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Enhancing aerospace products quality with ISOMAP key factor identification

Shen, D.Y.[a,b], Liu, N.Z.[a,*], Liu, W.[b], Wang, Z.[b]

[a]College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing, P.R. China
[b]Beijing System Design Institute of the Electro-mechanic Engineering, Beijing, P.R. China

A B S T R A C T

The nonlinear and high-dimensional nature of the impact factors affecting the production quality of aerospace products represents a major difficulty for the quality control in the aerospace industry. To obtain the impact factors affecting the product quality, it is plausible to perform dimensionality reduction on acquired samples before further manipulation. In this work, the isometric feature mapping (ISOMAP) algorithm of stream learning is employed to perform nonlinear dimensionality reduction on aerospace data. This enables a calculation of the correlation coefficients between the principal components after dimensionality reduction and the original factors, the classification of the correspondence, and the ranking of the principal components according to their degree of influence. The experimental results show that the algorithm is able to carry out correlation analysis of 17 factors affecting the production quality of aerospace products, and analyze the 13 main factors affecting the production quality of aerospace products, and the degree of influence, in descending order, are the rationality of measurement methods, the rationality of test point design, tool wear, equipment normalization rate, the degree of equipment aging, the rationality of program design, the degree of material defects, the rationality of process route design, the rationality of tooling design, the technical level of personnel, the level of personnel experience, the personnel work status, and operational standardization. The ISOMAP algorithm was used to reduce the dimensionality of these 13 factors to form and rank the six main influence components, thus eliminating redundant factors, highlighting main influence features and extracting the intrinsic relation in data. The data analysis conclusions can facilitate a prevention of potential quality issues in aerospace production. To ensure the enhancement of the quality of aerospace product production, it is recommended that standard automated measurement methods be employed wherever feasible. Additionally, it is recommended that the regular maintenance of machining tools and equipment be strengthened to ensure that the machining tools and equipment are in perfect condition.

A R T I C L E I N F O

Keywords:
Aerospace products;
Production quality;
ISOMAP;
Nonlinear dimensionality reduction;
5M1E framework;
Correlation analysis;
Quality control

**Corresponding author:*
liunz_tx@163.com
(Liu, N.Z.)

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1. Introduction

The development of aerospace products is contingent upon the attainment of exceptionally high reliability standards. Consequently, the supervision and prevention of the production quality of aerospace products represents a pivotal aspect of the aerospace product development process. The production of aerospace products is susceptible to the potential for the creation of substandard items if the procedures and equipment utilized are not sufficiently standardized. With the rapid development of manufacturing intelligence technology, big data, artificial intelligence and other new technologies are deeply integrated with manufacturing, becoming an important support for the transformation and upgrading of manufacturers [1-3]. Currently, research on applying big data and artificial intelligence technologies to manufacturing focuses on optimizing the power consumption of integrated systems for flexible manufacturing [4], increasing production capacity [5], optimizing manufacturing schedules [6, 7], analyzing nonconforming production [8], evaluating production efficiency [9] and classifying faults [10]. Mature methods have been developed in these areas. Aerospace product manufacturers have implemented digital production through the implementation of a MES system, thereby accumulating substantial data regarding the production process and forming industrial big data [11, 12]. However, the question of how to utilize this data to identify the main factors affecting the production quality of aerospace products remains a significant challenge that requires immediate attention.

The main factors affecting the production quality of aerospace products are typically nonlinear and high-dimensional data, which pertain to all aspects of the production process. The use of high-dimensional data presents a number of evident challenges when undertaking decision-making analysis. Firstly, the processing of high-dimensional data is inherently challenging due to its multidimensional nature, which often results in inefficiencies in computational operations. Secondly, the presence of redundancy between factors makes it challenging to ascertain the contribution rate of each factor. Furthermore, it is difficult to identify the specific affecting factors that truly determine the quality of the production.

In the context of high-dimensional data processing, the fundamental dimensionality reduction algorithms can be classified into two categories: linear and nonlinear ones. Linear dimensionality reduction algorithms mainly include Principal Component Analysis (PCA) algorithm [13] and Multi-Dimensional Scaling (MDS) algorithm [14]. PCA algorithm projects N-dimensional features to a K-dimensional orthogonal space through a linear transformation, thereby maximizing the variance of the projected data. The obtained K orthogonal components are designated as the principal component. Currently, PCA has been widely used in network abnormal traffic detection [15], port throughput forecasting [16], image classification [17], predictions in precision agriculture [18], coin classification [19], etc. The core idea of the MDS algorithm is to utilize the distance matrix to illustrate the degree of similarity or the correlation between the data points. In contrast to the PCA algorithm, the MDS algorithm preserves the distance relationship between the original data points throughout the dimensionality reduction process. While, the PCA algorithm prioritizes the preservation of the primary trends within the data. With the advancement of computer technology, artificial intelligence technology, bioinformatics technology, and other multidisciplinary application technologies, an increasing number of high-dimensional data sets exhibit nonlinear structural characteristics. Consequently, linear dimensionality reduction algorithms have to be extended to effectively restore the low-dimensional structure in nonlinear data.

