Identification Method of Key Risk Control Points in Mechanical Product Assembly Process

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Abstract: In order to improve the assembly process quality of mechanical products, a structuralized decomposition method of Function-Movement-Action (FMA) was used to obtain the meta-action (MA) of minimum assembly granularity of mechanical products. Secondly, taking the performance index of the moving layer as the object of assembly process quality analysis, the state space model of the hybrid type MA was established, and the relationship models between the quality of the serial, parallel and hybrid type assembly process and the internal influencing factors were given. Then, the Partial Least Squares Regression (PLSR) method was used to solve the problem of multicollinearity and small sample among the influencing factors of each MA, and the key risk control points in the assembly process were obtained by the importance index analysis of variable projection. Finally, the effectiveness of the proposed method is proved by taking a numerical control turntable as an example.

1. Introduction
Assemble is the process of combining the parts that make up a product into components, components, and even the whole product [1]. Assembly process is an important part of manufacturing process, and the quality of assembly process is the main factor determining product quality, so it is necessary to guarantee the quality of assembly process. Many studies have been carried out on the quality control of assembly process at home and abroad. For example, Suzuki et al. proposed an assembly reliability evaluation method and conducted a quantitative study on the assembly failure rate by analyzing design factors and workshop factors [2]. Su Qiang et al. improved the evaluation method of design complexity and established a binary statistical model of human assembly defects of photocopier products to predict the assembly quality [3]. RAN Yan et al. used grey relational analysis to find the main work steps affecting assembly reliability, introduced polychromatic set theory to establish the relationship between assembly influencing factors and each process, and finally determined the corresponding reliability control measures [4]. Song Tingting et al. established the Markov model of the associated process assembly system considering the influence of the assembly processes, and determined the quality bottleneck processes and assembly parameters that affected the system [5].

Most of the above studies are based on the parts and assembly processes of mechanical products, mostly static analysis of the assembly process, without considering the motion characteristics of mechanical products, and the assembled products often fail to meet the expected functional requirements. Moreover, the relationship between the quality of assembly process and the influencing factors is nonlinear and dynamic, so it is difficult to establish the quantitative relationship between the quality of assembly process and the influencing factors [6]. Based on mechanical product Function, the FMA
decomposition method for meta-action, to Action for the smallest granularity, sports performance parameters as the assembly process quality evaluation index, introducing the state space model, consider the meta-action, motion and dynamic relationship between mixed type meta-action of the state space model, build quality and the relationship between various influencing factors of assembly process model, by using Partial Least Square Regression (PLSR) modeling solves the multiple-collinearity problem among the internal influencing factors of each layer meta-action, identifies the key risk control points in the assembly process, and provides a theoretical basis for further implementation of assembly process quality.

2. Theoretical basis of meta-motion

2.1. FMA decomposition model

FMA decomposition method is a top-down decomposition method [7],[8], which takes the product functions as the research object and decomposes the product functions into the minimum granularity of the FMA according to the basic order of FMA ensures the total functional requirements of the whole product by controlling the performance characteristics and functions of meta-actions. The FMA structured decomposition model is shown in Fig.1.

![Figure 1 FMA structural decomposition model](image)

T-F- total function; S-F- sub-function; 1-M- first level movement; 2-M- second order movement; 1-A- level 1 meta-action; j-A- intermediate meta-action; n-A- level n meta-action

2.2. Meta-action

Meta-action (MA) is the most basic form of movement to transfer motion and power in mechanical products. It is the smallest movement in mechanical products. For mechanical products, its function and performance are realized and guaranteed through the movement of each component, and the realization of component movement is inseparable from the movement of its components.

