Abnormal Judgment of Blade Machining Process Based on SVDD

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Abstract. Aiming at the problem of stability monitoring of blade processing, this paper proposes a method to judge the stability of blade machining process. The measured point deviation of the blade pattern can represent the processing quality of the blade. Firstly, the dimension of the normalized deviation is reduced by the kernel principal component analysis, and appropriate kernel functions and parameters can be determined. Eigenvectors of samples are trained by support vector data description, and the parameters of model are determined with false alarm rate. In addition, the radius of hyperspheres are calculated to obtain control limits. The example data is applied to verify the feasibility of the method. The experimental results show that abnormal fluctuation of blade machining process can be effectively detected by the method.

Key words: Stability Monitoring; Deviation; Kernel Principal Component Analysis; Support Vector Data Description; Abnormal Judgment.

1. Introduction

The Blades belong to precision parts and its quality determination is critical to the safe operation of the blade. Quality is the degree to which a set of inherent characteristics meets the requirements. The blade machining quality can be judged by the difference between the measured blade pattern and the theoretical blade pattern. At present, the coordinate data of the blade pattern is often measured by the three-coordinate, and the quality indicators of the blade pattern are calculated by relevant algorithm such as thickness, chord length, deviation, etc. During blade processing, the blade quality characteristics fluctuate due to changes in the 5M1E factor. When some factors are abnormal, the quality characteristic value fluctuates abnormally. The blades are automatically processed in the machining center at present, and automatic processing has the characteristics of fast processing rhythm and large production inertia. Once the quality fluctuation occurs in the production process, it may lead to batch rework or scrap [1]. Therefore it is important to quickly and accurately identify abnormal fluctuation in the steady-state control of the blade machining process.

The statistical process control theory proposed by Shewhart is an important tool for quality process control. The Control charts used in the actual production process are usually based on assumptions that the process or product quality can be adequately described by a single quality characteristic distribution. And the multivariate control chart proposed by many scholars is also based on the distribution of relevant
mass characteristics obeying the multivariate statistical distribution [2]. There is a complex correlation between thickness, chord length, contour and other quality indicators calculated from the coordinate data of blade pattern. Document 3 and Document 4 do not consider the correlation of quality indicators and use the MEWM control chart to detect the process exceptions caused by the error deviation assuming that thickness chord length of blade pattern obeying the normal distribution [3,4]. The essence of the control chart is a classification method, so the classification algorithm of machine learning can also be used to distinguish between a controlled process and the process out of control, such as decision trees [5,6], neural networks [7,8]. In order to monitor the stability of the blade machining process, the process monitoring can be constructed based on the classification method of machine learning to distinguish between a controlled process and the process out of control. However, the classification method of decision tree and neural network requires a large number of controlled and out-of-control samples, and the ration of samples has a great influence on the training accuracy. And it is difficult to collect out-of-control samples in the actual machining process, which limits the application of classification algorithm to the processing stability judgment in the process.

Aiming at the above problems, this paper proposes a method for judging the stability of blade machining process based on support vector data description. Due to the machining quality indicators difference of blade pattern and the deviations of measured points of blade pattern have a certain complex function relationship. After the reference of the measured data and the theoretical blade pattern are unified, the deviation vector of measured blade pattern is calculated. Then the dimensionality reduction of the deviation vector is carried out by the kernel principal component analysis, and the dimension vector after dimension reduction is used as the input of the support vector data description so as to judge the stability of the blade machining process. The performance analysis and verification of the method are carried out by using the simulation data.

2. Kernel principal component analysis
The characteristics of the kernel method make it a popular method to deal with nonlinear problems. The kernel method has been applied in various data mining fields, such as support vector machine and kernel principal component analysis [9]. Principal component analysis (PCA) algorithm is a simple method about the linear dimensionality reduction, which can cancel linear relationship well, but it is not suitable for high-order correlation, so kernel principal component analysis (KPCA) is used as nonlinear extension of PCA algorithm, which can effectively mine the nonlinear relationship in the data set.

The basic principle of KPCA is that firstly the nonlinear mapping maps original data to the high-dimensional feature space, and then feature extraction and dimensionality reduction are completed in the high-dimensional feature space by PCA. However, since nonlinear mapping is not easy to obtain, a kernel function is usually used to perform the nonlinear mapping from the input space to the feature space. Commonly used kernel function is an arbitrary symmetric function that satisfies the Mercer condition (Positive Definite Function) [10]:

(1) Gaussian kernel.

\[
k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)
\]

Where \(\sigma\) is a parameter.

