Asynchronous parallel disassembly sequence planning for multi-manipulator based on improved shuffled frog leaping algorithm

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Abstract

To solve the problem of low disassembly efficiency of complex products, an asynchronous parallel disassembly sequence planning method of multi-manipulator based on improved shuffled frog leaping algorithm was proposed. Depending on the characteristics of this method, the disassembly manipulators are taken as the research object, and the minimum completion time of disassembly is taken as the optimization objective. Based on the basic disassembly time of parts, the disassembly preparation time caused by the change of disassembly tools and directions is considered, so that the objective function evaluation model is more realistic. Then, the mathematical model of asynchronous parallel disassembly sequence planning is constructed and the disassembly information modeling method is optimized. We proposed a new method based on the fastener constraint matrix and the part constraint matrix to build the information model of product disassembly. Based on this model, the detachable conditions are derived and the feasible disassembly sequence is obtained. In order to improve the performance of the proposed algorithm, a double-link encoding method and an efficient decoding operator is proposed. The adjustment orders which based on adjustment position and the substitution formulas are constructed to carry out the new segmental local evolution of frog individuals, and the update formula of frog position is reconstructed. Furthermore, the two-point mutation operator is added to the global information exchange strategy to enhance the search ability of the algorithm. The proposed algorithm is applied to a screw lifting mechanism and four products of varying complexity, and the results are compared with two algorithms. The results show that the proposed method can solve disassembly problems of different scales and is especially effective in solving large-scale disassembly problems.

Keywords Asynchronous parallel disassembly · Disassembly modeling · Improved shuffled frog leaping algorithm · Disassembly sequence planning · Disassembly solution

1 Introduction

With the increasingly serious problems of resources and environment, green manufacturing has received extensive attention from academia and industry. Remanufacturing, as a typical form of green manufacturing, uses advanced technology or means to repair and transform waste products so that the quality of the transformed products can

reach or exceed new products, thereby achieving the recycling of waste resources [1]. Disassembly is a key process of remanufacturing. It is not only an essential means to achieve an efficient recycling strategy, but also a key step to ensure the quality of remanufacturing products [2]. A good method of Disassembly Sequence Planning (DSP) can effectively improve disassembly efficiency and reduce the disassembly cost [3–6].

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DSP can be divided into two types: sequential disassembly sequence planning (sDSP) and parallel disassembly sequence planning (pDSP) [7, 8]. The disassembly process of large and complex mechanical products usually has the characteristics of multiple participants, numerous parts and complex constraints, so the research of pDSP is of great significance to the actual disassembly work. According to the execution mode of the task, the pDSP can be divided into synchronous parallel disassembly sequence planning (spDSP) and asynchronous parallel disassembly sequence planning (apDSP). The start time of the disassembly task for each manipulator in spDSP is synchronized. The apDSP allows each manipulator to immediately begin performing their own disassembly tasks if the disassembly priority constraint is met [9]. The solution process of apDSP is more complex than the solution process of spDSP. However, when disassembling complex products, apDSP can reduce the disassembly time and has practical guiding significance.

At present, there are relatively few studies with apDSP. Only the basic disassembly time of the part is considered in the sequence evaluation, which does not meet the actual disassembly. In addition, many algorithms will generate a large number of invalid solutions during the solution process, so that the solution efficiency is low. In view of the above problems and difficulties, we have proposed a novel algorithm for solving apDSP. In the solution process, we will fully consider multi-manipulator collaboration and scheduling, and ensure the feasibility of the solutions in each step of the algorithm. At the same time, during the disassembly process, we will consider the disassembly preparation time caused by the change of disassembly direction and disassembly tool to make the disassembly evaluation more realistic.

The rest of this paper is organized as follows: Sect. 2 reviews the literature on DSP. Section 3 describes the disassembly information model and a mathematical model of apDSP. Section 4 proposes an efficient algorithm based on improved shuffled frog leaping algorithm (ISFLA) to solve the problem of apDSP. Section 5 shows the experimental results of the proposed approach using three study cases. Finally, Sect. 6 concludes our work.

2 Literature review

Based on the information model of product disassembly, DSP is aiming at optimizing the given evaluation function of the disassembly sequence and determining the optimal or approximately optimal disassembly sequence that meets the disassembly constraints [10]. DSP is a NP-hard problem [11], many heuristic or metaheuristic methods have been used to solve DSP problems because of the

advantages of fast solution speed, convenient parameter setting and the high modularity, such as the, a method to solve DSP which based on genetic algorithm (GA) [12–15], ant colony algorithm [16, 17], particle swarm algorithm (PSO) [18, 19], artificial bee colony algorithm [20, 21], flower pollination algorithm [22], etc.

All the above studies are to solve sDSP, much less work has been done on pDSP. Zhang [23] constructed a disassembly hybrid graph model (DHGM) to describe constraint relationships of product components and got a solution based on the branch-and-bound algorithm, but the solution time will increase dramatically as the scale of the disassembly increases. Tian [24] obtained optimal parallel sequences by constructing chromosome coding structure of parallel sequences and improving crossover and mutation operators of GA. However, a large number of invalid sequences would be generated in the solution process, which would affect the solution efficiency. Cai [25] used the stratified graph to express the parts assembly relationship and proposed a phased iteration strategy based on the ant colony algorithm to solve pDSP problems, however, it is assumed that the basic disassembly time of all components is equal. Zhang [7] proposed a pDSP approach based on fuzzy-rough sets, but this method may produce a sequence that does not meet the disassembly constraint. Ren introduced exclusive and cooperative relationships based on precedence relationships, and optimized the artificial bee colony algorithm to solve the problem of pDSP.

By analyzing the literature on pDSP in the previous paragraph, we can get that they all focus on spDSP, which requires that all disassembly tasks must start simultaneously. In reality, it is unnecessary. The manipulator should be able to perform its next disassembly task immediately if the relevant disassembly constraints are met. However, there is only a very few of literature has studied apDSP, Smith [26] used modular design theory to group parts into modules, created a novel method of DSP for green design, but it was complicated to use modular theory to group parts when the disassembly scale is large. Ren [27] designed an encoding and decoding strategy and solved apDSP by the improving genetic algorithm, but the crossover operation process under the premise of meeting the disassembly constraints is more complicated and only the basic disassembly time of the components is used as the evaluation index.

In summary, although the above methods have achieved significant results in the pDSP, there are still some problems: (1) It does not fully consider multi-manipulator collaboration and scheduling on the disassembly process, (2) The current researches are mainly based on spDSP, and there are relatively few studies on apDSP, (3) many algorithms are prone to generate a large

number of invalid solutions, affecting the efficiency of the solution, (4) the disassembly model does not express the disassembled components of manipulator at any time, (5) The disassembly evaluation function does not adequately reflect on the actual disassembly process.

In addition, the shuffled frog leaping algorithm (SFLA) [28] is a sub-heuristic collaborative searching swarm intelligent algorithm, which is combined with memetic algorithm (MA) based on genetic genes and particle swarm optimization (PSO) based on the feeding behaviors of particle swarm. It has the characteristics of fast calculation speed, excellent global optimization ability, and strong robustness. The algorithm has been successfully applied to the combinatorial optimization problem of the traveling salesman [29, 30], 0/1 knapsack [31, 32], timetable [33] and Shop Scheduling [34–36]. The algorithm has shown excellent performance. However, no scholars in the literature have applied SFLA to solve DSP problems. Therefore, it is necessary to explore the performance of SFLA in solving DSP problems. In this paper, an improved SFLA is proposed to solve the apDSP problem, which not only ensures the precedence constraints but also takes the disassembly task assignment, human scheduling, asynchronous operations, and sequence evaluation into account.

3 Problem statement

To solve the problem of apDSP, we first set up the disassembly information model which represents disassembly constraint through the fastener constraint matrix G_1 and the part constraint matrix G_2 , then, we set up the mathematical model of apDSP.

3.1 Construction of disassembly information model

The disassembly information model is used to represent disassembly constraints and generate a feasible disassembly sequence. The precedence relationships between components must be strictly followed when solving DSP problems. To depict precedence relations, we supplement and optimize Gonzalez's [37] modeling method and set up a model based on the fastener constraint matrix and the part constraint matrix.