2.3. Meta-action unit

Meta-action unit (MAU) is an action unit with relatively independent structure that can complete the most basic actions (movement or rotation) in the working process of the movement mechanism to realize the product function. It can be controlled and analyzed without (nor can be) further subdivided [9]. As the most basic component of mechanical products, the most basic function of MAU is the transmission of movement and power. The MAU includes two kinds of moving unit and rotation unit. A typical meta-action unit includes five elements: power input, power output, transmission, intermediate transmission, fasteners and supports, as shown in Fig. 2.
3. The quality characteristic relation model of meta-action assembly process

Mechanical products by FMA contains more than one MA after FMA decomposition, meta-action power output quality reflect meta-action motion state, can be measured by MA output motion parameters, from the perspective of the types of MAU, including displacement \( s \), velocity \( v \), force \( \sigma \) for the mobile unit of motion parameters, angular displacement \( \theta \), angular velocity \( \omega \) and torque \( \tau \) for rotating motion parameters of class units[10]. The motion can be realized by a plurality of meta-actions in series, or a plurality of meta-actions in parallel, and the form of a plurality of meta-actions in series and parallel to realize the movement requirements. In order to solve the problem of motion state accumulation and transmission caused by the power output of each level of MA, and to find out the internal influencing factors of each level of MA which are most closely related to the final quality of meta-motion output, this paper introduces the state-space model to construct the quality transfer model of assembly process of MA. In this paper, Jin et al improved the traditional state space model by referring to the ideas in the research of parallel structure multistage manufacturing process control method [11], and constructed the hybrid structure model as shown in the Fig.3.

![Figure 3 The state space model of a hybrid type meta-action](image)

Meta-action state space model shown in Fig.3, meta-action \( A_j \) quality \( q_j \) can be made of its internal factors \( x_j \) and the meta-moves upstream \( A_{j-1} \) quality \( q_{j-1} \) said together, \( q_{j-1} \) is \( A_{j-1} \) output quality characteristics and \( A_j \) input quality characteristics, meta-action internal factors \( x_j(j = 1,2,\ldots,n) \) are independent of each other, \( w_j \) average random error vector is zero, independent with each other.

3.1. Relationship model of assembly process quality characteristics of serial type meta-action

According to the idea of state space [12], the mass characteristic relation of adjacent two elements of action can be expressed as Equation (1)

\[
q_i = b_{i,j}q_{i-1} + c_{i,j}x_i + w_i
\]  

Where, \( q_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \) is the i-th quality characteristic of the meta-action \( A_j \). \( b_{i,j}q_{i-1} \) is the influence of the output quality characteristic \( q_{i,j-1} \) of the meta-action \( A_{j-1} \) on the
quality of the meta-action \( A_j \), \( c_{ij}x_j \) is the influence of the internal influencing factors \( x_j \) of the meta-action \( A_j \) on the quality of the meta-action \( A_j \), and \( w_j \) is the systematic error of the meta-action \( A_j \).

Since there are usually multiple output quality characteristics of each level of meta-action, Formula 1 can be represented by a vector to obtain the quality characteristic relationship model of the serial meta-action.

\[
Q_j = B_{j-1}Q_{j-1} + C_jX_j + w_j
\]

Where, \( Q_j = (q_{1,j}, q_{2,j}, ..., q_{m,j})^T \) and \( Q_{j-1} = (q_{1,j-1}, q_{2,j-1}, ..., q_{m,j-1})^T \) represent the quality characteristic vectors of the meta-action \( A_j \) and \( A_{j-1} \), \( X_j = (x_{1,j}, x_{2,j}, ..., x_{k,j})^T \) represents the internal influencing factor vectors of the quality characteristic of the meta-action \( A_j \). \( B_{j-1} \) is the influence coefficient matrix of the output quality characteristics of the meta-action \( A_{j-1} \) on the quality characteristics of the meta-action \( A_j \), \( C_j \) is the influence coefficient matrix of the internal influence factors of the meta-action \( A_{j-1} \) on the quality characteristics of the element action \( A_j \).

