Design Engineering

ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

Matching and Recognition Method of Architectural Decoration Elements Based on Hybrid Particle Swarm Optimization Algorithm

Ping Gong*
School of Civil and Architectural Engineering, Jiaozuo University, Henan Jiaozuo 454000 China
*Corresponding Author:Ping Gong

Abstract:

TImage matching and recognition of architectural decoration elements is the basis of architectural decoration design. The traditional matching and recognition methods have low precision and high complexity, so they are not suitable for the image matching and recognition of architectural decoration elements under complex conditions. Based on the analysis of the basic particle swarm optimization algorithm, the nonlinear asynchronous strategy is adjusted to change the fixed constant mode of the learning factor to balance the local and global search ability of the algorithm in the iterative process. At the same time, the vitality factor was introduced to mutate the inactivated particles to improve the population diversity. The experimental results show that compared with the traditional algorithm, this method improves the image matching and recognition accuracy of architectural decoration elements.

***Keywords**: Architectural decoration elements, Recognition, Fuzzy,Hybrid PSO.*

I. INTRODUCTION

With the rapid development of computer technology, image matching technology is becoming more and more mature. As one of the important image processing technologies, image matching has been widely used in target recognition, stereo vision, aircraft guidance and other fields [1-2]. At present, the research on image matching methods mainly focuses on matching accuracy, matching speed and anti-interference performance of matching algorithm.

In the process of image matching, feature space, search strategy and similarity measure are the three key elements. Choosing the appropriate matching method for different elements is helpful to improve the efficiency of image matching. In this paper, gray value is used as image matching feature, and template matching is combined with particle swarm optimization (PSO) algorithm [3]. On the basis of improved PSO algorithm, the similarity measurement

ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

mathematical model between reference image and template image is constructed to realize the accurate matching of target image.The experimental results show that the improved PSO algorithm improves the population diversity, has higher convergence accuracy and speed, and has outstanding global optimization ability. On this basis, the improved algorithm can achieve fast gray image matching, and its matching accuracy, speed and anti-interference performance are better than the contrast algorithm.

II. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

PSO algorithm was proposed by Dr. Kendy and Dr. Eberhart in 1995. It is a population intelligent evolutionary algorithm based on the study of the foraging behavior of birds. The algorithm can find the optimal location of food by imitating the foraging behavior of birds by group cooperation and information sharing.In the PSO algorithm, a single particle represents a solution in the search space, and each particle has a certain flying speed. In the D-dimensional space, assuming that the population size is n, the flying speed of each particle can be expressed as $v_i = (v_{i1}, v_{i2},, v_{id})^T$, and the position of the particle is expressed as $x_i = (x_{i1}, x_{i2},, xid)^T$, then the ith particle updates its own speed and position according to formula (1) and formula (2) [4-9]:

$$\upsilon_{id}^{k+1} = \omega \cdot \upsilon_{id}^{k} + c_1 \cdot r_1 \cdot \left(pbest_{id}^{k} - x_{id}^{k} \right) + c_2 \cdot r_2 \cdot \left(gbest_{gd}^{k} - x_{gd}^{k} \right) \quad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + \upsilon_{id}^{k+1} \quad (2)$$

Among them, i = 1,2,…,N; d = 1,2,…, D. w is the inertia weight, the value range is [0.4,0.9]; c_1 and c_2 are learning factors, reflecting the influence of individual and global extremum on the next state; r_1 and r_2 are random numbers between [0,1];k is the kth iteration; in the kth iteration, v_{id}^k is the flight speed of the ith particle; x_{id}^k is the position of the ith particle; $pbest_{id}^k$ is the individual optimal position of the ith particle; $gbest_{id}^k$ is the global optimal position of the entire particle swarm.

III. IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 Learning Factor Adjustment Strategy

Due to the fast convergence speed of the basic PSO algorithm at the initial stage of iteration, it is easy to produce premature convergence phenomenon and fall into local minimum, which makes the convergence accuracy of the algorithm is not high and the global optimization ability is poor. Therefore, a large number of scholars at home and abroad have improved and optimized the standard PSO algorithm, such as Shi and other scholars who adjust the inertia weight linearly;The PSO algorithm with shrinkage factor proposed by CLERC and other scholars; particle swarm optimization algorithm with sinusoidal inertia weight adjustment proposed by Jiang Changyuan and others; an improved particle swarm optimization algorithm with adaptive inertia weight proposed by Dong Pingping, etc., all of which have significantly improved the

ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

convergence performance index.