We make some explanation for the product disassembly modeling: the part refers to the minimum disassembly unit except the fastener. Fasteners are mechanical parts used for fastening two or more parts, such as screws, bolts, studs, etc. Components are the collective name for parts and fasteners.

3.1.1 Fastener constraint matrix (G_1)

It represents the constraint relationship between the fastener and the part of the disassembly product.

$$G_1 = \{co_{ij}\}_{m \times n} = \begin{bmatrix} co_{11} & co_{12} & \cdots & co_{1n} \\ co_{21} & co_{22} & \cdots & co_{2n} \\ \vdots & \vdots & & \vdots \\ co_{m1} & co_{m2} & \cdots & co_{mn} \end{bmatrix} \quad (1)$$

i : the index of fastener, $i \in \{1, 2, \dots, m\}$, where m is the number of all fasteners in disassembly model; j : the index of part, $j \in \{1, 2, \dots, n\}$, where n is the number of all parts in disassembly model.

$$co_{ij} = \begin{cases} 0, & \text{if fastener } i \text{ has no constraint relationship with part } j \\ 1, & \text{if fastener } i \text{ fastens part } j \\ 2, & \text{if fastener } i \text{ is blocked by part } j \end{cases}$$

3.1.2 Part constraint matrix (G_2)

It represents the constraint relationship between different parts of the disassembly product.

$$G_2 = \{re_{ij}\}_{n \times n} = \begin{bmatrix} re_{11} & re_{12} & \cdots & re_{1n} \\ re_{21} & re_{22} & \cdots & re_{2n} \\ \vdots & \vdots & & \vdots \\ re_{n1} & re_{n2} & \cdots & re_{nn} \end{bmatrix} \\ = \begin{bmatrix} re_{11}^1, re_{11}^2, \dots, re_{11}^5 & re_{12}^1, re_{12}^2, \dots, re_{12}^5 & \cdots & re_{1n}^1, re_{1n}^2, \dots, re_{1n}^5 \\ re_{21}^1, re_{21}^2, \dots, re_{21}^5 & re_{22}^1, re_{22}^2, \dots, re_{22}^5 & \cdots & re_{2n}^1, re_{2n}^2, \dots, re_{2n}^5 \\ \vdots & \vdots & & \vdots \\ re_{n1}^1, re_{n1}^2, \dots, re_{n1}^5 & re_{n2}^1, re_{n2}^2, \dots, re_{n2}^5 & \cdots & re_{nn}^1, re_{nn}^2, \dots, re_{nn}^5 \end{bmatrix} \quad (2)$$

i, j : both the index of the part, $i, j \in \{1, 2, \dots, n\}$, where n is the number of all parts in disassembly model

$$re_{ij}^d = \begin{cases} 0, & \text{part } i \text{ has no interference with part } j \text{ in direction } d \\ 1, & \text{part } i \text{ is interfered by part } j \text{ in direction } d \end{cases}$$

d : the index of disassembly directions, $d \in \{1, 2, \dots, s\}$, where s is the number of all disassembly directions.

Through G_1 and G_2 , we can fully express the disassembly model information. In this modeling approach, the conditions that fastener i can be disassembled are as follows:

$$\begin{cases} \sum_{j=1}^n Judge(co_{ij}) = 0 \\ Judge(co_{ij}) = \begin{cases} 0, & co_{ij} \neq 2 \\ 1, & co_{ij} = 2 \end{cases} \end{cases} \quad (3)$$

The condition for the disassembly of part i without relevant fastener fixation is as follows:

$$\prod_{d=1}^s \left(\sum_{j=1}^n re_{ij}^d \right) = 0 \quad (4)$$

One disassembly product showed in Fig. 1, it is assembled with 6 fasteners and 4 parts. Since it is a two-dimensional assembly drawing and the bottom of the product is fixed, only 3 disassembly directions are considered: $+x$, $-x$, $+y$. According to the above modeling method, the fastener constraint matrix G_1 and the part constraint matrix G_2 of the product can be obtained as follows:

$$G_1 = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 1 & 2 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 2 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

$$G_2 = \begin{bmatrix} 0 & 1 & 5 & 3 \\ 0 & 0 & 5 & 3 \\ 2 & 2 & 0 & 0 \\ 4 & 4 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 000 & 001 & 101 & 011 \\ 000 & 000 & 101 & 011 \\ 010 & 010 & 000 & 000 \\ 100 & 100 & 000 & 000 \end{bmatrix}$$

3.2 The construction method of feasible disassembly sequences

The feasible disassembly sequence refers to the disassembly sequence that satisfies the disassembly constraint relationship. The steps for generating a feasible disassembly sequence according to the above disassembly information modeling method are as follows:

1. Define A as the set of disassembly components, X is one feasible disassembly sequence, make $A = \emptyset$, $X = \emptyset$;

2. In the initial state, according to matrix G_1 and matrix G_2 , search for all disassembly components and put them into A , define temporary transformation matrix G_3 and G_4 , make $G_3 = G_1$, $G_4 = G_2$;
3. Randomly select an element a from A , put it into the left-most end of X and delete element a in A ; then judge the type of element a , if element a is a fastener, go to **step4**, if element a is a part, then go to **step5**;
4. Update matrix G_3 (delete all the elements in row of a in G_3). According to matrix G_1 , for each part connected by fastener a , judge whether these parts can be disassembled according to formula (4). If it is, put the index of this part into A ; if not, go to **step6**;
5. Update G_3 (delete all the elements in line of a in G_3) and update G_4 (delete all the elements in column of a in G_4). According to G_1 , for each fastener blocked by part a , judge whether it is can be disassembled according to formula (3). If it is, put the index of the corresponding fastener into A . In addition, according to G_2 , for each part blocked by part a in any disassembly direction, judge whether it can be disassembled according to formula (4). If it can be disassembled and the part is not in X , put the index of the corresponding part into A ;
6. Determine if all fasteners and parts in the product have been disassembled. If it completes, output X , otherwise go to **step3**.

3.3 Mathematical model

The notations in model are summarized as follows:

1. p_i —the index of a component, $i \in \{1, 2, \dots, N\}$, $N = n + m$, where n is the number of all parts in disassembly product, and m is the number of all fasteners.
2. m_k —the index of a manipulator, $k \in \{1, 2, \dots, l\}$, where l is the number of all manipulators.
3. x_k^j —the index of a disassembly task, it represent the j th disassembly task of manipulator m_k , $j \in \{1, 2, \dots, Q_k\}$,

Fig. 1 An example of a product to be disassemble

where Q_k is the number of all disassembly task for manipulator m_k .

4. st_k^j —the start disassembly time for the j th disassembly task of manipulator m_k .
5. bt_k^j —the basic disassembly time for the j th disassembly task of manipulator m_k .
6. rt_k^j —the preparation time before the j th disassembly task of manipulator m_k .
7. et_k^j —the completion time for the j th disassembly task of manipulator m_k .
8. nf_k —the index of the disassembly task currently being executed by manipulator m_k .
9. cp_k^j —the set of feasible disassembly tasks after m_k completes the j th disassembly task.

In order to efficiently disassemble all components, we aim to minimize the disassembly completion time and determine the optimal feasible disassembly sequence that satisfies the following constraints:

1. Meet precedence constraints;
2. All components are disassembled and can only be disassembled once;
3. Each manipulator must execute at least one disassembly task;
4. The manipulator can only disassemble one part at a time.

In fact, it is to determine the optimal disassembly task allocation plan for all manipulators under the condition of comprehensively considering disassembly constraints and disassembly resources. We make the following assumptions:

1. There is no interference in the working area of manipulators;
2. The basic disassembly time for disassembling the same components by different manipulators is the same.

