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Improved Adaptive Genetic Algorithm in Optimal Layout of Leather Rectangular Parts

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Abstract

In the mass customization of Leather products (such as sofa), the intelligent layout is the key technology to improve material utilization. The paper faces artificial leather fabric cutting problem, most can be converted into a rectangle packing layout problem. This paper proposes a new improved adaptive genetic algorithm. Crossover and mutation probability of genetic algorithm adaptively adjust on the basis of logistic curve equation and the shortcomings of traditional adaptive genetic algorithm solved well. The remaining rectangle algorithm as the decoding algorithm and adopting New cross-ways, the niche technology controlled whether the child individual replacement the parent individual or not accelerating convergence rate. Examples show that the algorithm of leather fabrics nesting is effective and a substantial increase in the utilization of leather fabric.

Key words: Optimal layout of rectangular parts; Adaptive genetic algorithm; Niche technology; The remaining rectangle algorithm

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INTRODUCTION

Leather fabric used in clothing, automobile, home, airplane seats, luggage, and other industries. Nesting optimization technology is essential in the leather industry and an important means to save raw materials and make full use of the resources. The merits of nesting cutting directly impact on the leather production efficiency and economic benefits. Artificial leather nesting cutting is generally based on two-dimensional rectangular sample rule nesting. For irregular leather nesting, complementary sample makes the fight against and filling, cluster analysis, take the smallest envelope rectangle and other Pretreatment, irregular sample transformed into a rectangular sample, finally, in the rules of artificial leather fabrics to optimize nesting. Such as artificial leather sofa nesting cutting is a typical two-dimensional rectangular Nesting engineering problems. It requires a set of leather rectangle samples which are distributed over a given specification leather fabric with an optimal arrangement, various leather samples do not overlap each other and not more than leather fabric border, making full use of leather fabrics, improving their utilization. Algorithms have a reliable fast convergence and nesting calculation is efficient.

Optimal layout of rectangular pieces is NP-hard problem, there is still more literature that dedicated to finding efficient algorithms to solve a wide variety of two-dimensional rectangular pieces of packing problem. Research work in this area as early as linear programming and the knapsack problem (Reda & Abd, 1994; Cao & Zhou, 1994) thinking applied to the problem of nesting, but it has a great computational complexity, suitable for small-scale problem solving, not very practical in engineering.

With the development of intelligent algorithms and successfully applied to TSP and space allocation, literature (Huang, Qi, & Tan, 2012; Thiruvady, Meyer, & Ernst, 2008; Jiang & Lu, 2008) make the particle swarm optimization, ant colony algorithm, genetic algorithms, simulated annealing algorithm apply to the Rectangular Strip Packing Problem. However, due to the limitations of the algorithm itself, the nesting effect is not too satisfied. In Literature (Tang & Tang, 2005; Jia, Yin, & Luo, 2002). GA combined with layout algorithm of BL, BLF to optimize the layout, however, the algorithm is not very good stability and convergence rate.

After a lot of genetic iterative, genetic algorithm eventually evolved to the optimal layout in probability theory from the random search method. It has the advantage of strong global search capability, but has the disadvantage of premature and local convergence. Adaptive genetic algorithm (Lee, Lin, & Chen et al., 2011) solve the problem that the crossover rate is too large, the best individual structures destroyed, and the crossover probability is too small to make evolutionary stagnation. It also solves the question that the mutation probability value is too small to difficult produce a new individual, mutation probability value is too large, GA has no evolutionary effect and other issues. However, since the value of the adaptive genetic algorithm crossover and mutation probability close to zero in later evolution, evolution will occur stagnation. In addition, adaptive genetic algorithm only consider the average value of group fitness and optimal fitness value and it does not consider the impact of its evolution from the entire group setting produces.

In this paper, an improved adaptive genetic algorithm is employed. First, obtain Optimal into the row order of a set of rectangular leather samples. In the process of Leather rectangular sample layout, automatically adjust the crossover and mutation probability depending on the circumstances, it well overcomes the shortcomings of traditional adaptive genetic algorithm. In order to make the evolutionary process does not fall into local optimum, this paper adopted a new way of cross. Finally, the remaining rectangle decoding algorithm to determine the rules of the row of rectangular samples of leather, achieving automatic nesting.

