Global Journal of Arts Humanity and Social Sciences ISSN: 2583-2034

Glob. J.Arts.Humanit.Soc.Sci
ISSN: 2583-2034
Vol-2 Iss-12, page 865-875

Analysis of multivariate measurement system based on KPCA method

BY

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Article History
Received: 09/11/2022
Accepted: 03/12/2022
Published: 05/12/2022

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Abstract
Measurement system analysis is an important content of statistical quality improvement. In multivariate measurement system analysis, most researchers ignore the impact of variation caused by environmental factors on the whole measurement system. However, in the actual production process, environmental factors are not constant, and some changes always occur. In this paper, Kernel Principal Component Analysis(KPCA) based multivariate measurement system analysis, combined with dimensional analysis of nonlinear environmental factor data to raise dimension first and then reduce dimension, multivariate variables reduced to one or two variables, using variance analysis to evaluate the capacity of the measurement system. Finally, this paper uses the data of a food manufacturing company in the production of milk tea companion solid beverage to evaluate the capability of the multivariate measurement system and verify the effectiveness of the method.

Keywords: Measurement system analysis; Environmental factors; Kernel Principal Component Analysis (KPCA); Dimensional analysis

1. Introduction

At present, with the rapid development of science and technology, the requirements for manufacturing industry are also gradually improving. The quality requirements for products are an important standard for China's manufacturing industry to meet and catch up with the world. Measurement is one of the important ways to test product quality. The measurement system is a collection of instruments or measuring tools, standards, operations, methods, fixtures, software, personnel, environment, and assumptions used to quantitatively measure or qualitatively evaluate the characteristics under test [1]. The measurement system is divided into counting type measurement system and measurement type measurement system.

The measurement system can be divided into unitary measurement system and multivariate measurement system by distinguishing the evaluation objects. Compared with multivariate measurement system, the research on unitary measurement system has been relatively mature, and many scholars have deeply studied the repeatability and reproducibility methods. Scholars' research on multivariate measurement system analysis mainly focuses on dimensionality reduction. Wang and Yang [2] used Principal Component Analysis to decompose multiple related variables into a single variable for analysis and comparison. He [3] et al. proposed an online multivariate measurement system capability evaluation method for a multi-site parallel measurement system on a production line so that there would be no interruption before identifying the faulty instrument in the production process. The improved Principal Component Analysis (PCA) method was used to convert the high-dimensional measurement data into multivariate measurement data with independent principal components. It provides a certain supplement for the PCA method in the multi-system complex environment. Peruchi et al. [4] believe that the Principal Component Analysis method should consider the proportion of each principal component when multiple principal components coexist. On this basis, the Weighted Principal Components is proposed. Another part of scholars applied dimension enhancement method to expand one-dimensional variables to multi-dimension for comparison, for example, MANOVA was applied to multiple variables [5]. Shi Liangxing [6] et al. implemented a case study of multivariate analysis of variance in chip specifications and its vision measurement system. Projection pursuit method is a statistical method to deal with high-dimensional complex problems of multivariate variables. Its basic idea is to project high-dimensional data to low-dimensional space (1-3 dimensions), and study the characteristics of high-dimensional data by fitting the structure of low-dimensional projection direction [7]. With the help of iterative operation of intelligent group decision algorithm, Wu (2013) et al. [8] extracted the projection length of each dimension from the measurement data matrix, fitted the unary new projection data matrix from the multivariate data matrix, and evaluated the capability state of the measurement system with unary ANOVA.

To sum up, for the study of multi-measurement system, most scholars have focused on analysing the measuring equipment, measuring technology and measuring procedure of the measuring system in the analysis of the measuring equipment, measuring technology and measuring procedure of the measuring system, and the analysis of the variation of the environmental factors of the whole measurement system is analysed, which is the focus of this paper.

The aim of this study is to analyse and improve the multivariate measurement system with the participation of environmental factors. Environmental factors are a nonlinear multivariate, using Kernel Principal Component Analysis to data dimension reduction processing, using Kernel Principal Component Analysis and dimensional unified concept, with environmental factors cause variation of multivariate measurement system is analysed, and through a case study using this method and traditional method were analysed.