Based on the above-mentioned modeling method and notation description, a mathematical model of apDSP is formulated as follows:

$$\text{Min} \left\{ \max \left(et_1^{Q_1}, et_2^{Q_2}, \dots, et_k^{Q_k}, \dots, et_l^{Q_l} \right) \right\} \quad (5)$$

$$\sum_{k=1}^I \sum_{j=1}^{Q_k} x_k^j = \sum_{i=1}^N p_i \quad (6)$$

$$\sum_{j=1}^{Q_k} x_k^j \geq 1 \quad (7)$$

$$\bigcap_{k=1}^I \sum_{j=1}^{Q_k} x_k^j = \emptyset \quad (8)$$

$$et_k^j = st_k^j + bt_k^j, 1 \leq j \leq Q_k, \forall k \quad (9)$$

$$\begin{cases} st_k^j \geq et_k^{j-1} + rt_k^j \\ st_k^j = et_k^{j-1} + rt_k^j, \text{ if } x_k^j \in cp_k^j \end{cases}, 2 \leq j \leq Q_k, \forall k \quad (10)$$

$$rt_k^j = r_1 t_k^j + r_2 t_k^j, 2 \leq j \leq Q_k, \forall k \quad (11)$$

$$\bigcap_{j=1}^{Q_k} cp_k^j = \emptyset, \forall k \quad (12)$$

Constraint (5) addresses the optimization goal is to minimize the disassembly completion time; Constraint (6) addresses all components must be disassembled; Constraint (7) addresses each manipulator must execute the disassembly task at least once; Constraint (8) addresses that each component can only be disassembled once, there is no intersection of the disassembly tasks for each manipulator; Constraint (9), (10) and (11) address the relationship between t start disassembly time, basic disassembly time, preparation time, and completion time. In constraint (12), $r_1 t_k^j$ represents the preparation time added by the replacement of the disassembly tool, and $r_2 t_k^j$ represents the preparation time due to the change of the disassembly direction. We define it as follows:

$$r_1 t_k^j = \begin{cases} 1, & \text{if } m_k \text{ needs to change the disassembly tool} \\ & \text{when executing the disassembly task } x_k^j \\ 0, & \text{if } m_k \text{ does not needs to change the disassembly tool} \\ & \text{when executing the disassembly task } x_k^j \end{cases} \quad (13)$$

$$r_2 t_k^j = \begin{cases} 1, & \text{if } m_k \text{ needs to change the disassembly direction} \\ & \text{when executing the disassembly task } x_k^j \\ 0, & \text{if } m_k \text{ does not needs to change the disassembly direction} \\ & \text{when executing the disassembly task } x_k^j \end{cases} \quad (14)$$

4 The proposed approach

This section presents an improved SFLA to solve the apDSP problem. The main steps of the proposed approach are shown as follows:

1. Solution encoding and population initialization;
2. Decoding approach

3. Evaluation of objective functions;
4. Frog grouping method
5. Local evolution method of frog groups
6. Strategy of global information interaction
7. Termination rule

4.1 Solution encoding and population initialization

The encoding structure of the frog corresponds to the solution of the apDSP problem, each frog individual is represented as a feasible parallel disassembly sequence. The following definitions are made for the encoding structure of frogs:

$$\begin{aligned} \text{Frog} &= \left\{ \{f_p\}_{1 \times n} \mid \{f_m\}_{1 \times n} \right\} \\ &= \{p_1, p_2, \dots, p_i, \dots, p_N \mid m_1, m_2, \dots, m_k, \dots, m_l\} \quad (15) \end{aligned}$$

We design a double-link encoding structure that includes disassembly task sequence f_p and the disassembly manipulator sequence f_m , where both the length of f_p and f_m are N . The elements of the same position in the two sequences are one-to-one correspondence. It indicates that the disassembly task of the position is executed by the corresponding manipulator.

For instance, $\text{Frog} = \{4, 5, 3, 1, 2, 6, 8, 7, 9 \mid 3, 1, 1, 2, 3, 1, 3, 2, 2\}$. The sequence represents 9 disassembly tasks are performed by 3 manipulators, so that we can get the disassembly task of each manipulator:

$$\begin{aligned} x_1^1 &= 5, x_1^2 = 3, \quad x_1^3 = 6; \quad x_2^1 = 1, x_2^2 = 7, x_2^3 = 9; \\ x_3^1 &= 4, x_3^2 = 2, x_3^3 = 8 \end{aligned}$$

In addition, f_p is a feasible disassembly sequence generated based on the disassembly information model; f_m is a randomly generated disassembler sequence, and the frog's encoding structure ensures that each frog in the initial population is a feasible sequence, which helps to improve search efficiency. The generation of a feasible individual *Frog* is presented as follows:

- Step 1* Set N (the total number of disassembly tasks) and I (the total number of manipulators),
Step 2 Construct a feasible disassembly task sequence according to the method described in Sect. 3.2,
Step 3 According to the number of manipulators, randomly generated f_m .

4.2 Decoding approach

In this paper, our optimization goal is to minimize the disassembly completion time. In fact, the apDSP is a

scheduling scheme for the start disassembly time and the end disassembly time of each disassembly task for each manipulator, so it is necessary to decode individual into the timing of each disassembly task. Further, under the condition of precedence constraint, we perform parallel scheduling of the disassembly time of each disassembly task. In view of the individual coding mode and the characteristics of apDSP, we propose the frog individual decoding operator. The specific steps are as follows:

1. According to the individual code, determine the disassembly task x_k^j of each manipulator m_k , initialize $st_k^j, bt_k^j, rt_k^j, et_k^j, nf_k, cp_k^j$, generate a component set vP that can be disassembled in an initial state based on G_1 and G_2 ;
2. For the first disassembly task x_k^1 of each m_k , judge whether it belongs to vP ; if it belongs, set $st_k^1 = 0$, update et_k^1 according to formula (9), and update cp_k^1 and nf_k ;
3. Judge the current disassembly task $x_k^{nf_k}$ of each m_k in turn, if $x_k^{nf_k} \in [vP \cup (\sum_{j=1}^{nf_k-1} cp_k^j)]$, update $st_k^{nf_k}, et_k^{nf_k}$ based on formulas (9), (10) and (11), also update $cp_k^{nf_k}$ and nf_k ; otherwise go to **step4**;
4. For the current disassembly task $x_k^{nf_k}$, judge whether it belongs to other manipulator's set cp_{k_other} , if only one set includes $x_k^{nf_k}$, determine the position of $x_k^{nf_k}$ in cp_{k_other} . Assume that the location is $cp_{k_other}^{pos}$, if $(et_k^{nf_k-1} + rt_k^{nf_k}) \geq et_{k_other}^{pos}, st_k^{nf_k} = et_k^{nf_k-1} + rt_k^{nf_k}$, else $st_k^{nf_k} = et_{k_other}^{pos} + rt_k^{nf_k}$, and also update $et_k^{nf_k}, cp_k^{nf_k}$ and nf_k . otherwise go to **step5**;
5. If $x_k^{nf_k}$ in many sets, determine the position of $x_k^{nf_k}$ in there sets, assume the location set is $\{cp_{k_other1}^{pos1}, cp_{k_other2}^{pos2}, \dots, cp_{k_otheri}^{posi}\}$, set $t_{temp} = \min\{et_{k_other1}^{pos1}, et_{k_other2}^{pos2}, \dots, et_{k_otheri}^{posi}\}$, if $(et_k^{nf_k-1} + rt_k^{nf_k}) \geq t_{temp}, st_k^{nf_k} = et_k^{nf_k-1} + rt_k^{nf_k}$, else $st_k^{nf_k} = t_{temp} + rt_k^{nf_k}$, and also update $et_k^{nf_k}, cp_k^{nf_k}$ and nf_k ;
6. Judge whether all disassembly task has been scheduled. If yes, output of the scheduling plan. Otherwise, return to **step3**.

Take the product to be disassembled in Fig. 1 as an example, fix the part 1, and set the basic disassembly information as follows.

In Table 1, *Dir* represents disassembly direction; *Bt* represents the basic disassembly time; Next, take a feasible sequence as an example to explain its decoding process in detail.

