

A machining partition method for local features with dimensional correlations of large cabin

Jianwei Ma

Dalian University of Technology <https://orcid.org/0000-0002-2177-529X>

Hechen Sun (✉ 15524857728@163.com)

Dalian University of Technology

Huiteng Yan

Dalian University of Technology

Hongyuan Zhang

Dalian University of Technology

Qiang Tao

China Academy of Space Technology

Zhenyuan Jia

Dalian University of Technology

Wei Liu

Dalian University of Technology

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Title page

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Author information:

Full names	Institutional addresses	Email addresses
Jianwei Ma	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	mjw2011@dlut.edu.cn
Hechen Sun	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	15524857728@163.com
Huiteng Yan	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	yanhuiteng@foxmail.com
Hongyuan Zhang	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	1589378816@qq.com
Qiang Tao	Beijing Spacecraft, China Academy of Space Technology	taoqiang911@163.com
Zhenyuan Jia	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	16404476@qq.com
Wei Liu	Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology	lw2007@dlut.edu.cn

Corresponding author: Jianwei Ma

Abstract

Integrated in-situ partition manufacturing mode of large cabins based on the mobile serial robots is adopted for machining tasks of outboard local features currently. However, the existing partition criteria of large-scale components only consider the geometric features and structure, ignoring the dimensional correlations of local features and the effective workspace of serial robots. This tends to cause that features with the same dimensional correlation are divided into different sub-regions,

resulting in extra machining adjustment which reduces the machining efficiency. Aiming at the machining partition problem for local features of the large cabin, a machining partition method is proposed for local features with dimensional correlations of the large cabin based on clustering. Considering positions and dimensional correlations of local features, a multi-objective optimization model of partition based on clustering validity indexes is established to pre-solve partition schemes. To solve the reachable region of the large cabin, the effective workspace of serial robots is taken into account. With the reachable region as the constraint and the machining efficiency as the decision basis, the optimal partition scheme for local features of the large cabin is determined. The contrast validation is conducted on a reference cabin. The results indicate that the proposed method both satisfies the dimensional correlations of local features and the effective workspace of serial robots, which improves the machining efficiency. This research provides significant machining partition bases for robot machining in the integrated in-situ partition manufacturing mode of large cabins.

Keywords

Large cabin; Partition manufacturing; Dimensional correlation; Clustering; Mobile serial robot

1 Introduction

The large cabin, a cylindrical component with outboard local features, is a significant part of spacecraft. [1] To ensure the service performance of the spacecraft, high requirements for dimensional and position accuracy of outboard local features of the large cabin are put forward. [2, 3] For the machining tasks of local features on the cabin, the traditional manufacturing mode that feature parts are machined and refitted apart from the cabin is inefficient and difficult to ensure the

stability of machining quality. While the integrated manufacturing mode based on gantry machining centers suffers from high cost and limited machining technology. Aiming at above manufacturing problems, an integrated in-situ horizontal manufacturing mode of large cabins is proposed based on mobile serial robots. [4-6] In this mode, the cabin assembled with rough machining feature parts is supported horizontally on the supporting mechanism, and the finishing machining tasks of local features are accomplished by mobile serial robots. To satisfy the machining requirements of surrounding features, a deflection machine is connected at one end of the cabin, and the transformation of spatial positions of features is realized by multiple displacement of the deflection machine, as shown in Figure 1.

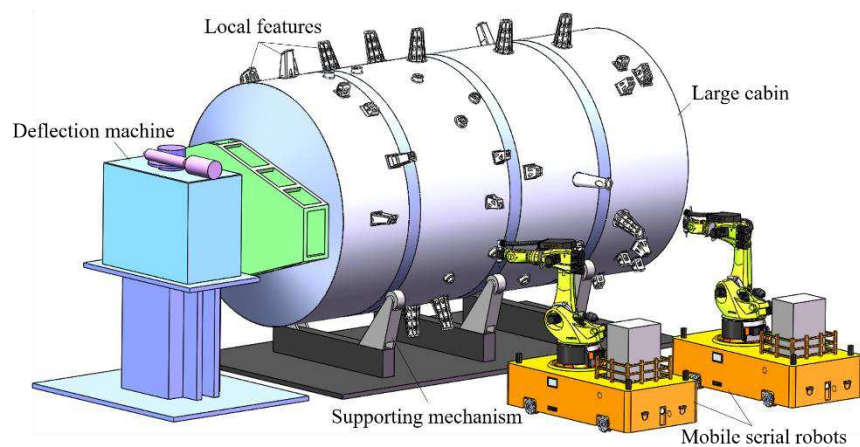


Figure 1 Integrated in-situ horizontal manufacturing mode of a large cabin.

Due to the large scale of the cabin and the discrete distribution of local features, robots cannot realize all machining tasks of local features at certain fixed working position. The partition manufacturing mode is adopted currently. In this mode, the large cabin is divided into several machining sub-regions. For a single mobile serial robot, it completes all machining tasks of a sub-region at the optimal working position considering the machining performance. [7, 8] However, on account of the limited workspace of serial robots, if sub-regions are divided improperly, it is easy

to cause the distance between local features of the same sub-region exceeding the machining range of serial robots. In that case, the machining tasks of all features in the sub-region are bound to be accomplished with space transformation of the cabin, which prolongs the auxiliary time and reduces the machining efficiency.

Among local features, some features possess dimensional correlations. The existence of dimensional correlations also brings challenges to partition. If local features with the same dimensional correlation are divided into different sub-regions (as shown in Figure 2), these features will be machined separately by multiple serial robots or by one serial robot at multiple working positions. In that case, the machining benchmarks of these features are not unified, which requires extra machining adjustment to ensure the machining accuracy of the dimensional correlation. Therefore, to improve the machining efficiency, it is necessary to consider position distribution and dimensional correlations of local features comprehensively, and establish an effective machining partition method for local features of large cabins.

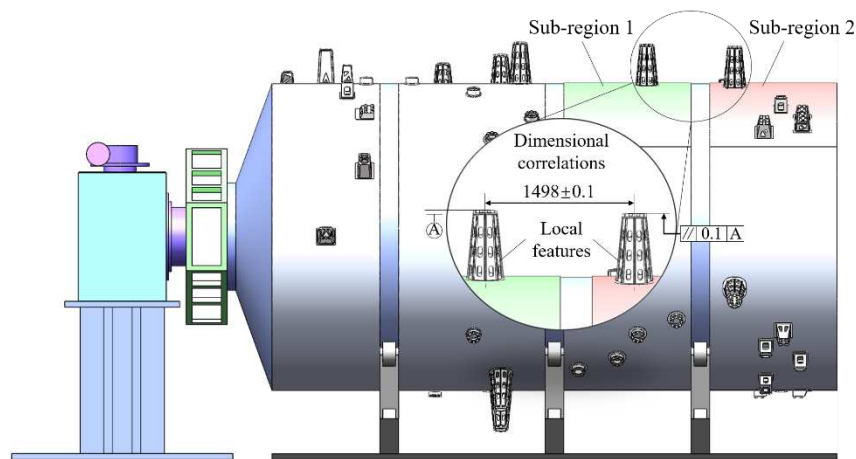


Figure 2 Local features with same dimensional correlation in different sub-regions.

The integrated manufacturing mode of large-scale components based on distributed working positions of mobile robots is one of research hotspots in the field of aerospace engineering. [7-9]

Aiming at the layout problem of multi-robot work cells in the manufacturing of large fuselage panels, Tao [10] proposed a nonlinear programming method to maximize the overlapped workspace of robots. For the inspection tasks of outboard local features on a large cabin, based on the simplified workspace of robots, Lin [11] divided the axial and radial working regions of the cabin preliminarily, and obtained the optimal robot working position meeting inspection requirements. Further, in view of the grinding problem of a large wind turbine blade, Fan [8] proposed a base position optimization method for mobile robots considering both kinematics and stiffness performance, which improved the machining quality of sub-regions significantly. However, the above methods ignore the partition criterion of large-scale components. This especially tends to cause improper partition oriented to local features with dimensional correlations, so that the machining benchmarks of features with dimensional correlations are not unified, which leads to extra machining adjustment and reduces machining efficiency.

The research on machining partition mainly focuses on manufacturing of complex surfaces. To reduce machining errors and improve the machining efficiency, complex surfaces are divided into sub-regions, and the partition criterion is determined based on geometric features of surfaces or machining technologies. [12-14] For the integrated manufacturing mode of large-scale components, the idea of partition manufacturing is followed due to the workspace limitation of machining equipment. For the contour feature machining tasks of aircraft structural parts, Gao [15] proposed a contour feature partition method considering convex constraints and interference information, and realized feature-based machining decisions and automatic programming. Aiming at the machining task of a super-large flange, Wu [16] established a tree model of regional segmentation and proposed a component subdivision method based on geometric features of components and the workspace of

1 machine tools considering the integrity, feasibility, continuity and efficiency of machining.