2. The basis of multivariate measurement system analysis model based on KPCA method

2.1. Kernel Principal Component Analysis principle

In the real world, not all data are linearly separable, and many data are nonlinear data, such as arrays, generalized tables, bifurcated trees and graph data, etc., which cannot be directly analysed by linear classification. However, these data can be mapped in the data space of higher latitude by the method of projection, and the sample data can still maintain the opposition of data in the high-dimensional space so that these data can be linearly distinguished in the high-dimensional space. This data processing method has been proved by researchers. As shown in Figure 2.1, the difference between linear data and nonlinear data lies in whether the data can be segmented in a linear way.

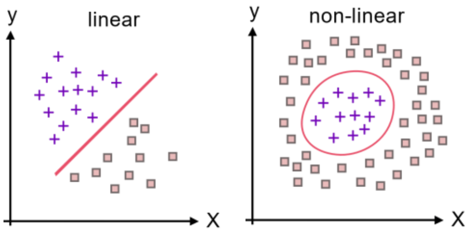

Figure 2.1 Comparison of linear data and nonlinear data

Principal Component Analysis is a traditional method to map to higher dimensional space. This method can only deal with linear data, but it cannot be used for nonlinear data sets. Therefore, in order to make up for the lack of Principal Component Analysis in dealing with nonlinear data sets, researchers proposed kernel PCA, which can project and classify nonlinear data in high-dimensional space, and deal with nonlinear data sets well.

Kernel Principal Component Analysis (KPCA) is the shortcoming of principal component analysis (PCA) which cannot deal with nonlinear data. KPCA maps the nonlinear data to the feature space of higher dimension in a nonlinear way and then projects the feature space to the lower space where the principal components are located. The data in this dimension space will become linearly separable and uncorrelated. The basic principles of Kernel Principal Component Analysis (KPCA) are as follows:

Suppose that a certain data set is collected under normal working conditions, which belongs to the whole sample space, the data set $x_j \in R^{1\times n}, j = 1,\ldots,M$, where M represents the size of the number of samples in the data set, and N is the number of variables.

The nonlinearity is mapped to $\phi : x_j \in R^M \to \phi_j = \phi\left(x_j\right) \in R^f$.

The variance matrix in the higher dimensional space is:

$$C = \frac{1}{M}\sum_{j=1}^{M}\phi\left(x_j\right)\phi^T\left(x_j\right) \qquad (2.1)$$

Where $\phi\left(x_j\right)$ is the *jth* sample with mean 0 and variance 1 in the high-dimensional space, the solution formula for its eigenvalues and eigenvectors is:

$$\lambda_k v_k = C v_k \qquad (2.2)$$

Where $\lambda_k \in R$ and $v_k \in R^{1\times M}$ are the *kth* eigenvalue and eigenvector respectively, the eigenspace existence coefficient has the following form:

$$v_k = \sum_{i=1}^{M}\alpha_k^i\phi\left(x_i\right) \qquad (2.3)$$

Among them, A is $\alpha_k^i \in R, i = 1,\ldots,M$. However, it is very difficult to solve the product of two vectors in high-dimensional space. In most cases, it cannot be solved directly as in low dimensional space. Therefore, the Gram matrix $K \in R^{M\times M}$ needs to be constructed. The formula is as follows:

$$\left[K\right]_{ij} = \left\{\phi\left(x_i\right), \phi\left(x_j\right)\right\} = k\left(x_i, x_j\right), i, j = 1, 2, \ldots, M \qquad (2.4)$$

Because of this important feature change, the vector inner product of the feature space is obtained by introducing kernel function $k\left(x, y\right) = \left[\phi\left(x\right), \phi\left(x\right)\right]$ into the input feature. By solving the eigenvalues and eigenvectors of matrix K, the eigenvectors and eigenvalues of high-dimensional spatial data can be obtained.

Kernel Principal Component Analysis (KPCA) still needs to divide principal component space and residual space and construct corresponding statistics to realize data processing. Assuming that the number of pivot entries is l, the pivot vector and residual vector after partition are respectively:

$$\begin{cases} P = \left[\dfrac{1}{\lambda_1} x^T \alpha_1, \ldots, \dfrac{1}{\lambda_l} x^T \alpha_l \right] \\ P = \left[\dfrac{1}{\lambda_{l+1}} x^T \alpha_{l+1}, \ldots, \dfrac{1}{\lambda_n} x^T \alpha_n \right] \end{cases} \quad (2.5)$$