1. LEATHER RECTANGLE PACKING PROBLEM MATHEMATICAL MODEL

Leather rectangular nesting optimization problem is described as follows: In the wide W, height H of the rectangular artificial leather motherboard emissions without overlapping rectangular leather samples $\{P_1, P_2 \ldots. P_i \ldots. P_n\}$, anyone leather rectangular samples P_i (i = 1,2, ..., n) can be expressed using a dimensional binary array:

$$P_i = (w_i, h_i)\ ,$$

where w_i, h_i are the leather rectangular sample P_i's width and height.

Optimization constraints: Each rectangle leather sample does not exceed the edges of the rectangular artificial leather motherboard and its edges must be parallel to the edges of the rectangular artificial leather motherboard. After completion of the maximum height of nesting (that is the highest leather rectangular sample boundary of figure nesting, also known as the highest nesting contour) $H_{\text{high}} \leqq H$ (referring to Figure 3 H_{high}). While meeting certain cutting process requirements.

Optimization objectives: The minimum gap of between Leather rectangular sample to make leather fabric maximum utilization (η).

Since guarantee the lowest H_{high} of the highest contour nesting figure, between leather rectangular sample gap is the minimum in nesting figure, so the optimization modeling in this paper can be simplified to only consider the impact of the highest contour nesting map. Due to the width of Motherboard leather and the total area of all leather Rectangular samples is constant, the utilization of leather fabric η only relevant with total area of all rectangles and area of using motherboard sample, the optimization objective function is:

$$\eta = h/H_{\text{high}}\ , \tag{1}$$

where:

$$h = \sum_{i=1} w_i \times h_i \,/\, W\ . \tag{2}$$

where, h is theoretical optimal height, which is the resulting all the leather samples rectangular area divided by the width of leather motherboard. h is constant, H_{high} is variable. The objective function value η the closer 1, the closer optimal nesting.

2. THE KEY TECHNOLOGY AND BASIC FLOW ALGORITHM OF LEATHER RECTANGULAR SAMPLE LAYOUT

In this paper, using the improved adaptive genetic algorithm to obtain the optimal order of the row of rectangular leather sample group, and then use the remaining rectangle algorithm to determine the rules of the row of rectangular samples of leather, automatic nesting. In this paper, using leather rectangular optimal layout sample problem describes the improved adaptive genetic algorithm basic flow.

2.1 Genetic Encoding

Optimization leather rectangular sample nesting use decimal integer coding. To a group of n rectangular leather samples P_1, P_2, ... P_n with a natural number 1 to n correspond to numbered，the number of leather rectangular samples constitute a random integer string $X=\{x_1, x_2, \ldots x_i \ldots . x_n\}$ (x_i represents a rectangle leather sample), thus forming an individual, that is, a group of leather rectangle row sample group which has been determined to be the order of the rows. Coding sequence of the individual elements in the sample is the order of leather rectangle. x_i has positive and negative points, representing nesting manner of leather rectangular sample, that is horizontal or vertical. When $x_i > 0$, leather rectangular sample does not rotate, horizontal nesting. When $x_i < 0$, leather rectangular sample rotation 90°, vertical nesting. For example, a set of random samples of rectangular leather{2, 7，-3，-5, 1, 8，-6, 4}, representing the discharge order is 2 →7 → 3 → 5 → 1 → 8 → 6 → 4, the number -3,-5, -6 of leather rectangular sample rotation 90°, others is horizontal. Each individual sample corresponds to one kind of leather rectangular nesting diagram, *m* numbers of aforementioned individuals constitute a population.

2.2 The Size of the Initial Population

The size of the population has a large impact on optimization of final results and the convergence rate. The larger the population size, the more mode of leather rectangular sample nesting processing, the more the rich diversity of the population, the greater the opportunity to evolve into optimal layout map, but the convergence slows down. Population size is too small, it will affect the final result of nesting. In this paper, using the adaptive population size m, whichever *m* twice the number *n* of rectangle leather sample, $m = 2n$.