Set $\text{Frog} = \{5, 9, 7, 10, 3, 4, 6, 8, 2 \mid 2, 1, 2, 1, 1, 2, 2, 1, 1\}$, This sequence represents 9 disassembly tasks are performed by 2 manipulators. It can be obtained from the encoding structure and the disassembly information matrix G_1 and G_2 :

Table 1 Disassembly information of a product

Index	Component	Tool	Dir	Bt/s
1	Part 1	Handwork T0	+Y	0
2	Part 2	Handwork T0	+Y	2
3	Part 3	Handwork T0	+Y	4
4	Part 4	Handwork T0	+Y	3
5	Fastener 1	Wrench T1	+X	3
6	Fastener 2	Screwdriver T2	+Y	3
7	Fastener 3	Wrench T1	+Y	2
8	Fastener 4	Wrench T1	+Y	2
9	Fastener 5	Wrench T1	-X	2
10	Fastener 6	Wrench T1	-X	2

1. $x_1^1 = 9, x_1^2 = 10, x_1^3 = 3, x_1^4 = 8, x_1^5 = 2; x_2^1 = 5, x_2^2 = 7, x_2^3 = 4, x_2^4 = 6; vP = \{5, 7, 9, 10\};$
2. Because $x_1^1, x_2^1 \in vP, st_1^1 = 0, st_2^1 = 0;$ then $et_1^1 = st_1^1 + bt_1^1 = 2, et_2^1 = 3, nf_1 = 2, nf_2 = 2;$
3. As for $x_1^2,$ because $x_1^2 \in vP$ and $rt_1^1 = 0,$ $st_1^2 = et_1^1 + rt_1^1 = 2, et_1^2 = 4, nf_1 = 3, cp_1^2 = \{4\};$
4. As for $x_2^2,$ because $x_2^2 \in vP$ and $rt_2^1 = 1,$ $st_2^2 = et_2^1 + rt_2^1 = 4, et_2^2 = 6, nf_2 = 3, cp_2^2 = \{3\};$
5. As for $x_1^3,$ because it does not belong to $vP \cup cp_1^2,$ but $x_1^3 \in cp_2^2,$ because $et_1^2 + rt_1^3 = 6 = et_2^2,$ then $st_1^3 = 6, et_1^3 = 10,$ and $nf_1 = 4, cp_1^3 = \{8\};$
6. According to the above method, we can get the disassembly time of the remaining disassembly tasks. The result is shown in Fig. 2.

In Fig. 2, the number of each color block presents the index of disassembly task number, the length of the color block presents the disassembly time, and the shaded portion presents the preparation time. The apDSP is a more complex disassembly problem than spDSP. It eliminates the limitation of sPDP (i.e., the cooperative tasks must begin at the same time). Further, the disassembly time of each part might affect the disassembly process of aPDP. If we use the synchronous disassembly method to disassemble the above example, the result is shown in Fig. 3.

Fig. 2 Asynchronous parallel disassembly planning result

The experimental results show that the decoding method proposed in this paper can effectively shorten the disassembly completion time.

4.3 Evaluation of objective functions

In this paper, we use the optimization objective function as the fitness function and define it as follows:

$$fit(Frog) = Min \left\{ \max \left(et_1^{Q_1}, et_2^{Q_2}, \dots, et_k^{Q_k}, \dots, et_l^{Q_l} \right) \right\} \quad (16)$$

According to the decoding operator, it can be obtained and the fitness function value can be obtained based on the disassembly completion time of each manipulator. The smaller the fitness value, the better the individual quality.

4.4 Frog grouping method

After constructing the initial frog group according to the coding structure rules of the frog individual, the fitness of all frog individuals in the population can be calculated according to formula (16), and then arrange all fitness values in ascending order. The grouping formula is as follows:

$$Y^i = \left\{ Frog_{i+q_{sp}(j-1)} | 1 \leq j \leq q_{sf} \right\}, 1 \leq i \leq q_{sp} \quad (17)$$

where Y^i is the index of frog subpopulations, q_{sp} is the number of frog subpopulations, q_{sf} is the number of frog individuals in each subpopulation, i, j is an integer.

4.5 Local evolution method of frog groups

Since the local search strategy of the standard frog leaping algorithm is not suitable for solving the apDSP problem, we introduce the adjustment factor and the adjustment order to optimize the local search strategy. The adjustment order based on the adjustment position is used to adjust the disassembly task sequence, and the double-point replacement method is used to adjust the manipulator sequence. In final, we rebuilt the position update formula of the frog individual.

Fig. 3 Synchronous parallel disassembly planning result

4.5.1 Adjustment method for disassembly task sequence

In the solution of the traveling salesman (TSP) problem, the adjustment factor is expressed as changing the order of access of the two cities, and the adjustment order is an ordered sequence composed of multiple adjustment factors. In this paper, based on the apDSP problem, the adjustment order based on the adjustment position is used to adjust the disassembly task sequence.

1. Adjustment factor

$f_p = \{p_1, p_2, \dots, p_i, \dots, p_n\}$, which present a disassembly task sequence; We define the adjustment factor as $Ap(\alpha, \beta)$, which is to take the component β th in f_p insert into the front of the α th component, and generate a new sequence.

For example, $f_p = (3, 2, 1, 5, 6, 4)$, adjustment factor is $Ap(3, 5)$, so $newf_p = f_p + Ap(3, 5) = (3, 2, 6, 1, 5, 4)$.

2. Adjustment order based on adjustment position

$Aps(\gamma, \delta) = (Ap_1, Ap_2, \dots, Ap_n)$, it presents an adjustment order and the number of adjustment factors are n ; where γ, δ presents adjustment position which randomly generated and $1 \leq \gamma \leq \delta \leq n$; where $Ap_1, Ap_2, \dots, Ap_n$ represent adjustment factor, the order between them is meaningful. The adjustment order acts on the disassembly sequence, which corresponds to all of the adjustment factors in the adjustment order acting in turn on the disassembly sequence.

There are two different disassembly task sequences f_{pa}, f_{pb} ; The formula $Aps(\gamma, \delta) \otimes (f_{pa} \Theta f_{pb})$ represents that the sequence between the component γ th and the component δ th in f_{pa} is adjusted according to the arrangement of the sequence in f_{pb} :

$$\begin{aligned} new f_{pa} &= f_{pa} + Aps(\gamma, \delta) \otimes (f_{pa} \Theta f_{pb}) = f_{pa} + (Ap_1, Ap_2, \dots, Ap_n) \\ &= [(f_{pa} + Ap_1) + Ap_2] + \dots + Ap_n \end{aligned} \quad (18)$$

The specific steps of constructing the adjustment order are as follows:

1. Set i, j ; where j is the position of the component in f_{pa} , $\gamma \leq j \leq \delta$; where i is the relative position of this component in f_{pb} , $1 \leq i \leq \delta - \gamma + 1$; let $i = 1, j = \gamma$;
2. Judge whether $f_{pb}(i)$ is equal to $f_{pa}(j)$, if $f_{pb}(i) \neq f_{pa}(j)$, then find the component position v in f_{pa} which can make $f_{pb}(i) = f_{pa}(v)$, so that we can get one adjustment factor $Ap(j, v)$, $newf_{pa} = f_{pa} + Ap(j, v)$; if $f_{pb}(i) = f_{pa}(j)$, go to **step3**;
3. $i = i + 1, j = j + 1$; if $i > \delta - \gamma + 1$, the adjustment ends, otherwise, go to step 2 and continue.

For example, $f_{pa} = (3, 6, 1, 5, 4, 2)$, $f_{pb} = (1, 6, 4, 5, 2, 3)$, based on the above construction method, we can get:

$$Aps(2, 5) \otimes (f_{pa} \Theta f_{pb}) = (Ap_1(2, 3), Ap_2(4, 5)).$$

4.5.2 Adjustment method for manipulator sequence

In this paper, the manipulator sequence f_m is adjusted by the method of double-point replacement. The replacement formula is defined as follows:

$$Am(\epsilon, \tau) \otimes (f_{ma} \Theta f_{mb}) \quad (19)$$

where ϵ, τ is a randomly generated replacement position; where f_{ma} is the sequence to be adjusted, and f_{mb} is the reference sequence.

Its role is to replace the element ϵ th and element τ th in f_{ma} with the element where in the corresponding position in f_{mb} , so that $f_{ma}(\epsilon) = f_{mb}(\epsilon), f_{ma}(\tau) = f_{mb}(\tau)$.