2 Although the existing research has achieved partition for some specific large-scale components
3 based on geometric features and structure, the machining partition for local features of the large
4 cabin faces new challenges due to the differences of machining objects and equipment. (1)
5 Dimensional correlations among local features. To improve the machining efficiency of local
6 features with dimensional correlations, it is supposed to be avoided local features with the same
7 dimensional correlation divided into different sub-regions. (2) Numerousness and wide distribution
8 of local features. To reduce needless space transformation of the large cabin, it is supposed to be
9 avoided sub-regions beyond the workspace of serial robots. (3) Weak stiffness and limited
10 workspace of serial robots. The stiffness of serial robots is affected by machining poses significantly.
11 [17] At boundary poses, the stiffness of serial robots is insufficient to achieve machining tasks of
12 high precision, resulting in the effective workspace of serial robots less than the reachable
13 workspace.

14 Aiming at the machining partition problem for local features of the large cabin, considering
15 positions and dimensional correlations of local features and the effective workspace of serial robots,
16 a machining partition method is proposed for local features with dimensional correlations of the
17 large cabin based on clustering. Firstly, considering positions and dimensional correlations of local
18 features, a multi-objective optimization model of partition is established to pre-solve partition
19 schemes. Then, based on the stiffness model of serial robots, the effective workspace of serial robots
20 and the reachable region of the large cabin are solved. Finally, with the reachable region of the large
21 cabin as the constraint and the machining efficiency as the decision basis, the optimal partition
22 scheme for local features of the large cabin is determined.

The remainder of this paper is organized as follows. In Section 2, the multi-objective optimization model of partition is established based on clustering validity indexes, and the pre-solutions to partition are obtained. In Section 3, the reachable region of the large cabin is solved by analyzing the effective workspace of serial robots considering stiffness, and the optimal partition scheme is determined. In Section 4 the method is validated on a reference cabin, and the conclusions are summarized in Section 5.

2 Pre-solutions to partition for local features of large cabin

In this section, the partition problem of local features of the large cabin is transformed into a clustering problem of local features. Considering the position distribution and dimensional correlations, a multi-objective optimization model of partition is established for local features based on K-Medoids algorithm and clustering validity indexes. Then, the partition schemes of local features are pre-solved. The specific process is shown in Figure 3.

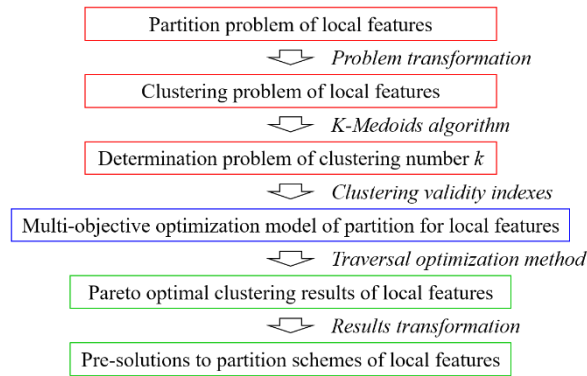


Figure 3 Mind map of pre-solutions to partition for local features of large cabin.

To begin with, the coordinate system of the large cabin is established. Positions and dimensional correlations of outboard local features are extracted, as shown in Figure 4. The position data set of local features is obtained as

$$\mathbf{P} = \{ \mathbf{p}_s = (x_s, y_s, z_s)^T \mid s \in [1, n] \} \quad (1)$$

where $\mathbf{P}$ is the position data set of local features, $\mathbf{p}_s$ is the coordinate vector of the centroid of the local feature s , x_s , y_s and z_s are the x-axis, y-axis and z-axis coordinates of the centroid of the local feature s respectively, and n is the count of local features.

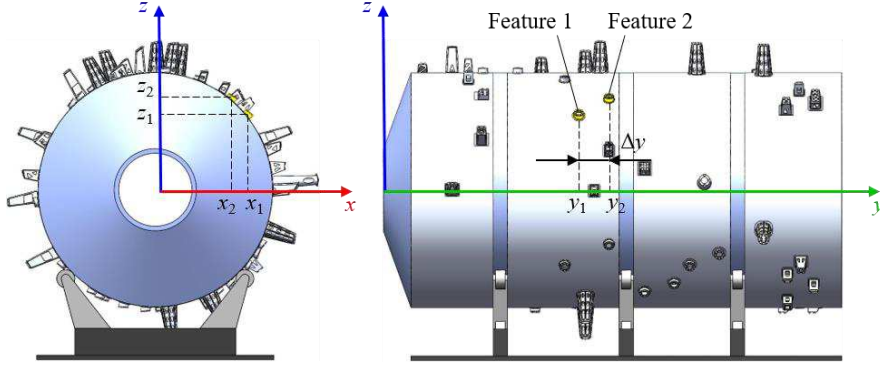


Figure 4 Positions and dimensional correlations of outboard local features. x_1 , y_1 and z_1 are the x-axis, y-axis and z-axis coordinates of the centroid of feature 1 respectively, x_2 , y_2 and z_2 are the x-axis, y-axis and z-axis coordinates of the centroid of feature 2 respectively, and Δy is the dimensional correlation of feature 1 and feature 2.

To avoid sub-regions beyond the workspace of serial robots, the positions of local features in the same sub-region are supposed to be close. Meanwhile, for the consideration of machining efficiency, the concentrated distribution of local features in the same sub-region is beneficial to reduce the empty stroke from one feature to another. Therefore, the partition problem is transformed into a clustering problem. The core purpose is to divide local features with similar position data into the same cluster.

Clustering algorithms include partitioning-based, hierarchy-based, density-based, model-based and mesh-based clustering according to the principle. [18] For the partition problem, the partitioning-based clustering is the most suitable. As a classical partition clustering algorithm, K-

1 Medoids algorithm is effective and robust to outliers. [19, 20] Thus, K-Medoids is adopted for the
 2 clustering problem of local features according to their positions. The specific process is summarized
 3 in Algorithm 1.

Algorithm 1: K-Medoids algorithm for the clustering problem of local features.

Input: the position data set $\mathbf{P}$ of local features and the clustering number k .

Output: the clustering result.

```

1  Set initial medoids from sample points by K-Means++ algorithm.
2  Calculate the Euclidean distance between each sample point and each medoid in turn.
3  Divide each sample point into the cluster where the nearest medoid is located.
4  for  $i \leftarrow 1$  to  $k$  do
5      Extract the number  $m_i$  of sample points in the cluster  $i$ .
6      for  $j \leftarrow 1$  to  $m_i$  do
7          Calculate the sum of Euclidean distance between the sample point  $j$  and other sample points in the cluster
8           $i$ .
9      end for
10     Set the sample point with the minimum sum of distance as the medoid of the cluster  $i$ .
11 end for
12 if any medoid is changed then
13     Repeat rows 3 to 10.
14 else
15     Obtain the clustering result.
16 end if

```

4 The clustering result obtained by K-Medoids algorithm is mainly affected by the clustering
 5 number and initial medoids. [21] For the impact of initial medoids, K-Means++ algorithm [22] is
 6 adopted to optimize the selection of initial medoids. The specific process is summarized in
 7 Algorithm 2.

Algorithm 2: K-Means++ algorithm for the selection of initial medoids.

Input: the position data set $\mathbf{P}$ of local features and the clustering number k .

Output: clustering medoids $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k$.

```

1  Extract the number  $n$  of sample points in the data set  $\mathbf{P}$ .

```

```

2  Set the first medoid  $c_1$  from sample points at random.
3  for  $i \leftarrow 2$  to  $k$  do
4      for  $s \leftarrow 1$  to  $n$  do
5          Calculate the Euclidean distance between the sample point  $s$  and each existing medoid in turn.
6          Find the shortest distance  $D_s$  and then calculate the probability  $\xi_s$  of the sample point  $s$  as  $\xi_s = D_s / \sum_{s=1}^n D_s$ .
7      end for
8      Set the sample point with the biggest probability as a new medoid  $c_i$ .
9  end for

```

1 Based on the above process, the selection of initial medoids is only related to the first medoid. To
 2 ease the computational burden, the influence of initial medoids on clustering results is eliminated
 3 as follows. The data set is repeated n times based on the process shown in Algorithm 1. During
 4 the process, each sample point is set as the first medoid in turn. Through this method, all possible
 5 clustering results are traversed. The average intra-cluster variance σ_0 of each clustering result is
 6 calculated according to Eqs. (2) and (3), [23] and the result corresponding to the minimum value of
 7 σ_0 is selected as the final clustering result. Then, the clustering result is uniquely determined by
 8 the clustering number.

$$9 \quad \sigma(c_i) = \frac{1}{m_i} \sum_{j=1}^{m_i} \left((x_j - cx_i)^2, (y_j - cy_i)^2, (z_j - cz_i)^2 \right)^T \quad (2)$$

$$10 \quad \sigma_0 = \frac{1}{k} \sum_{i=1}^k \|\sigma(c_i)\| \quad (3)$$

11 where c_i is the clustering medoid of the cluster i ($i \in [1, k]$), $\sigma(c_i)$ denotes the intra-cluster
 12 variance of the cluster i , x_i , y_i and z_i are the x-axis, y-axis and z-axis coordinates of the
 13 sample point j ($j \in [1, m_i]$) in the cluster i respectively, and cx_i , cy_i and cz_i are the x-axis,
 14 y-axis and z-axis coordinates of the medoid of the cluster i respectively.