\[
B_{j-1} = \begin{bmatrix}
  b_{11,j-1} & b_{12,j-1} & \cdots & b_{1m,j-1} \\
  b_{21,j-1} & b_{22,j-1} & \cdots & b_{2m,j-1} \\
  \vdots & \vdots & \ddots & \vdots \\
  b_{m1,j-1} & b_{m2,j-1} & \cdots & b_{mm,j-1}
\end{bmatrix}
\]

\[
C_j = \begin{bmatrix}
  c_{11,j} & c_{12,j} & \cdots & c_{1k,j} \\
  c_{21,j} & c_{22,j} & \cdots & c_{2k,j} \\
  \vdots & \vdots & \ddots & \vdots \\
  c_{m1,j} & c_{m2,j} & \cdots & c_{mk,j}
\end{bmatrix}
\]

### 3.2 Quality characteristic relation model of assembly process of parallel meta-action

In FMA decomposition, there is a parallel relation between the meta-action units, and a certain motion can only be realized by the joint action of multiple parallel meta-actions. It can be discussed three cases: parallel case, dispersion case and convergence case.

1. **Parallel case**
   
   Parallel situation has seen as a series of two input process, the two input each other, still can use its quality relationship model series under the structure of the state space model representation, and through the recursive iteration respectively from each of the parallel direction to continue forward analysis, find out a process to the influence of the quality characteristics, eventually forming quality of the whole manufacturing process of the linear relation model.

2. **Dispersion case**

   In the case of decentralization, an output of layer \( j-1 \) as shown in the Fig. 3 serves as the input of the two meta-actions of layer \( j \). Therefore, we can set and as two dummy variables to represent the quality characteristic vector of the first meta-action in \( j-1 \) layer

\[
\begin{bmatrix}
  Q_{j,1} \\
  Q_{j,2}
\end{bmatrix} = B_{j-1}Q_{j-1} + X_j + w_j = \begin{bmatrix}
  B_{j-1} & 0 \\
  0 & B_{j-1}
\end{bmatrix} \begin{bmatrix}
  \tilde{Q}_{j-1,1} \\
  \tilde{Q}_{j-1,2}
\end{bmatrix} + \begin{bmatrix}
  X_{j,1} \\
  X_{j,2}
\end{bmatrix} + \begin{bmatrix}
  w_{j,1} \\
  w_{j,2}
\end{bmatrix}
\]

   Where, \( \tilde{Q}_{j-1,1} \) and \( \tilde{Q}_{j-1,2} \) is \( Q_{j,1} \) and \( Q_{j,1} \) quality characteristics of the transmission respectively, and obey the same statistical distribution. The presentation layer \( j \) will affect the quality characteristics of the meta-action of the layer \( j-1 \) together.

3. **Convergence case**

   In the case of decentralization, an output of layer \( j+1 \) as shown in the figure serves as the input of the two meta-actions of layer \( j \). Therefore, we can set and as two dummy variables to represent the quality characteristic vector of the first meta-action in \( j+1 \) layer.

\[
\begin{bmatrix}
  Q_{j+1,1} \\
  Q_{j+1,2}
\end{bmatrix} = B_jQ_j + X_j + w_j = \begin{bmatrix}
  B_j & 0 \\
  0 & B_j
\end{bmatrix} \begin{bmatrix}
  \tilde{Q}_{j,1} \\
  \tilde{Q}_{j,2}
\end{bmatrix} + \begin{bmatrix}
  X_{j,1} \\
  X_{j,2}
\end{bmatrix} + \begin{bmatrix}
  w_{j,1} \\
  w_{j,2}
\end{bmatrix}
\]

   Where, \( \tilde{Q}_{j+1,1} \) and \( \tilde{Q}_{j+1,2} \) is \( Q_{j,1} \) and \( Q_{j,1} \) quality characteristics of the transmission respectively, and obey the same statistical distribution. The presentation layer \( j \) will affect the quality characteristics of the meta-action of the layer \( j+1 \) together.
3.3. Quality relation model of assembly process of hybrid type meta-action