After space partition, the calculation formula of principal component and residual score is

$$\begin{cases} t = p_f^T \phi(x) = \Lambda^{-\frac{1}{2}} p^T k(x) \\ \tilde{t} = p_f^T \phi(x) \end{cases} \quad (2.6)$$

Where, the calculation method of $k(x)$ is

$$k(x) = \left[k(x_1, x), k(x_2, x), \cdots, k(x_n, x) \right]^T \quad (2.7)$$

2.2. Dimensional

Dimension refers to the basic properties of a physical quantity. The study of physics can quantitatively describe all kinds of physical phenomena. There is a close relationship between all kinds of physical quantities used in the description, that is, there is a definite functional relationship between them. In order to accurately describe these relations, physical quantities can be divided into fundamental quantities and derived quantities. Fundamental quantities are physical quantities with independent dimensions, and derived quantities refer to physical quantities whose dimensions can be expressed as a combination of fundamental quantities and dimensions. All the derived quantities can be derived from the basic quantities, thus establishing the functional relationship between the whole physical quantities. This functional relationship is often referred to as the system of quantities.

Dimensional analysis, also known as dimensional analysis, is a mathematical analysis method. Through dimensional analysis, the relationship between variables can be correctly analysed, and the test and results can be simplified. Therefore, dimensional analysis is a powerful tool for us to analyse fluid motion. Dimensional analysis is an important research method in natural science, which analyses and judges the general law of the quantitative relationship between things according to the form that all quantities must have. Dimensional analysis can be used to check whether the equations reflecting the laws of physical phenomena are correct in terms of measurement, and even provide clues to find some laws of physical phenomena.

The existence of relations between physical quantities shows that their structure must consist of a number of uniform basic components and that the quantities differ according to their abundance, just as all things are composed of only a hundred chemical elements. In the SI system of units, there are seven basic dimensions, which are length, mass, time, current, thermodynamic temperature, amount of matter, and luminescence intensity, and the remaining dimensions can be derived from two or more basic dimensions.

The basic principle of dimensional analysis is the Theorem of π, that is, all complete relations can be dimensionless. The derivation process is as follows:

Suppose the following relationship exists between the relevant parameters $x, x_1, \ldots, x_k, \ldots, x_n$ of a physical phenomenon:

$$f\left(x, x_1, \ldots, x_k, \ldots, x_n\right) = 0 \quad (2.8)$$

If k parameters $x_1, x_2, \ldots, x_k$ out of N parameters in Equation 2.8 above are dimensionally independent, the above equation 2.8 can be converted to:

$$f\left(1, 1, \ldots, 1, x_1, x_2, \ldots, x_{n-k}\right) = x \quad (2.9)$$

Where $x_1, x_2, \ldots, x_{n-k}$ is dimensionless parameter composed of k dimensionally independent parameters in $x_1, x_2, \ldots, x_n$. Dimensional independence means that the dimensional form of any one of the quantities cannot be formed by the power products of the dimensional forms of the remaining quantities.

These two formulas are both descriptions of a physical system, one is from the perspective of physical variables, the other is from the perspective of dimensionless variables, the meaning of this transformation is actually to play a role in reducing dimension.

3. Multivariate measurement system analysis of improved KPCA method

3.1. Construction of analysis model of improved KPCA method measurement system

Most current dimension reduction type multiple measurement system analysis method will default to the measuring system environment is the same, that is to say, regardless of environmental factors, but the environment is always part of the change in the process of manufacturing production, some products are greatly influenced by environmental change cannot be ignored environmental changes caused by the variation. The multivariate measurement model of complex products is shown in Figure 3.1.