15 As a prominent problem of K-Medoids algorithm, the selection of the clustering number mainly

depends on prior knowledge and characteristics of data set. To determine the optimal clustering number, clustering validity indexes [24] are introduced to evaluate clustering results. Oriented to the machining partition task for local features of the large cabin, considering machining efficiency, there are following requirements. (1) Positions of local features in the same sub-region are supposed to be close. (2) Local features with the same dimensional correlation are supposed to be divided into the same sub-region. Based on the above requirements for partition, two types of clustering validity indexes, S_Dbw [23] and Jaccard Coefficient [25], are introduced to establish the optimization objectives to characterize the position similarity and the dimensional correlation consistency of local features.

S_Dbw is an internal index to evaluate the similarity among the data in the same cluster and the differences among the data in different clusters, as shown in Eq. (4). Aiming at the clustering result of local features, the smaller S_Dbw is, the closer local features in the sub-regions are.

$$\overline{S_Dbw} = \overline{Scat} + \overline{Dens_bw} \quad (4)$$

where $\overline{S_Dbw}$ is the S_Dbw index, $\overline{Scat}$ is a variance-based compactness index, and $\overline{Dens_bw}$ is a density-based separation index. [23] The detailed definition of two indices is shown in Appendix 1.

Jaccard Coefficient is an external index to evaluate the matching degree between the clustering result and the reference model known in advance. Aiming at the machining partition problem of local features with dimensional correlations, local features with the same dimensional correlation are supposed to be divided into the same sub-region. Based on dimensional correlations, the reference model is established. In the reference model, local features with the same dimensional correlation are divided into the same cluster, while the local features without dimensional

correlations are not involved in the evaluation. From the reference model, the modified Jaccard Coefficient is obtained as Eq. (5). The smaller the modified Jaccard Coefficient is, the more consistent the clustering result is with the reference model.

$$\overline{mJC} = \frac{\beta_2}{\beta_1 + \beta_2} \quad (5)$$

where $\overline{mJC}$ is the modified Jaccard Coefficient index, and β_1 and β_2 are the numbers of sample couples of class (1) and class (2) respectively. The sample couple (p_{11}, p_{12}) of class (1) is defined that sample points p_{11} and p_{12} are in the same cluster both in the clustering result and the reference model. The sample couple (p_{21}, p_{22}) of class (2) is defined that sample points p_{21} and p_{22} are in the same cluster in the reference model but in different clusters in the clustering result.

It is supposed to be noted that both clustering validity indexes mentioned above are unrelated to the clustering algorithm.

To optimize the position similarity and the dimensional correlation consistency of local features simultaneously, a multi-objective optimization model of partition is established for local features of the large cabin as Eq. (6). The clustering number k is the optimization variable, and S_Dbw and the modified Jaccard Coefficient are optimization objects.

$$\begin{cases} \min f_1(k) = S_Dbw \\ \min f_2(k) = \overline{mJC} \\ s.t. \quad 1 < k \leq n \end{cases} \quad (6)$$

where $f_1(k)$ and $f_2(k)$ are objective functions.

To solve the above multi-objective optimization problem, the Pareto optimality [26] is demanded since the relationship between the optimization variable and objective functions is unclear.

Considering the clustering number k is an integer variable and its values are limited in the

definition domain, the traversal optimization method is adopted to obtain the Pareto optimal clustering numbers. Then, K-Medoids algorithm is adopted to solve the clustering results corresponding to the Pareto optimal clustering numbers. Based on the clustering results, the pre-solutions to partition for local features of the large cabin are obtained.

3 Determination of partition for local features of large cabin

For most of large cabins, their radial dimensions far exceed the longitudinal machining range of mobile serial robots, which leads to the existence of a reachable region and an unreachable region of a large cabin in the in-situ horizontal manufacturing mode, as shown in Figure 5.

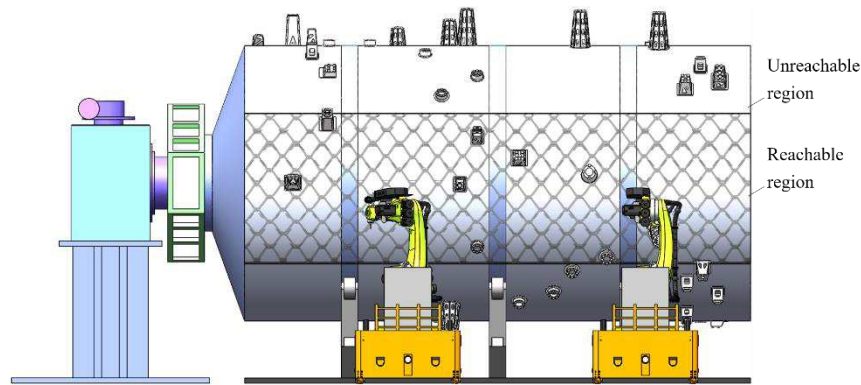


Figure 5 Reachable region where end of mobile serial robots can reach and unreachable region where end of mobile serial robots cannot reach.

The existence of the reachable region of the large cabin provides a critical constraint for the determination of partition schemes. To reduce needless space transformation of the large cabin, the circumferential span of sub-regions is supposed to be within the circumferential span of the reachable region of the large cabin. Therefore, it is necessary to solve the reachable region of the large cabin based on the longitudinal machining range of serial robots.

3.1 Solution to effective workspace of serial robots

1 Since the longitudinal machining range of a mobile serial robot (as shown in Figure 6) depends on
2 the workspace of the serial robot in the vertical direction, the workspace of the serial robot is solved
3 first. The workspace of a serial robot can be regarded as a set of reachable positions of the end of
4 the serial robot. [27] Due to the structure characteristics of serial links of serial robots, the stiffness
5 of serial robots is affected by the poses significantly. [17, 28] At fully extended or other boundary
6 poses, the stiffness of serial robots is insufficient to achieve machining tasks of high precision,
7 resulting in the effective workspace of serial robots less than the reachable workspace. To ensure
8 sufficient operating stiffness of serial robots, based on the kinematics model and the stiffness model
9 of serial robots, the improved Monte Carlo method [29] is used to solve the effective workspace of
10 serial robots.

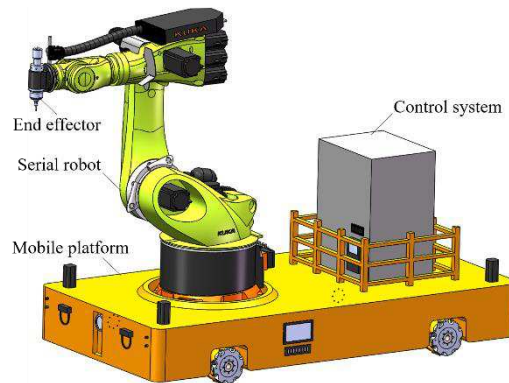


Figure 6 Mobile serial robot.

13 KUKA KR500 robot is taken as a case in this research. The kinematics model of KR500 robot is
14 established by the modified Denavit-Hartenberg (DH) method [30] as shown in Figure 7. The
15 corresponding DH parameters are shown in Table 1.

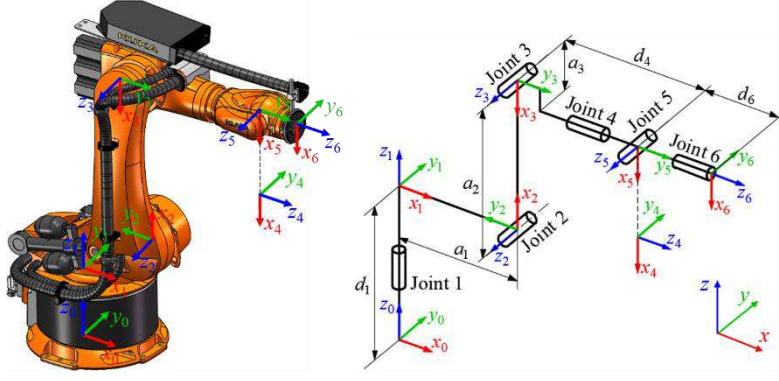


Figure 7 Kinematics model of KR500 robot.

Table 1 DH parameters of KR500 robot. θ_l is the angle of the joint l ($l \in [1, 6]$), and α_l , a_l and d_l are the twist angle, the length and the offset distance of the link l respectively.

l	θ_l (rad)	α_l (rad)	a_l (mm)	d_l (mm)
1	θ_1	0	0	1045
2	$\theta_2 + \pi / 2$	$\pi / 2$	500	0
3	$\theta_3 + \pi$	0	1300	0
4	θ_4	$-\pi / 2$	55	1025
5	θ_5	$\pi / 2$	0	0
6	θ_6	$-\pi / 2$	0	290

To avoid the singular poses during robot machining, the dexterity index [31] is introduced to describe the motion ability of a serial robot as

$$\overline{DI} = \frac{1}{\kappa(\mathbf{J})} \quad (7)$$

where $\overline{DI}$ is the dexterity index of the serial robot, $\mathbf{J}$ is the Jacobian matrix of the serial robot, and $\kappa(\mathbf{J})$ de-notes the condition number of the normalized Jacobian matrix [32] of the serial robot based on the Frobenius norm. The larger $\overline{DI}$ is, the better the dexterity of the serial robot is.