To address the challenge of nonlinear dimensionality reduction within the linear dimensionality reduction framework, several nonlinear dimensionality reduction methods have been proposed. For instance, Shawe-Taylor *et al*. employed nonlinear dimensionality reduction algorithms based on kernel methods to conduct research on nonlinear high-dimensional data dimensionality reduction [20]. Schölkopf *et al*. proposed the kernel principal component analysis (KPCA) [21], which has since become a widely used technique in fields such as face recognition [22], speech recognition [23] and novelty detection [24]. Maaten *et al*. proposed the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm [25]. The t-SNE algorithm is primarily employed for the analysis of local data structures, with a focus on the extraction of local clusters. This capability is particularly advantageous for the visualization of high-dimensional data sets comprising multiple streams of varying types (e.g., the MNIST dataset). However, it is important to note its limitation in preserving the global structure of the data. The t-SNE algorithm finds primary application in fields such as bioinformatics, image processing, and related domains. McInnes *et al*. proposed the Uniform Manifold Approximation and Projection (UMAP) algorithm [26], which was developed to address the limitations of t-SNE. t-SNE has been shown to lack scalability for large data sets, does not support model persistence, and does not preserve the global structure. The UMAP algorithm has been demonstrated to be well-suited for large-scale data downscaling and visualization applications. Tenenbaum *et al*. put forth the concept of ISOMAP (Isometric Mapping) [27], which integrates PCA and MDS. Thereafter, the geodesic distance matrix has been used as the input to the MDS algorithm, leading to an improved performance.

Presently, the ISOMAP algorithm has been employed in a variety of applications, including generating training parameters for ROMs [28], fault diagnosis [29], equipment condition analysis [30], EEG classification analysis [31], groundwater systems analysis [32], and other fields. The findings from these applications have been encouraging, suggesting the potential of the ISOMAP algorithm in a variety of domains. Despite extensive research efforts have been paid on various dimensionality reduction algorithms, a notable gap persists in applying these algorithms to the production quality analysis of aerospace products.

The analysis of the main factors affecting the production quality of aerospace products is a typical small sample data analysis scenario, and the factors affecting the production quality of aerospace products have strong non-linear coupling relationships. This paper presents an analysis of the production features of aerospace products and the various types of quality-affecting factors. Compared with algorithms such as t-SNE and UMAP, the ISOMAP algorithm is more suitable for the small sample non-linear data dimension reduction scenario in the analysis of the main factors affecting the production quality of aerospace products. To achieve this, the ISOMAP algorithm is employed to carry out nonlinear dimensionality reduction, enabling a calculation of correlation coefficients between the principal component after dimensionality reduction and the original factors, a clarification of the correspondence, and a ranking of the principal component according to the degree of influence. This approach allows for the identification of the main factors that most affect the production quality of aerospace products. The algorithm is capable of effectively eliminating redundant factor interference, highlighting the main affecting features, and obtaining the inner law of the data. This can assist in addressing relevant issues in a timely manner and preventing potential quality issues in production.

2. Algorithm design

In this paper, the ISOMAP algorithm is employed for the purpose of analyzing the production quality data of aerospace products through the use of dimensionality reduction, with the objective of identifying the main affecting factors. The design of the algorithm is presented in Fig. 1.

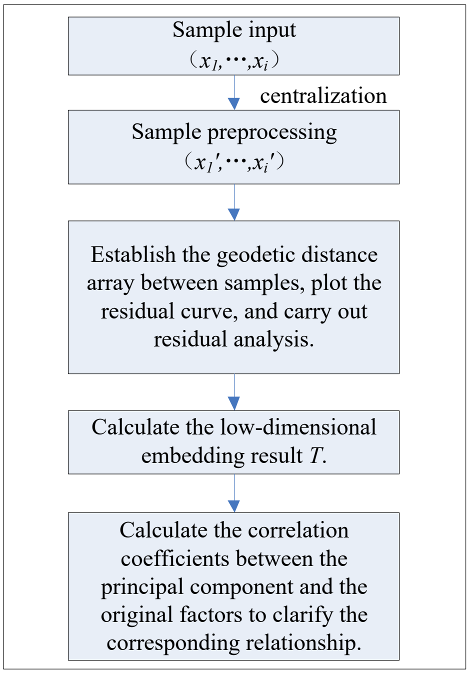

Fig. 1 Algorithm for production quality analysis of aerospace products

The ISOMAP-based algorithm for production quality analysis of aerospace products comprises the following steps: sample preprocessing, residual analysis, calculation of low-dimensional embedding results, calculation of correlation coefficients between the principal component and the original factors, and clarification of the corresponding relationship.