A large number of experiments show that the nonlinear change of learning factor can better solve various nonlinear optimization problems. The main idea of this paper is: in the process of algorithm iteration, the learning factor c_1 decreases nonlinearly with the increase of iteration times, while the learning factor c_2 increases nonlinearly and asynchronously. Through the adjustment, the self-regulation ability of particles in the initial stage of the algorithm is enhanced, and the population diversity is increased; in the later stage of the algorithm, the cooperation ability of particles is gradually improved, and the social experience is enhanced, which is conducive to the global optimal search. The mathematical model of the adjusted learning factor is as follows:

$$c_1 = c_1^{start} - \left(c_1^{start} - c_1^{end}\right) \cdot \left[1 - \alpha(k)\right]^3 \tag{3}$$

$$c_2 = \left[c_2^{end} - \left(\frac{c_2^{start}}{4}\right)^2\right] \cdot \left(c_2^{start} / c_2^{end}\right)^{\alpha(k)} \tag{4}$$

Where α (k) is expressed as follows:

$$\alpha(k) = \frac{1}{\left(1 + \lambda \cdot \frac{k}{k_{max}}\right)^2} \tag{5}$$

The experimental results show that the convergence speed and accuracy of the algorithm can be greatly improved when the upper and lower limits of learning factor are changed in the following range.

$$\begin{cases} 2 < c_1^{start}, c_2^{end} < 2.5 \\ 0.2 < c_2^{start}, c_1^{end} < 0.8 \end{cases}$$

3.2 Introduction of Vitality Factor

In this paper, the standard PSO algorithm is further improved while constructing the learning factor strategy model. According to the updated formula of PSO algorithm, when the current position of the particle gradually approaches the global optimal position, that is, when the distance between the two approaches zero, the flight speed of the particle gradually decreases and tends to zero, at this time, the vitality of the particle decreases, resulting in stagnation; on the contrary, the larger the distance between the two, the faster the flight speed of the particle.Therefore, the current position of particles can be mutated to better control the flight speed of particles, so as to increase population diversity and make particles jump out of local extremum. Therefore, the particle vitality factor σ ($\sigma \geq 0$) is introduced. By selecting the appropriate σ, when the current position and the global optimal position of the particle are less than σ, the mutation operation is performed on the current position to enhance the global search

ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

ability.

In the kth iteration, the distance between the current position x_i (k) of particle i and the global optimal position $p_g(k)$ is defined as d (k):

$$d(k) = \|x_i(k) - p_g(k)\|_2 \quad (6)$$

In formula (6), when d (k) < σ, the flight speed of the particle will be stagnant with a large probability, which will cause the algorithm to fall into the local extreme value. At this time, mutation operation is performed on the current position xi(k) of particle i to change the flight direction of the particle. The population diversity is increased by initializing the position of the current inactivated particle, so that the particle can jump out of the local optimum with a large probability.

IV. IMAGE MATCHING BASED ON AMPSO ALGORITHM

4.1 Template Matching Of Images

Because of the advantages of simple operation and strong anti-interference performance, template matching method has been widely used in image matching technology. As shown in Fig. 1, template matching is to search the position of target subgraph S^{ij} closest to template t in the reference image s to be matched. Among them, the size of S is M×N, the size of template T is X×Y, i, j are the coordinates of the upper left corner pixel of the target subgraph in the reference image S, i, j satisfy $1 \le i \le M - X + 1$, $1 \le j \le N - Y + 1$.

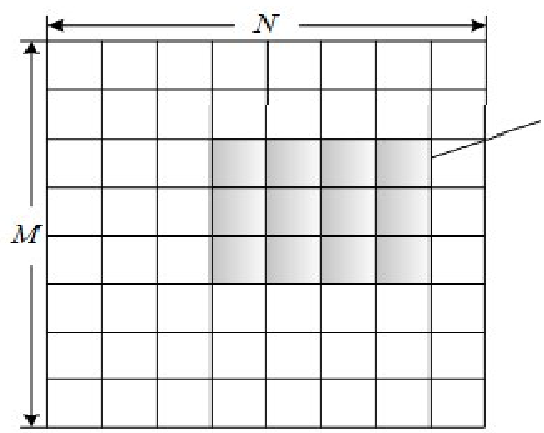


Fig 1: Benchmark and template drawings

In this paper, the improved particle swarm optimization algorithm is combined with the template matching method, then the template matching of the image can be transformed into using PSO algorithm to search the optimal matching position in two-dimensional space. The basic process is shown in Fig 2.

ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

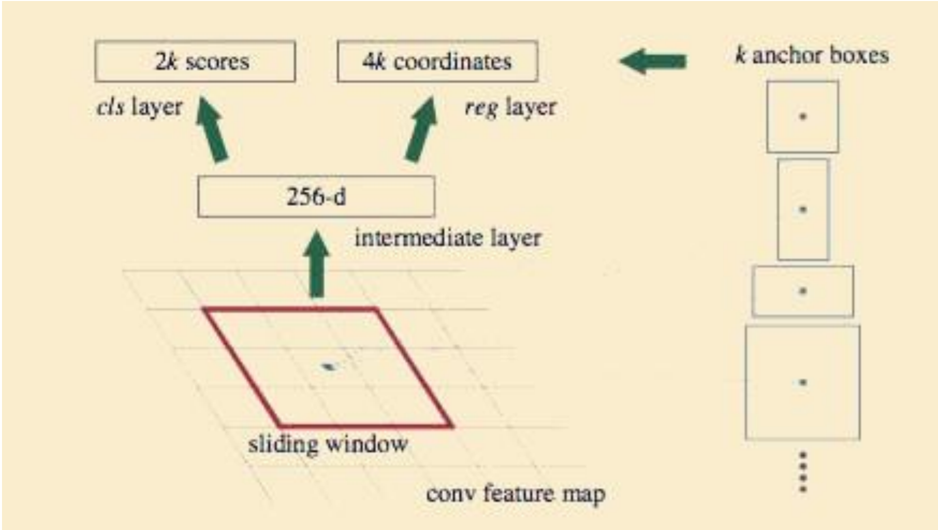


Fig 2: Image matching flow chart based on AMPSO algorithm

There are many template matching algorithms, including mean absolute difference (MAD), normal cross correlation (NCC) and sequential similarity detection algorithm (SSDA). Considering the matching speed and difficulty, MAD algorithm is selected as the fitness evaluation function of the improved PSO algorithm. The mathematical formula is as follows:

$$d(x,y)=\frac{1}{XY}\sum_{i=1}^{X}\sum_{j=1}^{Y}\left|S(i+x,j+y)-T(i,j)\right| \quad (7)$$

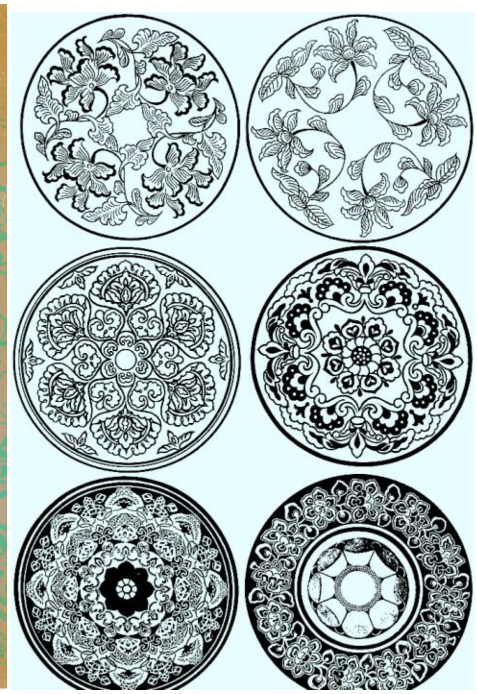
In formula (7), d (x, y) represents the corresponding matching measure value when the offset is (x, y). When d (x, y) takes the minimum value, the optimal matching position (x, y) can be obtained.

Based on the above analysis, the image matching algorithm based on Improved PSO algorithm is called AMPSO algorithm for short.

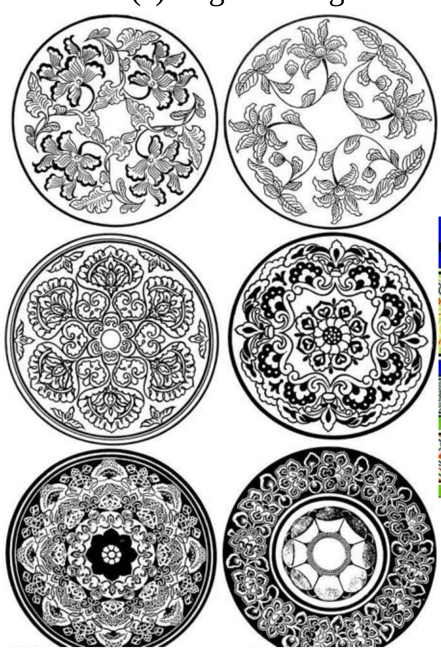
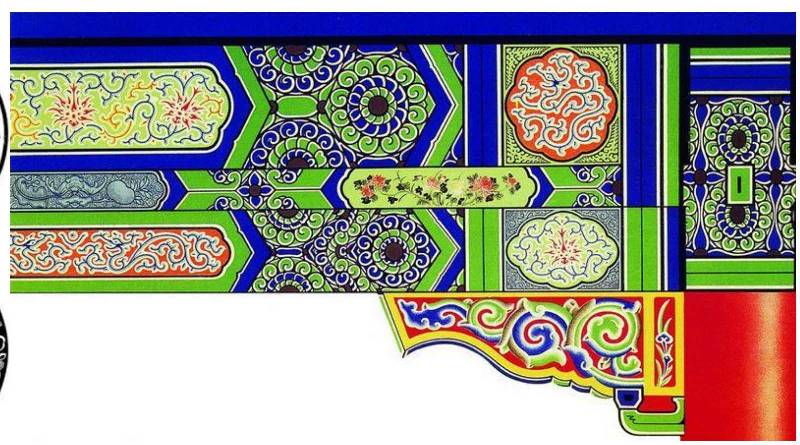
4.2 Experimental Simulation