It can be seen from the above quality relation model that the action quality characteristics of the adjacent two layers of elements can be represented by a linear state space model. Set $Y$ is movement parameters. According to Equations (1) to (4), the quality characteristics of the assembly process are output from the end MA layer by recursive iteration, and the following equation can be obtained:

$$
Y = B_{n,1}B_{n-2} \cdots B_{i,0}a_0 + C_{n,1}X_{n,1} + B_{n,1}B_{n-2}C_{n-1}X_{n-2} + \cdots + B_{n,1}B_{n-2} \cdots B_{i,0}C_{i,0}X_{i,0} + \cdots + B_{n,1}B_{n-2} \cdots B_{i,0}w_0
$$

(Eq. 5)

Equation (3) is summarized and sorted as follows:

$$
Y = \sum_{i=1}^{n} \phi_{n,i} C_i X_i + \phi_{n,0} Q_0 + \sum_{i=1}^{n} \phi_{n,i} w_i
$$

(Eq. 6)

Where, $\phi_{n,i}$ is the state transition matrix, when $i < n$, $\phi_{n,i} = B_{n-1}B_{n-2} \cdots B_{i,0}$; when $i = n$, $\phi_{n,n} = 1$.

If we don't consider the system's random error $w_j$, and the measurement value of is not available, it can be used as an additional process to affect the input without loss of generality, $Q_0 = 0$.

$$
Y = \sum_{i=1}^{n} \phi_{n,i} C_i X_i
$$

(Eq. 7)

Equation (7) is the meta-action state space model. Different MA relationship between the power output of processing could be sent through space state, dynamic parameters can be eventually meta-action output by various internal influence factors in the MA said, and this model can be regarded as final motion parameters $Y$ and all levels of MA output action of internal influence factors $X_j$ in the multivariate linear equation, if you can get the influence coefficient matrix $B_{j-1}$ and $C_j$ can identify which meta-action internal influence factors on the movement of the biggest influence in MA, the key quality control points of risk is the assembly process.

4. Identification of key risk control points in assembly process based on Partial Least Squares Regression

Action of each layer of MA against MA internal multicollinearity between influencing factors and problems such as too little sample points. This paper introduced PLSR, will last MA into which the state space model, use assistive technology, analysis the key factor affecting the quality of yuan action chain assembly quality control points [13].

Step 1: Standardize data processing. Set the motion parameter as the dependent variable $y$, and the internal influencing factors in the actions of each layer meta-action constitute the independent variable set $\{x_1, x_2, \ldots, x_m\}$. n sample points are collected to form the independent variable data matrix $X$ and the dependent variable data matrix $Y$. The standardized independent variable matrix $E = (x_1^*, x_2^*, \ldots, x_m^*)_{m \times n}$ and the dependent variable matrix $F_0 = (y^*)_{n \times 1}$ are obtained by eliminating the influence of different dimensions among the variables through standardized processing of the sample data.

$$
x_{ij}^* = \frac{x_{ij} - \bar{x}_i}{s_i}
$$

Step 2: PLSR analysis of $Y$. Starting from the final product quality $Y$, according to Equations (2) to (4) and (7), the input and output values of the quality characteristics of each layer element in the serial and parallel assembly process were analyzed by PLSR software SIMCA-P, and the component number and variable projection importance index of the model were obtained according to the auxiliary analysis technology of PLSR.

Step 3: Establish the state space model of hybrid type element action. According to Equations (5) and (7), the multiple linear regression model of the final quality $Y$ of the product and the internal quality characteristics of each layer element is obtained by iterating successively.

$$
Y = \mu_1 X_1 + \mu_2 X_2 + \cdots + \mu_n X_n
$$

(Eq. 8)

Where, $\mu_j (j = 1, 2, \ldots, n)$ is the influence coefficient in Equation 7.

Step 4: Identify key quality characteristics. In PSR analysis, the importance index of variable
projection is used to measure the importance of independent variables in explaining dependent variables.

\[ VIP_j = \frac{m}{R_d(y; t_1, t_2, ..., t_k)} \sum_{i=1}^{h} R_d(y; t_i) w_i^2 \]  

(9)

5. Example

As a key part of CNC machine tool, the quality assurance of NC turntable during assembly ensures the function and performance of the machine tool. According to the operation principle of CNC turntable, its FMA decomposition tree can be expressed as the following Fig.4.

