

## Quality Abnormal Pattern Recognition of Dynamic Process Based on MSVM

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### Abstract

The improvement of the effective recognition of quality abnormal patterns in dynamic process has seen increasing demands nowadays in the real-time monitor and diagnose of automatic manufacturing. Based on the analysis of the dynamic process of quality abnormal pattern, this paper presents a recognition model of quality abnormal pattern recognition using a Multi-SVM. Contrasting with performance of recognition model based on different kernel functions, suitable kernel functions were selected for the recognition model. Furthermore, we have contrasted the model proposed in this paper with the model adopted by Vahid. Simulation results show that the recognition model proposed in this paper has very high recognition accuracy for all patterns, and the overall average recognition accuracy is 97.78%.

**Keywords:** pattern recognition, dynamic process, MSVM, kernel function

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### 1. Introduction

Quality abnormal pattern recognition of dynamic process plays a very important role in monitoring both the manufacturer process running in its intended mode and the presence of abnormal patterns and realizing online quality diagnose of automatic production process. Since modern industries, such as petroleum, metallurgy, machinery and other industries, have become more large-scale, complex and continuous, the monitoring and diagnosis of the dynamic process has attracted many scholars' attention and now it becomes the research hotspot in the field of quality control [1-3]. Since a large number of dynamic dataflow has been generated through the process of automatic production, the key problem of dynamic process quality control is how to monitor and diagnosis the dynamic data flow's variation tendency effectively.

Support vector machine (SVM) performs classification tasks of various kinds quality abnormal data by constructing optimal separating hyperplane [4]. This method can effectively solve several practical problems, such as the small sample problem, nonlinear problem and high dimensional pattern recognition problem and so on [5].

Currently, SVM has widely applied to quality of the industry process monitoring and diagnosis. The variation tendency of dynamic dataflow consists of several patterns, including trend pattern, shift pattern and cyclic pattern. The recognition of variation tendency for dynamic dataflow is typical of multi-class classification. However, the basic SVM deals with two-class problems. Thus, it can be developed for multi-class classification to deal with dynamic dataflow. Nowadays, MSVMs are gaining application in the area of control chart pattern recognition and fault diagnose in industrial processes [6-7]. Jiang (2009) establishes a MSVM model based on four SVM classifiers, all of which have chosen Gaussian kernel function to diagnose the fault of blast furnace [8]. Vahid (2010) presents a MSVM model using the "one-against-all" method to recognize the quality pattern for all six patterns [9]. Wu (2010) presents a MSVM model, and four SVM classifiers are established to recognize trend pattern, shift pattern, cyclic pattern and mixed pattern [10]. Xiao (2010) presents a least square MSVM model to recognize three different shift patterns of the TE process and simulation experiment indicates that MSVM can recognize all the quality patterns effectively [11]. As mentioned above, many studies of MSVM recognition model are restricted to some special industrial process and always adopt "one-against-all" method which is one kernel function to diagnose different quality abnormal patterns. Thus the recognition effect of this MSVM recognition model will be greatly weakened. Owing to

the characters of dynamic dataflow, such as nonlinear, non-normal. There are large difference on variation tendency of quality abnormal patterns. Consequently, the largest problems encountered in setting up the MSVM model are how to select the kernel functions and its parameter values, when we using MSVM model to recognize the quality patterns of dynamic process.

Based on the analysis of the dynamic process of quality abnormal pattern, this paper presents a recognition framework of quality abnormal pattern recognition by using a Multi-SVM model. Through the simulation experiment, a MSVM recognition model of quality abnormal pattern in dynamic process is proposed in this paper after comparing and analyzing different kernel functions' accuracy. Furthermore, a quality abnormal recognition model of dynamic process based on MSVM is established, which proves the effectiveness achieved by quality abnormal pattern of dynamic process.

## 2. Quality Pattern of Dynamic Process

Through the continuous production process or automatic equipment treating process, we obtained a mound of dynamic dataflow reflecting the operating condition which effects the quality and changes of products under a continuous production process.