(2) Polynomial kernel.

\[
k(x_i, x_j) = (b \ast s(x_i, x_j) + c)^d
\]

Where \(b, c, d\) are parameters,

\[
s(x_i, x_j) = x_i^T x_j
\]

(3) Sigmoid kernel.
\[
\begin{align*}
k(x_i, x_j) &= \tanh(e \ast s(x_i, x_j) + f) \\
\end{align*}
\]  
\(3\)

Where \(e, f\) are parameters and \(s(x_i, x_j) = x_i^T x_j\)

The kernel principal component analysis algorithm steps are as follows [11].

Step1. The number of training sample \(X\) is \(m\). Calculate the kernel matrix \(K\) of the training sample \(X\).

\[
K_{ij} = k(x_i, x_j)
\]  
\(4\)

Step2. Centralize the kernel matrix.

\[
\tilde{K} = K - AK - KA + AKA, A_j = 1/m
\]  
\(5\)

Step3. Eigenvalue decomposition for matrix \(\tilde{K}\) is completed to obtain the eigenvalues \(\lambda_1, \ldots, \lambda_n\) and its corresponding eigenvector \(\nu_1, \ldots, \nu_n\).

Step4. The eigenvalues \(\lambda_1, \ldots, \lambda_n\) are sorted in descending order to get \(\hat{\lambda}_1, \ldots, \hat{\lambda}_n\) and the corresponding adjusted eigenvector \(\hat{\nu}_1, \ldots, \hat{\nu}_n\).

Step5. Unit orthogonalized eigenvector and get \(\alpha_1, \ldots, \alpha_n\).

Step6. Calculate the cumulative contribution rate of eigenvalues \(L_1, \ldots, L_n\). According to the given contribution degree \(p\), if \(L_i \geq p\), then extract principal component \(\alpha_1, \ldots, \alpha_i\).

Step7. Calculate the feature of training sample \(X\).

\[
Y = \hat{K} [\alpha_1, \ldots, \alpha_t]
\]  
\(6\)

For new test data \(x_{new}\), the feature is get after dimension reduction.

\[
x_{new} = [k(x_{new}, x_1), \ldots, k(x_{new}, x_m)] [\alpha_1, \ldots, \alpha_t]
\]  
\(7\)

3. Support vector data description

Support Vector Data Description(SVDD) is a common method of one-class classification, and its purpose is to obtain a hypersphere of a high dimensional feature space and cover as many target classes as possible [12]. Compared with other classification methods, SVDD has the greatest advantage that only positive samples are needed in the training process and no negative samples are needed, which is suitable for situations where it is difficult to collect abnormal samples in the production process [13].

3.1. Support Vector Data Description Principle

Let \(X\) be the target training sample with \(n\) dimensions of \(m\) numbers, and that is \(X = [X_{i1}, X_{i2}, \ldots, X_{in}] (i = 1, 2, \ldots, n)\). SVDD searches for the smallest hypersphere, which can be expressed as a quadratic programming problem [14].

\[
\begin{align*}
\text{Min} R^2 + C \sum_{i=1}^{n} \xi_i \\
\text{s.t.} \|\phi(X_i) - q\| \leq R^2 + \xi_i, i = 1, 2, \ldots, n \\
\xi_i \geq 0, i = 1, 2, \ldots, n
\end{align*}
\]  
\(8\)
Where $\xi_i$ is the relaxation variable, $a$ is the center of the hypersphere, $C$ is the penalty coefficient, and $R$ is the radius of the hypersphere. The above formula is a non-convex problem. Let $R = R^2$, and the above problem is transformed into a convex problem. The above constrained optimization problem can be transformed into an unconstrained optimization problem by the Lagrangian Method.

$$L = R + C \sum_{i=1}^{n} \xi_i - \sum_{i=1}^{n} a_i \left( R^2 + \xi_i - \| \phi(X_i) - a \|^2 \right) - \sum_{i=1}^{n} \gamma_i \xi_i [a_i, \ldots, a_i]$$  \hspace{1cm} (9)

Where $a_i \geq 0, \gamma_i \geq 0$ is the Lagrangian multiplier. Calculate partial derivative of formula (9) with respect to $R, a$ and $\xi_i$ respectively and set the partial derivative to zero.

