A Cooperative Co-evolutionary Method with Consistency Coordination Mechanisms and its Application to Complex Layout Problem

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ABSTRACT: *Complex spatial layout design problems contain mutual conflicting objectives and constraints. These types of problems can be divided into several layout sub-problems based on their structure or assemble component. The main difficulties in solving these problems lie in combinational explosion of computational complexity, engineering complexity, and pragmatic approaches in engineering practice. Recently, cooperative co-evolutionary algorithms (CCEA) have proven to be an efficient way to solve complex engineering problems. CCEAs decompose the problem into several sub-problems using a cooperative co-evolutionary multi-population architecture. Based on the framework of CCEA, this paper presents a cooperative co-evolutionary method with consistency coordination mechanisms for a complex layout design problem. This method extracts objectives from all technical requirements by analyzing the nonlinear coupling relations among the sub-problems. The method then coordinates consistency among the sub-populations during a co-evolution process, and ensures all sub-populations converge on a global consistency objective. Compared with a traditional CCEA method, results show that the proposed method can improve the computational accuracy of solutions. The proposed consistency coordination mechanisms can better reduce the conflicting of the sub-populations and make all the sub-populations sustained coevolve within short runtime.*

Keywords: Cooperative Co-evolutionary Algorithm, Complex Layout Problem, Consistency Coordination Mechanisms

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1.Introduction

Spatial layout designs have been widely applied to various fields. Different layout problems usually have different theoretical bases or engineering complexities. Dowsland and Cagan point out that the spatial layout problem concerns the placement of components in an available space such that a set of objectives can be optimized while satisfying optional spatial or performance constraints (Dowsland 1991, Cagan 1998). According to the constraints, spatial layout problems can be divided into layout problems that have no performance constraints and layout problems that have performance constraints. The introduction section should provide a context for your manuscript. When preparing the introduction, please bear in mind that some readers will not be experts in your field of research.

Recently, spatial layout problems of different fields have been studied more widely. This mainly consists of three kinds of research: First, the layout algorithms or methods; Second, the solving strategies or frameworks of layout problems. Third, the professional layout system; considering a three-dimensional component layout problem, Cagan and Dowsland systematical reviewed the present layout approaches and classified them into different categories according to search strategies (Cagan 2002, Dowsland 1992). These classifications were as follows. First, traditional optimization algorithms (e.g. liner programming methods); Second, heuristic rule-based algorithms (e.g. octree representation approaches); Third, stochastic algorithms (e.g. hybrid approach of heuristic rules and neural network algorithms).

With an increase in layout problem size and complexity, it is not sensible to pursue a general all-purpose packing method in the near future. There is a need for solving strategies from an in-depth the study of complex layout problems, such as co-evolutionary methods, and human-computer cooperation methods. This paper studies a co-evolutionary method for solving spatial layout problems.

The co-evolutionary method is an evolutionary method which simulates competition and cooperation based on the notion of symbiosis among natural species and their co-evolution (Hillis 1990). According to biological models, co-evolutionary methods can be divided into the competitive co-evolutionary algorithm; the predator based co-evolutionary algorithm and the cooperative co-evolutionary algorithm (CCEA). It is essentially similar to the process used to solve complex layout problems. That is, to pursue the global optimum via decomposing the problem into several sub-problems. Therefore, this paper adopts the CCEA to solve complex layout problems. Potter proposed a CCEA that adopted multiple cooperating sub-populations to coevolve subcomponents of a solution (Potte 1990). Bergh proposed a cooperative particle swarm optimization (CPSO) algorithm based on the CCEA (Bergh 2004). In addition, Jansen only provided a formal proof for a very specific case of the CCEA (Jansen 2004).

It can be concluded that research on the CCEA mainly focus on problem decomposition and the fitness evaluation of sub-populations. Coordination among the sub-populations is maintained only by cooperative fitness evaluation. It is an implicit coordination mechanism and very sensitive to the degree of coupling between sub-populations. The objectives and the performance constraints of complex layout problems couple with each other. This study presented a cooperative co-evolutionary method with consistency coordination mechanisms for solving the satellite module layout problem. This method extracts objectives from technical requirements by analyzing nonlinear coupling relations among sub-problems. A global coupling state vector then coordinates a search among sub-populations during a co-evolution process. This ensures that all sub-populations converge on a global consistency objective.