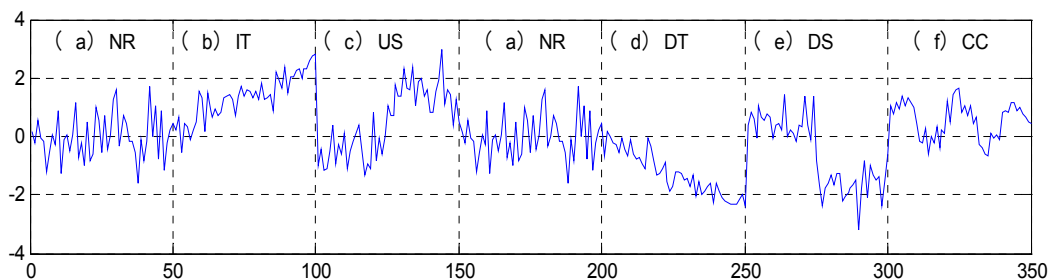


Figure 1. Quality Abnormal Pattern of Dynamic Process

The productive process is under a normal running status when dynamic dataflow fluctuating around the designing target numerical value randomly. The follow variation trend shown by Figure 1(a) is the normal pattern (NR) of dynamic process basic quality pattern. When the dynamic dataflow tending to trend, shift or cycle, there are abnormal factors leading to a quality problem among productive process. The abnormal condition of dynamic productive quality contains three types: trend, shift and cyclic. The trend of dataflow includes two types which are increasing trend (IT) and decreasing trend (DT) (shown by Figure 1(b) and 1(d)) as well as the shift pattern contains upward shift (US) and downward shift (DS) (shown by Figure 1(c) and 1(e)). Therefore, the dynamic process quality abnormal model can be illustrated as increasing trend, decreasing trend, upward shift, downward shift and cyclic pattern (CC). Figure 1 shows details of dynamic process basic quality model which includes normal pattern and five abnormal patterns.

During the actual continuous productive process or automatic treating process, the abnormal changes of dataflow will lead to the problems of products on varying degrees. Therefore, in order to reduce the problems in productive process, it is necessary to recognize effectively the quality abnormal model of dynamic dataflow.

## 3. Establishment the Recognition Model Based on MSVM

In this section, we established the quality patterns recognition model of dynamic pattern. We combined the rough SVM classifier and subdivision SVM classifier to establish the recognition model of dynamic pattern. In order to provide theoretical basis for kernel function selection of single supporting vector machine in the recognition model, three kinds of kernel functions, including Linear, Polynomial and RBF, which are typically used to SVM will be introduced in this section as well.

### 3.1. Recognition Model Based on MSVM

An SVM performs classification tasks by constructing optimal separating hyper planes (OSHS) [12]. There are six basic quality patterns in the dynamic dataflow to recognize, so Multi-SVM model is necessary. There are two widely used methods to extend SVM to Multi-class problems [9]. One of them is called the “one-against-all” (OAA) method. Another method is called “one-against-one” (OAO) method. The two methods all have good recognition effect.

In term of trend, shift and cyclic three patterns of dynamic dataflow, we first should adopt OAA method and try to recognize these three quality abnormal patterns with the establishment of SVM<sub>1</sub>, SVM<sub>2</sub> and SVM<sub>3</sub> classifiers. And then, we established SVM<sub>4</sub> and SVM<sub>5</sub> classifiers and recognize increasing trend or decreasing trend and upward shift or downward shift. In order to classify the six basic quality patterns of dynamic process, we constructed a model of quality abnormal pattern recognition based on MSVM. The structure of the recognition Model is shown in Figure 2.