As determined by previous research, the stiffness of serial robots is primarily affected by the torsional stiffness of gearboxes and the drive shaft of joints. [33] In this research, the conventional stiffness model, which is proposed by Salisbury [34] and widely used, is adopted to describe the

Cartesian stiffness matrix $\mathbf{K}$ of a serial robot as

$$\mathbf{K} = \mathbf{J}^{-T} \mathbf{K}_\theta \mathbf{J}^{-1} \quad (8)$$

where $\mathbf{K}$ is a real symmetric matrix, and $\mathbf{K}_\theta$ is the joint stiffness matrix of the serial robot which is a diagonal matrix composed of joint stiffness coefficients. [35] The joint stiffness matrix of KR500 robot is obtained by referring to the identification result of KR500 robot in the reference [36] as

$$\mathbf{K}_\theta = \text{diag}([8.9 \times 10^9, 6.78 \times 10^9, 1.13 \times 10^{10}, 2.01 \times 10^9, 1.65 \times 10^9, 1.35 \times 10^9]^T) \text{ N} \cdot \text{mm} / \text{rad} \quad (9)$$

where $\text{diag}()$ transforms a vector into a diagonal matrix.

The Cartesian stiffness matrix $\mathbf{K}$ of a serial robot consists of 4 submatrices as

$$\mathbf{K} = \begin{pmatrix} \mathbf{K}_{11} & \mathbf{K}_{12} \\ \mathbf{K}_{21} & \mathbf{K}_{22} \end{pmatrix} \quad (10)$$

where $\mathbf{K}_{11}$, $\mathbf{K}_{12}$, $\mathbf{K}_{21}$ and $\mathbf{K}_{22}$ are the force-translation submatrix, the force-rotation submatrix, the moment-translation submatrix and the moment-rotation submatrix respectively. The units of elements in different submatrices are different. [34]

Since the translation deformation is the major influential factor of the end deformation of serial robots and the effect of the force on the translation deformation is more significant than the moment, [37] only the relationship between the force $\mathbf{f}$ and the translation deformation $\mathbf{t}$ is considered as

$$\mathbf{f} = \mathbf{K}_{11} \mathbf{t} \quad (11)$$

When the end of a serial robot is subjected to the unit force

$$\|\mathbf{f}\|^2 = \mathbf{f}^T \mathbf{f} = 1 \quad (12)$$

Substitute Eq. (11) into Eq. (12)

$$\mathbf{t}^T \mathbf{K}_{11}^T \mathbf{K}_{11} \mathbf{t} = 1 \quad (13)$$

Since $\mathbf{K}$ is a real symmetric matrix, $\mathbf{K}_{11}$ is also a real symmetric matrix. Then, $\mathbf{K}_{11}$ can be decomposed by eigenvalues as

$$\mathbf{K}_{11} = (\mathbf{e}_1 \quad \mathbf{e}_2 \quad \mathbf{e}_3) \begin{pmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \lambda_3 \end{pmatrix} \begin{pmatrix} \mathbf{e}_1^T \\ \mathbf{e}_2^T \\ \mathbf{e}_3^T \end{pmatrix} \quad (14)$$

where λ_1 , λ_2 and λ_3 are the eigenvalues of $\mathbf{K}_{11}$ respectively ($\lambda_1 \geq \lambda_2 \geq \lambda_3$), and $\mathbf{e}_1$, $\mathbf{e}_2$ and $\mathbf{e}_3$ are the corresponding eigenvectors.

Substitute Eq. (14) into Eq. (13)

$$(\mathbf{t}^T \mathbf{e}_1 \quad \mathbf{t}^T \mathbf{e}_2 \quad \mathbf{t}^T \mathbf{e}_3) \begin{pmatrix} \lambda_1^2 & & \\ & \lambda_2^2 & \\ & & \lambda_3^2 \end{pmatrix} \begin{pmatrix} \mathbf{e}_1^T \mathbf{t} \\ \mathbf{e}_2^T \mathbf{t} \\ \mathbf{e}_3^T \mathbf{t} \end{pmatrix} = 1 \quad (15)$$

For variable substitution, the new variables t_x , t_y and t_z are set as

$$\begin{cases} t_x = \mathbf{e}_1^T \mathbf{t} \\ t_y = \mathbf{e}_2^T \mathbf{t} \\ t_z = \mathbf{e}_3^T \mathbf{t} \end{cases} \quad (16)$$

Substitute Eq. (16) into Eq. (15)

$$t_x^2 \lambda_1^2 + t_y^2 \lambda_2^2 + t_z^2 \lambda_3^2 = 1 \quad (17)$$

The geometry description of Eq. (17) in the Cartesian space is an ellipsoid described as the stiffness ellipsoid. [38] For a serial robot at certain pose, the stiffness ellipsoid characterizes the end translation deformation in all directions. Its semi-axes are along the eigenvectors of matrix $\mathbf{K}_{11}$, and its values of the semi-axes are equal to the eigenvalues correspondingly. [28] The maximum value of the semi-axis, which is equal to λ_3^{-1} ($\lambda_3^{-1} \geq \lambda_2^{-1} \geq \lambda_1^{-1}$), characterizes the biggest end translation deformation of serial robots subjected to the unit force. To comprehensively improve the stiffness of serial robots, the minimum eigenvalue of the force-translation stiffness matrix is

designed as the stiffness index of serial robots, just as

$$\overline{SI} = \lambda_3 \quad (18)$$

where $\overline{SI}$ is the stiffness index of serial robots, and λ_3 is the minimum eigenvalue of $\mathbf{K}_{11}$. The larger $\overline{SI}$ is, the smaller the end translation deformation of a serial robot is, and the better the stiffness of the serial robot is.

As a numerical method, Monte Carlo method is widely used to solve the workspace of serial robots. [29] To improve the solution accuracy of the conventional Monte Carlo method at the boundary of workspace, the improved Monte Carlo method proposed by Xu [39] is adopted to solve the effective workspace of serial robots. The specific process is summarized as Algorithm 3.

Algorithm 3: the improved Monte Carlo method for the effective workspace of serial robots.

Input: DH parameters of the serial robot, the joint stiffness matrix $\mathbf{K}_\theta$ of the serial robot and the expected value ν .

Output: the effective workspace of the serial robot.

- 1 Generate ν groups of joint angles satisfying the constraints of joint limits randomly.
 - 2 Calculate the corresponding dexterity indexes $\overline{DI}$ and stiffness indexes $\overline{SI}$ according to Eqs. (7) and (18).
 - 3 Set the thresholds of $\overline{DI}$ and $\overline{SI}$, and retain the groups of joint angles satisfying both thresholds.
 - 4 **while** the number of groups of joint angles is below the expected value ν **do**
 - 5 Generate new groups of joint angles near the retained joint angles randomly.
 - 6 Calculate the corresponding dexterity indexes $\overline{DI}$ and stiffness indexes $\overline{SI}$ according to Eqs. (7) and (18).
 - 7 Retain the groups of joint angles satisfying both thresholds.
 - 8 **end while**
 - 9 Calculate the end poses corresponding to the groups of joint angles.
 - 10 Plot the end positions in the Cartesian coordinate system.
 - 11 Obtain the effective workspace of the serial robot.
-

In view of the fact that the dexterity index and the stiffness index of serial robots are without units, their values only represent the quality of serial robots in dexterity and stiffness. Therefore, the thresholds set in the third row in Algorithm 3 are baseless in numerical reference. [40] To avoid singular poses and ensure sufficient operating stiffness of serial robots, the thresholds of dexterity

and stiffness are set as the average values of the dexterity indexes and stiffness indexes calculated in the second row in Algorithm 3 respectively.

Since the limit of joint 1 of KR500 robot is $-185^\circ \leq \theta_1 \leq 185^\circ$, the effective workspace in the XOZ plane is solved first, and then the plane workspace is rotated 360° around the z-axis to obtain the effective workspace of KR500 robot in the Cartesian coordinate system, as shown in Figure 8.

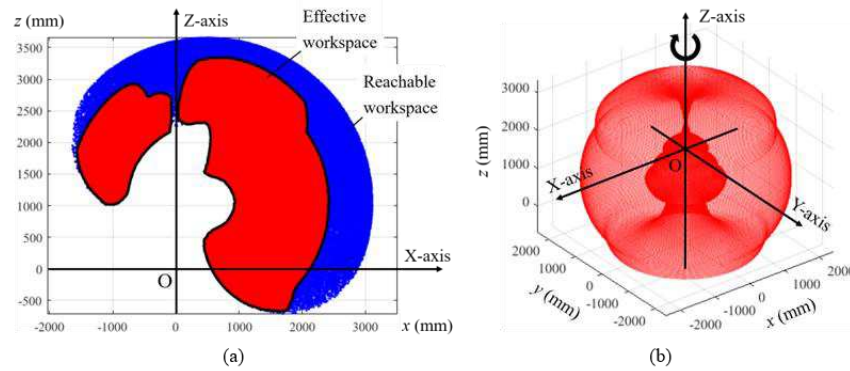


Figure 8 Effective workspace of KR500 robot: (a) XOZ plane, (b) Cartesian coordinate system. ($\nu = 10^5$)

3.2 Solution to reachable region of large cabin

Restricted by the longitude machining range of mobile serial robots, there is a banded reachable region on the surface of the cabin, as shown in Figure 9. The geometric features of the reachable region include arc radius r , arc central angle φ , arc length γ_0 and stretching length η . Since the motion of mobile serial robots is omnidirectional on the horizontal plane, the reachable region of the large cabin is not limited in the axial direction. Besides, the arc radius equals to the radius of the cabin. Therefore, among above geometric features, only the arc central angle φ and the arc length γ_0 need to be solved. The specific solution process is as follows.