2.3 Leather Rectangular Layout Sample Decoding Algorithm

In order to evaluate the fitness of the individual, individuals need to decode operation, the population of individuals transformed into rows comp image. Nesting algorithm determines the rules of the row of leather rectangular sample. In this paper, the remaining rectangular nesting algorithm as a decoding method. The remaining rectangular nesting algorithm (Jaya Thomas·Narendra, 2014) with a rectangle Data set to represent currently remaining of leather fabric, any unused space emissions (including isolation gap) are included in the remaining rectangle collection; Before rectangular pieces of leather into the row, The most reasonable position emission based on the remaining rectangle centralized data to overcome the lowest level algorithm can not enter the hollow area of the defect row. Individuals with a coding example, its the sort listed (1, 2, 3, 4, 5). Using different algorithms for nesting, the results shown in Figure 1, 2

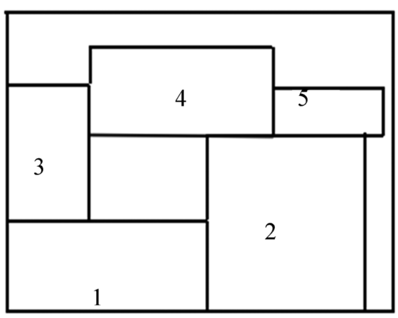

Figure 1
"Minimum Level" Algorithm Nesting

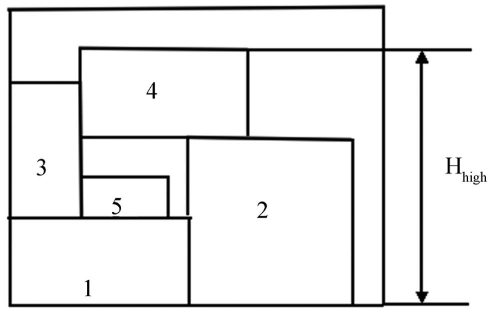

Figure 2
Remaining Rectangular Nesting Algorithm

2.4 Fitness Function

In Genetic Algorithm evolutionary process, individuals decoding nesting, with the fitness *F* to evaluate the quality of nesting map (Nesting Results). Individual fitness are associated with utilization, *H* value of the formula (1) is a fixed value, so fitness function simplifies to:

$$F = 1/H_{\text{high}} \tag{3}$$

2.5 Choose Operator

According to the principle of survival of the fittest, choosing large fitness individuals from the population. Before selecting the population, to accelerate the search speed of optimal solution, to prevent the destruction of the preferred individual in the crossover and mutation operations processes, using elite selection strategy. Selecting (1-GGAP) × *m* of the best individual directly inherited to the next generation, not through crossover and mutation operations. In this paper, using roulette selection method, setting the gap to GGAP, the population size is m, selecting GGAP × *m* (if not an integer rounding) individuals do genetic manipulation.

2.6 Crossover Operator

Cross operations mainly generate a new order of the row of rectangular leather samples. In order to prevent the emergence of local optimal solution, using a new cross-way. The selection of the individuals was divided into two groups in accordance with the fitness value from small to large order: Large fitness value into one group, the smaller fitness value is divided into one group. During cross-operation, from each of the two groups were selected to do a pair crossover, so making optimum individual and poor individuals have a greater probability of mating, so that the whole population is close to the optimal solution, to prevent local optima the emergence. In this paper, using two-point crossover mode, from two groups each selected an individual pair, producing a total of n / 2 (rounded) groups. Choosing a pair of cross matched group of X_1, X_2 regard as a parents. In [1, *n*] random generate two integers r_1, r_2 ($0 \le r_1 \le r_2 \le n$), **rand** randomly generated in [0,1], If crossover probability Pc <rand, not cross operation, otherwise cross operation. In the crossover operation, X_2 genes of located between r_1 and r_2 are copied to **Offspring$_1$** in same position, the rest position

by X_1 gene duplication. In order to avoid the generation of invalid individuals, if gene copied from X_1 conflict with a cross section, using some method map copied to the corresponding position of **Offspring$_1$** by the order of appearing in X_2. Using the same method of generating **Offspring$_2$.** For example:

ParentX_1

3	-5	1	10	-2	9	-8	6	4	7

↑ r_1 ↓   ↑ r_2 ↓

ParentX_2

6	-9	3	-7	-4	2	1	8	10	5

Progeny *Offspring$_1$*

3	-5	-9	-7	-4	2	1	6	8	10

Progeny *Offspring$_2$*

6	1	3	10	-2	9	-8	4	7	5

2.7 Mutation Operator

Variation of generating a new order of the rows of leather rectangular sample is auxiliary operations. Because the individual is an integer encoding with a symbol, so variation in two ways. One is the rotation variation, namely leather rectangular sample 90^0 after the row rotation; the other is the position variation. In this paper, the use of two variants of a combination of ways. For the individual X mutation , Firstly, rand randomly generated in [0,1]. If the mutation probability $Pm \geq$rand, as follows: In [0, n] randomly generated r_1, r_2, r_3 ($r_2 \geq r_1$), the $\boldsymbol{r_1}$th gen and $\boldsymbol{r_2}$th gen are exchanged, the first r3 alleles reverse signs. As X = {- 2,7, -3,5,1, -4,6}, when $r1$ = 2, $r2$ = 6, $r3$ = 4, After mutation, X '= {- 2, -4, -3, -5,1,7,6}; When Pm <rand, do not do mutation.