Step 1: Sample preprocessing

In accordance with Eq. 1, the input samples ($x_1, \dots, x_i$) are normalized so that the transformed data are mapped between [0,1], thereby eliminating the influence of disparate factors due to the discrepancy in magnitude and size of the values. The transformed data ($x_1', \dots, x_i'$) are then obtained.

$$x_i' = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \tag{1}$$

Step 2: Establish the geodetic distance array between samples, plot the residual curve, and carry out residual analysis

The residual curve is plotted in accordance with Eq. 2, wherein D_g represents the geodetic distance array, D_Y denotes the Euclidean distance array, and R signifies the correlation coefficient ($R = \rho_{x,y}$). Based on the residual curve, the sample eigen-dimension d is determined. Eq. 3 illustrates the calculation of the correlation coefficient, wherein: ρ is the correlation coefficient; E is the mathematical expectation; X is the composite factor vector; and Y is the original factor vector.

$$e_d = 1 - R^2(D_g, D_y) \tag{2}$$

$$\rho_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)}\sqrt{E(Y^2) - E^2(Y)}} \tag{3}$$

Step 3: The results of the low-dimensional embedding are calculated

In accordance with Eq. 4, the low-dimensional embedding result T, that is to say the eigen samples ($z_1, \dots, z_d$), is computed. Where: ($\lambda_1, \dots, \lambda_d$) represents the largest d eigenvalue of D_g, and its corresponding eigenvector is ($u_1, \dots, u_d$). The matrix U is defined as ($u_1, \dots, u_d$). As the eigenvalue increases, the importance of each factor increases.

$$T = diag\left(\lambda_1^{1/2}, \dots, \lambda_d^{1/2}\right) U^T \tag{4}$$

Step 4: The correlation coefficients between the principal component and the original factors are calculated

The correlation coefficients between the principal component and the original factors are calculated using Eq. 3. By comparing the size of the correlation coefficients, the most relevant original factors to the principal component after dimensionality reduction are identified.

3. Example analysis

An analysis of the production process for a given product is conducted within an aerospace company. The experiment obtains the on-site processing information of this product in recent years from the MES system and takes 500 samples, including qualified and unqualified samples of 250 cases for verification. The experiment employs the PyCharm 2020 runtime environment.

3.1 Sample selection and pre-processing

The production process of aerospace products is influenced by a multitude of factors, including the interactions between men, machines, materials, methods, measurements, and the environment (5M1E). Each of these categories contains a multitude of affecting factors that collectively determine the quality of the product and its qualification status. These factors are causal regarding quality outcomes.

By combing the historical records of the production process of aerospace products in an aerospace company, we have identified the factors that influence the quality of aerospace product production around the 5M1E and determined the threshold value of each factor. This initial phase of the study represents the fundamental research component, providing the foundation for subsequent analysis of the main factors affecting the production quality of aerospace products. The factors affecting the production quality of aerospace products are presented in Fig. 2.

In terms of man factors, the following variables have been identified as affecting factors: the technical level of personnel, the level of personnel experience and the personnel work status. The technical level of personnel reflects the technical level of production personnel, encompassing primary, intermediate, and senior levels. The level of personnel experience is defined as the work experience of the production personnel involved in manufacturing and processing. According to the number of years of experience, it can be divided into three levels: level 1 (0-2 years of experience), level 2 (3-5 years of experience), and level 3 (more than 5 years of experience). Personnel work status refers to the personal status of production personnel while performing production work, reflects the degree of personal fatigue, and is closely related to individual continuous working time. The personnel work status is divided into two categories: "good" and "bad." If the personnel work continuously for more than eight hours or for more than five days, the status is designated as "bad." Conversely, if the personnel work continuously for less than eight hours or for less than five days, the status is designated as "good."