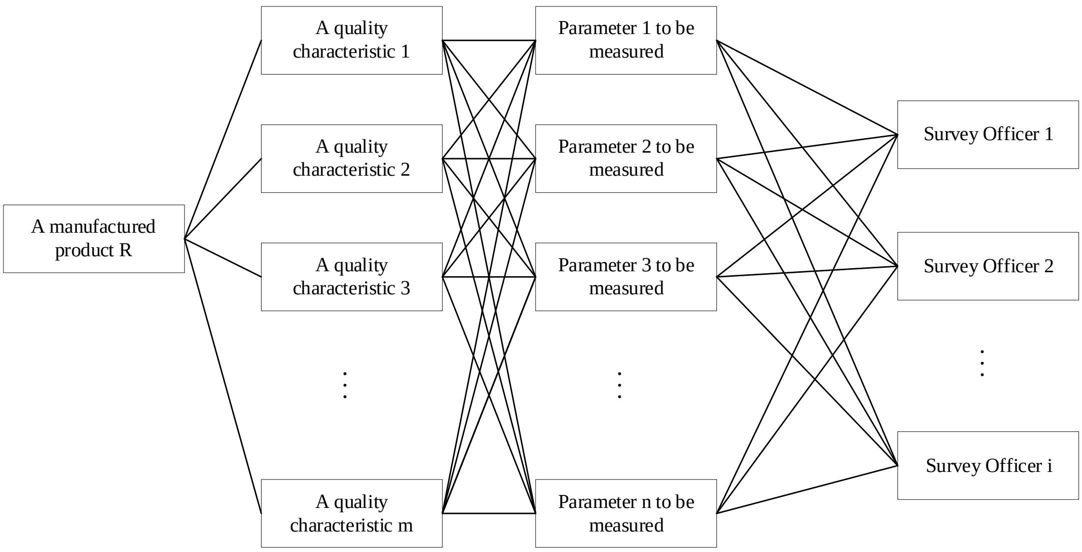

FIG. 3.1 Multivariate measurement model

In the analysis of multivariate measurement system, the main factors considered by most researchers are multivariate quality characteristics, parameters to be measured, and measurement personnel. In this paper, environmental factors are added. In this paper, the Kernel Principal Component Analysis (KPCA) is used to process the data, and the nonlinear environmental data is firstly increased and then reduced so that the nonlinear data can be better processed. KPCA algorithm uses statistics and SPE statistics to calculate the principal space and residual space. Formula follows：

$$T^2 = t^T \Lambda^{-1} t = k^T(x) D k(x) \qquad (3.1)$$

$$D = p \Lambda^{-2} p^T \qquad (3.2)$$

Similar to principal component analysis (PCA), the SPE statistic of KPCA is calculated as follows：

$$SPE = \tilde{t}^T \tilde{t} = k(x,x) - k^T(x) C k(x) \qquad (3.3)$$

In the calculation of KPCA algorithm statistical threshold, the confidence level is generally set as 99%, and the calculation formula of SPE statistical threshold is shown in Equation 3.4, Including $g = b/2a, h = 2a^2/b$. The calculation formula of the threshold of statistic T^2 is shown in Equation 3.5. Where $F_\alpha(l, n-l)$ is the fractional site of F distribution with l and $n-l$ degrees of freedom

$$SPE_{\lim} \sim g\chi_h^2 \qquad (3.4)$$

$$T_{\lim}^2 = \frac{l(n-1)(n+1)}{n(n-l)} F_\alpha(l, n-l) \qquad (3.5)$$

The multivariate measurement system can be approximated as a univariate measurement system after dimensionality reduction by KPCA method, so the analysis of variance can be used to analyse the measurement system. The general ANOVA model is

$$M = Q + G \qquad (3.6)$$

Among them, M is the measurement value of randomly selected components in the manufacturing process, Q is the unknown true value of the sample under test, and G is the measurement error of the measurement system, where Q and G are normal random variables. On this basis, a two-way analysis of variance model with interaction effect was adopted. Its linear statistical model is:

$$M_{ijk} = \mu + P_i + O_j + (PO)_{ij} + E_{ijk} \qquad (3.7)$$

Among the rest $i = 1, 2, ..., p; j = 1, 2, ..., o; k = 1, 2, ..., r$; P_i represents the measurement variation fluctuation caused by the *ith* component to be tested; O_j represents the measurement variation fluctuation caused by the *jth* operator; E_{ijk} represents the random variation generated when the same operator performs the measurement operation on the same part to be tested; $(PO)_{ij}$ represents the interaction between the component under test and the operator, μ is constant in the expression.

Anova table for typical measurement system analysis:

Table 3.1 Variance Analysis Table

Wave source	Sum of squares	Degree of freedom	Mean square	Expected mean square

Parts(p)	SS_p	n_p	MS_P^2	$\theta_P = \sigma_E^2 + r\sigma_{PO}^2 + op\sigma_P^2$
Handlers(o)	SS_o	n_o	MS_O^2	$\theta_O = \sigma_E^2 + r\sigma_{PO}^2 + pr\sigma_O^2$
Interaction（$p \times$ o）	SS_{po}	n_{po}	MS_{PO}^2	$\theta_{PO} = \sigma_E^2 + r\sigma_{PO}^2$
Error term(E)	SS_E	n_E	MS_E^2	$\theta_E = \sigma_E^2$

３.2. Evaluation of analytical ability of multivariate measurement system with improved KPCA method

The acceptability of the measuring system refers to the degree that the measuring system meets the demand of production accuracy. The acceptability of measurement system is higher when the degree of change is smaller. Repeatability, percentage of reproducibility (%R&R) and signal-to-noise ratio (SNR) are the main quantitative indicators reflecting the acceptability of a measurement system in the field of multivariate measurement system analysis and research.