2.8 Based on the Niche Technology of Primary Election System

Using the niche technology of primary election system (Dong & Yan, 2013) decided to whether offspring replace parent individuals after crossover and mutation operations to maintain the diversity of population.

Cross operation: for X_1 parent and offspring Offspring$_1$, if F (Offspring$_1$) $\geq F$

(X_1), the offspring substitute parent, otherwise leave the parent X_1; for X_2 parent and offspring Offspring$_2$, if F (Offspring$_2$) $\geq F$ (X_2), the offspring substitute parent, otherwise leave the parent X_2.

Crossover and mutation operation select the best individuals into the next generation in between the parent and offspring, the offspring is always better than or equal to the parent, evolutionary direction is always towards the optimal direction of development.

2.9 Re-Insert Operation

Re-insert operation: After the operations of crossover, mutation and niche technology of primary election system, the offspring population and elite individuals together to form a new generation of populations, in order to maintain constant population size.

2.10 Crossover and Mutation Probability of Adaptive Genetic Algorithm

In crossover and mutation operation of GA, the adaptive crossover probability Pc and mutation probability Pm significant impact on the performance of the algorithm, the genetic algorithm convergence performance depends primarily on two core operations of the crossover and mutation operator. Srinivas proposed adaptive genetic algorithm whose a dynamic adjustment of crossover and mutation probability based on adaptation values (Patnailklm, 1994). Adaptive crossover probability Pc and mutation probability Pm can automatically change over the fitness value, but individual fitness value close to or equal to the maximum fitness value, Pc and Pm close or equal to zero, the algorithm is easy to fall into local optimum. Ren Ziwu put forward an improved adaptive genetic algorithm (Ren & San, 2006) to solve the above problems. But poor individuals have poor ability to crossover and mutation, prone to stagnation. Furthermore, do not consider setting Pc and Pm from the entire population evolution. Pc and Pm of adaptive genetic algorithm of adjustment formula based on literature (Chen, 2011): Individuals of poor adaptation, should have a larger Pc and smaller Pm. For individuals with high fitness, should impart corresponding values of Pc and Pm according to the degree of evolution and adaptation of times. For individual with fitness value which approaching best individuals, should have a larger Pc and a smaller Pm. This is mainly basis makes a strong global search ability and weak local search capability in early evolution. As evolution progresses, global search ability dwindling, local search capabilities continue to strengthen, which prevent the individuals of high fitness destruction, to facilitate the evolution to the optimal solution, to prevent premature phenomenon appearing. In this paper, on the basis of logistic curve equation, using an improved adaptive genetic algorithm Pc and Pm dynamically adjusting the formula, adopting a new Pc and Pm, well meeting the above requirements.

Reflecting fitness value of the population's average expectation *EX*:

$$EX = F_{\text{avg}} = \frac{F_1 + F_2 + \cdots F_m}{m}. \tag{4}$$

Reflecting the value of individual fitness level discrete *DX*:

$$DX = \frac{F_1^{\,2} + F_2^{\,2} + \cdots F_m^{\,2}}{m} - f_{\text{avg}}^{\,2}. \tag{5}$$

The degree of similarity between individuals of the population represented by the similarity coefficient ω:

$$\omega = \frac{EX + 1}{\sqrt{DX}}, \tag{6}$$

$$P_c = \frac{1}{1 + e^{\frac{-k_1}{\omega}}} - 0.1, \tag{7}$$

$$P_m = \frac{k_2}{5(1 + e^{\frac{1}{\omega}})}. \tag{8}$$

Where, F_{avg} represents the average fitness of the population of individuals, m represents the size of the population, F_i (i = 1, 2 … n) represents the fitness of individual i, k_1 and k_2 are two constants, k_1 of the range (0, +∞), k^2 of the range (0,1).