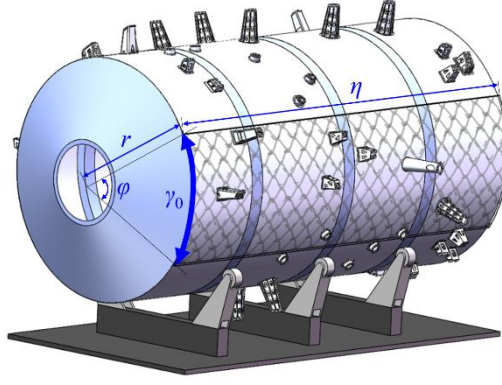


Figure 9 Geometric features of reachable region of large cabin.

(1) The longitudinal machining range h_0 of the mobile serial robot is calculated as

$$h_0 = h_M - h_m \quad (19)$$

where h_M and h_m are the vertical distance from the highest and lowest point of the robot end to the robot base respectively. According to the effective workspace of KR500 robot, h_M is 3342.40mm. Since the lowest point of the robot end is below the robot base, to avoid collisions between the robot and the mobile platform, h_m is set according to the practical working condition.

(2) The vertical distance h_1 from the highest point of the arc to the arc center and the vertical distance h_2 from the lowest point of the arc to the arc center are calculated as

$$\begin{cases} h_1 = h_M + h_r - h_c \\ h_2 = h_0 - h_1 \end{cases} \quad (20)$$

where h_c is the height of the rotary axis of the large cabin from ground, which can be calculated as Eq. (21), and h_r is the height of the robot base from ground, which can be obtained according to the dimensions of mobile platform.

$$h_c = h_3 + h_4 + r \quad (21)$$

where h_3 is the height of the pedestal of the supporting mechanism from ground, and h_4 is the vertical distance from the lowest point of the large cabin to the pedestal of the supporting mechanism.

(3) Based on the geometric relationship shown in Figure 10, the arc central angle φ and the arc length γ_0 are calculated as

$$\begin{cases} \varphi = \arcsin(h_1 / r) + \arcsin(h_2 / r) \\ \gamma_0 = r\varphi \end{cases} \quad (22)$$

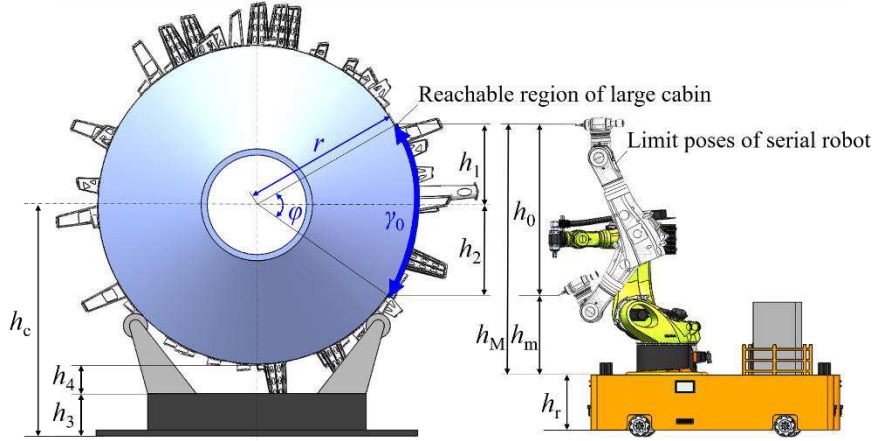


Figure 10 Geometric relationship between reachable region of large cabin and longitudinal machining range of serial robot.

3.3 Determination of optimal partition scheme

Aiming at partition schemes for local features of the large cabin pre-solved in Section 2, the maximum circumferential span γ_k (k is the number of sub-regions) of each partition scheme is calculated. With the reachable region of the large cabin as the constraint, the partition schemes that satisfy $\gamma_k \leq \gamma_0$ are retained to reduce needless space transformation of the large cabin.

Considering that excessive sub-regions lead to extra position transformation of mobile serial robots, which prolongs the auxiliary time, the number of sub-regions is supposed to be as small as possible with the constraint of the reachable region. To improve the machining efficiency, the partition scheme with the minimum number of sub-regions is determined as the optimal partition scheme for local features of the large cabin.

4 Method validation and discussion

To validate the effectiveness of the proposed machining partition method, the proposed method is applied to divide sub-regions for local features on a reference cabin shown in Figure 11. The main information of the reference cabin is as follows.

(1) The radius of the reference cabin is 2620mm.

(2) The height h_3 of the pedestal of supporting mechanism is 700mm, and the vertical distance h_4 from the lowest point of the reference cabin to the pedestal of the supporting mechanism is 480mm.

(3) The reference cabin is installed with 62 typical feature parts outside. Among them, 23 local features are with 9 groups of dimensional correlations, as shown in Table 2.

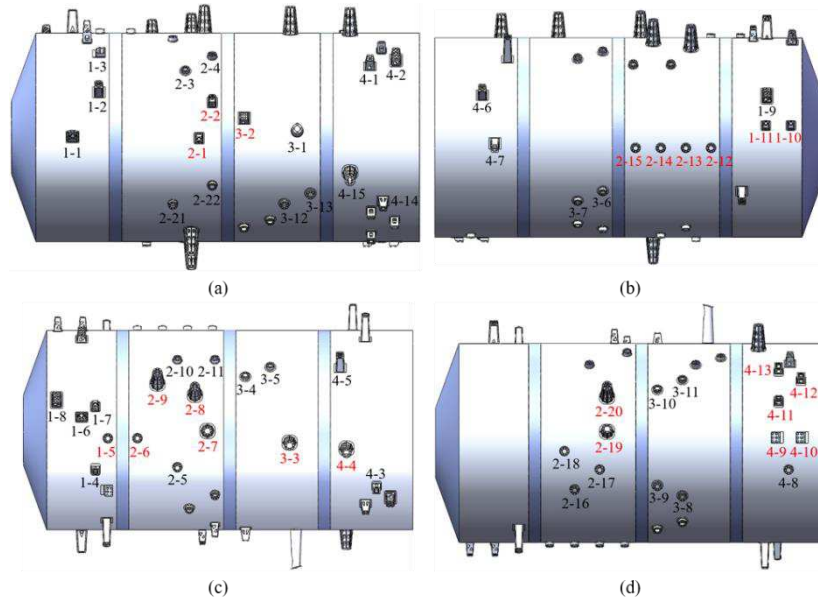


Figure 11 Reference cabin: (a) Front view, (b) Rear view, (c) Top view, (d) Bottom view. Red serial numbers refer to local features with dimensional correlations, and black serial numbers refer to local features without dimensional correlations.

Table 2 Dimensional correlations of local features of reference cabin.

Serial number of dimensional correlations	Number of local features	Serial numbers of local features
1	2	1-5, 2-6
2	2	1-10, 1-11
3	3	2-1, 2-2, 3-2
4	3	2-7, 2-8, 2-9
5	4	2-12, 2-13, 2-14, 2-15
6	2	2-19, 2-20
7	2	3-3, 4-4
8	2	4-9, 4-10
9	3	4-11, 4-12, 4-13

1 In the practical working condition, a mobile milling robot machining system developed
2 independently by Beijing Spacecraft is adopted as shown in Figure 12. [41] In the system, a KR500
3 robot is equipped with a high-precision end effector for milling and carried by an omnidirectional
4 intelligent mobile platform. Relevant parameters about the mobile serial robot in Section 3.2 are
5 obtained as follows.

6 (1) The height h_t of the robot base from ground is equal to the height of mobile platform from
7 ground, which is 1000mm.

8 (2) At each corner of the mobile platform, a hydraulic support is designed for supporting during
9 machining. To avoid collisions between the robot and the hydraulic supports of the mobile platform,
10 the vertical distance h_m from the lowest point of the robot end to the robot base is calculated as

$$11 \quad h_m = \varepsilon h_5 \quad (23)$$

12 where h_5 is the height of the hydraulic support from the mobile platform equaled to 400mm, and
13 ε is the safety factor set as 1.2.