4.5.3 Update strategy for frog individual

Assume that the worst individual in the current iteration subgroup is $Frog_w$, the best individual is $Frog_b$, and the global optimal individual is $Frog_g$. The position adjustment strategy of the worst frog individual $Frog_w$ is as follows:

$$s = \min\{int[r \cdot length(Aps(\gamma, \delta) \otimes (f_{pw} \Theta f_{pb}))], s_{max}\} \quad (20)$$

$$\begin{cases} newf_{pw} = f_{pw} + \sum_{i=1}^s (Ap_i) \\ Ap_i \in Aps(\gamma, \delta) \otimes (f_{pw} \Theta f_{pb}) \end{cases} \quad (21)$$

$$newf_{mw} = Am(\epsilon, \tau) \otimes (f_{mw} \Theta f_{mb}) \quad (22)$$

where r represents a random number distributed between $[0, 1]$; $length(Aps(\gamma, \delta) \otimes (f_{pw} \Theta f_{pb}))$ represents the length of the adjustment order; int means to convert it to an integer; and s_{max} represents the max leapfrog step; $\sum_{i=1}^s (Ap_i)$ represents the adjustment orders of f_{pw} . After executing the above update strategies, if $fit(newFrog_w) < fit(Frog_w)$, update $Frog_w$, otherwise, execute the following update strategy:

$$s = \min\{int[r \cdot length(Aps(\gamma, \delta) \otimes (f_{pw} \Theta f_{pg}))], s_{max}\} \quad (23)$$

$$\begin{cases} newf_{pw} = f_{pw} + \sum_{i=1}^s (Ap_i) \\ Ap_i \in Aps(\gamma, \delta) \otimes (f_{pw} \Theta f_{pg}) \end{cases} \quad (24)$$

$$newf_{mw} = Am(\epsilon, \tau) \otimes (f_{mw} \Theta f_{mg}) \quad (25)$$

Continue to execute the above updating strategy. If the fitness value of $Frog_w$ is still not improved, then, reconstruct

a $newFrog_w$ according to the construction method of the initial frog individual.

4.6 Strategy of global information interaction

Because the frog individuals may be trapped in the local optimal solution, the mutation operation is added to enhance the diversity of the population in the process of global information interaction. We use the two-point mutation method to construct the mutation operator. The basic idea is as follows.

Two mutation points are randomly generated in f_m , the manipulator at the position is mutated and randomly changed to other manipulators.

As mentioned above, the encoding and decoding methods of the frogs mentioned in this paper can ensure the feasibility of the initial solution. At the same time, the frog individuals directly generate feasible solutions

after local evolution and global information interaction, which improves the convergence speed of the algorithm.

4.7 Termination rule

The termination condition of the algorithm proposed in this paper is the number of population iterations. Flow chart is shown in Fig. 4.

5 Experimental results and analysis

This section assesses the performance of the proposed method through several test cases. All experiments are executed in VS2015 and run on an Intel(R) Core(TM) i3-4170 CPU (3.7 GHz/4.00-GB RAM) PC with a Windows 7 operating system.

Fig. 4 Basical flow chart of improved SFLA

First, the proposed algorithm is verified by the disassembly of one screw lifting mechanism shown in Fig. 5 (including 33 parts and 13 fasteners). The disassembly information about this model is shown in Table 2, further, the fastener constraint matrix G_1 and the part constraint matrix G_2 are available (considering the disassembly direction $\pm x, \pm y \pm z$).

$$G_1 = \begin{bmatrix} 1 & 10000000000000000000000000000 \\ 0 & 100110000000000000000000000000 \\ 2 & 210000100000000000000000000000 \\ 0 & 000001000000000000000000000000 \\ 0 & 00000100000000000000000001000000 \\ 0 & 00000100000000000000000001000000 \\ 0 & 00000100000000000000000001000000 \\ 0 & 0000021000000000000001202000000000 \\ 0 & 0000000000000000000000001110000000 \\ 0 & 0000000000000000000000001110000000 \\ 0 & 0000000000000000000000000001000001 \\ 0 & 0000000000000000000101000000000000 \\ 0 & 0000010000000001100000001000000000 \end{bmatrix}$$

$G_2 =$	00 29 00 00 00 00 29 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	30 00 00 01 29 00 00 29 00 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 02 00 01 29 00 00 29 00 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 02 02 00 29 00 00 29 01 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 30 00 30 00 29 00 00 28 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 30 00 00 30 00 00 28 00 00 00 05 05 05 16	21 00 00 00 00 00 00 01 00 00 00 00 05 05 08 13 00
	30 00 00 00 00 28 00 30 00 00 00 00 00 00 00	00 00 00 00 00 29 00 29 29 29 29 00 00 00 00 01
	00 30 30 30 28 28 29 00 30 30 30 00 00 00 00	00 00 00 29 29 29 00 29 00 00 00 00 00 00 00 00
	00 00 00 02 30 00 00 29 00 01 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 28 00 29 02 00 01 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 00 00 00 02 30 00 29 00 02 00 00 00 00 00	00 00 00 00 00 00 00 29 00 00 00 00 00 00 00 00
	00 00 00 00 00 30 00 00 00 00 00 00 23 23 07	23 23 23 00 00 00 00 29 00 00 00 00 00 15 00 00 08 00
	00 00 00 00 00 30 00 00 00 00 00 15 00 16 00	00 00 00 00 00 00 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 30 00 00 00 00 00 15 08 00 00	16 00 00 00 00 00 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 08 00 00 00 00 00 07 00 00 00	23 00 00 00 00 00 00 08 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 14 00 00 00 00 00 15 00 00 15	00 23 23 00 00 00 00 13 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 00 00 00 00 00 15 00 00 00	15 00 16 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 00 00 00 00 00 15 00 00 00	15 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 00 29 30 00 00 00 00 00 00 00	00 00 00 00 01 00 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 00 29 30 00 00 00 00 00 00 00	00 00 00 00 00 02 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 00 30 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 00 02 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 29 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 02 30 30 00 00 00 06 06 06 16	22 00 00 30 00 30 00 00 01 29 01 00 00 06 06 08 14 00
	00 00 00 00 00 00 30 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 02 00 29 00 00 00 00 00 00 00
	00 00 00 00 00 00 30 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 30 30 00 29 29 00 00 00 00 00 00
	00 00 00 00 00 00 30 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 30 00 29 00 00 00 00 00 00 00
	00 00 00 00 00 00 30 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 30 02 00 00 00 00 00 00 00 01
	00 00 00 00 00 00 00 27 00 00 28 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00
	00 00 00 00 00 30 00 00 00 00 00 23 00 00 00 00	00 00 00 00 00 00 00 29 00 00 00 00 00 00 08 00 00 00
	00 00 00 00 00 30 00 00 00 00 00 23 00 00 00 00	00 00 00 00 00 00 00 29 00 00 00 00 00 16 00 00 08 00
	00 00 00 00 00 16 00 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 16 00 00 00 00 00 00 00 00 15 00
	00 00 00 00 00 22 00 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 21 00 00 00 00 00 00 16 23 00 00
	00 00 00 00 00 00 00 00 00 00 00 00 00 00 00 00	00 00 00 00 00 00 00 00 00 00 00 00 02 00 00 00 00 00

Fig. 5 Explosion view of screw lifting mechanism

Some parameters are set as follows:

The number of manipulators $l = 3$; population size $pop = 100$, the number of frog subgroup $q_{sp} = 10$; the iteration number of frog subgroup $lc = 20$; the iteration number of population $lp = 100$;

We first conduct an experimental analysis of the parameter s_{max} . Comparing the different values of 6 groups, each group runs 10 times, and the distribution of 10 solutions obtained by different s_{max} are shown in Fig. 6.

It can be seen from Fig. 6 that the quality of the solution is poor when $s_{max} = 5$, because s_{max} is too small, so that the frog individual moves slowly during the evolution process. It always moves around itself and reduces the global search ability of the algorithm. It is easy to fall into local search. When $s_{max} \geq 25$, the stability of the solution is poor. This is because s_{max} is too large, which makes the individual jump too much in the evolutionary process, so that it easily leads to the algorithm not finding the global optimal solution. The optimal value is obtained when s_{max} between 10 and 20, but the overall quality of the solution is better when $s_{max} = 15$. Therefore, it is more appropriate to set $s_{max} = 15$.

