# Anomaly Detection of Manufacturing Process for Multi-Variety and Small Batch Production

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**Abstract.** A series of quality control problems arise in multi-variety and small batch production due to the lack of data and other factors. In this paper, an integrated model in which control chart pattern (CCP) recognition is applied for anomaly detection is proposed to solve the problems. The integrated model is made up of four parts: feature extraction module, feature selection module, classifier module and anomaly diagnosis module. In the first module, thirteen shape features and eight statistical features of control charts are extracted. In the second module, the most representative feature set is selected by the sequential floating forward selection (SFFS) method. In the third module, a multiclass support vector machine (MSVM) which is optimized by beetle antennae search (BAS) algorithm is used to identify abnormal CCPs. In the last module, the results of pattern recognition are utilized to analyze the possible causes. The simulation results show that the CCP recognition method proposed in this paper has higher classification accuracy than other competing methods in the case of small sample with small amount of data. Finally, an example verifies that the proposed anomaly detection method is effective in multi-variety and small batch manufacturing environment.

## 1. Introduction

Adapting to the development of the new era, multi-variety and small batch manufacturing are becoming mainstream [1]. Recently, an increasing number of research has been conducted in order to solve the quality control problems in multi-variety and small batch production due to the lack of data and other factors [2, 4]. One of the most commonly used methods is to increase the amount of data by means of group technology and data transformation, and then to monitor and control the production processes by control charts. However, due to the existence of interference information in quality data, the effect of traditional rule-based methods is limited.

Through a lot of research, scholars use the control chart pattern (CCP) to summarize the various situations presented by the control chart. The CCPs can generally be divided as eight basic types, including normal (NOR), increasing trend (IT), decreasing trend (DT), upward shift (US), downward shift (DS), cyclic (CYC), stratification (STR) and systematic (SYS), as shown in Figure 1 [5]. Their descriptions and possible causes are listed as follows.

- Normal patterns: The control chart is in normal pattern means that the manufacturing process is under control.
- Trend patterns: In a trend pattern, points move continuously in positive or negative direction. Typical causes include operator error, equipment failure, tool wear, etc.

- Shift patterns: In a shift pattern, points change suddenly above or below the process mean. Possible causes are replacement of raw material, a change in process setting, introduction of new workers, failure of machine parts, etc.
- Cyclic patterns: In a cyclic pattern, points change periodically. It may be caused by a systematic environmental change, periodic rotation of operators, fluctuation of production equipment, etc.
- Stratification patterns: The data in a stratification pattern comes from two or more different processes. Possible causes include adjustment of equipment, data cheating, etc.
- Systematic patterns: In a systematic pattern, a low point and a high point always appear alternately. Possible causes are equipment vibration, sampling problems, etc.
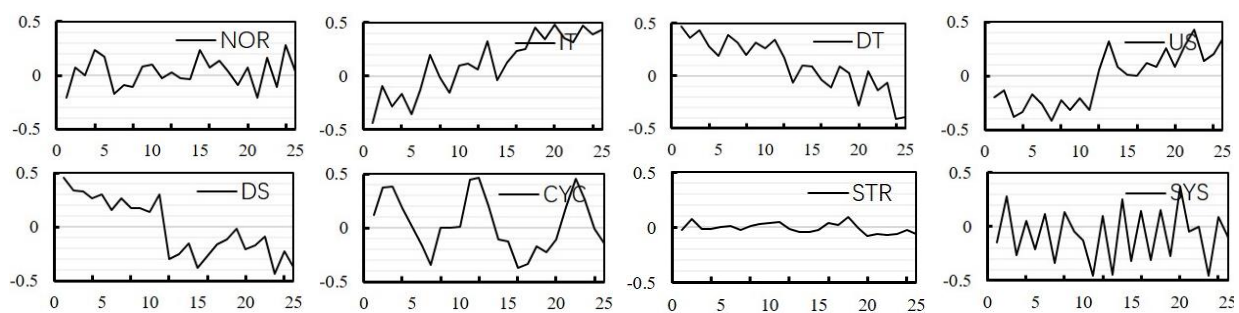


**Figure 1.** Types of control chart patterns.

Using machine learning algorithms for CCP recognition can effectively detect out-of-control situations, and significantly shorten diagnosis time. Artificial neural networks (ANNs) have been adopted widely in CCP recognition in recent years [6, 8]. However, there are still some defects in neural network algorithms, for example, the requirement for numerous training data, the easy trapped in a local extremum and so on. Support vector machine (SVM) overcomes these defects to some extent [9], so it has found an increasingly wide utilization in CCP recognition [10, 11].