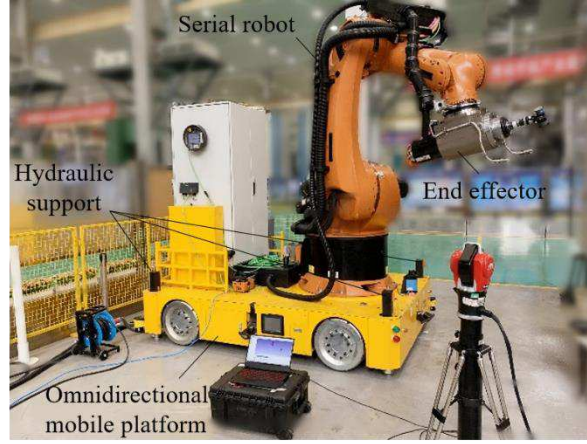


Figure 12 Mobile milling robot machining system.

To begin with, the coordinate system of the reference cabin is established, and positions and dimensional correlations of outboard local features are extracted. The position data set of local features is obtained as Eq. (1).

Then, K-Medoids algorithm is adopted for the clustering problem of local features. With the clustering number as the optimization variable and two types of clustering validity indexes as objective functions, the multi-objective optimization model of partition is established for local features of the reference cabin as Eq. (6). The relationship between the optimization variable and objective functions is analyzed. It is obvious that the variation tendency of objective functions is opposite, as shown in Figure 13.

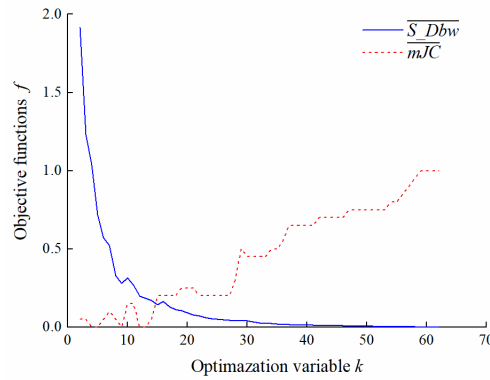


Figure 13 Relationship between optimization variable and objective functions.

1 To optimize the position similarity and the dimensional correlation consistency of local features
2 simultaneously, the Pareto optimal clustering numbers are obtained by traversal, as shown in Figure
3 14 and Table 3. K-Medoids algorithm is adopted to solve the clustering results corresponding to the
4 Pareto optimal clustering numbers, and the pre-solutions to partition for local features of the
5 reference cabin are obtained.

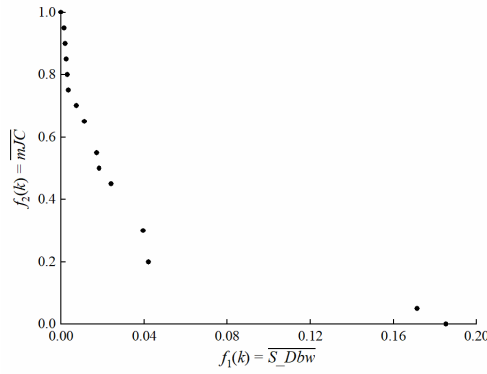


Figure 14 Objective functions corresponding to Pareto optimal clustering numbers.

Table 3 Pareto optimal clustering numbers and corresponding objective functions.

Clustering number k	$\overline{S_Dbw}$	$\overline{mJC}$
13	0.1852	0
14	0.1714	0.05
27	0.0449	0.20
28	0.0422	0.30
33	0.0235	0.40
35	0.0178	0.45
36	0.0167	0.50
41	0.0109	0.60
46	0.0071	0.65
53	0.0033	0.70
55	0.0027	0.75
56	0.0018	0.85
57	0.0013	0.90
58	0.0009	0.95

With parameters of the reference cabin and the mobile serial robot, the arc central angle and the arc length of the reachable region of the reference cabin are solved according to Eqs. (19) to (22).

$$\begin{cases} \varphi = 1.2961 \text{ rad} \\ \gamma_0 = 3395.78 \text{ mm} \end{cases} \quad (24)$$

Afterwards, the maximum circumferential spans of partition schemes pre-solved are calculated, as shown in Figure 15. To reduce needless space transformation of the large cabin, the partition schemes which satisfy $\gamma_k \leq \gamma_0$ are retained.

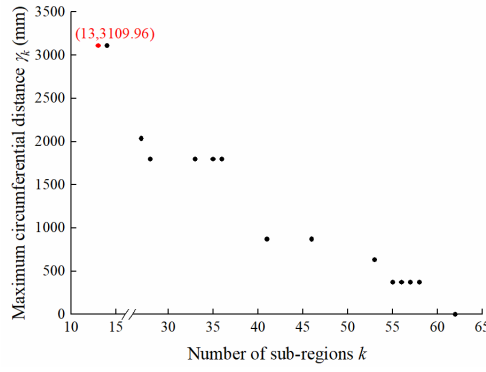


Figure 15 Maximum circumferential spans of partition schemes pre-solved.

Finally, the partition scheme with the minimum number of sub-regions, which is the scheme with 13 sub-regions, is determined as the optimal partition scheme for local features of the reference cabin for the sake of machining efficiency. The optimal partition result is shown in Figure 16. (Details of the optimal partition result are shown in Table A2.)

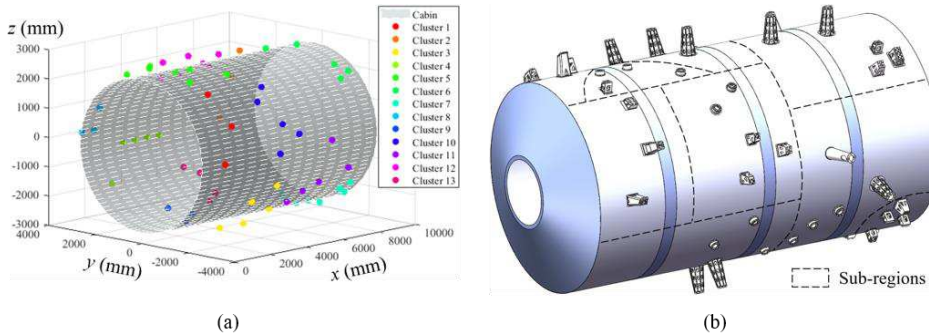


Figure 16 Optimal partition result for local features of reference cabin by proposed method: (a) Clustering result,
(b) Partition result.

To verify the advantages of the proposed method, two types of existing high-efficiency methods are applied as contrast methods to divide sub-regions for local features based on the same reference cabin respectively.

Method (1): partition according to the principle of the equal number of local features.

Method (2): partition according to the principle of the equal axial and circumferential span of sub-regions.

To ensure the effectiveness of contrast tests, method (1), method (2) and the proposed method are based on the same sub-region number. The partition results of two high-efficiency methods and the proposed method are evaluated in Table 4. (Details of the partition results of method (1) and method (2) are shown in Table A3 and Table A4 respectively.)

Table 4 Evaluation of partition results of high-efficiency methods and proposed method.

Partition method	Sub-region k	number	Maximum circumferential span γ (mm)	Serial numbers of local features with same dimensional correlation in different sub-regions
Method (1)	13		4165.38 ($> \gamma_0$)	1-5, 2-6; 2-7, 2-8, 2-9 (2 groups)
Method (2)	13		4913.57 ($> \gamma_0$)	1-5, 2-6; 2-1, 2-2, 3-2; 3-3, 4-4 (3 groups)
Proposed method	13		3109.96 ($< \gamma_0$)	None

From Table 4, the proposed method effectively obtains the partition result that both satisfies the dimensional correlations of local features and the effective workspace of serial robots based on the reference cabin. On the contrast, the maximum circumferential spans of partition results from both contrast methods exceed the arc length of the reachable region, which is hard to realize all machining tasks of the largest sub-region without space transformation of the cabin. Moreover, the problem that local features with the same dimensional correlation are divided into different sub-regions exists

in partition results of both contrast methods (as shown in Figure 17), which requires extra machining adjustment to ensure the machining accuracy of the dimensional correlation and reduces the machining efficiency.

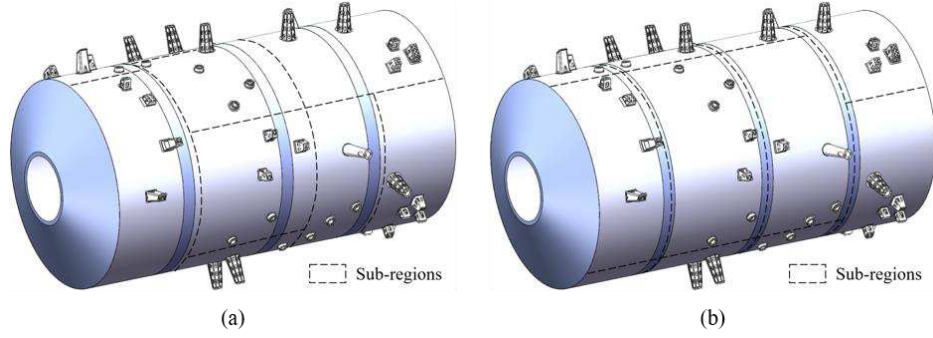


Figure 17 Problems that local features with same dimensional correlation in different sub-regions: (a) Partition result of method 1, (b) Partition result of method 2.