Table 2 Disassembly information of screw lifting mechanism

Index	Component	Tool	Dir	Bt/s
1	Upper end cap	Handwork T0	+Z	5
2	Upper cap	Handwork T0	+Z	10
3	Fixative collar 1	Special tool T1	+Z	3
4	Axle bearing 1	Hand hammer T2	+Z	6
5	Bearing support	Handwork T0	+Z	15
6	Epivalve	Handwork T0	+Z	25
7	Ballscrew	Special tool T3	+Z	20
8	Axle	Hand hammer T2	+Z	20
9	Washer	Special tool T1	+Z	5
10	Collar	Hand hammer T2	+Z	8
11	Worm gear	Special tool T4	+Z	10
12	Worm	Special tool T4	+Z	12
13	Worm bearing 1	Hand hammer T2	+Z	4
14	Shield ring 1	forceps T4	+X	4
15	Gasket 1	Special tool T1	+X	3
16	Worm cap1	Handwork T0	+X	4
17	Small washer	Special tool T1	+X	3
18	Small cap	forceps T4	+X	2
19	Axle bearing 2	Hand hammer T2	-Z	12
20	Fixative collar 2	Special tool T1	-Z	3
21	Bottom bearing	Hand hammer T2	-Z	8
22	Box washer	Special tool T1	+Z	8
23	Box	Handwork T0	-Z	0
24	Soffit gasket	Special tool T1	-Z	3
25	Soffit cap	Handwork T0	-Z	6
26	Worm sleeve gasket	Special tool T1	-Z	3
27	Worm sleeve	Handwork T0	-Z	4
28	Bond	forceps T4	+Y	2
29	Worm bearing 2	Hand hammer T2	-X	4
30	Shield ring 2	forceps T4	-X	4
31	Gasket 2	Special tool T1	-X	3
32	Worm cap 2	Handwork T0	-X	4
33	Oil hole gasket	Special tool T1	-Z	2
34	Setscrew of upper end cap	Wrench T5	+Z	8
35	Setscrew of end cap	Wrench T5	+Z	16
36	Jam nut 1	Special Wrench T6	+Z	6
37	Dipstick setscrew	Wrench T5	+Z	4
38	Epivalve setscrew 1	Wrench T5	+Z	8
39	Epivalve setscrew 2	Wrench T5	+Z	10
40	Setscrew of worm cap 2	Wrench T5	-X	9
41	Jam nut 2	Special Wrench T6	-Z	4
42	Setscrew of bottom cap	Wrench T5	-Z	9
43	Setscrew of worm sleeve	Wrench T5	-Z	8
44	Circumflex screw of oil hole	Wrench T5	-Z	3
45	Setscrew of worm cap 1	Wrench T5	+X	4
46	Setscrew of small cap	Screwdriver T7	+X	9

Fig. 6 Solution results under different leapfrog step

Fig. 7 Convergence curve at $s_{max} = 15$

When $s_{max} = 15$, the optimal value, average value and worst value convergence curve of test results are shown in Fig. 7.

Fig. 8 Gantt chart of optimal disassembly sequence

Table 3 Disassembly information of P3

Index	1	2	3	4	5	6	7	8	9	10
Bt/s	1	2	1	2	2.5	3	2	4	1.5	2
Dir	+X	+X	+Y	+Y	+Y	+Y	+X	+X	-X	-X
Index	11	12	13	14	15	16	17	18	19	20
Bt/s	2.5	2.3	3	2	4	3	3	4	4	0.8
Dir	-X	-X	-X	-X	+Z	+Z	+X	+X	-Y	+X

It can be seen from Fig. 7 that as the number of iterations increases, all the convergence curves are steadily decreasing, and the average curve is approached to the optimal value curve. During the local evolutionary process, the worst individual of the frog groups evolved to the optimal individual of the sub-group or the optimal individual of the frog group and completed the location update. At the same time, in the function convergence process, there is no phenomenon that the individual function values are too concave or convex, which indicates that the proposed method has good stability and good order in the optimization process.

The optimal disassembly sequence is shown in Fig. 8. The disassembly completion time is 143 s.

5.2 Case study 2

In order to verify the feasibility and superiority of the proposed algorithm, the examples of different disassembly scales are selected and compared with genetic algorithm (GA) [9] and particle swarm optimization (PSO) [19]. The population size of the three algorithms $pop = 100$, the number of iterations $lp = 100$. Four different scales of disassembly examples (P1–P4) were selected. The examples P1 and P4 are the products to be disassembled shown in Figs. 1 and 5 respectively, the examples P2 and P3 are respectively in the literature [38, 39]. Because the literature [39] does not give relevant disassembly information about the parts to be disassembly, therefore, the disassembly tool for all the parts is set to handwork T0, and other disassembly information is shown in Table 3.

Table 4 basic information of 6 tests

Test Index	Disassembly instance	The number of components	The number of manipulators
T1	P1	10	2
T2	P2	23	2
T3	P3	39	2
T4	P3	39	3
T5	P4	46	2
T6	P4	46	3

According to different disassembly scales and manipulators, a total of 6 tests (T1–T6) are set up. The basic information of each test is shown in Table 4. Each test runs for 10 times. The test results of each group are shown in Table 5. The convergence curve of optimal value under different algorithms is shown in Fig. 9.

In Table 5, the meanings of some parameters are as follows:

Et: the end time of disassembly, At: the average time of disassembly, Rt: the running time of the program.

It can be seen from the test result of T1 that when performing small-scale disassembly instance, all three algorithms can get the optimal or approximate optimal solution, and the running time and convergence speed of three algorithms are almost the same, but the overall quality of solution results of SFLA is better. By testing T2, the three algorithms show good stability when performing medium-scale disassembly. The optimal, worst, and average values of SFLA solution are better than GA and PSO, but SFLA converges slowly and the run time is a little longer. By testing T3 and T4, it can be seen that the SFLA solution is better than GA and PSO when the medium-large-scale disassembly is performed, and the convergence speed of SFLA is better than GA, but the advantage in terms of running time is not obvious. In addition, as the number of dismantling personnel increases, the disassembly completion time is significantly reduced. By testing T5 and T6, the optimal value, average value and worst values solved by SFLA are obviously better than GA and PSO when performing large-scale instances. SFLA has strong ability to jump out of local optimal solution, and the running time is slightly longer than GA and PSO.

According to the comparison and analysis of the test results of the different algorithms mentioned above, it can be known that the algorithm proposed in this paper shows excellent performance in solving disassembly instances of different sizes. Because the double-link encoding method proposed in this paper can effectively ensure the diversity of frog individuals. At the same time, the decoding method can achieve the full scheduling of disassembly personnel and disassembly tasks while ensuring the disassembly

prior constraints. This paper adopts the idea of adjusting order based on the adjustment position to discretize the local evolution of frog individuals. A regulatory factor is expressed as a frog hop step size. By controlling the frog hop step size, the frog local search progress can be effectively controlled. This adjustment method can effectively avoid situations where the frog jump step is too large and no optimal solution can be found, or the frog jump step is too small and the search speed is too slow. In the process of global information interaction, mutation operators are added to effectively ensure the depth and diversity of information interaction.

In summary, the proposed algorithm can successfully solve disassembly examples of different scales, and the quality of the solution results is high. The optimization ability is especially excellent when solving large-scale disassembly examples.

5.3 Case study 3

In order to further testify the feasibility and superiority of the proposed algorithm, the algorithm in this paper is used to solve the examples in Ref. [38] and compared with the estimation of distribution algorithm (EODA) [38], branch and bound algorithm (BABA) [23], and genetic algorithm (GA) [39]. To ensure that the parameter settings are consistent with the literature [11], only the basic disassembly time of components is considered, and the population size $pop = 100$, the number of iterations $lp = 100$. The test results are shown in Table 6.

As can be seen from Table 6, both ISFLA and EODA can obtain the optimal disassembly completion time, but the algorithm in this paper has an advantage in terms of running time. In addition, compared with the other two algorithms, the quality of the results solved by ISFLA is better. This is because the two other algorithms assume that each step of the task is performed simultaneously when solving parallel disassembly sequence planning, and do not fully consider the scheduling of the disassembly personnel and the disassembly tasks. Therefore, the algorithm proposed in this paper has certain advantages.