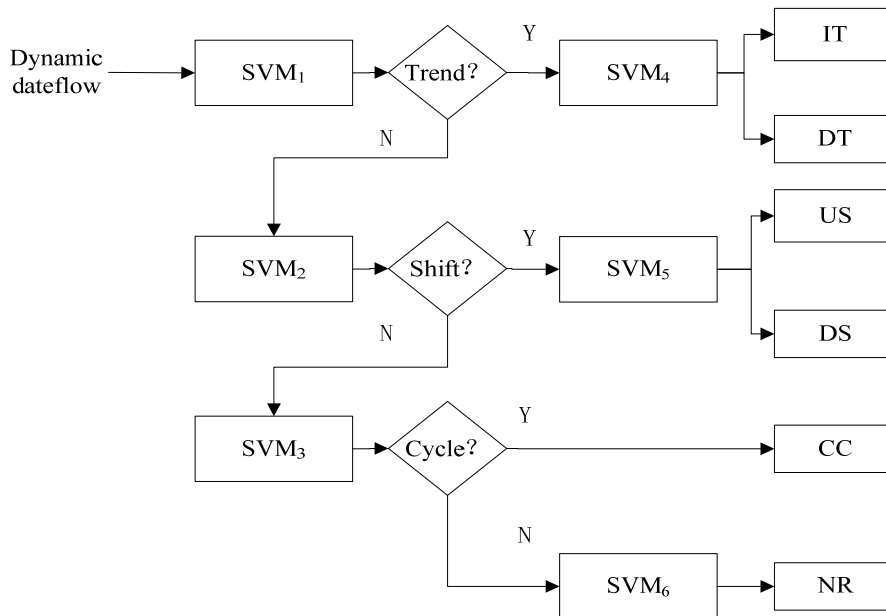


Figure 2. Recognition Model Based on MSVM

In the Figure 2, trend, shift and cyclic three patterns of dynamic dataflow through SVM<sub>1</sub>, SVM<sub>2</sub> and SVM<sub>3</sub> classifiers be recognized firstly. When the current dataflow be identified as trend pattern through SVM<sub>1</sub>, the dataflow will be classified by SVM<sub>4</sub> which can recognize the increasing trend and decreasing trend two quality abnormal patterns. Subsequently, upward shift and downward shift two quality abnormal pattern with SVM<sub>2</sub> and SVM<sub>5</sub> classifiers be classified as the same mechanism. When SVM<sub>3</sub> identified the dataflow is not an cyclical pattern after SVM<sub>1</sub> and SVM<sub>2</sub> classifiers, SVM<sub>6</sub> will undertake the recognition for normal pattern.

### 3.2. Kernel Function Selection of MSVM

The basic principle of SVM is to solve linearly separable problems through finding a linear hyperplane. In the linearly separable condition, a set of  $(x_i, y_i)$ ,  $i=1,2,\dots,n$ ,  $x \in \mathbb{R}^d$  as training sample of dynamic dataflow which have known the value of category. The  $y_i$  is the label value of training sample and selecting the value from 1 or -1.

The purpose of training SVM model is to find an optimal hyperplane that divides the two abnormal patterns so that it can turn the error of training into zero while maximum margin. Thus, the problem finding this hyperplane transformed this optimization problem:

$$\min J(\omega) = \frac{1}{2} \|\omega\|^2 = \frac{1}{2} \omega^T \omega$$

$$\text{s.t: } y_i(\omega^T x_i + b) \geq 1, i = 1, 2, \dots, n \quad (1)$$

It can adopt Lagrange optimize method to treat the primal problem as one simple dual problem. The optimal decision function (ODF) is then given by:

$$f(x) = \text{sgn}[\sum_{i=1}^n a_i^* y_i(x_i, x) + b^*] \quad (2)$$

Where the  $a_i^*$  are optimal Lagrange multipliers, when  $a_i^* \neq 0$  the training sample is SV (support vector), and  $b^*$  are classification threshold. As the sample data of quality abnormal pattern all are linearly inseparable, SVMs can efficiently perform non-linear classification using kernel function, implicitly mapping these linearly inseparable sample data into high-dimensional feature spaces so that can solve linearly inseparable problems. Thus the problem to find an optimal hyperplane transformed another optimal problem as follow:

$$\begin{aligned} \min J(\omega) &= \frac{1}{2} \omega^T \omega + C \sum_{i=1}^n \xi_i \\ \text{s.t: } y_i(\omega^T x_i + b) &\geq 1 - \xi_i, i = 1, 2, \dots, n \end{aligned} \quad (3)$$

$\xi_i$  is a slack variable and  $\xi_i > 0$ ,  $c$  defined as penalty coefficient ( $c > 0$ ). The greater the  $C$  is, the heavier punishment for misclassification will be. After adding the kernel function  $k(x_i, x)$ , the classify function turn to:

$$f(x) = \text{sgn}[\sum_{SV} a_i^* y_i k(x_i, x) + b^*] \quad (4)$$

According to above-mentioned analysis, it should be choose different kernel functions for different SVM classifiers. Thus, it is essential to select a suitable kernel function for improving the performance of SVM classifiers. There are three basic kernel functions in the application of SVM. These mathematic expression of kernel functions are shown in Table 1 [13].

