urban pattern to explore whether the layout of these buildings plays a positive role in the operation of city [2]. Therefore, the layout mode of high-rise building is a subject to be studied.

The research results of building layout can be mainly divided into two aspects: the external features and the evolution law of space; the internal organization, the demand and the evolution of space. Pivo Cary put forward the distribution theory like the mixed beads, and pointed out that the cluster points were interlaced in the highway corridor and the maximum namely the highest density cluster point was located at the intersection of the highway [3]. Gad G. studied the Toronto City in Canada and found that the face to face link was the main reason for the construction of the building clustering. In order to reduce the cost of contact to the smallest, most of the central city are gathering places of the buildings. The construction will be relocated out of urban city only in the case of the expansion of the scale of the building and the lack of space [4]. Ge made a survey about the function relation, space layout and traffic relation of urban buildings in London, and obtained a certain of correspondence between space of construction activity and site selection [5]. On the basis of Ge's buildings location equilibrium theory, Sang divided the construction activities into three levels: executive function, planning function and guiding function. Low-level executive function is usually distributed in the suburbs outside the city where rent is low while high-level guide function will continue to stay in the central district [6]. Scott summed up the internal factors such as industry type, management strategy, management mode, investment strategy and other factors affecting the construction of the site and determining whether the construction was located in the central area or in the suburbs [7]. Kim Kabsung did a sample survey on the intelligent industry in South Korea, and found start-up companies were more sensitive to rent which chose firstly local office with cheap rent and moved to urban area after success [8]. Ning studied the spatial distribution characteristics of production service industry and office buildings in Shanghai city through telephone directory, found that Shanghai had a pattern of multi centers and the office building distribution and production service industry distribution space dislocated [9]. The natural control rate of the office in Guangzhou was studied by Chen Lifu, with the help of basic model, the expansion of the basic model and two-way decision model. Chen still discussed the existing problems and future trends and gave some suggestions [10]. Yang Yunpeng analyzed the spatial distribution characteristics of the manufacturing independent offices in Beijing, and thought the decision factor was the customer, the rent and the adjacent partners [11].

In view of the existing problems of standard genetic algorithm in the application of architecture plane layout optimization, this paper proposes a layout optimization model based on genetic algorithm with probability optimization and conducts the simulation experiments to test the effectiveness of improved strategy.

Architecture composition simulation based on genetic algorithm

Genetic algorithm (GA) is an iteration process based on fitness function and realizes individual structure reengineering in the population by implementing genetic manipulation. In this process, the individuals in the population can be improved and optimized to the optimal solution[10].

GA uses the fitness function to evaluate the good and bad individual in the operation. The design of fitness function has an important effect on the performance on the genetic algorithm.

(1) Maximum optimization problem

$$Fitness(f(x)) = f(x) \tag{1}$$

Minimum optimization problem

$$Fitness(f(x)) = -f(x) \tag{2}$$

This simple expression of fitness function has problems in reality: it sometimes doesn't meet the non-negative requirement of roulette selection; if some function values differ greatly, average fitness value doesn't reflect the average performance and finally affect the algorithm performance.

(2) Maximum optimization problem

$$Fitness(f(x)) = \begin{cases} f(x) + C_{\min}, & f(x) + C_{\min} > 0 \\ 0 & , f(x) + C_{\min} \le 0 \end{cases} \tag{3}$$

$C_{\min}$ is preset suitable small value, usually the estimated minimum value of objective function.

Minimum optimization problem

$$Fitness(f(x)) = \begin{cases} C_{\max} - f(x), & C_{\max} - f(x) > 0 \\ 0 & , C_{\max} - f(x) \le 0 \end{cases} \tag{4}$$

$C_{\max}$ is preset suitable large value, usually the estimated maximum value of objective function.

Because abovementioned $C_{\min}$ and $C_{\max}$ is preestimated, it is not accurate enough to make the fitness function sensitive. The algorithm performance will be decreased.