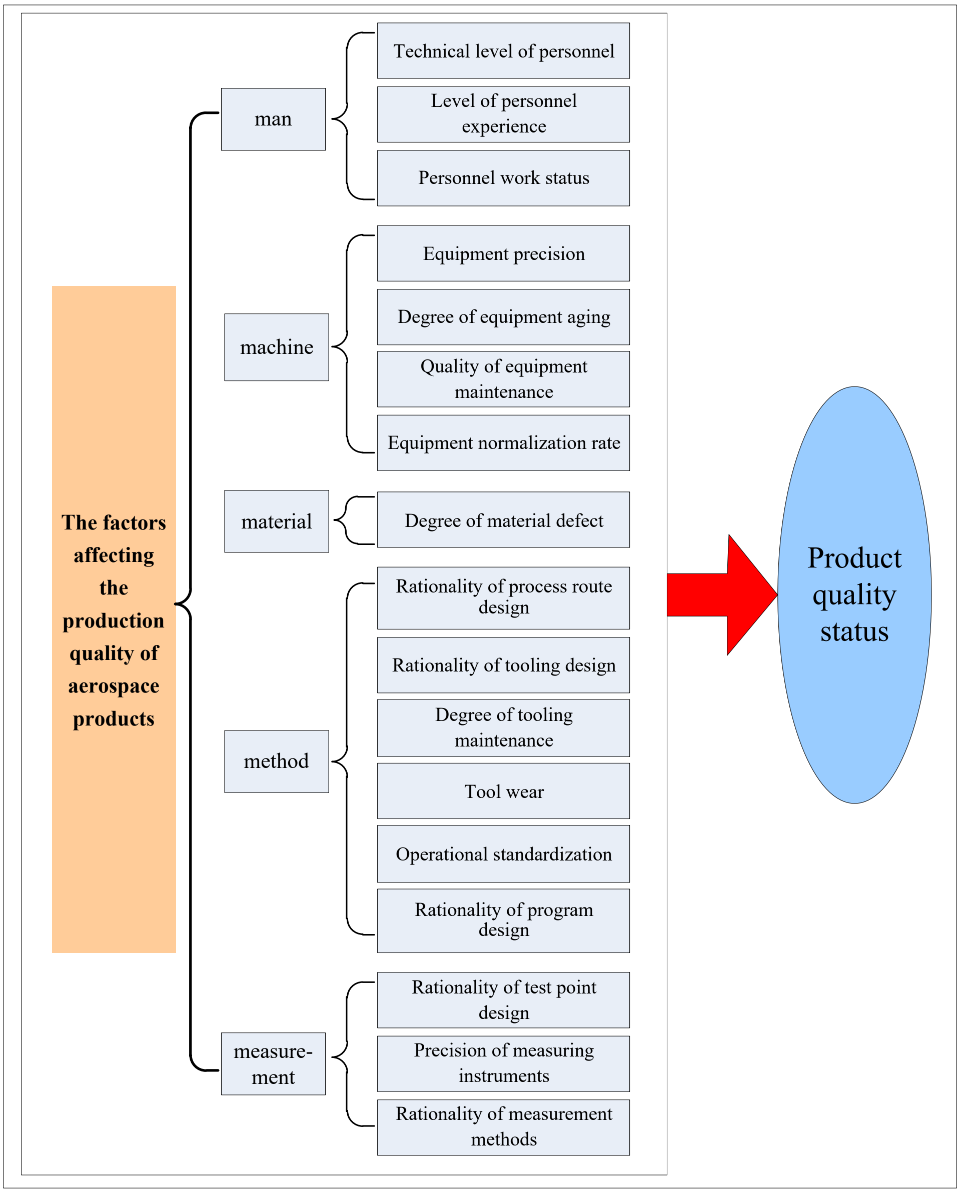

Fig. 2 The factors affecting the production quality of aerospace products

Affecting factors with regard to the machine are mainly the equipment precision, the degree of equipment aging, the quality of equipment maintenance, and the equipment normalization rate. The term "equipment precision" is used to describe the degree of refinement of equipment processing, including ordinary, computer numerical control (CNC), or precision machine tools and other equipment. There is a notable difference in precision between these categories. The degree of aging is directly proportional to the cumulative usage time of the equipment in question. Therefore, the longer the cumulative usage time of the equipment, the greater the degree of aging will be. The quality of equipment maintenance can be defined as the degree and quality to which equipment is maintained. The equipment normalization rate refers to the normal work time of the equipment/the production time of the product. The impact of the aforementioned factors on production results will vary in accordance with their differences.

The main factor affecting the material is the degree of material defects. The presence of material defects, such as cracks, impurities, and sand holes, will inevitably exert an influence on the quality of the final product to a certain extent.

Affecting factors in terms of production methods are the rationality of process route design, the rationality of tooling design, the degree of tooling maintenance, tool wear, operational standardization, and the rationality of program design. Process route refers to the processing route of the product, and rationality of tooling design refers to the operability of the process equipment for the processing of the product. The more reasonable the process route and tooling design, the greater the likelihood of successful product processing. Furthermore, the degree of tooling maintenance, tool wear, operational standardization, and the rationality of program design also have an impact on the quality of the processing.

Affecting factors with regard to the measurement are the rationality of the test point design, the precision of the measuring instruments, and the rationality of the measurement methods employed. The quality of the processing will be adversely affected by the unreasonable setting of test points, the low precision of measuring instruments, and the use of unreasonable measuring methods.