Through the above three case studies and analysis of the results, the method proposed in this paper can effectively solve disassembly cases of different sizes and types, and effectively solve the five problems raised in the literature review section of this article. The encoding and decoding methods proposed in this paper fully consider the cooperation and scheduling of multi-manipulator on the basis of apDSP. In addition, each step of the proposed method guarantees the feasibility of solutions. Therefore, the solution efficiency is higher and the results obtained when solving different cases are better than GA, PSO, and

Table 5 Comparison of test results of three algorithms under different test conditions

Nos.	Method	The result of disassembly sequence	Et/s	At/s	Rt/s
T1	SFLA	Best: m1: 5 → 7 → 3 → 6; m2: 9 → 10 → 4 → 8 → 2	15	15.4	1.278
		Worst: m1: 5 → 4 → 8 → 2; m2: 10 → 9 → 7 → 3 → 6	16		
	GA	Best: m1: 5 → 7 → 3 → 6; m2: 10 → 9 → 4 → 8 → 2	15	16.3	1.281
		Worst: m1: 7 → 10 → 3 → 6; m2: 5 → 9 → 4 → 8 → 2	17		
	PSO	Best: m1: 7 → 10 → 4 → 8 → 2; m2: 9 → 5 → 3 → 6	16	16.6	1.349
		Worst: m1: 10 → 7 → 3 → 6; m2: 5 → 9 → 4 → 8 → 2	17		
T2	SFLA	Best: m1: 18 → 20 → 21 → 22 → 8 → 7 → 4 → 1 → 3 → 10 → 12 m2: 14 → 13 → 15 → 16 → 19 → 17 → 23 → 2 → 6 → 9 → 11 → 5	161	162.7	12.369
		Worst: m1: 15 → 23 → 14 → 16 → 22 → 2 → 1 → 3 → 6 → 9 → 8 → 7 m2: 18 → 20 → 19 → 17 → 13 → 21 → 4 → 11 → 10 → 12 → 5	164		
	GA	Best: m1: 15 → 23 → 22 → 21 → 17 → 1 → 11 → 10 → 12 → 9 m2: 19 → 18 → 20 → 16 → 14 → 13 → 4 → 8 → 7 → 6 → 2 → 3 → 5	164	164.9	10.814
		Worst: m1: 21 → 20 → 16 → 15 → 22 → 19 → 8 → 7 → 1 → 3 → 9 → 12 m2: 18 → 14 → 17 → 13 → 23 → 4 → 2 → 6 → 10 → 11 → 5	166		
	PSO	Best: m1: 20 → 18 → 19 → 14 → 15 → 16 → 2 → 8 → 7 → 6 → 1 → 3 → 5 m2: 13 → 17 → 21 → 23 → 22 → 12 → 9 → 4 → 11 → 10	164	165.3	11.817
		Worst: m1: 17 → 22 → 21 → 16 → 2 → 4 → 3 → 6 → 12 → 11 → 8 m2: 19 → 14 → 15 → 23 → 13 → 20 → 18 → 1 → 7 → 10 → 9 → 5	167		
T3	SFLA	Best: m1: 37 → 20 → 35 → 16 → 31 → 28 → 36 → 25 → 19 → 2 → 8 → 17 → 32 → 27 → 10 → 15 → 18 m2: 30 → 29 → 23 → 34 → 39 → 22 → 3 → 4 → 12 → 21 → 26 → 9 → 1 → 38 → 24 → 5 → 7 → 6 → 33 → 11 → 13 → 14	49.6	50.32	82.483
		Worst: m1: 29 → 20 → 35 → 16 → 31 → 12 → 26 → 8 → 9 → 3 → 24 → 38 → 25 → 7 → 27 → 5 → 6 → 11 → 10 m2: 37 → 30 → 34 → 39 → 23 → 22 → 28 → 36 → 21 → 1 → 4 → 2 → 19 → 17 → 18 → 32 → 33 → 15 → 14 → 13	51.9		
	GA	Best: m1: 23 → 39 → 35 → 16 → 31 → 24 → 25 → 36 → 19 → 21 → 1 → 7 → 38 → 17 → 33 → 32 → 1 0 → 15 → 11 m2: 37 → 20 → 30 → 34 → 29 → 22 → 3 → 4 → 28 → 27 → 12 → 26 → 9 → 8 → 2 → 6 → 5 → 1 8 → 14 → 13	51.5	53.53	70.87
		Worst: m1: 23 → 29 → 34 → 39 → 35 → 22 → 28 → 31 → 12 → 25 → 26 → 7 → 9 → 1 → 38 → 5 → 8 → 15 → 14 → 13 m2: 30 → 37 → 20 → 16 → 36 → 19 → 4 → 3 → 24 → 21 → 6 → 27 → 33 → 11 → 17 → 18 → 32 → 10 → 2	56.9		
	PSO	Best: m1: 35 → 16 → 28 → 31 → 12 → 21 → 26 → 8 → 19 → 25 → 24 → 38 → 1 → 17 → 5 → 33 → 1 1 → 15 m2: 37 → 20 → 30 → 23 → 29 → 39 → 34 → 36 → 22 → 3 → 2 → 4 → 9 → 27 → 7 → 18 → 32 → 13 → 10 → 14 → 6	53.9	56.12	72.328
		Worst: m1: 23 → 29 → 30 → 39 → 35 → 4 → 28 → 3 → 19 → 27 → 7 → 24 → 38 → 6 → 10 → 17 → 32 → 14 m2: 37 → 34 → 20 → 16 → 22 → 36 → 31 → 25 → 12 → 26 → 21 → 9 → 1 → 2 → 8 → 5 → 18 → 33 → 11 → 15 → 13	58.6		
T4	SFLA	Best: m1: 20 → 39 → 29 → 30 → 22 → 4 → 25 → 1 → 9 → 8 → 2 → 5 → 18 → 14 m2: 23 → 35 → 16 → 36 → 19 → 26 → 28 → 24 → 27 → 33 → 15 → 11 → 13 m3: 37 → 34 → 31 → 12 → 21 → 3 → 7 → 38 → 17 → 6 → 10 → 32	35.6	37.07	97.265
		Worst: m1: 35 → 16 → 31 → 22 → 4 → 21 → 1 → 5 → 38 → 6 → 32 → 13 m2: 20 → 39 → 34 → 29 → 12 → 26 → 8 → 9 → 2 → 7 → 17 → 15 → 14 → 37 m3: 23 → 30 → 28 → 36 → 19 → 3 → 24 → 27 → 25 → 11 → 10 → 33 → 18	38.3		
	GA	Best: m1: 35 → 16 → 36 → 12 → 26 → 9 → 2 → 8 → 18 → 32 → 13 → 14 m2: 37 → 20 → 31 → 28 → 25 → 27 → 38 → 17 → 11 → 33 → 15 m3: 23 → 29 → 39 → 34 → 30 → 22 → 4 → 3 → 21 → 19 → 1 → 7 → 10 → 24 → 5 → 6	37.7	40.55	80.327

Table 5 (continued)