Repeatability refers to the same operator using the same measuring equipment for the same measuring part. The characteristic of the error between results carried out many times in a short time interval is that it is manifested under repeatability conditions

Random error in continuous measurement. Reproducibility is the variation among evaluators, which refers to the error reproducibility of the average value of the same measurement object measured by different evaluators using the same measuring equipment. Combined measurements with repeatability and reproducibility are combined estimates. The calculation rule is the ratio of the standard deviation of the measurement error to the standard deviation of the measured value, and the calculation formula is as follows:

$$\%R\&R = \left(\frac{\sigma_E}{\sigma_M}\right) \times 100\% \qquad (3.8)$$

Specific evaluation criteria are shown in Table 3.2:

To measure the capability of a measurement system, you can also evaluate the exponential signal-to-noise ratio (SNR). It is expressed as the ratio of its standard deviation to the correlation linear function of the measurement, that is, the standard deviation of the error

$$SNR = \sqrt{2}\left(\frac{\sigma_T}{\sigma_E}\right) \qquad (3.9)$$

Table 3.2 Criteria for the percentage of repeatability and reproducibility

The value of %R&R	Corresponding judging criteria
$0 < \%R\&R < 10\%$	The measuring system is sufficiently capable and the measuring system is good
$10\% \le \%R\&R \le 30\%$	The ability of the measuring system is good, which should be judged according to the comprehensive factors
$\%R\&R > 30\%$	Measurement system capacity is insufficient, measurement system needs to be improved

Specific evaluation criteria are shown in Table 3.3.

Table 3.3 Signal-to-noise ratio evaluation criteria

The value of SNR	Corresponding judging criteria
$SNR \ge 5$	The measuring system is sufficiently capable and the measuring system is good
$2 \le SNR < 5$	The ability of the measuring system is good, which should be judged according to the comprehensive factors
$SNR < 2$	Measurement system capacity is insufficient, measurement system needs to be improved

4. Case Study

4.1. Basic parameters and measurement sample data

The data used in this paper are the measurement data of a food manufacturing company in the production of milk tea companion solid drink. The main experimental equipment of the measuring system is Mettler's moisture measuring instrument, model XY100MW, measuring range 0~110g, the sensor is strain type sensor, the diameter of the scale pan is 90mm, and the readability is 1mg. The operating temperature range is from 5℃ to 35℃, the heating mode is halogen lamp, and the temperature sensor is PT-100-2. The temperature azimuth is 40℃~199℃, the temperature interval is 1℃, the moisture measurement range is 0.00%~100.00%, and the moisture readability accuracy is 0.01%.

There are three kinds of quality characteristics in this measurement system :(1) the moisture content of the product x_1, the upper and lower limits are set as (0,4.0); (2) Density x_2, the upper and lower limits are set as (0.40,0.45); (3) solubility x_3, which is basically set as the dissolution rate of 10 grams of product in water (s, s), and the upper and lower limits are set as (0,20). Since the product is a solid beverage, the impact of environmental factors such as temperature and humidity on the measurement system error should be considered in the measurement.

In the analysis experiment of the whole multivariate measurement system, three surveyors were used to measure 10 samples for three times under five groups of different temperatures and humidity, namely $P=10, O=3, R=3$. In the analysis experiment of the whole measurement system, some measurement data are shown in Table 4.1.