The aforementioned five affecting factors collectively determine the quality of production of aerospace products. An analysis of these factors, coupled with the identification of the most significant factors and the establishment of a correlation between them, can effectively inform the classification of production quality and facilitate decision-making.

The affecting factors and factor value settings are presented in Table 1.

Information regarding the on-site processing of a product in recent years is obtained from the MES system, as detailed in Table 2. The following table presents the actual data on some of the original affecting factors and the actual processing results.

The correlation coefficients between the original affecting factors of the production quality of aerospace products and between the original affecting factors and the production results (qualified) have been calculated and presented in Fig. 3 for purposes of illustration. The magnitude of the correlation coefficients serves to reflect the strength of the relationship between the various original affecting factors and the extent to which they impact the production outcomes. As demonstrated by the correlation coefficient calculation, 13 original affecting factors with a notable impact on production results have been identified as the original factors for subsequent dimensionality reduction. The 13 original affecting factors are as follows: the technical level of personnel (x_1), the level of personnel experience (x_2), the personnel working status (x_3), the degree of equipment aging (x_5), the equipment normalization rate (x_7), the degree of material defects (x_8), the rationality of process route design (x_9), the rationality of tooling design (x_{10}), tool wear (x_{12}), operational standardization (x_{13}), the rationality of program design (x_{14}), the rationality of test point design (x_{15}), and the rationality of measurement methods (x_{17}).

Table 1 Affecting factors and thresholds

Category	Factor	Factor name	Factor value	Description of factor
Man	x_1	Technical level of personnel	{1,2,3}	primary, intermediate and senior
	x_2	Level of personnel experience	{1,2,3}	Years of experience in this position: 1: 0-2 years 2: 3-5 years 3: more than 5 years
	x_3	Personnel working status	{1,2}	Personnel work status: 1: Bad (more than 8 hours of continuous work or more than 5 days of continuous work) 2: Good (less than 8 hours of continuous work and less than 5 days of continuous work)
Machine	x_4	Equipment precision	[0,1]	The degree of refinement of equipment processing, such as ordinary, CNC or precision machine tools, etc.
	x_5	Degree of equipment aging	[0,1]	Based on cumulative usage time of equipment
	x_6	Quality of equipment maintenance	[0,1]	Quality of equipment repair and maintenance
	x_7	Equipment normalization rate	[0,1]	Normal working time of the equipment / Production time
Material	x_8	Degree of material defects	[0,1]	Material integrity, material processing features
Method	x_9	Rationality of process route design	[0,1]	Design rationality of processing sequence and content
	x_{10}	Rationality of tooling design	[0,1]	Operability of tooling design
	x_{11}	Degree of tooling maintenance	[0,1]	maintenance level
	x_{12}	Tool wear	[0,1]	Tool wear level
	x_{13}	Operational standardization	[0,1]	Operational standardization
	x_{14}	Rationality of program design	[0,1]	Organizational rationality, operability
Measurement	x_{15}	Rationality of test point design	[0,1]	Reasonable level of test point setup
	x_{16}	Precision of measuring instruments	[0,1]	Precision of measuring instruments
	x_{17}	Rationality of measurement methods	[0,1]	Reasonableness of the test engineer's measurement method

Table 2 Each original affecting factor in MES system and actual results (partial data)

No.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	Result
1	2	3	2	0.9	0.7	0.8	0.9	0.9	0.9	0.8	0.7	0.8	0.8	0.8	0.7	0.7	0.8	1
2	3	3	2	0.8	0.6	0.7	0.6	0.8	0.6	0.7	0.8	0.9	0.8	0.8	0.8	0.5	0.9	1
3	2	2	2	0.9	0.8	0.8	0.9	0.9	0.9	0.8	0.9	0.8	0.8	0.9	0.8	0.9	0.8	1
4	1	2	2	0.7	0.7	0.7	0.9	0.8	0.9	0.9	0.6	0.7	0.9	0.9	0.9	0.7	0.8	1
5	1	3	1	0.8	0.6	0.7	0.9	0.9	0.9	0.8	0.8	0.8	0.9	0.9	0.8	0.8	0.8	1
6	3	1	2	0.9	0.6	0.9	0.9	0.9	0.9	0.8	0.6	0.9	0.8	0.9	0.9	0.9	0.9	1
7	1	1	1	0.7	0.8	0.7	0.9	0.8	0.9	0.9	0.8	0.5	0.8	0.9	0.6	0.7	0.6	-1
8	2	2	1	0.9	0.9	0.6	0.8	0.7	0.3	0.6	0.7	0.6	0.8	0.3	0.5	0.8	0.6	-1
9	2	3	1	0.8	0.8	0.8	0.9	0.7	0.7	0.2	0.8	0.4	0.8	0.9	0.6	0.9	0.5	-1
10	1	1	2	0.8	0.9	0.9	0.2	0.8	0.8	0.9	0.9	0.5	0.9	0.9	0.7	0.8	0.4	-1
11	2	3	1	0.9	0.6	0.7	0.9	0.8	0.6	0.8	0.7	0.6	0.8	0.2	0.3	0.9	0.5	-1