Nos.	Method	The result of disassembly sequence	Et/s	At/s	Rt/s
T5	PSO	Worst: m1: 37 → 34 → 36 → 22 → 12 → 28 → 25 → 21 → 8 → 11 → 33 → 32 m2: 23 → 39 → 20 → 31 → 4 → 26 → 24 → 38 → 5 → 2 → 1 → 18 → 15 m3: 29 → 30 → 35 → 16 → 19 → 3 → 27 → 9 → 7 → 6 → 17 → 10 → 13 → 14	43.6		
		Best: m1: 20 → 35 → 16 → 28 → 24 → 36 → 19 → 7 → 9 → 1 → 18 → 33 m2: 37 → 23 → 29 → 30 → 34 → 39 → 22 → 3 → 4 → 25 → 26 → 21 → 6 → 10 → 2 → 14 → 13 → 15 m3: 31 → 12 → 27 → 11 → 5 → 8 → 38 → 17 → 32	42.1	43.48	82.534
		Worst: m1: 39 → 37 → 20 → 35 → 16 → 28 → 12 → 27 → 9 → 11 → 17 → 14 → 19 m2: 29 → 31 → 3 → 24 → 26 → 7 → 33 → 38 → 10 → 32 → 18 → 21 → 2 m3: 30 → 23 → 34 → 22 → 4 → 25 → 36 → 8 → 5 → 15 → 6 → 13 → 1	45.8		
	SFLA	Best: m1: 37 → 35 → 1 → 46 → 2 → 36 → 3 → 4 → 5 → 6 → 22 → 9 → 14 → 10 → 29 → 41 → 20 → 1 9 → 8 m2: 44 → 42 → 34 → 43 → 38 → 45 → 39 → 40 → 32 → 31 → 18 → 17 → 16 → 15 → 33 → 27 → 26 → 25 → 24 → 30 → 7 → 13 → 12 → 11 → 21 → 28 → 23	186	191	133.886
		Worst: m1: 40 → 38 → 39 → 43 → 34 → 1 → 2 → 36 → 33 → 16 → 15 → 27 → 26 → 25 → 24 → 22 → 1 4 → 13 → 7 → 41 → 20 → 8 m2: 45 → 46 → 42 → 35 → 44 → 37 → 18 → 32 → 17 → 31 → 3 → 4 → 5 → 6 → 30 → 9 → 29 → 10 → 12 → 11 → 28 → 21 → 19 → 23	197		
		GA Best: m1: 46 → 40 → 37 → 35 → 39 → 44 → 33 → 27 → 38 → 3 → 26 → 5 → 6 → 7 → 14 → 10 → 12 → 11 → 28 → 21 → 23 m2: 34 → 42 → 43 → 45 → 18 → 1 → 32 → 31 → 17 → 2 → 36 → 4 → 16 → 25 → 24 → 15 → 30 → 22 → 9 → 29 → 13 → 41 → 20 → 19 → 8	200	203.6	119.953
	PSO	Worst: m1: 40 → 44 → 45 → 38 → 42 → 46 → 33 → 32 → 37 → 36 → 34 → 5 → 6 → 30 → 29 → 14 → 1 0 → 24 → 41 → 19 → 8 m2: 34 → 43 → 39 → 35 → 1 → 2 → 31 → 18 → 17 → 27 → 16 → 26 → 15 → 25 → 9 → 22 → 7 → 13 → 20 → 12 → 11 → 28 → 21 → 23	207		
		Best: m1: 37 → 44 → 34 → 45 → 33 → 46 → 40 → 32 → 17 → 43 → 36 → 31 → 16 → 27 → 26 → 25 → 15 → 14 → 22 → 12 → 11 → 21 → 8 m2: 42 → 38 → 39 → 18 → 35 → 1 → 2 → 3 → 4 → 5 → 6 → 24 → 9 → 30 → 29 → 13 → 10 → 7 → 41 → 20 → 19 → 28 → 23	211	219.5	122.824
		Worst: m1: 34 → 44 → 45 → 43 → 40 → 18 → 46 → 1 → 27 → 2 → 17 → 25 → 31 → 15 → 24 → 5 → 6 → 7 → 41 → 14 → 13 → 12 → 11 → 28 → 21 m2: 38 → 39 → 42 → 35 → 33 → 32 → 37 → 26 → 36 → 16 → 3 → 4 → 22 → 30 → 29 → 9 → 10 → 20 → 19 → 8 → 23	226		
T6	SFLA	Best: m1: 38 → 45 → 1 → 2 → 36 → 3 → 4 → 5 → 6 → 22 → 13 → 12 → 8 m2: 35 → 43 → 18 → 40 → 46 → 17 → 32 → 27 → 31 → 25 → 24 → 30 → 29 → 7 → 41 → 20 → 19 m3: 44 → 34 → 37 → 42 → 39 → 33 → 16 → 15 → 26 → 14 → 9 → 10 → 11 → 21 → 28 → 23	143	147.17	166.676
		Worst: m1: 38 → 35 → 1 → 2 → 31 → 16 → 30 → 29 → 14 → 8 → 21 m2: 45 → 34 → 44 → 37 → 33 → 18 → 32 → 36 → 3 → 4 → 5 → 6 → 7 → 41 → 20 → 11 → 28 → 23 m3: 42 → 40 → 43 → 46 → 39 → 27 → 26 → 17 → 15 → 25 → 24 → 9 → 10 → 13 → 12 → 22 → 19	155		
		GA Best: m1: 35 → 39 → 38 → 32 → 31 → 18 → 17 → 4 → 6 → 24 → 6 → 7 → 22 → 41 → 20 → 11 m2: 43 → 40 → 42 → 1 → 2 → 36 → 5 → 15 → 14 → 13 → 29 → 12 → 19 → 28 m3: 44 → 33 → 34 → 37 → 45 → 46 → 27 → 26 → 25 → 3 → 30 → 9 → 10 → 8 → 21 → 23	164	167.9	143.375
	PSO	Worst: m1: 35 → 40 → 46 → 18 → 32 → 36 → 3 → 4 → 5 → 7 → 41 → 20 → 19 → 11 → 28 → 23 m2: 34 → 39 → 38 → 37 → 1 → 2 → 26 → 24 → 6 → 14 → 13 → 22 → 12 → 8 m3: 43 → 42 → 44 → 33 → 45 → 31 → 17 → 16 → 27 → 25 → 15 → 30 → 9 → 10 → 29 → 21	173		
		Best: m1: 18 → 39 → 38 → 44 → 33 → 32 → 31 → 42 → 37 → 46 → 26 → 25 → 15 → 24 → 11 → 21 → 8 → 28 → 23 m2: 45 → 35 → 27 → 2 → 36 → 4 → 5 → 6 → 9 → 22 → 14 → 30 → 12 → 19 m3: 43 → 34 → 40 → 17 → 1 → 3 → 16 → 7 → 13 → 29 → 41 → 20 → 10	166	173.5	153.814
		Worst: m1: 44 → 45 → 39 → 35 → 38 → 16 → 33 → 27 → 26 → 31 → 4 → 6 → 22 → 30 → 29 → 12 → 1 1 → 21 → 28 → 23 m2: 18 → 37 → 32 → 17 → 46 → 36 → 14 → 9 → 10 → 24 → 8 m3: 40 → 42 → 34 → 43 → 1 → 2 → 15 → 3 → 5 → 13 → 25 → 7 → 41 → 20 → 19	178

Fig. 9 Convergence curves of optimal solutions for three algorithms in different tests

Table 6 Comparison of test results

Algorithm	Minimum disassembly completion time/s	Running time of program
ISFLA	20.5	0.351
EODA	20.5	0.425
BABA	23	387.928
GA	23	0.233

other algorithms. The disassembly model and solution method proposed in this article can express the feasible disassembly component of each disassembly personnel at any time. Based on the basic disassembly time of parts, the disassembly preparation time caused by the change of disassembly tools and directions is considered, so that the evaluation model is more realistic to reflect the actual disassembly process.

6 Conclusions

This paper proposes a method based on improved shuffled frog leaping algorithm to solve the problem of apDSP. We take the minimization of disassembly completion time as the optimization goal, and consider the disassembly preparation time due to the change of disassembly tool and direction. In order to fully express the disassembly constraints, the disassembly information model is constructed by using the fastener constraint matrix and the part constraint matrix, and the mathematical model of apDSP is constructed. To solve the problem of apDSP, we construct a double-link encoding structure and decoding operator, use the idea of adjustment order and double-point replacement to locally evolve the frog individual, and rebuild the formula of the frog position. In addition, the two-point mutation operator is used for the global information exchange to enhance the optimization ability of the algorithm. Finally, the effectiveness and superiority of the proposed algorithm are verified by a disassembly example of screw lifting mechanism and some cases of different disassembly scales. The experimental results show that the method proposed in this paper can solve various scales of disassembly examples, and the optimization

ability is particularly excellent when performing large-scale disassembly planning. The proposed algorithm has guiding significance for the actual disassembly work of complex assemblies.

Although the effectiveness and superiority of the proposed algorithm are verified by some disassembly cases, there are still some limitations exist. This work does not consider factors such as disassembly cost and profit in the process of disassembly evaluation. In addition, the proposed approach is mainly focus on complete disassembly, but a selective disassembly may present a better solution under some situations. All of these need to be considered into future efforts on advancing DSP.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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