$$\sum_{i=1}^{n} a_i = 1$$  \hspace{1cm} (10)

$$\frac{1}{\sum_{i=1}^{n} a_i} = \sum_{i=1}^{n} a_i X_i$$  \hspace{1cm} (11)

$$C - a_i - \gamma_i = 0$$  \hspace{1cm} (12)

Substitute equations (10)–(12) into equation (9) and convert them into dual problems.

$$\max L = \sum_{i=1}^{n} a_i Q_{ij} - a^T Q a$$  \hspace{1cm} (13)

$$s.t. \sum_{i=1}^{n} a_i = 1, 0 \leq a_i \leq C, i = 1, 2, \ldots, n$$

$Q$ is the kernel matrix, and the optimal solution set $a = (a_1, a_2, \ldots, a_n)$ can be obtained by solving the above quadratic programming problem. Where the $x_i$ corresponding to $a_i$ that is not zero is the support vector that determines the boundary of the classifier. For any test sample $z$, the distance from this point to the center of the hypersphere is as follows.

$$D^2(z) = k(z, z) - 2 \sum_{i=1}^{n} a_i k(X_i, z) + \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j k(X_i, X_j)$$  \hspace{1cm} (14)

If $D^2(z) \leq R^2$, the test sample $z$ belongs to the target class, otherwise the sample $z$ belongs to the non-target class. The kernel function of support vector data description is generally selected as a Gaussian radial kernel function, and the parameters of the kernel function and the penalty coefficient have a great influence on the performance of the classification.

3.2. Support Vector Data Description Multi-Classification Algorithm

SVDD is a single classification algorithm with excellent performance which has been widely used in mechanical fault diagnosis, image recognition and other fields, and it can be extended to multi-classification.

The principle SVDD multi-classification algorithm is as follows:

Step 1. The hypersphere parameters of all kinds of samples were obtained by SVDD algorithm alone such as center and radius of hypersphere.
Step 2. Classify the test samples and use a multi-classification decision function.

There are three possible situations for the classification of test samples. (1) The distance from the test sample to the center of a hypersphere is less than or equal to the radius of the hypersphere, and the distances to other hyperspheres center are greater than the radius of the hypersphere. At this time, the test sample is classified into the hypersphere. (2) The distances from the sample to each hypersphere are greater than its corresponding radius, and the test sample belongs to the external class. (3) The distances from the sample to several hyperspheres are less than or equal to the radius of the hypersphere and the distances to other hyperspheres are greater than the corresponding radius. At this time, the test sample belongs to the uncertain class.

Because it is a multi-classification problem, it belongs to a hard decision and the number of classification types is determined. For a test sample, it must be attributed to a hypersphere, so a classification decision function is needed to determine the classification for external class and uncertain class. The classification decision function used in this paper is as fellows. For the external class the distance to the boundary of a certain type of hypersphere is smaller and the probability of belonging to the hypersphere is greater. For the uncertain class the distance to the boundary of a certain type of hypersphere is higher and the probability of belonging to the hypersphere is greater [15]. Decisions are made on external class and uncertain classes, the calculation formula is as follows. The number of classification types is \( m \), and there are \( m \) hyperspheres. The SVDD model parameters are trained separately for different types of training samples. If the sample \( x \) belongs to the external class, the probability is calculated by the formula 15. If the sample \( x \) belongs to the uncertain class, the probability is calculated by the formula 16. The probability of the sample \( x \) to all the classified hyperspheres is calculated and normalized by the formula 17.

\[
\begin{align*}
P(x_j) &= \frac{(dx_{aj} - R_j)}{R_j}, \ j = 1, \ldots, m \quad \text{(15)} \\
P(x_j) &= \frac{(R_j - dx_{aj})}{R_j}, \ j = 1, \ldots, m \quad \text{(16)} \\
\bar{P}(x_j) &= P(x_j) / \text{sum}(P(x_j)) \quad \text{(17)}
\end{align*}
\]

Where \( P(x_j) \) is the probability of the sample \( x_j \) to the hypersphere \( j \), \( dx_{aj} \) is the distance of the sample \( x_j \) to the center of the hypersphere \( j \), \( R_j \) is the radius of the hypersphere \( j \).