(3) Maximum optimization problem

$$Fitness(f(x)) = \frac{1}{1 + c - f(x)}, c \ge 0, c - f(x) \ge 0 \tag{5}$$

Minimum optimization problem

$$Fitness(f(x)) = \frac{1}{1 + c + f(x)}, c \ge 0, c + f(x) \ge 0 \tag{6}$$

where c is preset value which has the similar problem to (2)

During the analysis of architecture composition layout, there are n decision variables, m constraint conditions and k objective functions. These conditions have functional relationship. The optimization of the architecture plane layout is shown below.

$$\max imize\ y = f(x) = (f_1(x), f_2(x), ..., f_k(x)) \tag{7}$$

Subject to

$$e(x) = (e_1(x), e_2(x), ..., e_m(x)) \le 0 \tag{8}$$

where $x = (x_1, x_2, ..., x_n) \in X$ and $y = (y_1, y_2, ..., y_k) \in Y$

Here x is the determining vector in the layout analysis, X is the space determined by vector x. The component $\{x_1, x_2, ..., x_n\}$ in x is composed of special components that cause the bad and good performance in the layout analysis.

According to the equations, the close relationship among each element in the architecture plane layout will increase the dimension of x. In addition, constraints $e(x)$ also make sure some rules in the urban space growth analysis and determine the solution of decision vector within the feasible range. y is the vector of optimized object, and Y is the corresponding space of objective vector y.

However, the process of architecture plane layout should be an evolutionary process where the change of external environment and manual intervention will cause the mutation. Therefore, standard genetic algorithm exists the problem of low precision in the architecture plane layout analysis.

Genetic algorithm based on probability optimization

Pheromone optimization based on ant population

In view of the defects of standard genetic algorithm, this paper introduces the ant swarm algorithm and proposes an improved genetic algorithm.

$\tau_i(t)$ represents the size of pheromone in i at time t. It is formed by two parts: the pheromone left by ants passing by i; the superposition of pheromone at other time when ants cross the region of i. It can be expressed as follows.

$$\tau_i(t) = \delta_i(t) + \sum_{k \in M, k \ne i} \Delta_k(t) \tag{9}$$

where M indicates all the observation in the neighborhood of i. Ant k will randomly relate according to the pheromone left in observation. Each ant determines the relation to the observation j along the track i.

$$j = \begin{cases} \arg\max_{u \in U_k} \{[\tau_{iu}(t)[\eta_{iu}]^{\beta}]\}, q < q_0 \\ J \end{cases} \tag{10}$$

Here, U_k represents the allowed observation list of ant k at this track point; η_{iu} is the visibility (heuristic information) of relation a_{iu}, usually $\eta_{iu} = 1/d_{iu}$; q_0 is an initialized parameter, and q is random sampling number, $q_0, q \in [0,1]$; J is a random variable, and can be obtained as the probability of ant k allocating the track i to observation j from the following expression.

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l\in U_k}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}}, j\in U_k\\ 0\end{cases} \tag{11}$$

α and β indicates the influence weight of residual information and heuristic information in the observation on the transfer direction selection of ant, respectively. Simply speaking, α indicates the incidence of pheromone on an individual while β is the acceptation degree of the ant individual.

By combining some features of genetic algorithm, this paper reconstructs the pheromone model. In the nature world, the ant individuals in same ant swarm have the good and bad ones. Therefore, this paper randomly distributes a series of binary code 0-1 as the initial pheromone strength of each individual. When the number of population is lower than 60, a total of 6bit binary code can meet the requirement of each ant with different code.

Suppose m ants; n tracks; R_w and R_s are the set of unselected track and selected track. R_w is initially the set of all the track and R_s is empty. The flow chart is shown in Figure 1.