2.11 Convergence Criteria

In this paper, the convergence criteria set: if utilization of optimal nesting solution greater than the set value η_k, stop evolution; otherwise hereditary algebra greater than the set maximum number of evolutionary $G_{\max}$ stopped. Finally, exporting the optimal solution and the corresponding output nesting map. Rectangular Nesting algorithm with main flow chart shown in Figure 3.

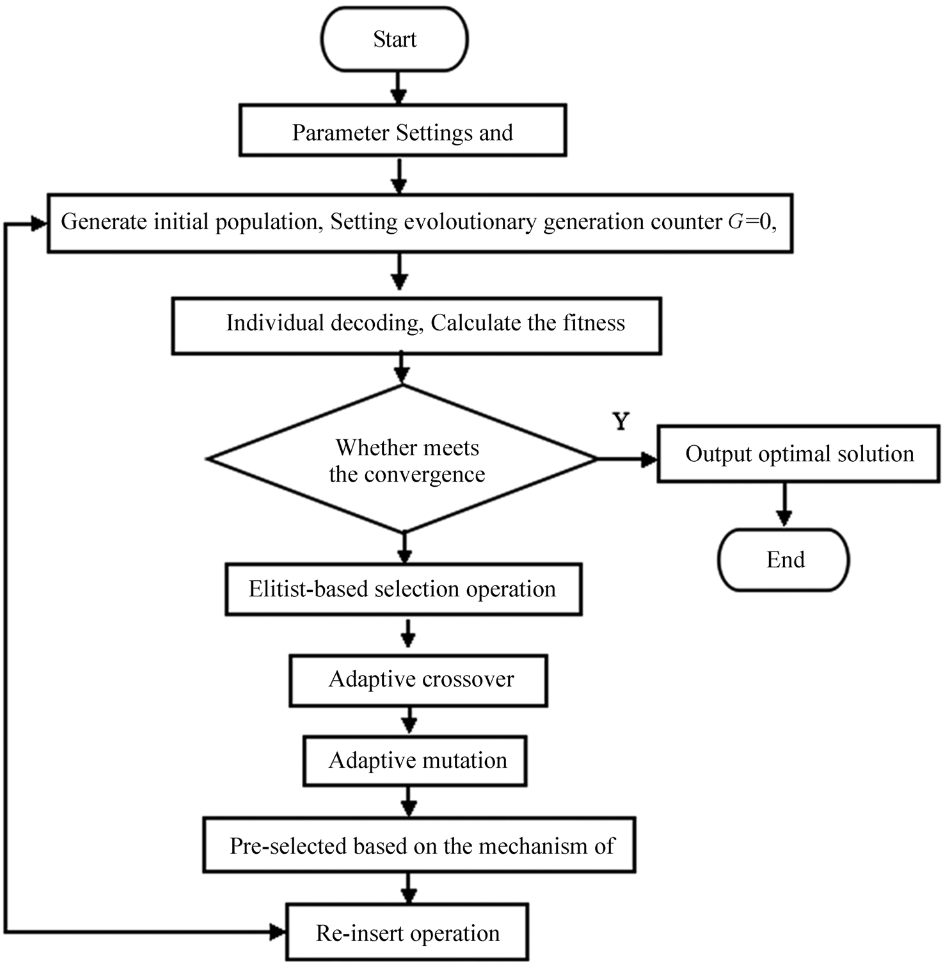

Figure 3
Rectangular Nesting Algorithm With Main Flow Chart

3. EXPERIMENTAL ANALYSIS

In order to verify the validity of firefly simulated annealing algorithm, a set of selected samples of rectangular leather sofa from a furniture plant for nesting computing. Set the parameters as follows: k_1=10, k_2=0.1, Convergence criteria $G_{\max}$=100, η_k=0.98, Generation Gap GGAP=0.9. Artificial leather fabric width is 2 m, assuming infinite length. The size and number of rectangular leather sofa fabric as shown in Table 1:

Using **matlab** software for simulation, nesting results shown in Figure 5 , nesting height of the evolutionary process diagram in Figure 6. The results can be seen from Figure , nesting height H_{high} = 4,395 mm, leather fabric utilization of 94.49%, obtaining the number of iterations of the final layout diagram for the first 62 times, the entire nesting process run time of 159.8s.