2. A Cooperative Co-evolutionary Method with Consistency Coordination Mechanisms (CCMCCM)

In order to solve the complex layout problems efficiently using a CCEA, four aspects of CCEA should be solved. First, decompose the problem into sub-problems represented by sub-populations. Second, coordinate the sub-populations. Third, select the cooperative individuals. Fourth, evaluate the individual fitness of each individual.

For the decomposition of the original problem, Potter used a static decomposition strategy that took every variable as a sub-problem to solve a function optimization problem (Potte 1990). In our study, the number of the variables for the complex layout problem is about 150. If a static decomposition strategy is used, the complex layout problem will be decomposed into about 150 sub-problems, and a huge amount of computing time would need to be invested. The basic rule of problem decomposition is to reduce the coupling complexity among the sub-problems (Bergh 2004).

The two driving mechanisms of sub-population interaction in CCEAs are competition and cooperation. Traditional evolutionary algorithms mainly simulate competition and less so cooperation (Liu 2004). For an engineering complex layout problem, competition and cooperation co-exist. It is important for an evolutionary algorithm to balance the cooperation and competition among the populations and thus reach a global state of balance.

We use the cooperative individuals to exchange information among the sub-populations. The individual of each sub-population is one part of a solution of the problem. Individual fitness evaluation of each sub-population requires individuals provided by other sub-populations. Suppose that x_{ij} denotes the jth individual of the ith sub-populations. When calculating the fitness value of x_{ij}, first a cooperative individual set (k = 1,2,…, i-1, i+1, …, q) is selected from other sub-populations, where q = the number of sub-population. The individual x_{ij} and the cooperative individual set form a whole solution $\boldsymbol{X}$ of the problem. A whole solution X denotes a complete scheme that can be evaluated to obtain a fitness value. This fitness value is used as the fitness value of individual x_{ij}.

In order to evaluate the individual of each sub-population, the cooperative individuals of other sub-populations need to be selected. Selection methods include the random selection method, the best selection method and the cooperative population selection method (Zhong 2000, Sharpe 1985). A random and a best selection method are used to evaluate individuals every *t* generations during the optimization process.

Coordination among the sub-populations is maintained only by the method of fitness evaluation. This is an implicit coordination mechanism and very sensitive to the degree of coupling among sub-populations. The coordination mechanisms are closely related to the complex layout problem studied in this article. It is hard to find a general coordination mechanism for the complex problem. Ryoo studies the genetic exchange mechanisms for co-evolution (Ryoo 2002). This method is only suitable to solve problems with two sub-problems. In addition, the mechanisms of individual fitness calculation are based on the differences of the variables, so computational times increase sharply with problem size.

Moreover, many researchers have studied the multidisciplinary coordination methods, such as the response surface model and the global sensitivity equation. However, usually, complex layout problems belong to a multimodal class of problems. The derivative information does not exist in some searching area, so it is hard to construct the response surface model and the global sensitivity equation. Moreover, the system level would use more times to coordinate the objective of the subsystem level. However, the heuristic coordinate strategies do not need the derivative information and can combine the engineers' experience with the solution methods to solve the problem efficiently. This paper studies mechanisms to couple constraint based coordination mechanisms, where the goal is to coordinate sub-populations such that the sub-populations converge to a global optimum.

First, this study defines a shared state vector for representing the global coupling constraints.

2.1 The Definition of the Shared State Vector of the Global Coupling Constraints

In the context of a CCEA, Wiegand defines the incompatible criteria between the sub-problems' objectives and the system objectives. Based on this definition, the incompatible constraints can be found from all the constraints (Wiegand 2003). These are called the global coupling constraints. The shared state vector is then abstracted by analyzing the global coupling constraints since contains important information and should be stated earlier. This vector can be formulated as:

$$\boldsymbol{U} = (U_1, U_2, \cdots, U_i, \cdots, U_n) \in R^n \quad i \in (1, 2 \cdots n) \tag{1}$$

where, n = the dimensions of state vector U. The shared state vector $\boldsymbol{U}$ is an independent set of variables set that can fully describe the global coupling constraints.

2.2 Coupling Shared State Vector-Based Coordination Mechanism (CSSVCM)

The coordinate procedure based on the coupling shared state vector is presented in Figure. 1.

```
Begin
      Select the source subpopulation;
      Select the compared guiding individual I(C) from
      the source subpopulation;
            For each individual I(i) of each subpopulation P(i)
            Calculate the difference DM(U) of the share
state vector between I(i) and I(C)ÿ
            Modify the fitness value of individual I(i)ÿ
      End For
End
```

Figure 1. The coordinate procedure based on the shared state vector

Given the shared state vector, when calculating the fitness value of individual (I) of any sub-population, select the compared guiding individual (*J*), calculate the differences value of the shared state vector between two individuals, then apply the difference value as a penalty to the objective function of individual (*I*). This coordination mechanism continuously guides all the sub-populations toward the global searching directions.