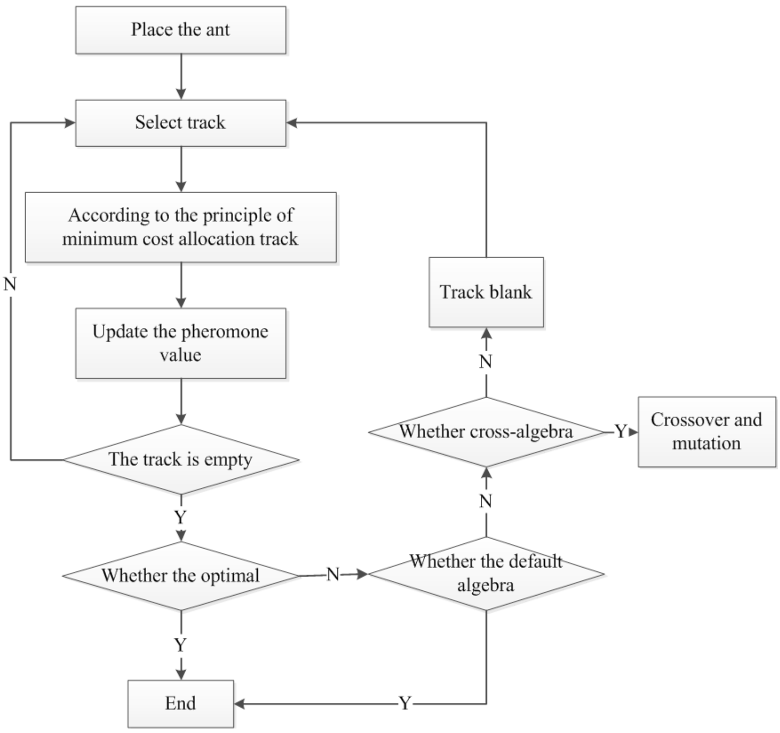

Figure 1. Improved genetic algorithm flowcharta

The ant in the population firstly selects a track point from the unselected track set before traversing all the tracks in light of the transition rule, namely the heuristic function to select the corresponding observation. Then this track will be added to the selected track set and the pheromone information of other observation points will be updated. When all the ants finish a path selection, threshold setting is updated following $\lambda D_{\max}$, λ is constant. For the observation point that has tiny probability to relate the track or has no corresponding track in the region of threshold, this algorithm will see it as noise and remove it. The chromosome in the ant individual and the offspring generated by crossover and mutation operator is illustrated in Figure 2, Figure 3 and Figure 4.

Feature No.	1	2	3	...		
Pheromone coding	1	1	0	1	0	1

Figure 2. Individual ants carrying pheromone coding

If the preset population updating generation is reached, the new individuals are generated by crossover and mutation rule and replacing current individuals with roulette selection strategy. The process to control the crossover and mutation with genetic algorithm is written as follows.

Step1: $t\leftarrow 1$, randomly generate N ant to form a new generation population P_1 and evaluate their individual diversity factor.

Step2: Crossover operation to generate next generation population Q_t.

selecting two individuals x and y from P_1 based on diversity value;

generating offspring by crossover operator and adding it to Q_t;

Step3: Mutation, applying mutation operator to each individual $x\in Q_t$ with preset mutation rate.

Step4: Selection, selecting N individuals from Q_t and copying them into population P_{t+1}.

Step5: Population diversity judgment based on individual diversity function, calculating individual diversity value of population P_{t+1}.

Step6: If it meets the ending condition, then go back to current population; otherwise, $t \leftarrow t+1$, turn to step 2 and continue the steps.