4. Abnormal judgment of blade machining process

4.1. Method for Determining Abnormal Machining Process of Blade

At present, the processing quality of the blade is mostly evaluated by the quality characteristic parameters of the key blade pattern. However the traditional multivariate statistical process control theory is not suitable to monitor the process of the blade machining due to the complex correlation between the quality feature parameters. Therefore, this paper proposes a process control method based on SVDD. The process of the algorithm is shown in Figure 1.
The blade pattern is a free-form curve and is a non-linear contour. Therefore the process of blade machining can be monitored by a nonlinear contour control chart method that has two methods based on parameters and difference metric. If the method of parameter is used to monitor the process of the blade, the fitting parameters are not suitable for the traditional multivariate statistical control theory.

The deviation between the measured point and the theoretical blade pattern can well characterize the difference between the measured contour and the theoretical contour. Therefore the method of differential metric is used to monitor the blade process. The kernel principal component analysis is used to reduce the deviation vector, and the deviation eigenvectors are extracted. The support vector data description algorithm is used to calculate the hyperspheres for different kinds of feature vectors, and the parameters of the hypersphere are obtained. Firstly it is judged whether it is normal class. If not, the multi-classification algorithm is used to judge the abnormal classification.

4.2. Sample Data Construction
After the blade machining is completed, the measured blade pattern coordinate data are measured by a three-coordinate machine so as to evaluate the processing quality of the blade. Since the deviation is a very small amount, the deviation shall be calculated after the coordinate measurement by unifying the datum between the measured coordinates and the theoretical contour.

For a certain blade, the number of its key blade pattern is determined, and the theoretical coordinate points are also determined. Since the measured coordinate numbers of the blade profiles of the same kind of blade may be inconsistent, in order to normalize the deviation input, and the mean deviation of the measurement points between the theoretical coordinate points is taken as the deviation of the theoretical interval, and if there is a missing, the mean value of the adjacent theoretical interval will be used to replace it. Normally the deviation obeys normal distribution, and the tolerance of the blade deviation is generally $T=(0,0.2]$. The level of processing is $6\sigma$ obeying the normal distribution of $N(0.1,0.032)$.

This section describes the process of the sample structure with tolerance $T=(0,0.2]$ as an example. And the deviation vector dimension is 350. The probability of interval $[0,0.2]$ of different normal distribution parameters is shown in Table 1. The distribution parameters are $u=[T_l:0.02:T_u]$ and $\sigma=[\sigma_l:0.01:2\sigma_u]$. And where $T_l=0$, $T_u=0.2$, $\sigma_l=0.01$, $\sigma_u=(T_u-T_l)/3$. 

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**Figure 1.** Method for determining abnormal machining process of blade
Table 1. The probability of interval [0,0.2] of different distribution parameter.

| u  | 0.01  | 0.02  | 0.03  | 0.04  | 0.05  | 0.06  | 0.07  |
|----|-------|-------|-------|-------|-------|-------|-------|
| 0.00| 0.50000 | 0.50000 | 0.50000 | 0.50000 | 0.49997 | 0.49957 | 0.49786 |
| 0.02| 0.97725 | 0.84134 | 0.74751 | 0.69146 | 0.65526 | 0.62921 | 0.60739 |
| 0.04| 0.99997 | 0.97725 | 0.90879 | 0.84131 | 0.78746 | 0.74368 | 0.70501 |
| 0.06| 1.00000 | 0.99865 | 0.97725 | 0.93296 | 0.88238 | 0.83153 | 0.78157 |
| 0.08| 1.00000 | 0.99997 | 0.99614 | 0.97590 | 0.93700 | 0.88604 | 0.83021 |
| 0.10| 1.00000 | 0.99999 | 0.99914 | 0.98758 | 0.95450 | 0.90442 | 0.84687 |
| 0.12| 1.00000 | 0.99997 | 0.99614 | 0.97590 | 0.93700 | 0.88604 | 0.83021 |
| 0.14| 1.00000 | 0.99865 | 0.97725 | 0.93296 | 0.88238 | 0.83153 | 0.78157 |
| 0.16| 0.99997 | 0.97725 | 0.90879 | 0.84131 | 0.78746 | 0.74368 | 0.70501 |
| 0.18| 0.97725 | 0.84134 | 0.74751 | 0.69146 | 0.65526 | 0.62921 | 0.60739 |
| 0.20| 0.50000 | 0.50000 | 0.50000 | 0.50000 | 0.49997 | 0.49957 | 0.49786 |

The probability limit of 0.95 divides the distribution parameters into four types of samples. These four types are normal, mean up, mean down and variance changed. The parameters of the normal distribution for four types of samples are shown in Table 2.