The weighted generalized distance between the vector U^1 and U^2 is formulated as:

$$DM\left(U^1, U^2\right) = \sum_{i=1}^{n}\left[\alpha_{(i)}\left(U^1_{(i)} - U^2_{(i)}\right)\right]^2 \tag{2}$$

where $\alpha_{(i)}$ denotes the weight of the *i*th state vector. The difference *DM* was applied as a penalty to the objective function of individual Ind_m. Suppose F_{m0} denotes the original fitness value of individual Ind_m, the modified fitness value of individual Ind_m can be calculated by Equation 9.

$$F_m = F_{m0} + DM \tag{3}$$

Compared with related methods (Ryoo 2002), the proposed method based on a shared state vector has the following differences. First, the CSSVCM can be used to solve the problems with more than two sub-problems; second, the CSSVCM is based on a shared state vector which guides each individuals evolution according to the constraints of a complex layout problem. During evolution, CSSVCM only maintains the shared state vector which denotes a set of constraints. The solution flowchart of CCMCCM in this study is shown as Figure. 2.

```
Begin
    Initialize the original problem P;
    Initialize the layout algorithm A;
    Decompose the original problem into n(n≥2)
subproblems SPi (i=1,2,3…n);
    For   the ith subproblems SPi(i=1,2,3…n)
        Subproblems SPi evluation population;
        For an evluation population
            Crossover;
            Mutation;
            Fitness Calculating;
          Each individual fitness modifing by
          using the consistency coordination
          mechanism;
            Selection;
        End For
    End For
    Output Ind(PBest) of the original problem;
End
```

Figure 2 .The solution flowchart of CCMCCM

3. A Satellite Module Layout Design Problem

The optimal layout problem of a simplified international commercial communication satellite can be described as follows. A total number of *n* objects must be located within a cylindrical satellite module shown in Fig. 3. The upper and lower surfaces of the two bearing plates attached on a standing column in the module are used to fix all the objects. The design objective here is to optimize the moments of inertia of the whole module, subjected to the following constraints: (a) All the objects should be contained within the module, with no overlap among the objects and no clash between the module wall and each object; (b) The position error of the centroid of the whole system should not exceed an allowable value, and the smaller the better; (c) The equilibrium error of the system should be as small as possible.

Sixty objects need to be located on four bearing surfaces in the satellite module. Their dimensions and masses of the module can be found in the reference (Sun 2003). The technological requirements for a final layout scheme of the whole module are given with parameters of the centroid of $x_c = 0$, $y_c = 0$, and $z_c = 552$; The moments of inertia of the whole module are: $\Delta I_{xx} + \Delta I_{yy} + \Delta I_{zz} \leq 625\ kg \cdot m^2$. The allowable error of the centroid is: $\delta x_c = \delta y_c = 3$mm. The allowable errors of the principal angles are: $\delta\theta_x = \delta\theta_y = \delta\theta_z = 0.03$ *rad*. The basic problem is to optimize the moments of inertia of the whole module while satisfying the technological constraints (the total amount of overlapping, the principal angles and the position of the centroid).

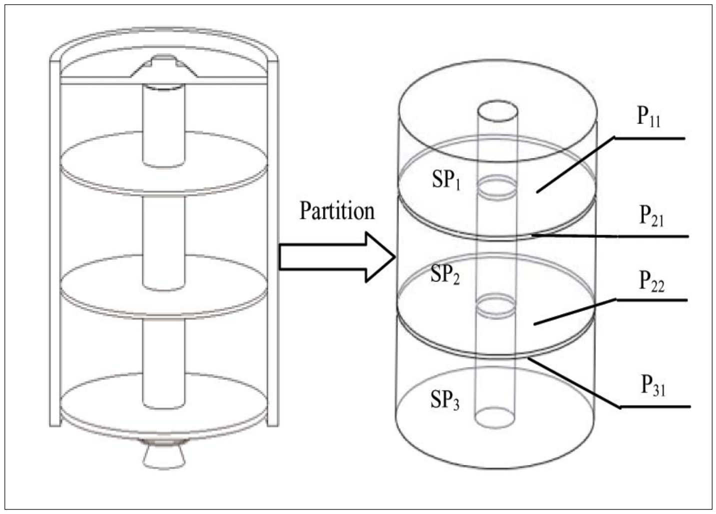


Figure 3. Layout subspace partition

For the satellite module layout problem, this paper adopted another decomposition strategy. As shown in Figure.3, a simplified satellite module can thus be divided into three layout subspaces that include four bearing bases. Two methods were used to solve the satellite layout problem and each of them ran 50 times with random initialization. The two methods were CCGA and the proposed method CCMCCM. The parameter settings of each method are shown in Table. 1.