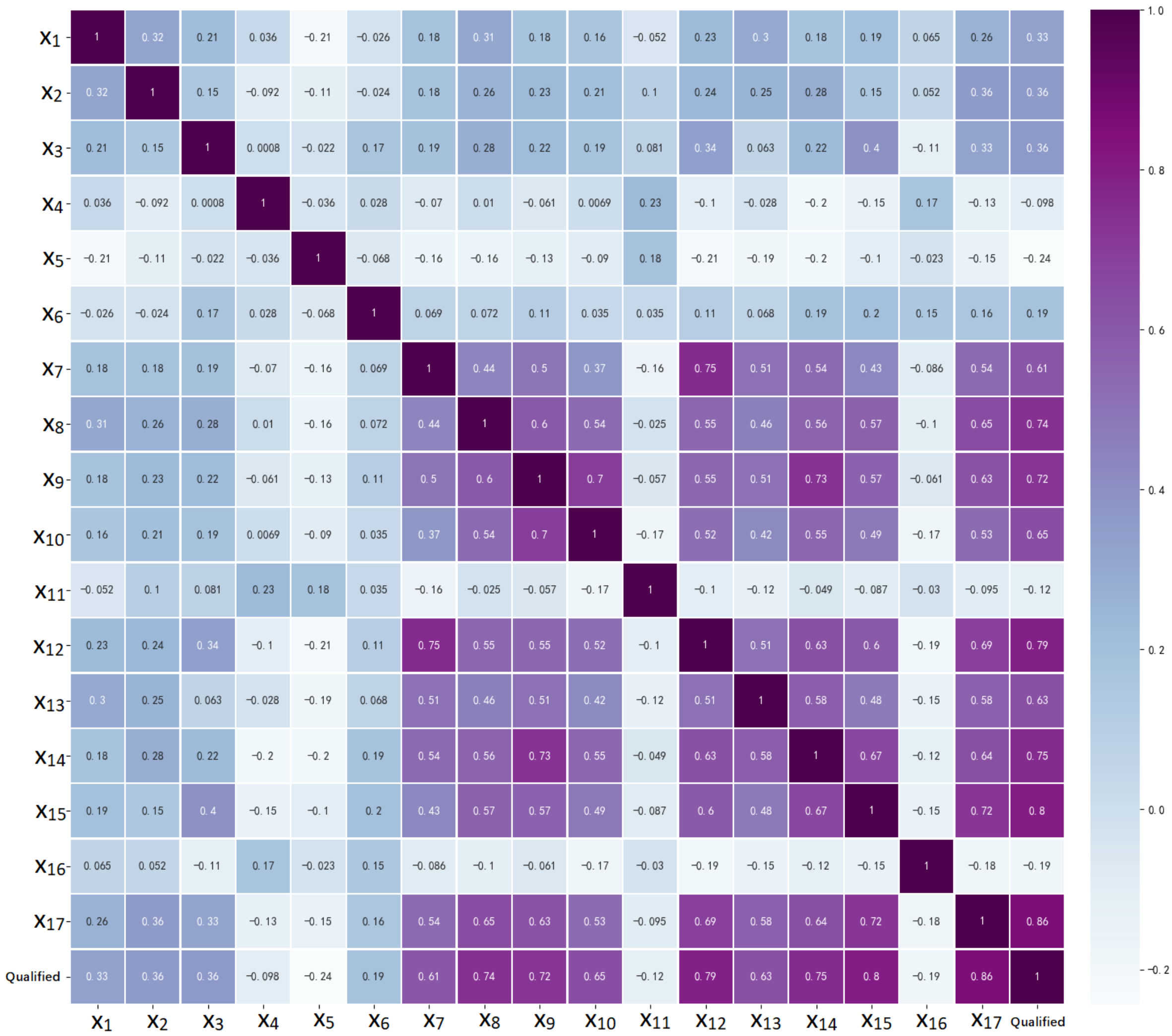

Fig. 3 The correlation coefficients between each original affecting factor and the qualified production results

3.2 Dimensionality reduction and data analysis

The geodetic distance array D_g between samples has been established, and in accordance with Eq. 2, the residual curve has been drawn and presented in Fig. 4. It is evident that as the dimensionality exceeds 6, the curve displays enhanced smoothness, with residual variations confined to a 5 % range. It is thus established that the intrinsic dimensionality of the sample is equal to 6, indicating that there are six principal features that collectively account for 95 % of the sample's features.