Table 1. Basic Kernel Function

Name	Expression
Linear	$K(x, x_i) = (x \square x_i)$
Polynomial	$K(x, x_i) = (1 + x \square x_i)^q, q = 1, 2, \dots, n$
RBF	$K(x, x_i) = \exp[-(x - x_i)^2 / 2\sigma^2]$

Currently, it has no general rule to select kernel function. Therefore, it needs consider the actual identify object to select kernel function by existing experience and simulation experiments. In the framework of quality abnormal pattern recognition, it is significant that to choose a suitable kernel function to improve the quality pattern recognition performance of MSVM classifiers. In our paper, we compered the performance of SVM classifier with using four different kernel functions, including Linear, Polynomial, RBF and Sigmoid, for different quality patterns. The simulation experiment is as follow.

#### 4. Results and Analysis

In this section, in order to ensure the performance of recognition model, we analyze performance of SVM classifiers based on different kernel functions for the different quality

abnormal patterns. First, we use Monte-Carlo method to simulate the data of dynamic process patterns. Then, we compare the accuracy of each SVM classify model based on different kernel function, so that it can offer some evidences for choosing parameters of SVM model. Compared with the recognition model proposed by Vahid, the model proposed in this paper was analyzed. Furthermore, it is significance that this recognition model be proved for quality diagnose of dynamic process.

#### 4.1. Data Description

In particular, the considered patterns refer to the following classes: normal (NR), cyclic (CC), increasing trend (IT), decreasing trend (DT), upward shift (US), and downward shift (DS). These patterns of all these different types were generated using the Monte-Carlo method. This equation as follows:

$$x(t) = \mu + d(t) + r(t) \quad (5)$$

In the Equation (1),  $x(t)$  is the data of quality pattern in dynamic process which needs to be simulated.  $\mu$  represents the value of design target, containing three parts. To simplify the simulation data, this paper sets  $\mu$  to zero.  $r(t)$  is the data change caused by the existed causal factors. Here white noise is adopted to represent the data change  $r(t)$  in our experiment.  $d(t)$  is the data change resulted by the abnormal factors. It causes five abnormal modes, including increasing trend, decreasing trend, upward shift, downward shift and cycle patterns. Data simulation formula of each quality pattern is as follows:

1) Normal patterns:

$$x(t) = r(t) \quad (6)$$

2) Increasing trend patterns:

$$x(t) = r(t) + k \times t \quad (7)$$

3) Decreasing trend patterns:

$$x(t) = r(t) - k \times t \quad (8)$$

4) Upward shift patterns:

$$x(t) = r(t) + b \times s \quad (9)$$

5) Downward shift patterns:

$$x(t) = r(t) - b \times s \quad (10)$$

6) Cyclic patterns:

$$x(t) = r(t) + a \times \sin(2\pi t / T) \quad (11)$$

Here,  $r(t)$  is a function that generates random numbers normally distributed ( $r(t) \sim N(0,1)$ ),  $k$  is the gradient of increasing or decreasing trend pattern trend pattern (set in the range 0.3 to 0.5),  $b$  indicates the shift position in an upward shift pattern and a downward shift pattern ( $b = 0$  before the shift and  $b = 1$  at the shift and thereafter),  $s$  is the magnitude of the shift (set between 1 and 2),  $a$  is the amplitude of cyclic variations in acyclic pattern (set in the range

0.8 to 2),  $T$  is the period of the cycle (set between 15 and 30),  $t$  is the discrete time at which the monitored process variable is sampled (set within the range 0 to 29), and  $x(t)$  is the value of the dynamic data point at time  $t$ . 360 above-mentioned patterns, 60 of each type, were previously generated. Former 20 groups are train samples, while the other 40 groups are testing.

#### 4.2. Experiment Settings

In order to compare the recognition accuracy of SVM in different kernel function, the penalty factor  $C$  of the SVM identifier needs to be set.  $C$  is the tradeoff between identify errors and algorithm complexity. If the value of  $C$  is too high, the algorithm will become very complex. And the lower the value of  $C$ , the stronger the model's generalization ability, but the error becomes bigger which was proposed by Cherkassky [14].

$$C = \max(|\bar{x} + 3\sigma_x|, |\bar{x} - 3\sigma_x|) \quad (12)$$

$\bar{x}$  is the mean value of the training samples in the dynamic process quality patterns,  $\sigma_x$  is the standard deviation of the training samples.

In the simulation experiment, the value of  $c$  is selected as 1.2 according to the Cherkassky's empirical formula (11) for Linear and Poly kernel function model, while grid search method is adopted for RBF kernel function model.