	CCGA	CCMCCM
Parameters Setting	Real code; the maximize generations is 10000; each sub-population size is 200. two-point crossover0Gaussian mutation operation, linear ranking selection; the number of sub problem is 3	Same to CCGA: the principal angles constraints are used as the global coupling constraints

Table 1. the parameters setting of the two methods

Experiment results for the number of success solutions are reported in Table. 2. The compared running times and successful times of the two methods were shown in Table. 3. The fitness values of the two methods are illustrated in Figure.4. The layout patterns obtained by the CCMCCM are illustrated in Figure. 5. The 3D layout pattern of the whole module by the CCMCCM is emulated on the CAD platform Pro/Engineer and illustrated in Figure. 6.

The CCMCCM was compared with the CCGA according to the objectives, the constraints, the success probability, and the running times (Table. 2 and Table. 3).

(1) The objectives: the sum of the best inertia and the average inertia of the whole system solved by the proposed CCMCCM was lower than those of the CCGA.

(2) The constraints: the total amount of overlapping of the best solution solved by the two methods is zero; the smallest amount of overlapping and the average amount of overlapping solved by CCMCCM for the 50 running times is lower than those of the CCGA; results are comparable with angles and the position of centroid.

(3) The probability of success of the CCMCCM is 66% higher than that of the CCGA.

(4) Compared to CCGA, the average running times of CCMCCM was between 0.8 and 2.38% less than the CCGA.

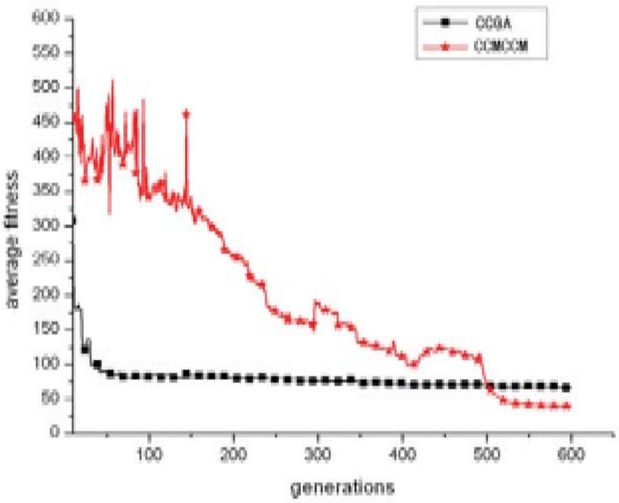
Method		CCGA	CCMCCM
The moments of inertia /Kg·m^2	$I_{x'}$	216.770	214.037
	$I_{y'}$	213.811	213.378
	$I_{z'}$	180.548	177.381
The principal angles /rad	$\theta_{x'}$	0.008	0.022
	$\theta_{y'}$	0.001	0.011
	$\theta_{z'}$	0.006	0.005
Position of centroid /mm	δx_c	0.250	0.674
	δy_c	0.023	0.150
Total amount of overlapping /mm^2		0.000	0.000
Running times/s		757.850	720.235