In matlab7.0 environment for experimental simulation, at the same time compared with the traditional template matching algorithm, including MAD algorithm and NCC algorithm. In the experiment, Lena gray image is selected as the original image to be matched. The original image size is 254 × 254, and the template size to be matched is 89 × 86, as shown in Fig. 3 (a) and (b). Using AMPSO algorithm to match Lena original image, the best matching result is shown in Fig. 3 (c).

Design Engineering
ISSN: 0011-9342
Issue: 1 | Pages: 443 - 449

(a)Original image (b)Template image

(c)Noiseless image matching results (d)Noisy image matching results

Fig 3: Original image, template image and matching result

In order to test the anti-interference performance of AMPSO algorithm, 15% salt and pepper noise is added to Fig. 3 (a), and the template matching of Lena image with noise is performed by AMPSO algorithm. The best matching result is shown in Fig. 3 (d). A large number of experiments show that the AMPSO algorithm can accurately match the noisy image under the premise of selecting the appropriate population size and iteration times.

At the same time, the noise image is taken as the reference image, and the AMPSO algorithm, MAD algorithm and NCC algorithm are compared and analyzed on the premise that the template image remains unchanged. Among them, the population size of AMPSO algorithm is 40, the maximum iteration number is m = 50, and other parameters remain unchanged. The number of experiments was 50. The experimental results show that in the noisy environment, the AMPSO algorithm has obvious advantages in matching speed and less time-consuming. At the same time, the AMPSO algorithm is better than the contrast algorithm in the matching accuracy, can accurately find the template image matching position coordinates, showing good anti-interference performance.

V. CONCLUSION

Through the improvement and optimization of the basic PSO algorithm, the fixed mode of learning factors is changed to realize its nonlinear asynchronous change. At the same time, the vitality factor is introduced to increase the population diversity, so that the algorithm can effectively jump out of the local extremum, and enhance the global optimization ability while improving the convergence speed. The improved PSO algorithm is introduced into the image matching technology. The experimental results show that the improved PSO algorithm can realize the accurate matching of the target image on the premise of ensuring the matching speed and matching speed. The improved PSO algorithm has outstanding anti-interference performance and strong robustness, which can meet the requirements of matching speed and matching accuracy in practical application, and has certain practical guiding significance in the optimization of image matching problems.

REFERENCES

[1] Fielding, C. R., (2006) Upper flow regime sheets, lenses and scour fills: extending the range of architectural elements for fluvial sediment bodies. Sedimentary Geology 190(1/4): 227-240

[2] Iwamura, Y., Miya, K.(1990) Numerical approach to inverse problem of crack shape recognition based on the electrical potential method [of ndt]. IEEE Transactions on Magnetics 26(2): 618-621

[3] Stepanov, G. V., (1973) Method of testing structural elements under overloads. Strength of Materials 5(7): 899-900

[4] Shirokov, D. S., (2012) Development of the method of quaternion typification of clifford algebra elements using k-fold commutators and anticommutators. Advances in Applied Clifford Algebras 22(2): 483-497

[5] ArminasŠtuopys, AlgimantasŠpokauskas. (2008) Attribution testing of marble statuary. Materials Science 14(2)

[6] Pan J.G. (1979) The influence of the display art in interior design over the architectural decoration design. AnnaliItaliani Di Chirurgia 51(6): 615-621

[7] Wang, S., Zhang, J. (2014) Study on quality control of architectural decoration engineering. International Journal of Technology Management5: 112-114

[8] Newcomb, Rexford. (1921) The volute in architecture and architectural decoration.Neurocomputing, 125(3): 3-6

[9] Blamires,S., J. (2010) Plasticity in extended phenotypes: orb web architectural responses to variations in prey parameters. Journal of Experimental Biology 213(18): 3207