#### 4.3. Comparison of the Models' Performance

After analyzing the effect of different kernel functions on performance, the suitable kernel functions were selected for recognition model proposed in this paper. According to above-mentioned data, 60 groups of data of each quality pattern will be merged into 360 groups of data, as the sample data of SVM<sub>1</sub>, SVM<sub>2</sub>, SVM<sub>3</sub> and SVM<sub>6</sub> parameter optimization based on RBF kernel function. 60 groups of data of two quality patterns will be merged into 120 groups of data, as the sample data of SVM<sub>4</sub> and SVM<sub>5</sub> parameter optimization based on RBF kernel function. The results of parameters optimization with grid search method for SVM<sub>1</sub> which recognize trend pattern and SVM<sub>4</sub> which recognize increasing and decreasing pattern are shown in Figure 3.

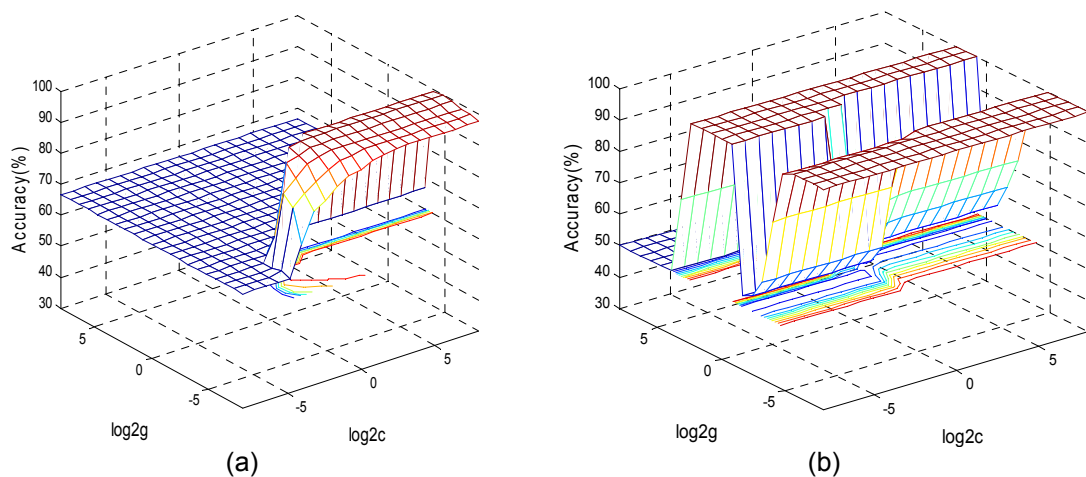


Figure 3. (a) Parameter optimization for trend SVM<sub>1</sub>, (b) Parameter optimization for SVM<sub>4</sub>

Through simulation experiment, the accuracies of recognition based on different kernel functions are shown in Table 2.

Table 2. The Accuracy of SVM on Different Kernel Function Under Optimized Parameters

Kernel function	RA	Parameters and recognition accuracy					
		SVM <sub>1</sub>	SVM <sub>2</sub>	SVM <sub>3</sub>	SVM <sub>6</sub>	SVM <sub>4</sub>	SVM <sub>5</sub>
Linear	85.21%	64.58%	66.67%	96.25%	C=1.2	100%	100%
					83.75%		
Polynomial	95.83%	q=2	q=2	q=2	q=2	q=3	q=3
		92.08%	97.92%	98.33%	86.67%	100%	100%
		c=1.74	c=3.03	c=0.189	c=3.03	c=0.004	c=0.004
RBF	98.4%	g=0.02	g=0.02	g=0.012	g=0.02	g=0.004	g=0.004
		98.33%	97.92%	100%	94.17%	100%	100%

Indicated by recognition results shown in Table 2, the recognition performances are quite different between the different quality patterns and their diverse kernel functions. The RBF function have excellent performance for all the patterns, and average RA reach 98.4%, while Linear and Polynomial functions also achieve high classification accuracy which equal to 100% for increasing trend pattern, decreasing trend pattern, upward shift pattern and downward shift pattern.

According to the results of experiment, the recognition model should choose RBF function for SVM<sub>1</sub>, SVM<sub>2</sub> and SVM<sub>3</sub>; Linear, Polynomial and RBF function is best for SVM<sub>5</sub> and SVM<sub>6</sub>. The Result of choosing kernel function for MSVM model are shown in Table 3.