Table 2. The performance indexes of the optimal layout scheme

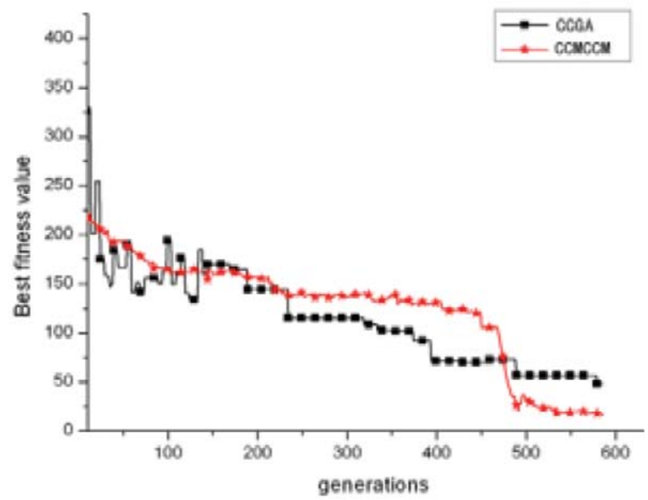
Method	CCGA	CCMCCM
Running times/s	(754.800，25.513，725.765，764.843)	(736.256，24.689，719.268，744.298)
Total amount of overlapping /mm^2	(146.875，3359.010，0.161，2781.040)	（77.050，412.610，0，24.1617）
The moments of inertia /Kg·m^2	(621.365,59.897,604.265,640.358)	(611.163,11.779,604.853, 617.078)
The principal angles /rad	(0.127,0.999,0.001,0.523)	（0.024，0.056，0.014，0.021）
Position of centroid /mm	(3.265,26.354,0.001,14.321)	（2.989，3.087，2.343，3.560）
The success probability /%	24	90

Table 3. Statistical data of 50 runs results of each algorithm

As shown in Figure 4, CCMCCM kept a high fitness value throughout the optimization process. This indicates that CCMCCM could reduce conflicting sub-problems and coordinate the sub-populations such that they converged upon a global optimum. It can be concluded that the CCMCCM is superior to CCGA in accordance with satisfying the objectives of the optimal. The proposed CCMCCM can continually transform the layout patterns to keep diversity in each sub-population. The consistency coordination mechanism can keep the consistency searching direction of each sub-population and improve the computational precision and the success probability. Compared with the traditional CCGA, the proposed CCMCCM can better balance the conflicting local and global searches, and encourages diversity and convergence.



(a) The Average Fitness value curves



(b) The best Fitness value curves

Figure 4. Fitness value curves

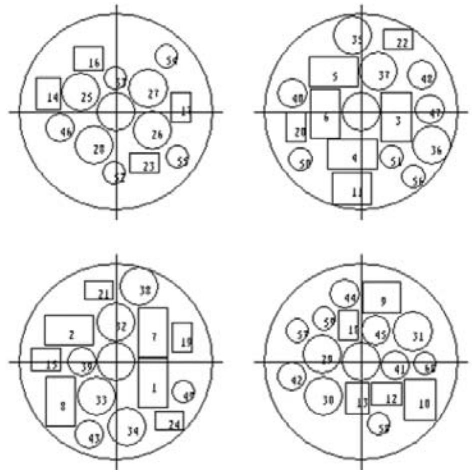


Figure 5. Layout scheme acquired from CCMCCM

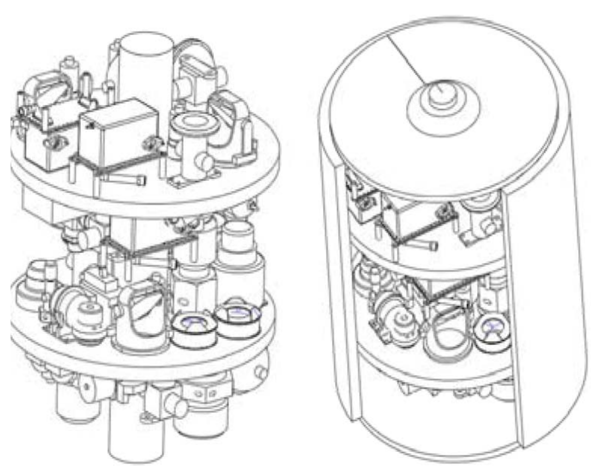


Figure 6. Communication satellite assembly diagram of the optimal scheme solved by CCMCCM

4 . Conclusions

For solving complex spatial layout problems, this paper presented a cooperative co-evolutionary method with consistency coordination mechanisms. This method extracted the global coupling constraints or objectives from all technical requirements by analyzing the nonlinear coupling relations among the sub-problems, and constructed the global coupling state vector to coordinate a search in each sub-population. This enabled all sub-populations to converge on a global consistency objective. Experimental results showed that:

(1) The proposed CCMCCM was superior in the CCGA to the objectives and the success probability for the optimal layout design of the satellite module;

(2) The proposed CCMCCM can continually transform the layout patterns to keep the diversity of each sub-population by the consistency coevolution of the sub-populations; +

(3) It also can be concluded that the complex layout problems cannot be fully solved only by the algorithms.

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