Table 4.1 Sample measurement data

Number of levels		Part Number	Water /%	Density g/ml	Rapid lysis /s	Temperature /℃	Humidity /%rh
			x1	*x2*	*x3*	*T*	*Q*
1	A1		3.36	0.45	20		
2	B1		3.35	0.44	19		
3	C1		3.32	0.45	19		
4	A2		3.34	0.43	20		
5	B2	1	3.35	0.45	19	28	72
6	C2		3.36	0.44	19		
7	A3		3.37	0.45	17		
8	B3		3.33	0.43	19		
9	C3		3.34	0.43	18		
10	A1		3.31	0.41	19		
11	B1		3.32	0.40	19		
12	C1		3.31	0.42	18		
13	A2		3.33	0.40	17		
14	B2	1	3.31	0.39	18	32	67
15	C2		3.33	0.41	16		
16	A3		3.34	0.42	18		
17	B3		3.32	0.42	18		
18	C3		3.31	0.40	17		
19	A1		3.10	0.40	18		
20	B1		3.19	0.41	17		
21	C1		3.12	0.39	18		
22	A2		3.11	0.41	17		
23	B2	1	3.13	0.40	18	34	61
24	C2		3.18	0.38	17		
25	A3		3.19	0.41	17		
26	B3		3.10	0.39	18		
27	C3		3.18	0.40	17		
28	A1		2.90	0.42	18		
29	B1	1	2.99	0.42	17	35	59
30	C1		2.92	0.42	18		

31	A2		2.91	0.44	16		
32	B2		2.93	0.42	18		
33	C2		2.98	0.42	17		
34	A3		2.99	0.44	18		
35	B3		2.90	0.44	18		
36	C3		2.98	0.43	17		
37	A1		2.80	0.42	16		
38	B1		2.79	0.42	17		
39	C1		2.82	0.42	15		
40	A2		2.81	0.44	16		
41	B2	1	2.83	0.42	17	36	54
42	C2		2.78	0.42	16		
43	A3		2.79	0.44	17		
44	B3		2.80	0.44	16		
45	C3		2.78	0.43	17		

4.2 Result analysis

4.2.1 Results of this model experiment

(1) Firstly, kernel principal component analysis was used to reduce the dimensionality of the data. There were 3*3*10*5=450 groups of data in the sample data. Due to the large amount of data, this paper used MATLAB to write programs to solve the Kernel Principal Component Analysis (KPCA). The program is shown in Figure 4.1.

The principal component space and residual space of the sample data set are calculated by MATLAB program. The statistics of principal component space and residual space and SPE statistics are calculated by using Equations 3.1 and 3.3. The distribution value is set to 99% at the confidence level, so as to get the contribution rate. The contribution rate of moisture *X1*, density *X2*, solubility, temperature *T*, and humidity *Q* was 67.31%, 73.26%, 57.49%, 38.64%, and 42.16%, respectively. The contribution rates of temperature and humidity are both lower than 50%, so the dimension reduction can be processed into the other three features. The multiple quality characteristics of the product have been reduced from five dimensions to three, and the data volume has been reduced to 90 sets of data.

(2) The newly obtained 90 groups of data were re-projected and assigned, and ANOVA analysis was conducted on these data as shown in Table 4.2 to calculate the capability evaluation index of the multivariate measurement system.

$$\%R\&R = \left(\frac{\sigma_E}{\sigma_M}\right) \times 100\% = 24.13\% \qquad (4.1)$$

$$SNR = \sqrt{2}\left(\frac{\sigma_T}{\sigma_E}\right) = 5.13 \qquad (4.2)$$

From the two indexes, it can be concluded that the repeatability, reproducibility, and signal-to-noise ratio indicate that the measurement system is acceptable and the measurement system has good capability.

Table 4.2 ANOVA analysis Table

Wave source	Sum of squares	Degree of freedom	Mean square
Parts(*p*)	1.093311	9	0.121479
Handlers(*o*)	0.002446	2	0.001223
Interaction（$p \times$ o）	0.002934	18	0.000163
Error term(*E*)	0.072120	60	0.001202

```
%%Read Data
fil ename="raw data acquisition.xlsx ';
 [ adata2 01, bdat a201 ,cdat a2el]=xlsread(filename ) ;
Xmat=adata201( :,1 : end-1);
 Ymat=adata201( :,end);
%%Set KPCA parameters
K2=5;%Number of core principal components
rbf_var=600;%Nuclear parameter selection
[train_kpc a,test_kpca,train_eigval ,eval200,ev ectors_1,evaltures_1,indexsort ,threshold,evals,ev als_p]=KPCAfun2 02(Xmat , Xmat,K2 ,rbf_var );
evals
%%output data
K1=size(train_kpc a,2) ;
outcel 1201=cell( 1,K1+2) ;
outcell201{1,1}='serial number';
outcell201{1 , end}='y '  ;
for i=1 :K1
 outcell201{1,i+1}=[ 'F' ,num2str(i)];
     end
outcell-[ outcell2 01;
num2cell([(1 : size( Ymat,1 )) ,train_kpca , Ymat ])]
xlswrite('Output the KPCA dimensionality reduction result.xlsx ' , outcell);
```