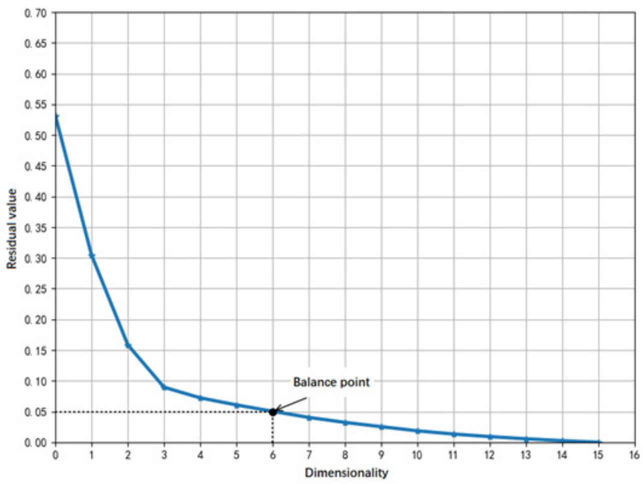

Fig. 4 Residual curve

In accordance with Eq. 4, the low-dimensional embedding result T can be calculated. This result is represented by the eigen-sample ($z_1, \ldots, z_6$), which comprises six principal components after dimensionality reduction. The correlation coefficients between each principal component after dimensionality reduction and the original factors are calculated in accordance with Eq. 3 and are presented in Table 3.

The size of the correlation coefficient between each principal component and the original factors allows us to elucidate the corresponding relationship between them and to ascertain which original factors are most pertinent to the principal component after dimensionality reduction. As illustrated in Table 3, the original factors with high correlation coefficients for the first principal component z_1 include the technical level of personnel, the level of personnel experience, the personnel working status and operational standardization, which are personnel-related factors. The original factors with high correlation coefficients for the second principal component z_2 include the degree of equipment aging, equipment normalization rate and tool wear, which are equipment-related factors. The original factor with a high correlation coefficient for the third principal component z_3 is the degree of material defects, which is material-related factor. The original factors with high correlation coefficients for the fourth principal component z_4 include the rationality of process route design and the rationality of tooling design, which are process design-related factors. The original factor with a high correlation coefficient for the fifth principal component z_5 is the rationality of program design, which is program design-related factor. The original factors with high correlation coefficients for the sixth principal component z_6 include the rationality of test point design and the rationality of measurement methods, which are measurement method-related factors.

Fig. 5 illustrates the two-dimensional spatial projection of the two original factors, namely the technical level of personnel and the level of personnel experience. It can be observed that the original sample features are not readily discernible. Fig. 6 illustrates the two-dimensional spatial projection of the first feature z_1 and the second feature z_2 after dimensionality reduction using an ISOMAP-based dimensionality reduction algorithm, which can be seen that the principal components are clearly featured and can reflect the main features that affect the quality of product production.

Table 3 The correlation coefficients between each principal component after dimensionality reduction and the original factors

Principal component	x_1	x_2	x_3	x_5	x_7	x_8	x_9	x_{10}	x_{12}	x_{13}	x_{14}	x_{15}	x_{17}
z_1	0.72	0.62	0.59	-0.02	0.07	0.04	0.06	0.06	0.07	0.74	0.07	0.06	0.10
z_2	0.06	-0.07	0.07	-0.72	-0.68	0.01	-0.02	-0.02	-0.71	0.01	-0.03	0.01	-0.03
z_3	0.22	0.13	-0.09	-0.01	-0.11	-0.75	-0.11	-0.09	-0.15	-0.03	-0.12	-0.16	-0.14
z_4	0.04	0.13	0.37	0.05	-0.36	-0.13	-0.73	-0.69	-0.30	-0.28	-0.36	-0.25	-0.31
z_5	0.01	-0.01	-0.01	0.07	-0.71	0.08	0.31	0.43	-0.32	-0.04	0.86	0.19	0.06
z_6	0.01	0.01	0.04	0.01	0.25	0.01	0.25	0.20	0.06	-0.23	-0.21	-0.62	-0.62