5.1. State space model of unit motion under indexing motion of turntable

In this paper, the series type MA under the numerical control turntable degree movement is selected, worm rotation \( A_1 \rightarrow \) gear shaft rotation \( A_2 \rightarrow \) turntable rotation \( A_3 \), to verify the feasibility of the method in this paper. The state space model of the unit action under the indexing movement of the turntable as the following Fig.5.

Select turntable dividing precision as a series of MA quality of assembly process analysis object is the dependent variable \( Y \), analyzed factors affecting each layer MA internal quality as the independent variable: worm rotation accuracy \( q_{11} \) and rotational stability \( q_{12} \), internal factors have a worm and worm machining precision \( x_{11} \) and the turbine reverse clearance \( x_{12} \), bearing pre-tightening force \( x_{13} \) on both ends of the worm and worm hole with coaxial degree \( x_{14} \). The quality characteristics of the gear shaft rotating assembly process include the gear rotation precision \( q_{21} \), the internal influencing factors include the installation verticality of the gear and the worm \( x_{21} \), the gear machining precision \( x_{22} \), the preloading force of the bearings at both ends of the gear \( x_{23} \), and the coaxiality of the gear shaft and the hole \( x_{24} \). The main quality characteristics of the rotary table assembly process include the rotary precision \( q_{31} \), the rotational stability of the rotary table \( q_{32} \), the internal influencing factors include the accuracy of the rotary table \( x_{31} \), the coaxiality of the rotary table \( x_{32} \), and the installation clearance of the rotary table \( x_{33} \). A total of 12 groups of experimental data were collected as samples, as shown in Tab.1,
Table 1 The 14 groups of sample data

| x_{11}/mm | x_{12}/mm | x_{13}/KN | x_{21}/mm | x_{22}/mm | x_{23}/mm | x_{31}/mm | x_{32}/mm | x_{33}/mm | Y/mm |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------|
| 1         | 0.006     | 0.017     | 3.8       | 0.005     | 0.008     | 0.009     | 5.2       | 0.010     | 0.012 | 0.008 |
| 2         | 0.005     | 0.014     | 3.9       | 0.004     | 0.006     | 0.006     | 5.5       | 0.008     | 0.009 | 0.006 |
| 3         | 0.008     | 0.018     | 3.6       | 0.011     | 0.007     | 0.006     | 5.3       | 0.006     | 0.013 | 0.005 |
| 4         | 0.004     | 0.012     | 3.7       | 0.006     | 0.005     | 0.008     | 5.7       | 0.008     | 0.008 | 0.009 |
| 5         | 0.006     | 0.014     | 3.8       | 0.008     | 0.004     | 0.006     | 5.6       | 0.012     | 0.009 | 0.012 |
| 6         | 0.006     | 0.022     | 4.1       | 0.009     | 0.006     | 0.008     | 5.9       | 0.014     | 0.008 | 0.006 |
| 7         | 0.007     | 0.016     | 4.3       | 0.007     | 0.010     | 0.005     | 6.2       | 0.009     | 0.007 | 0.018 |
| 8         | 0.005     | 0.019     | 4.2       | 0.006     | 0.008     | 0.009     | 5.8       | 0.005     | 0.012 | 0.009 |
| 9         | 0.008     | 0.016     | 3.8       | 0.008     | 0.006     | 0.012     | 6.2       | 0.009     | 0.007 | 0.008 |
| 10        | 0.006     | 0.017     | 3.4       | 0.004     | 0.009     | 0.008     | 5.5       | 0.010     | 0.009 | 0.006 |
| 11        | 0.006     | 0.013     | 3.7       | 0.010     | 0.008     | 0.006     | 5.8       | 0.007     | 0.010 | 0.010 |
| 12        | 0.011     | 0.016     | 3.6       | 0.005     | 0.007     | 0.014     | 5.7       | 0.012     | 0.005 | 0.010 |
| 13        | 0.008     | 0.018     | 3.6       | 0.008     | 0.012     | 0.007     | 5.4       | 0.009     | 0.007 | 0.016 |
| 14        | 0.007     | 0.015     | 3.4       | 0.009     | 0.008     | 0.009     | 5.9       | 0.011     | 0.008 | 0.010 |