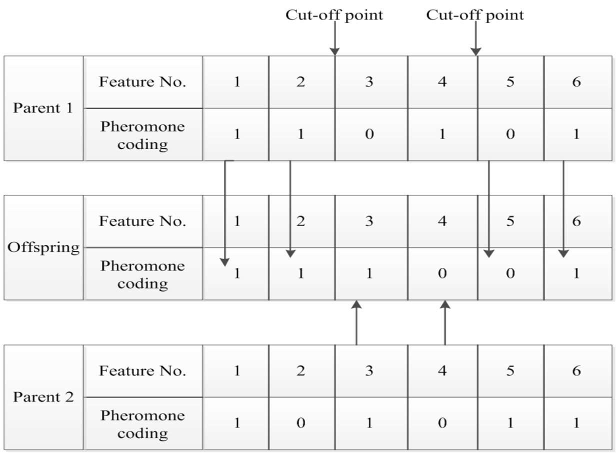

Figure 3. Crossover operator to produce offspring diagram

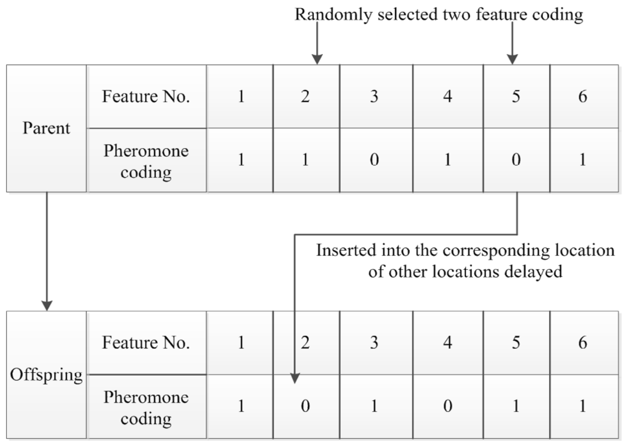

Figure 4. Mutation operator to produce offspring diagram

Fitness sharing function optimization based on mixed distance

The direct purpose of fitness sharing function is to distinguish geographically different peak values of searching space. Each peak accepts a certain proportion of individuals which is related with peak value. To realize this distribution, sharing method decreases the objective fitness of individual, namely fitness value f_i dividing *niche* count m_i to obtain sharing function. *niche* count m_i is an estimation of density of individual neighborhood.

$$m_i = \sum_{j \in Pop} sh[d[i,j]] \tag{12}$$

where $d[i,j]$ is the distance between i and j; $sh[d]$ is a decreasing sharing function. $sh[0]=1$ and $sh[d \geq \sigma_{share}]=0$.

The following is a typical triangle sharing function.

$$sh(d) = \begin{cases} 1-\dfrac{d}{\sigma_{share}}, d \leq \sigma_{share} \\ 0, d > \sigma_{share} \end{cases} \tag{13}$$

Here σ_{share} is the *niche* radius r defined manually which is the shortest distance between individuals with better peak values. In the range of σ_{share}, individuals reduce the fitness of each other, for their *niche* are same in size, which avoids the convergence of population. When *niche* is filled, the *niche* count increases making the sharing function lower than other *niche*.

In order to define a *niche*, this paper adopts a method of combining Hamming distance measure and fitness distance. If $d_1(x_i, x_j)$ is the Hamming distance between x_i and x_j and $d_2(x_i, x_j)$ is the fitness distance, then the sharing function can be defined as,

$$Sh(x_i,x_j) = \begin{cases} 1-\dfrac{d_1(x_i,x_j)}{\sigma_1}, d_1(x_i,x_j) < \sigma_1, d_2(x_i,x_j) \geq \sigma_2 \\ 1-\dfrac{d_2(x_i,x_j)}{\sigma_2}, d_1(x_i,x_j) \geq \sigma_1, d_2(x_i,x_j) < \sigma_2 \\ 1-\dfrac{d_1(x_i,x_j) d_2(x_i,x_j)}{\sigma_1 \sigma_2}, d_1(x_i,x_j) < \sigma_1, d_2(x_i,x_j) < \sigma_2 \\ 0, else \end{cases} \tag{14}$$

σ_1 and σ_2 is the *niche* radius, namely genotype and phenotype as the largest distance among individuals in *niche*.

Finally, the fitness function of individual after sharing can be expressed in following form.

$$f'(x_i) = \frac{f(x_i)}{\sum_{j=1}^{M} sh(x_i,x_j)} \tag{15}$$

Here, $f(x_i)$ and $f'(x_i)$ is the expression of individual fitness function before and after sharing, respectively.

Adaptive optimization of genetic operator

Genetic algorithm, as a kind of excellent population searching method, requires to do crossover and mutation operation on original population to generate new generation. The crossover probability P_c and mutation probability P_m influences the updating speed of crossover and mutation operation so as to affect the convergence of algorithm. When P_m is small, the searching speed is slow; when P_m is large, the generation speed is fast, but some better individuals will be destroyed. If P_m is much larger, genetic algorithm will become a common random searching algorithm; if much smaller, the generation speed will decrease.

In a simple genetic algorithm, P_c and P_m is initially set. This way cannot give a best value that meets the characteristic of population change. Moreover, the given P_c and P_m is easy to make the genetic algorithm to be premature.

In view of this condition, this paper adopts an adaptive method to give the P_c and P_m which adjusts the mutation and crossover probability dynamically in the operation process according to the characteristic of population change. P_c and P_m in this paper is obtained through Equation (16) and (17).

$$\begin{cases} P_c - \dfrac{P_{c1} \quad P_{c2}}{f_{\max} \quad f_{avg}}(f' - f_{avg}), f' \geq f_{avg} \\ P_c \qquad\qquad\qquad\qquad f' < f_{avg} \end{cases} \tag{16}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{P_{m1} - P_{m2}}{f_{\max} - f_{avg}}(f_{\max} - f), f \geq f_{avg} \\ P_{m1} \qquad\qquad\qquad\qquad , f < f_{avg} \end{cases} \tag{17}$$

Here, f_{avg} is the average fitness value of each generation; $f_{\max}$ is the maximum fitness in the population; f is the fitness value of individual to be mutated; f' is the larger fitness value of individual to be crossed.