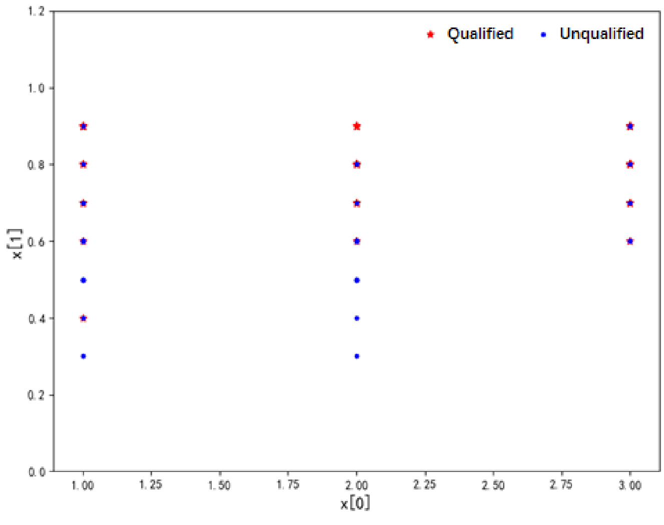

Fig. 5 2D feature space of the original factors sample

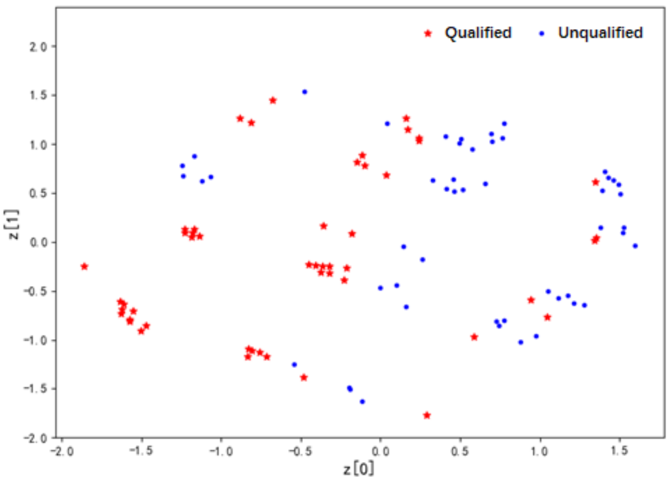

Fig. 6 2D feature space of the principal component after dimensionality reduction

3.3 Data analysis conclusion

From the correlation coefficients between each original affecting factor and the qualified production results presented in Fig. 3, as well as the correlation coefficients between the principal component after dimensionality reduction and the original factors detailed in Table 3, it can be observed that the rationality of measurement methods, the rationality of test point design, tool wear, equipment normalization rate, the degree of equipment aging, the rationality of program design, the degree of material defects, the rationality of process route design, the rationality of tooling design, the technical level of personnel, the level of personnel experience, the personnel work status, and operational standardization have a significant impact on production quality. The main features of the influence degree, in descending order of magnitude, are z_6, z_2, z_5, z_3, z_4, and z_1.

The sixth feature, z_6, pertains to the rationality of measurement methods and the rationality of test point design. To minimize the potential for error in on-site measurement results, it is recommended that standard automated measurement methods be employed wherever feasible.

The second feature, z_2, is associated with tool wear, equipment normalization rate, and the degree of equipment aging. It is recommended that regular maintenance of processing tools and equipment be conducted to ensure normalization of said tools and equipment.

The fifth feature, Z_5, pertains to the rationality of program design. It is imperative to reinforce training and review of the program design.

The third feature, Z_3, is associated with the degree of material defects and thus requires comprehensive examination through rigorous testing.

The fourth feature, Z_4, is associated with the rationality of process route design and the rationality of tooling design. It is of the utmost importance to reinforce the process route design and tooling design optimization, and these are subjected to the closest scrutiny by experts.

The first feature, z_1, pertains to the technical level of personnel, the level of personnel experience, the personnel work status, and operational standardization. It is of the utmost importance to reinforce the training and examinations of personnel.

4. Conclusion

This paper addresses the issue of identifying the main factors affecting the production quality of aerospace products. It begins by providing a comprehensive analysis of the characteristics of aerospace product production and the various types of quality-affecting factors. Secondly, the isometric feature mapping (ISOMAP) algorithm of stream learning is used to reduce the dimensionality of nonlinear data. Finally, the correlation coefficients between each principal component after dimensionality reduction and the original factors are calculated to elucidate their correspondence, and the main factors are ranked according to the degree of influence. The process can identify the factors that have the greatest impact on the quality of aerospace product production, mainly those related to inspection methods, the condition of equipment, etc. Therefore, to ensure that the quality of aerospace product production is improved, it is recommended that standard automated measurement methods be used wherever feasible. In addition, it is recommended that regular maintenance of machining tools and equipment be enhanced to ensure that they are in good condition. The proposed changes will enable the targeted use of costs to significantly improve the quality of aerospace product production and achieve cost savings. The experimental results certify the capability of the algorithm in analyzing the main factors affecting the production quality of aerospace products, eliminating redundant factor interference, highlighting the main affecting features, and obtaining the inner law of the data, with the limitation that the algorithm is only applicable to the scenarios of analysing the production quality of all kinds of aerospace products with small samples. On the basis of this study, further research and practice on online classification and prediction of aerospace product production quality will be carried out in the future.

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