Compared with two existing high-efficiency methods, the proposed method takes both optimization objectives into account. To further illustrate the rationality of the multi-objective optimization model, two types of single-object optimization methods are applied as contrast methods to divide sub-regions for local features based on the same reference cabin respectively.

Method (3): partition according to the optimization model as

$$\begin{cases} \min f_3(k) = \overline{\omega S_Dbw} + (1 - \omega)\overline{mJC} \\ s.t. \quad 0 \leq \omega \leq 1 \\ \quad 1 < k \leq n \end{cases} \quad (25)$$

where k is the optimization variable, $f_3(k)$ is the objective function, and ω is the weight of the first optimization object.

Method (4): partition according to the optimization model as

$$\begin{cases} \min f_4(k) = \overline{S_Dbw} \\ s.t. \quad \overline{mJC} = 0 \\ \quad 1 < k \leq n \end{cases} \quad (26)$$

1 where k is the optimization variable, and $f_4(k)$ is the objective function.

2 In method (3), the multi-objective optimization problem is transformed into a single-objective

3 optimization problem by weighting. In method (4), the challenge of dimensional correlations is

4 limited as a constraint rather than an optimization object. The constraint of $\overline{mJC}$ represents that

5 all correlative features are divided into corresponding sub-regions according to dimensional

6 correlations. To ensure the effectiveness of contrast tests, method (3), method (4) and the proposed

7 method are based on the same clustering method, and all optimization problems are solved by

8 traversal. The partition results of two single-object optimization methods and the proposed method

9 are evaluated in Table 5. (Details of the partition result of method (3) ($\omega = 0.6$) are shown in Table

10 A5.)

11 Table 5 Evaluation of partition results of single-object optimization methods and proposed method.

Partition method	Sub-region k	number	Maximum circumferential span γ (mm)	Serial numbers of local features with same dimensional correlation in different sub-regions
Method (3): $\omega = 0.5$	13		3109.96 ($< \gamma_0$)	None
Method (3): $\omega = 0.6$	27		1794.98 ($< \gamma_0$)	2-19, 2-20; 3-3, 4-4; 4-11, 4-12, 4-13 (3 groups)
Method (4)	13		3109.96 ($< \gamma_0$)	None
Proposed method	13		3109.96 ($< \gamma_0$)	None

12 From Table 5, the influence of the weight ω on the partition result is significant in method (3).

13 However, the selection basis for the weight is unclear. If the weight is improper, like $\omega = 0.6$ in

14 this case, the problem that local features with the same dimensional correlation are divided into

15 different sub-regions will arise, as shown in Figure 18. Besides, the sub-region number k of

16 method (3) ($\omega = 0.6$) is larger than the proposed method, which reduces the machining efficiency.

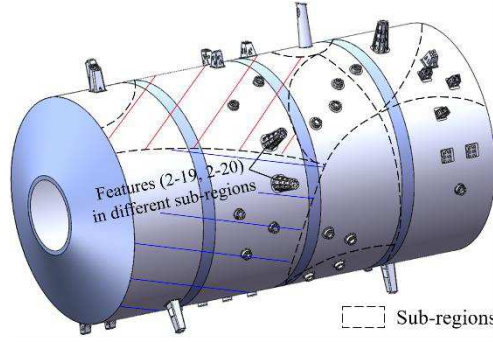


Figure 18 Problems that local features with same dimensional correlation in different sub-regions from method

(3) ($\omega=0.6$).

For the reference cabin, local features with dimensional correlations are densely distributed on the cabin, and the partition result obtained by method (4) is the same as the proposed method. However, if the circumferential spans of local features with dimensional correlations exceed the circumferential span of the reachable region of the large cabin, the applicability of methods is challenged. To compare the effectiveness of method (4) and the proposed method for the above challenge, feature 4-4 and feature 4-15 are set as correlative features additionally based on the reference cabin, as shown in Figure 19. The circumferential span of feature 4-4 and feature 4-15 is 4517.43mm larger than γ_0 .

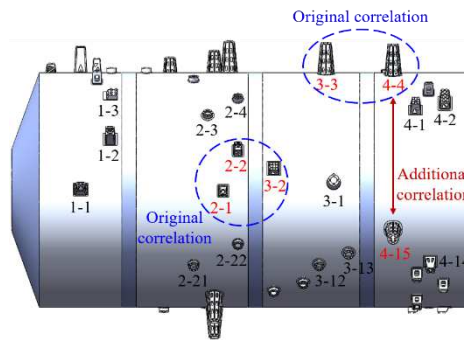


Figure 19 Front view of modified reference cabin. Red serial numbers refer to local features with dimensional correlations, and black serial numbers refer to local features without dimensional correlations.

Method (4) and the proposed method are adopted to divide sub-regions for local features based

on the same modified reference cabin respectively. The partition results of method (4) and the proposed method are evaluated in Table 6.

Partition method	Sub-region k	number	Maximum circumferential span γ (mm)	Serial numbers of local features with same dimensional correlation in different sub-regions
Method (4)	No solution		/	/
Proposed method	13		3109.96 ($< \gamma_0$)	3-3, 4-4, 4-15 (1 group)

At the extreme distribution case of local features, the optimization problem is without solutions with the constraints of method (4), while the proposed method still obtains an effective partition scheme. In the practical engineering, the situation that local features with large-span dimensions exists occasionally. Taking the challenge of dimensional correlations as a constraint increases the difficulty of solving the optimization model, and even lead to the case of no solution as Table 6. Therefore, it is rational to regard the challenge of dimensional correlations as an optimization object, and balancing two partition requirements by multi-objective optimization as the proposed method.

With the comparison of existing high-efficiency methods, single-object optimization methods and the proposed method, the proposed method makes full use of advantages of the clustering algorithm, balances two s partition requirements rationally, and is able to obtain stable and effective partition results for the extreme distribution case of local features

5 Conclusions

(1) A machining partition method is proposed for local features with dimensional correlations of the large cabin based on clustering in this research. Considering positions and dimensional correlations of local features comprehensively, the multi-objective optimization model of partition is established. With the reachable region as the constraint and the machining efficiency as the

1 decision basis, the optimal partition scheme for local features of the large cabin is determined.

2 (2) Method validation is conducted on a reference cabin compared with existing high-efficiency

3 methods and single-object optimization methods. The partition results indicate that the proposed

4 method effectively satisfies the dimensional correlations of local features and the effective

5 workspace of serial robots, which improves the machining efficiency.

6 (3) Further comparison on a modified reference cabin indicates that the multi-objective

7 optimization model of the proposed method is rational and is able to obtain effective partition results

8 for the extreme distribution case of local features.

9 (4) This research provides significant machining partition bases and technical support for robot

10 machining in the integrated in-situ partition manufacturing mode of large cabins.

11 Appendix 1

12 The variables used in the appendix 1 are shown in Table A1. These variables are used only in the

13 appendix 1.

14 Table A1 Variables in appendix 1.

Variable	Definition
$\overline{Scat}$	Average scattering for clusters
$\overline{Dens_bw}$	Inter-cluster density for clusters
$\overline{stdev}$	Average standard deviation of clusters
$\mathbf{P}$	Data set
$\mathbf{C}$	Clustering result of data set $\mathbf{P}$
n	Count of sample points
s	Count of attributes of sample points
k	Clustering number
l	Serial number of sample points

i, j	Serial number of clusters
$\mathbf{p}_l$	Sample point of data set $\mathbf{P}$
$x_{l,1}, x_{l,2}, x_{l,s}$	Attributes of $\mathbf{p}_l$
$\mathbf{c}_i$	Clustering medoid of cluster i
$\mathbf{c}_j$	Clustering medoid of cluster j
$cx_{i,1}, cx_{i,2}, cx_{i,s}$	Attributes of $\mathbf{c}_i$
$\sigma(\mathbf{c}_i)$	variance of cluster i
$\sigma(\mathbf{P})$	variance of data set $\mathbf{P}$
m_i	Number of sample points in cluster i
m_j	Number of sample points in cluster j
$mean(x_1), mean(x_2), mean(x_s)$	mean value of attribute of sample points in data set $\mathbf{P}$
$\mathbf{u}_{i,j}$	Middle point of line segment defined by clustering medoids $\mathbf{c}_i$ and $\mathbf{c}_j$
α_i	Sample point in cluster i
β_j	Sample point in cluster j
γ_l	Sample point in clusters i and j
$\mathbf{y}_1, \mathbf{y}_2$	Sample points
$f(\mathbf{y}_1, \mathbf{y}_2)$	Euclidean distance between sample points $\mathbf{y}_1$ and $\mathbf{y}_2$

1 The detailed definition of $\overline{Scat}$ and $\overline{Dens_bw}$ is as follows.

2 Let $\mathbf{P}$ be the data set which contains n sample points. Each sample point possesses s
3 attributes.

$$4 \quad \mathbf{P} = \{\mathbf{p}_l = (x_{l,1}, x_{l,2}, \dots, x_{l,s})^T \mid l \in [1, n]\} \quad (27)$$

5 where $\mathbf{p}_l$ is the sample point of data set $\mathbf{P}$ and $x_{l,s}$ is the attribute of $\mathbf{p}_l$.