In this research, we introduce a new approach of anomaly detection which using SVM to recognize CCPs and then analysis the cause of abnormality.

## 2. Methodology

The small amount of data in the multi-variety small-batch production limits the performance of various CCP recognition methods to a large extent. In this paper, the research on CCP recognition is conducted in this case, and the causes of the anomalies are analyzed based on the pattern recognition results. The proposed model is made up of four modules: feature extraction, feature selection, classifier and anomaly diagnosis. The main structure of the proposed anomaly detection model is shown in Figure 2. In the first module, the shape and statistical features of control charts are extracted from raw data. Then the best set of features are selected by the sequential floating forward selection method (SFFS) [12] as input of the classifier. In classifier module, a multi-class classifier is constructed based on support vector machine (SVM), which is optimized by beetle antennae search (BAS) algorithm [13]. Finally, the results of CCP recognition are utilized to analyze the possible causes.

### 2.1. Feature extraction

Due to the uncertainty of multi-variety and small batch production, the dimension of the raw control chart is uncertain, and the dimension may be large. Feature extraction can effectively solve the problem and improve the recognition effect. It is important to select which features to extract from the raw data, which greatly affects the effectiveness of CCP recognition.
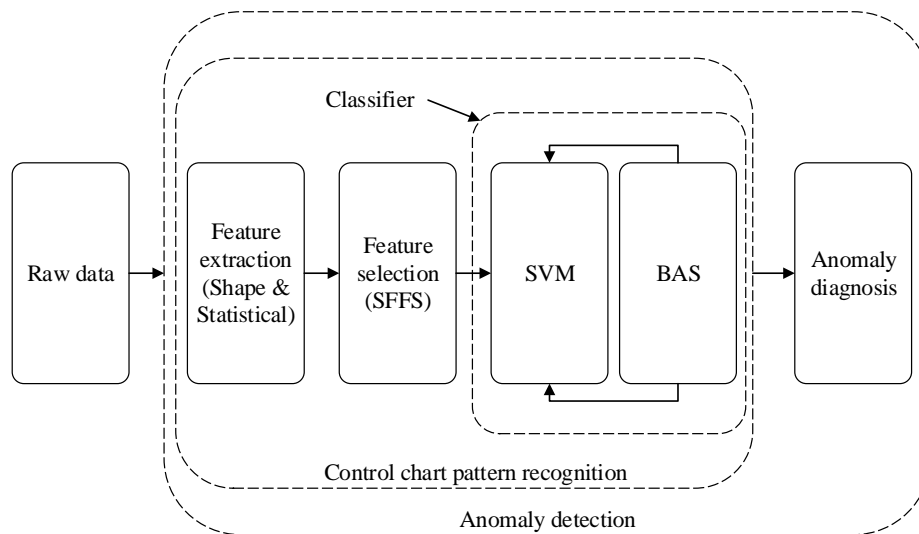
**Figure 2.** The main structure of proposed anomaly detection model.

Based on the analysis of various studies, thirteen shape features and eight statistical features of control charts are extracted in this paper. The extracted statistical features are as follows: mean, average amplitude, square root amplitude, maximum, mean square amplitude, standard deviation, skewness, kurtosis, peak, wave form, pulse, margin, average autocorrelation, their mathematical expressions can refer to [14] and [15].

In reference [16], the author describes several shape features for CCP recognition. They are as follows: the slope of the least-square line of the pattern (S), the number of mean crossings (NC1), the number of least-square line crossings (NC2), the average slope of the two line segments (AS), the slope difference between the least-square line and the two line segments (SD), the area between the mean line and the pattern (AMLP), the area between the least-square line and the pattern (ASLP), the area between the two line segments and the least-square line (ASS). According to the study, the eight shape features can effectively improve the performance of CCP recognition, so they are extracted as alternative features.

*2.2. Feature selection*

The extracted features are further selected to reduce the redundancy of features and improve the accuracy and speed of CCP recognition. In order to eliminate redundant features accurately, the sequential floating forward selection (SFFS) method is utilized to select the most discriminative subset from the extracted features. The method ensures the purpose is achieved by forward and backward operations, as described below.

(1) Forward / Insert operation

Step 1: Each feature is input into the classifier, and then sort them by recognition accuracy from largest to smallest.

Step 2: Set up a feature set (empty at the beginning), add each feature in turn and calculate the recognition accuracy. If the recognition accuracy increases after adding a feature, add it into the feature set, otherwise put it at the end of the queue.

Step 3: According to the results of step 2, the best feature set is selected.

Step 4: Add the features at the end of the queue to the set temporarily one by one and calculate the recognition accuracy, and then add the feature that enhances the performance to the feature set.