Figure 4.1 Kernel Principal Component Analysis algorithm program

4.2.2 Results of traditional methods

In this paper, the Principal Component Analysis method (PCA) was used for secondary analysis of the sample data. Since PCA could not analyze nonlinear data, it did not consider the influence of environmental factors such as temperature and humidity on the whole measuring system. Therefore, 90 groups of data at 28℃ and 72% RH were taken as samples.

The basic steps of PCA are as follows:

(1) Centralize all samples;
(2) Calculate the sample covariance matrix;
(3) Eigenvalue decomposition of covariance matrix;
(4) Take out the eigenvector corresponding to each eigenvalue of the largest *N*;
(5) Standardize the eigenvectors to get the eigenvector matrix;
(6) Transform each sample in the sample set;
(7) Get the output matrix.

After dimensionality reduction by PCA method, a new sample dataset is obtained, and then ANOVA analysis is carried out on the sample dataset as shown in Table 4.3 to calculate the capability evaluation index of the multivariate measurement system.

Table 4.3 PCA ANOVA analysis table

Wave source	Sum of squares	Degree of freedom	Mean square
Parts(p)	1.084312	9	0.120479
Handlers(o)	0.003513	2	0.001757
Interaction（$p\times o$）	0.003142	18	0.000175
Error term(E)	0.083071	60	0.0013852

$$\%R\&R=\left(\frac{\sigma_E}{\sigma_M}\right)\times100\%=26.03\% \qquad (4.3)$$

$$SNR=\sqrt{2}\left(\frac{\sigma_T}{\sigma_E}\right)=4.72 \qquad (4.4)$$

4.2.3.Comparison and analysis of results

As can be seen from the above, the repeatability and reproducibility data in the evaluation indexes of the improved KPCA method used in this paper indicate that the measurement system is acceptable, and the measurement system capability should be determined according to comprehensive factors. SNR indicates that the measurement system is acceptable and the measurement system has good capability. The repeatability and reproducibility data and signal-to-noise ratio (SNR) in the evaluation index of multivariate measurement system of PCA method are all acceptable, and the measurement system capability should be determined according to the comprehensive factors.

Table 4.4 contrastive analysis

	PCA method	Improved KPCA method	Rising yields	Relative increase
$\%R\&R$	26.03%	19.24%	-6.79%	-26.09%
SNR	4.72	5.13	0.41	8.69%

It can be seen from Table 4.4 that in the evaluation index of multivariate measurement system, the improved kernel principal component analysis method used in this paper reduces the repeatability and reproducibility of measuring tools by 6.79% and 26.09% relative to the traditional principal component analysis method, but both of them are within the range of 10%~30%. This still means that the capability of the measurement system should be determined according to comprehensive factors, as shown in Figure 4.2. The signal-to-noise ratio (SNR) was increased by 0.41, with a relative increase of 8.69%. The principal component analysis method indicated that the capability of the measurement system should be determined according to comprehensive factors, while the improved kernel principal component analysis method used in this paper indicated that the capability of the measurement system was good, as shown in Figure 4.3. The analysis results show that compared with the traditional principal component analysis method, the improved kernel principal component analysis method adopted in this paper decreases the repeatability and reproducibility of measuring tools, and increases the signal-to-noise ratio, which indicates that the improved kernel principal component analysis method has a good analysis effect on the multivariate measurement system involving environmental factors.