Table 2. Distribution parameter of four types of samples.

| Sample Type        | Distributed Parameter                                                                 | Number |
|--------------------|---------------------------------------------------------------------------------------|--------|
| normal sample      | (0.02-0.18,0.01^2),(0.04-0.16,0.02^2),(0.06-0.14,0.03^2),(0.08-0.12,0.04^2),(0.1,0.05^2) | 105    |
| mean up            | (0,0.01^2),(0-0.02,0.02^2),(0-0.04,0.03^2),(0-0.06,0.04^2),(0-0.08,0.05^2)              | 22     |
| mean down          | (0.2,-0.012),(0.18-0.2,0.022),(0.16-0.2,0.032),(0.14-0.2,0.042),(0.12-0.2,0.052)        | 22     |
| variance changed   | other                                                                                 | 22     |

4.3. Model Parameter Training

After normalizing the deviation, it is necessary to reduce the dimension and extract the nonlinear characteristics of the deviation by kernel principal component analysis. To ensure the validity of the feature extraction, it is necessary to choose proper kernel function for KPCA dimension reduction. The cumulative contribution rate with using the default parameters of the three kernel functions are calculated as shown in Figure 2.

![Figure 2. Cumulative Contribution Rate Curve of Different Kernel Functions.](image-url)
Where the dimension n of data is 350, Gaussian radial kernel parameter is $a=n^{0.5}$, polynomial kernel parameter is $b=1/n$, $c=1$, $d=3$, Sigmoid kernel parameter is $e=1/n$, $f=1$. The three kernel functions of this data set all perform well after observing the above curves. The key lies in the parameter selection of the kernel function. Since the sample bias obeys the normal distribution, so the Gaussian radial kernel is selected as the kernel function of the kernel principal component analysis.

In order to monitor the machining process and distinguish the normal process and the abnormal process like the control chart. The SVDD classification algorithm's control limits is generally determined by the false alarm rate, which is the probability of normal production misjudgment as abnormal. In this paper, the false alarm rate is 5%, and that is the accuracy of normal sample classification is 95%. The kernel function parameters of KPCA and the parameters of normal sample hypersphere should be the parameters when the classification accuracy of normal samples is 95%. The parameters of the hypersphere of abnormal samples are obtained by training three kinds of abnormal samples, and the accuracy is as high as possible.

After analysis in literature 12 when the penalty coefficient $C$ is 0.25, SVDD single classification effect is good. When the penalty coefficient is changed to 0.4, the classification result has not changed. The parameter selection of the Gaussian kernel is related to the sample size and feature dimension [16]. In order to determine the appropriate model parameters, the parameters of the KPCA kernel function and the parameters of the normal sample hypersphere are determined according to the classification accuracy of the normal sample with the method of meshing parameters. The parameters $a_1$ of the KPCA kernel function are selected as 2.03, and its classification accuracy under different SVDD parameters is shown in Table 3.

| $a_1$ | C     | 0.003  | 0.503  | 1.003  | 1.503  |
|-------|------|--------|--------|--------|--------|
| 0.1   | 1.00 | 0.8129 | 0.8187 | 0.8538 |
| 0.15  | 1.00 | 0.9474 | 0.7602 | 0.8304 |
| 0.2   | 1.00 | 0.9415 | 0.7953 | 0.8246 |
| 0.25  | 1.00 | 0.9123 | 0.7778 | 0.8363 |
| 0.3   | 1.00 | 0.9357 | 0.7719 | 0.8363 |
| 0.35  | 0.9708 | 0.8596 | 0.7895 | 0.8363 |
| 0.4   | 0.9825 | 0.9474 | 0.7895 | 0.8363 |

The selection basis of the kernel function parameters $a_1$ of KPCA is the parameters with the highest accuracy rate accumulation. After determining the kernel parameters of the kernel principal component analysis, the $C$ and $a_2$ parameter combinations whose accuracy is closest to the set probability limit of 0.95 are selected as the model parameters of the normal sample SVDD. According to the determined false alarm rate, we select the normal sample SVDD penalty coefficient $C$ is 0.15, and the SVDD kernel function parameter $a_2$ is 0.503. According to the previously divided $C$ and $a$ intervals, three abnormal samples are trained to determine their parameters. The model parameters are shown in Table 4.

| Sample Type            | (C,a)        |
|------------------------|--------------|
| Deviation mean up      | (0.25,0.003) |
| Deviation mean down    | (0.25,0.003) |
| Deviation variance changed | (0.25,0.003) |
4.4. Model Validity Verification

After determining the model parameters, the model can be applied to the process monitoring of blade machining. The blade deviation vector is reduced dimension and extract feature with the determined kernel function and parameters. Firstly the extracted feature vectors are input into the hypersphere model of normal classification to determine whether there is any abnormality. If there is any abnormality, the SVDD multi-class model is selected to determine the type of abnormality. The machining process is adjusted in time according to the abnormality type.