Table 1
The Size and Number of Rectangular Leather Fabric

Kind of rectangular pieces	The length of the rectangular pieces long (mm)	The width of the rectangle pieces wide (mm)	Quantity
1	700	410	6
2	650	300	6
3	650	150	6
4	650	650	6
5	500	400	2
6	500	250	4
7	700	500	2
8	550	265	2
9	550	400	2

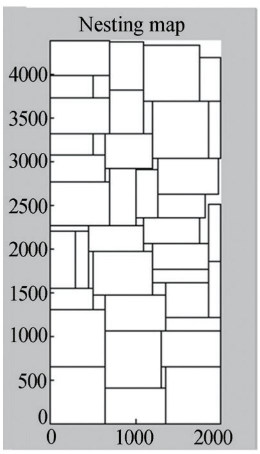

Figure 4
Nesting Results

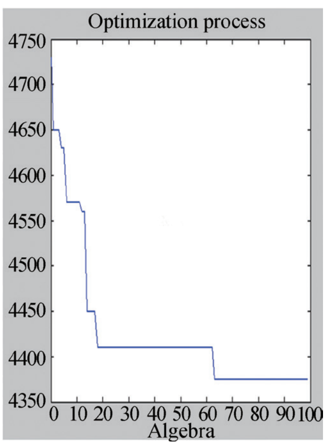

Figure 5
Nesting Height Evolution

In order to verify the efficiency of the algorithm, above a set of leather sofas rectangular sample respectively use GA (Standard genetic algorithm) and AGA (Adaptive Genetic Algorithm) algorithm nesting, the results were compared, remaining rectangle algorithm as the decoding algorithm; Based on this algorithm (improved adaptive genetic algorithm in this paper), using the lowest level algorithm as the decoding algorithm nesting. The results obtained for the above-described algorithm are compared, as shown in Table 2. In order to ensure comparability of the algorithm, parameter settings should be the same. GA parameters are set as follows: Population size m=72, GGAP=0.9, P_c=0.9, P_m=0.1, G_{max}=100, η_k=98%; AGA's parameters are as follows: Population size m=72, GGAP=0.9, Initial crossover probability P_{c1}=0.9, P_{c2}=0.6, Initial mutation probabilityP_{m1}=0.5, P_{m2}=0.1, G_{max}=100, η_k=98%; In this algorithm basis, using the lowest level algorithm as the decoding algorithm nesting algorithm uses the same parameters of this algorithm. For the four algorithms, respectively, running 10 times, obtaining the maximum height H_{max}, the minimum height H_{min}, average height H_{avg}. After each run, the maximum number K_{max} of iterations of the final solution, minimum K_{min}, average K_{avg}, average utilization η_{avg}.

Table 2
Compares the Four Algorithms Results

	GA	AGA	This paper algorithm(the remaining rectangle as the decoding algorithm)	This paper algorithm(the lowest level algorithm as the decoding algorithm)
H_{max}	4575	4510	4470	4480
H_{min}	4400	4360	4300	4320
H_{avg}	4459	4429.5	4410	4418.5
K_{max}	96	72	98	96
K_{min}	3	22	44	47
K_{avg}	61,5	55.1	66	65.4
η_{avg}(%)	93.56	94.18	94.59	94.42

Can be drawn from Table 2, for leather rectangular sample layout, the results obtained using this algorithm regardless of maximum height H_{max}, the minimum height H_{min}, average height H_{avg}, average η_{avg} are better than other algorithms. Each time, the final solution with maximum iterations K_{max}, minimum K_{min}, average K_{avg} generally greater than other algorithms. This further validates that the adaptive genetic algorithm used in the later stage of evolution is still a strong ability to mutate and local search ability, to avoid late algorithm stagnation and "premature" appearance.

CONCLUSION

(a) Improvement of Algorithms: In this paper, Based on the adaptive genetic algorithm, crossover and adaptive crossover probability, mutation probability are improved , using a mechanism based on a pre-selected niche technology, obtaining the best leather rectangular layout sample order, and then using the remaining rectangle algorithm to achieve automatic nesting.

(b) Effect of the algorithm: By comparison of the data with the GA and AGA experiments prove the algorithm is better and superior performance. For leather rectangular layout sample, using this algorithm obtains maximum utilization of material, later evolution remains the effective evolution. Improved adaptive genetic algorithm is proposed to solve the problem that production of good utilization and efficiency can not take into account in the leather rectangle sample layout. The algorithm not only improves utilization of leather sample material, but also has fast convergence rate. In the garment leather business applications, this algorithm significantly improves the economic efficiency of enterprises.

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