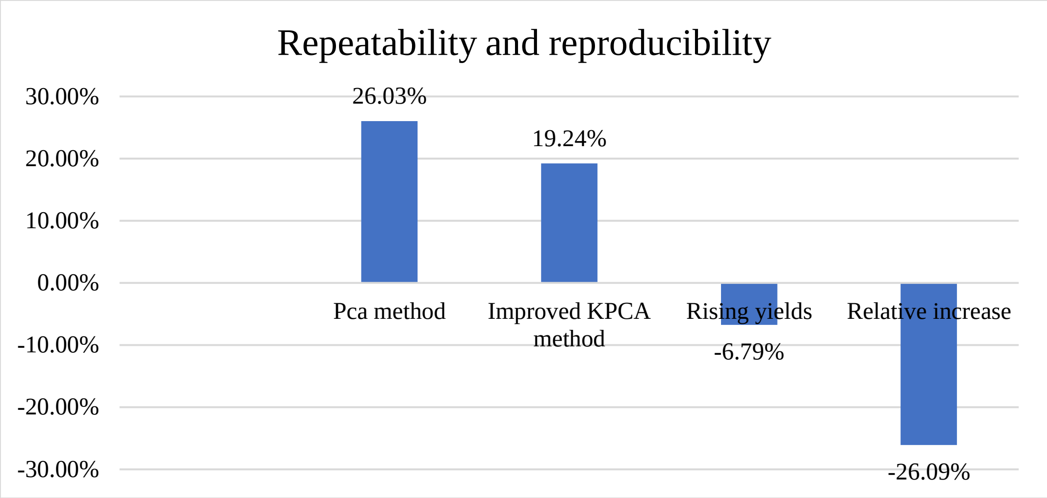

FIG. 4.2 Bar chart comparing repeatability and reproducibility

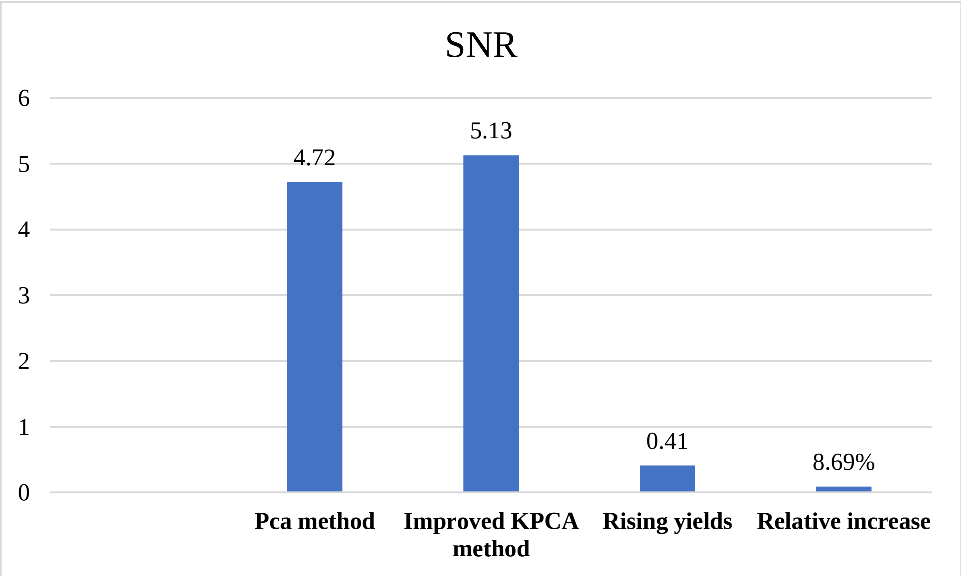

FIG. 4.3 Bar chart of signal-to-noise ratio comparative analysis

5. Conclusion

This paper studies the capability evaluation of the multivariate quality characteristics measurement system with the participation of environmental factors and uses the kernel principal component analysis and dimensional analysis to achieve the practical application of the capability evaluation. Finally, through the measurement data of the food manufacturing company in the production of milk tea companion solid beverage, the multivariate measurement system is analysed and applied. To demonstrate and test the effectiveness of the multivariate measurement system analysis ability evaluation method based on KPCA method. From this article, the research process and case application of research results, the kernel principal component analysis (KPCA) with the environmental factors involved in multiple measurement system evaluation has great advantages, through the KPCA method to nonlinear mapped to high-dimensional space environment data dimension reduction processing again, will be reduced to less variable, multiple variables to measure ability evaluation.

This article USES the improved KPCA method considering the environmental factors in the multivariate measurement system for temperature and humidity, but environmental factors not only two variables, temperature, and humidity, there are other variables involved in the whole measurement system, this paper did not discuss other environment variables influence on the whole measurement system analysis, it is of this article is insufficient, will be improved in the future.

Acknowledgment

The authors gratefully acknowledge the support of Liaoning Province Education Department Project (Grant NO. J2020049). The authors would like to thank the editor and reviewers for their constructive suggestions of the paper.

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