The deviation samples of four sets of dimensions 350 are generated by four normal distribution parameters of (0.1, 0.03), (0.2, 0.03), (0, 0.03), (0.1, 0.06), and the states are normal, deviation mean up, deviation mean down and deviation variance changed. The classification results are shown in Figure 3.

![Figure 3. Test sample classification result](image)

It can be seen from the above figure that the method can effectively judge the type of deviation distribution.

5. Conclusion

In this paper, a monitoring method of blade machining process based on support vector data description is proposed: The measured deviation vector is used as the original monitoring data, and appropriate kernel function and parameters are selected to extract the feature vector so as to judge the stability of blade machining state. If the process is abnormal, the type of the exception will be judged. Four kinds of samples are generated by simulation such as normal state, deviation mean up, deviation mean down and deviation variance changed. The parameters of the KPCA and the SVDD parameters of the normal sample are determined by the false alarm rate, and the SVDD parameters of the abnormal samples were trained by three kinds of abnormal samples. The result of test samples illustrates the established model
can effectively monitor the abnormal fluctuation caused by deviation mean or variance and judge the type of abnormality.

References
[1] Zhu Bo. Research on quality control method of automatic machining process based on support vector machine[D]. Chongqing University. 2013.
[2] Zhang Yang. Research on Contour Control Chart method in blade processing[D]. Tianjin University. 2010.
[3] Ma Ruixue. Research on performance of Control Chart in aeronautical blade Processing[J]. Aviation Precision Manufacturing Technology, 2015(4): 24-26.
[4] Ma Ruixue, Ma Guanghui. Research on Control Chart performance based on Matlab[J]. Journal of Automation & Instrumentation, 2015(8): 176-178.
[5] Guh R S , Shue Y R . An effective application of decision tree learning for on-line detection of mean shifts in multivariate control charts[J]. Computers and Industrial Engineering, 2008, 55(2):475-493.M. P. Brown and K. Austin, The New Physique (Publisher Name, Publisher City, 2005), pp. 25–30.
[6] He S G , He Z , Wang G A . Online monitoring and fault identification of mean shifts in bivariate processes using decision tree learning techniques[J]. Journal of Intelligent Manufacturing, 2013, 24(1):25-34.
[7] Guh R S . On-line Identification and Quantification of Mean Shifts in Bivariate Processes using a Neural Network - based Approach[J]. Quality and Reliability Engineering, 2007, 23(3):367-385.
[8] Ahmadzadeh F , Lundberg J , Thomas Strömberg. Multivariate process parameter change identification by neural network[J]. The International Journal of Advanced Manufacturing Technology, 2013.
[9] JohnShawe2Taylor, NelloCristianini. Nuclear method for pattern analysis [M]. Beijing: Mechanical Industry Press, 2006.
[10] Lee J M, Yoo C K, Choi S W, et al. Nonlinear process monitoring using kernel principal component analysis[J]. Chemical engineering science, 2004, 59(1): 223-234.
[11] Duan Qing, ZHAO Jian-guo, MA Yan. Feature Extraction of KPCA Transient Stability Assessment Model Based on Optimization[J]. Control and Decision, 2010, 25(9): 1403-1407.
[12] Li Li. Research on Linear Contour Monitoring Based on Support Vector Data Description[J]. Combined Machine Tool & Automatic Processing Technology, 2015(10):80-83.
[13] Li Linjun, Zhang Zhouruo, He Zhengjiia. Research of Mechanical System Fault Diagnosis Based on Support Vector Data Description[J]. Journal of Xi'an JiaoTong University, 2003, 37(9):910-913.
[14] Chang, Wei-Cheng, Ching-Pei Lee, and Chih-Jen Lin. "A revisit to support vector data description." Documents in the CiteSeerx database (2013).M. P. Brown and K. Austin, Appl. Phys. Letters 85, 2503–2504 (2004).
[15] Li Chen. Research on multi-classification support vector data description method based on extreme learning[D]. 2015.
[16] Tax D M J, Duin R P W. Support vector domain description[J]. Pattern Recognit Lett, 1999, 20(11 - 13):1191-1199.