According to Equation (2), the following can be obtained,
Worm rotation meta-action \( A_1: Q_1 = B_1Q_0 + C_1X_1 + w_1 \)
Gear shaft rotation meta-action \( A_2: Q_2 = B_1Q_1 + C_2X_2 + w_2 \)
Rotational action of turntable \( A_3: Q_3 = B_2Q_2 + C_3X_3 + w_3 \)
In this paper, we set \( Q_0 = 0 \), without considering the random error \( w_j \) of the system, and obtained the quality characteristic correlation model of the element action chain through iteration as,

\[
Y = B_1B_2C_1X_1 + B_1C_2X_2 + C_1X_3 + C_2X_4
\]

5.2 Partial least squares regression modeling analysis and identification of key risk control points
In this paper, SIMCA-P software is used for PLSR modeling analysis.

(1) Cross validation analysis.
The test results were shown in Tab.2. Only the third principal component \( Q^2 = -0.124878 < 0.0975 \), therefore, the model only needs to extract the first two principal components, and the comprehensive interpretation ability of the model to the dependent variables is as high as 96.49%, with high accuracy.

Table 2 The result of cross validation test

| Var ID (primary) | \( R^2 \) | \( R^2 \)(cum) | \( Q^2 \) | \( Q^2 \)(cum) |
|-----------------|----------|----------------|----------|---------------|
| Comp1           | 0.779121 | 0.779121       | 0.448535 | 0.448535      |
| Comp2           | 0.185799 | 0.96492        | 0.243987 | 0.692522      |
| Comp3           | 0.03208  | 0.99772        | -0.124878| 0.543642      |

(2) Specific point analysis
SIMCA-P software was used to draw the elliptic diagram of the model \( T^2 \), as shown in Fig.6. It can be seen that all the sample points fall in the elliptic plane, which proves that there are no specific points in the sample data and that the sample data is reasonable.
After principal component extraction and specific point elimination, the standardized partial least squares regression equation is finally obtained as follows:

\[
y = 0.466x_{11} + 1.268x_{12} + 0.813x_{13} + 0.021x_{14} - 0.161x_{21} + 0.453x_{22} + 0.292x_{23} + 0.117x_{24} + 0.074x_{31} + 0.017x_{32} + 0.622x_{33}
\]

Identification of key assembly quality influencing factors

As shown in Fig.6, visible worm \(x_{12}\) and turbine reverse clearance \(x_{13}\), bearing pre-tightening force on both ends of the worm \(x_{33}\), VIP > 1. Instructions, and \(x_{12}, x_{13}, x_{33}\) is one of the important factors affect the dependent variable Y. Therefore, in the design phase and assembly process should adopt strict measures to control the three main influencing factors in order to ensure the accuracy of the indexing motion accuracy of NC rotary table.

6. Conclusions

In this paper, an identification method of key risk control points in mechanical product assembly process based on MA is developed, which solves the following problems: (1) difficulty in quality modeling of assembly process, (2) multiple nonlinearity of influencing factors. In order to solve the above problems, firstly, the state space model of the hybrid type MA is established based on the minimum granularity of the component action obtained by FMA structural decomposition, and the relationship model of the assembly process quality characteristics of the serial type MA, the parallel type MA and the hybrid type MA is given. Secondly, PLSR was used to eliminate the multicollinearity among the influencing factors within each movement, and the key risk control points in the assembly process under each movement were identified based on the importance index of variable projection. Finally the example shows that the proposed method is correct and effective.
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