6 Let $\mathbf{C}$ be the clustering result of the data set $\mathbf{P}$ which is divided into k clusters.

$$7 \quad \mathbf{C} = \{\mathbf{c}_i = (cx_{i,1}, cx_{i,2}, \dots, cx_{i,s})^T \mid i \in [1, k]\} \quad (28)$$

8 where $\mathbf{c}_i$ is the clustering medoid of the cluster i and $cx_{i,s}$ is the attribute of $\mathbf{c}_i$.

9 For the data set $\mathbf{P}$, the average scattering for clusters is defined as

$$10 \quad \overline{Scat} = \frac{\sum_{i=1}^k \|\sigma(\mathbf{c}_i)\|}{k \|\sigma(\mathbf{P})\|} \quad (29)$$

1 The term $\sigma(\mathbf{c}_i)$ is the variance of the cluster i and $\sigma(\mathbf{P})$ is the variance of the data set $\mathbf{P}$

$$2 \begin{cases} \sigma(\mathbf{c}_i) = \frac{1}{m_i} \sum_{l=1}^{m_i} (x_{l,1} - cx_{i,1})^2, (x_{l,2} - cx_{i,2})^2, \dots, (x_{l,s} - cx_{i,s})^2 \\ \sigma(\mathbf{P}) = \frac{1}{n} \sum_{l=1}^n ((x_{l,1} - \text{mean}(x_1))^2, (x_{l,2} - \text{mean}(x_2))^2, \dots, (x_{l,s} - \text{mean}(x_s))^2) \end{cases}^T \quad (30)$$

3 where m_i is the number of sample points in the cluster i , and $\text{mean}(x_s)$ denotes the mean value
4 of the attribute of the sample points in the data set $\mathbf{P}$.

5 Let $\overline{stdev}$ be the average standard deviation of clusters.

$$6 \overline{stdev} = \frac{1}{k} \sqrt{\sum_{i=1}^k \|\sigma(\mathbf{c}_i)\|} \quad (31)$$

7 Then the inter-cluster density for clusters is defined as

$$8 \overline{Dens_bw} = \frac{1}{k(k-1)} \sum_{i=1}^k \left(\frac{\sum_{l=1}^{m_i+m_j} f(\gamma_l, \mathbf{u}_{i,j})}{\sum_{j=1, j \neq i}^k \max \left\{ \sum_{l=1}^{m_i} f(\alpha_l, \mathbf{c}_i), \sum_{l=1}^{m_j} f(\beta_l, \mathbf{c}_j) \right\}} \right) \quad (32)$$

9 where m_j is the number of sample points in the cluster j , $\mathbf{c}_j$ is the clustering medoid of the
10 cluster j , $\mathbf{u}_{i,j}$ is the middle point of the line segment defined by the clustering medoids $\mathbf{c}_i$ and
11 $\mathbf{c}_j$, α_l is the sample point in the cluster i , β_l is the sample point in the cluster j , and γ_l is
12 the sample point in the clusters i and j . The function $f(\mathbf{y}_1, \mathbf{y}_2)$ is defined as

$$13 f(\mathbf{y}_1, \mathbf{y}_2) = \begin{cases} 0, & \text{if } d(\mathbf{y}_1, \mathbf{y}_2) > \overline{stdev} \\ 1, & \text{otherwise} \end{cases} \quad (33)$$

14 where $d(\mathbf{y}_1, \mathbf{y}_2)$ denotes the Euclidean distance between the sample points $\mathbf{y}_1$ and $\mathbf{y}_2$.

15 Appendix 2

16 Table A2 Details of optimal partition result.

Serial number of sub-regions	Number of local features	Serial numbers of local features
------------------------------	--------------------------	----------------------------------

1	3	1-1, 1-2, 1-3
2	7	1-4, 1-5, 1-6, 1-7, 1-8, 2-5, 2-6
3	3	1-9, 1-10, 1-11
4	5	1-12, 2-12, 2-13, 2-14, 2-15
5	5	2-1, 2-2, 2-3, 2-4, 3-2
6	7	2-7, 2-8, 2-9, 2-10, 2-11, 3-4, 3-5
7	3	2-16, 2-17, 2-18
8	5	2-19, 2-20, 2-21, 2-22, 3-10
9	5	3-1, 3-11, 3-12, 3-13, 4-15
10	5	3-3, 4-1, 4-2, 4-3, 4-4
11	4	3-6, 3-7, 3-8, 3-9
12	3	4-5, 4-6, 4-7
13	7	4-8, 4-9, 4-10, 4-11, 4-12, 4-13, 4-14

1

Table A3 Details of partition result of method (1).

Serial number of sub-regions	Number of local features	Serial numbers of local features
1	4	1-1, 1-2, 1-3, 1-4
2	4	1-5, 1-6, 1-7, 1-8
3	4	1-9, 1-10, 1-11, 1-12
4	5	2-1, 2-2, 2-21, 2-22, 3-2
5	5	2-3, 2-4, 2-5, 2-6, 2-7
6	5	2-8, 2-9, 2-10, 2-11, 3-4
7	5	2-12, 2-13, 2-14, 2-15, 3-6
8	5	2-16, 2-17, 2-18, 2-19, 2-20
9	5	3-1, 3-10, 3-11, 3-12, 3-13
10	5	3-3, 4-1, 4-2, 4-3, 4-4
11	5	3-5, 3-7, 4-5, 4-6, 4-7
12	5	3-8, 3-9, 4-8, 4-9, 4-10
13	5	4-11, 4-12, 4-13, 4-14, 4-15

2

Table A4 Details of partition result of method (2).

Serial number of sub-regions	Number of local features	Serial numbers of local features
1	4	1-1, 1-2, 1-3, 1-4
2	7	1-5, 1-6, 1-7, 1-8, 1-9, 1-10, 1-11

3	1	1-12
4	7	2-1, 2-2, 2-3, 2-4, 2-5, 2-21, 2-22
5	10	2-6, 2-7, 2-8, 2-9, 2-10, 2-11, 2-12, 2-13, 2-14, 2-15
6	5	2-16, 2-17, 2-18, 2-19, 2-20
7	4	3-1, 3-2, 3-12, 3-13
8	3	3-3, 3-4, 3-5
9	6	3-6, 3-7, 3-8, 3-9, 3-10, 3-11
10	4	4-1, 4-2, 4-3, 4-4
11	2	4-5, 4-6
12	2	4-7, 4-8
13	7	4-9, 4-10, 4-11, 4-12, 4-13, 4-14, 4-15

1

Table A5 Details of partition result of method (3) ($\omega=0.6$).

Serial number of sub-regions	Number of local features	Serial numbers of local features
1	1	1-1
2	1	1-2
3	2	1-3, 1-4
4	2	1-5, 2-6
5	3	1-6, 1-7, 1-8
6	3	1-9, 1-10, 1-11
7	1	1-12
8	3	2-1, 2-2, 3-2
9	3	2-3, 2-4, 2-5
10	4	2-7, 2-8, 2-9, 2-10
11	3	2-11, 3-4, 3-5
12	4	2-12, 2-13, 2-14, 2-15
13	4	2-16, 2-17, 2-18, 2-19
14	3	2-20, 2-21, 2-22
15	1	3-1
16	1	3-3
17	2	3-6, 3-7
18	2	3-8, 3-9
19	3	3-10, 3-11, 3-12
20	2	3-13, 4-15

21	3	4-1, 4-2, 4-3
22	1	4-4
23	1	4-5
24	1	4-6
25	1	4-7
26	4	4-8, 4-9, 4-10, 4-11
27	3	4-12, 4-13, 4-14

1 **Declarations**

2 **Availability of data and materials**

3 The data that support the findings of this study are available from Beijing Spacecraft but restrictions
4 apply to the availability of these data, which were used under license for the current study, and so
5 are not publicly available. Data are however available from the authors upon reasonable request and
6 with permission of Beijing Spacecraft.

7 **Competing interests**

8 The authors declare that they have no competing interests.

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14 **Authors' contributions**

15 JM was in charge of the entire research; HS proposed the method, conducted the analysis and wrote
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QT provided technical support; ZJ and WL supervised the research. All the authors read and approved the final manuscript.

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Authors' information

Jianwei Ma is currently a professor and a PhD candidate supervisor in School of Mechanical Engineering, Dalian University of Technology, China. His research interests include issues related to the numerical control technology, unconventional processing and robot-assisted machining.

Hechen Sun is currently a postgraduate candidate in School of Mechanical Engineering, Dalian University of Technology, China.

Huiteng Yan is currently a PhD candidate in School of Mechanical Engineering, Dalian University of Technology, China.

Hongyuan Zhang is currently a postgraduate candidate in School of Mechanical Engineering, Dalian University of Technology, China.

Qiang Tao is currently an engineer at Beijing Spacecraft, China Academy of Space Technology, China.

Zhenyuan Jia is currently a standing committee of Party committee, a standing vice president, a professor and a PhD candidate supervisor in Dalian University of Technology, China.

Wei Liu is currently a vice president, a professor and a PhD candidate supervisor in School of Mechanical Engineering, Dalian University of Technology, China.

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