It can be seen from (16) and (17) that when the fitness value of population is relatively disperse, the equations will automatically decrease the value of P_c and P_m; when the fitness values of individuals are close to each other or close to the local optimum, the equations will automatically increase P_c and P_m to update the quality of population; when the fitness value of individual is smaller than f_{avg}, this individual will have larger value of P_c and P_m; when the fitness value of individual is larger than f_{avg}, this individual only obtains smaller P_c and P_m so as to keep it in the new generation.

Simulation experiment

In order to verify the performance of improved algorithm, this paper uses the Sphere function, Rosenbrock function and Rastrigrin function. The simulation results are shown in following tables.

Table 1. The Sphere function optimization results

Iterations	GA		Improved-GA	
	Optimizing value	Error	Optimizing value	Error
50	13.2	24.1%	13.6	11.3%
100	22.4	28.3%	29.8	9.4%
150	27.3	29.1%	40.1	11.5%
200	37.4	30.2%	47.8	10.2%
250	51.2	22.6%	61.0	9.7%
300	68.3	26.8%	77.9	8.8%
350	79.3	27.0%	94.4	11.0%

Table 2. The Rosenbrock function optimization results

Iterations	GA		Improved-GA	
	Optimizing value	Error	Optimizing value	Error
50	51.2	21.1%	72.4	1.3%
100	64.2	29.4%	81.6	3.1%
150	89.2	16.4%	91.7	1.2%
200	91.1	20.9%	107.2	5.3%
250	100.9	25.3%	111.3	3.4%
300	110.3	11.2%	122.2	2.3%
350	121.1	17.7%	132.5	5.2%

Table 3. The Rastrigrin function optimization results

Iterations	GA		Improved-GA	
	Optimizing value	Error	Optimizing value	Error
50	2.1	8.2%	3.7	1.3%
100	5.6	5.3%	8.3	1.6%
150	9.3	7.3%	11.9	0.3%
200	15.8	5.2%	16.8	1.2%
250	19.7	4.7%	20.4	0.8%
300	21.4	6.4%	22.7	0.9%
350	23.1	7.9%	27.3	1.3%

Then this paper applied this improved genetic algorithm to simulate the architecture plane layout and calculate its space utility rate. The results are compared with that of standard genetic algorithm as shown in figure 5.

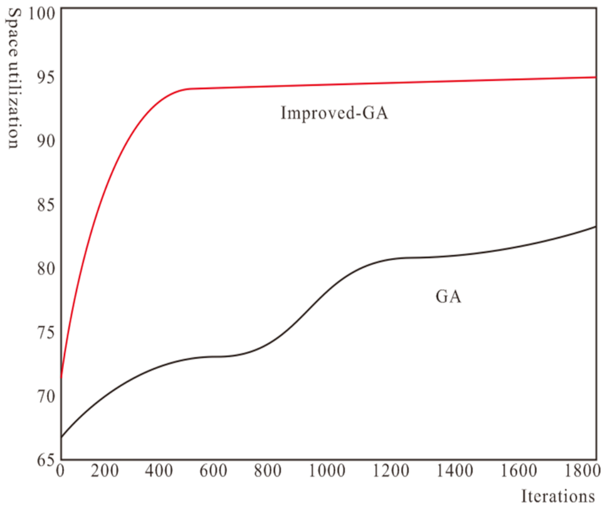

Figure 5. Space utilization analysis of improved algorithm

The results show that the proposed genetic algorithm has better optimizing performance than standard genetic algorithm and improves the space utilization rate in the architecture plane layout

Conclusions

The layout of high-rise buildings reflects the deep cultural connation of a city. It is external materialization of city culture, a generalized one that includes history, society, economy, environment and other elements. As the overall background of urban development, these elements function together to influence the layout of high-rise buildings. Considering the defects of standard genetic algorithm in the application of architecture plane layout, this paper proposes an improved model based on genetic algorithm with probability optimization. The simulation experiments show that the proposed genetic algorithm has better optimizing performance than standard genetic algorithm and improves the space utilization rate in the architecture plane layout.

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