Table 3. Selection of Kernel Function for MSVM

NO.	Type
SVM <sub>1</sub>	RBF
SVM <sub>2</sub>	RBF
SVM <sub>3</sub>	RBF
SVM <sub>4</sub>	RBF
SVM <sub>5</sub>	Linear, RBF, Polynomial
SVM <sub>6</sub>	Linear, RBF, Polynomial

Afterwards, comparing the recognition accuracy with two models based on RBF kernel function, validity of quality abnormal recognition model for dynamic process proposed by this paper was proved. The MSVM model proposed by Vahid be selected as the contrast model. We set above-mentioned MSVM model as model I, while the model proposed in this paper as model II. In order to compare the recognition accuracy of these two model, RBF kernel function is adopted by kernel function of these two SVM models. According to above quality pattern sample data of dynamic process by simulation, the optimal parameter combination based on RBF was found with grid-search method. The recognition results of two model are shown in Table 4.

Table 4. The Recognition Accuracy of Two Models under the Optimized Parameters

Type	RA	The recognition accuracy under the optimized parameters					
		IT	DT	US	DS	CC	NR
Model I	96.6%	98.33%	92.5%	97.5%	97.08%	100%	94.17%
Model II	97.78%	98.33%	98.33%	97.92%	97.92%	100%	94.17%

Compared with the MSVM model proposed by Vahid, the MSVM model adopted in this paper has higher recognition accuracy and the overall average recognition accuracy reach 97.78%. The validity of recognition model proposed by this paper for quality abnormal pattern of dynamic process be verified.

## 5. Conclusion

Through the simulation experiment, a MSVM recognition model of quality abnormal pattern in dynamic process is proposed in this paper after comparing different accuracies of several kernel functions. Furthermore, this paper contrast the method we proposed in this paper with the methods commonly adopted. The simulation results indicate that the proposed algorithm has very high recognition accuracy. This high efficiency is achieved with quality abnormal patterns of dynamic process. Besides, it offers a novel technique and thought for real-time quality monitoring and diagnosis in dynamic process.

Several issues should be explored further. For example, it has very high recognition accuracy for single quality pattern with RBF kernel function. However, how to recognize mixed patterns with RBF kernel function needs further study.

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## References

- [1] Chen N, Zhou S. Detectability study for statistical monitoring of multivariate dynamic processes. *IIE Transactions*. 2009; 41(7): 593–604.
- [2] Shi J, Zhou S. Quality control and improvement for multistage systems: A survey. *IIE Transactions*. 2009; 41(9): 744–753.
- [3] Qiang L, Tianyou C. Progress of data-driven and knowledge-driven process monitoring and fault diagnosis for industry process. *Control and Decision*. 2010; 25(6): 801–807.
- [4] Burges C. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*. 1998; 2(1): 21-67.
- [5] Shiyuan Y, Dehui W. Control Chart Pattern Recognition Based on PCA and SVM. *Journal of System Simulation*. 2006; 18(5): 1314–1318.
- [6] Xiaoxia Z. Support Vector Machine with Gauss Kernel Classified Method and Model Selection, *Computer Engineering and Applications*. 2006; (1): 76-79.
- [7] Xiao-kai G. Inertial navigation condition data analysis and establishment of diagnostic model based on SVM. *Systems Engineering Theory & Practice*. 2012; 2(32): 405-410.
- [8] Shaohua J. Monitoring model based on kernel principal component analysis and multiple support vector machines and its application. *Systems Engineering Theory & Practice*. 2009; 29(9): 153-159.
- [9] Vahid R, Ata E Reza G. Application of the PSO-SVM model for recognition of control chart patterns. *ISA Transactions*. 2010; (49): 577-586.
- [10] Changkun W. The pattern recognition of control chart based on wavelet analysis and SVM. *China Mechanical Engineering*. 2010; 21(13): 1572-1576.
- [11] Yingwang X. Process Monitoring Based on Wavelet Transform Kernel Principal Component Analysis and Multiple Support Vector Machines. *Journal of Chinese computer systems*. 2011; 32(7): 1348-1353.
- [12] Cortes C, Vapnic V. Support vector network. *Machine Learning*. 1995; (20): 1-25.
- [13] Huazhong W, Jinshou Y. Study on the Kernel-Based Methods and Its Model Selection. *Journal of Southern Yangtze University*. 2006; 5(4): 500-504.
- [14] Cherkassky V, Ma Y. Practical selection of SVM parameters and noise estimation for SVM regression. *Neural Networks*. 2004; 17(1): 113-126.