(2) Backward / Delete operation

Step 5: Take a feature in the feature set and calculate the recognition accuracy of the set except the feature, and remove the feature from the feature set if the accuracy increases, otherwise, retain the feature.

After the above steps, the remaining features are the selected features.

*2.3. Classifier*

Researches show that support vector machine (SVM) performs well on a small number of dataset [17, 18]. Therefore, SVM is chosen as the classification algorithm for CCP recognition in multi-variety and small batch production. There are four common solutions to construct SVM multi-class classifiers, e.g. one against rest (OAR) [19], one against one (OAO) [20], binary-tree (BT) [21] and directed acyclic graph (DAG) [22]. Related studies show that OAO scheme has the highest classification accuracy among all four schemes [23]. The experimental analysis shows that it is also true in multi-variety and small batch production. Therefore, OAO method is used to build the classifier in this study. The main steps are given as follows.

Step 1: Create a SVM for binary classification between each of the two patterns. Eight patterns are classified in this paper, so twenty-eight SVMs need to be created.

Step 2: Count the classification results of each SVM, and use majority voting method (max wins) to determine the final result.

For linear inseparable data, SVM converts the original input space into a high-dimensional feature space by using the kernel method, which makes the data become linear separable in the mapping space. Among all kernel functions, Gaussian kernel function is the most widely used, which has the best performance in most cases [15]. Therefore, it is chosen in this paper.

*2.4. Beetle antennae search algorithm*

Reasonable selection of parameters can effectively improve the CCP recognition accuracy, the parameters include penalty factor, kernel function parameters, etc. In this research, the parameters of SVM are optimized by BAS algorithm, because beetle antennae search (BAS) algorithm is faster than other optimization methods in the same accuracy.

BAS is an effective algorithm inspired by the foraging principle of long-horn beetles, which is an extension of the biological behavior of long-horn beetles in any dimensional space. Compared with other optimization algorithms, BAS only needs one individual, that is, a long-horn beetle, which greatly reduces the computational complexity. A brief description of the beetle model is as follows.

- The left and right horns are on both sides of the center of mass.
- The ratio of the beetle's step length to the distance between the two horns is a fixed constant, that is, a big beetle (the distance between the two horns is long) takes a big step and a small beetle takes a small step.
- After flying to the next step, the direction of the head is random.

**3. Experiments and results**

*3.1 Samples generation*

In this section, Monte Carlo method is used to generate training and testing samples. All the procedures are coded in MATLAB.

According to the quality control method of multi-variety and small batch production in reference [2], when the process capability index is 1, the quality data are transformed into $N(0, \frac{1}{6})$, and the data transformation formula is $y_i = \frac{x_i - M}{T}$ ($x_i$ is the original data, $M$ is the center of tolerance, $T$ is the tolerance, $y_i$ is the transformed data). Based on the formulas given in reference 5, a total of $8 \times 300 \times 25$ simulation data for CCPs are generated, that is, 300 sets of data are generated for each pattern, and 25 samples for each set. Among them, 200 sets of data are used for training the classifier, and the remaining 100 sets are used for testing. The detailed equations and parameters are shown in Table 1. In this table, i represents the discrete time points of the pattern (i = 1,2⋯,25), $r_i$ represents a random variable of the standard normal distribution at ith time point.

**Table 1.** Parameters used to simulate control chart patterns.

| Index | Control chart patterns | Equations | Parameter values |
|-------|------------------------|-----------|------------------|
| 1 | Normal | $y_i = \mu + r_i\sigma$ | $\mu = 0, \sigma = 1/6$ |
| 2 | Increasing Trend | $y_i = \mu + r_i\sigma + ig$ | $g \in [0.1\sigma, 0.26\sigma]$ |
| 3 | Decreasing Trend | $y_i = \mu + r_i\sigma - ig$ | |
| 4 | Upward Shift | $y_i = \mu + r_i\sigma + ks$ | $s \in [1.5\sigma, 2.5\sigma]$ |
| 5 | Downward Shift | $y_i = \mu + r_i\sigma - ks$ | If $i \in [9,18], k = 1$; else $k = 0$ |
| 6 | Cyclic | $y_i = \mu + r_i\sigma + a \times \sin(\dfrac{2\pi i}{T})$ | $a \in [1.5\sigma, 2.5\sigma]$ $T \in [6,13]$ |
| 7 | Stratification | $y_i = \mu + r_i\sigma'$ | $\sigma' \in [0.2\sigma, 0.4\sigma]$ |
| 8 | Systematic | $y_i = \mu + r_i\sigma + d \times (-1)^i$ | $d \in [\sigma, 3\sigma]$ |

*3.2. Comparison with different methods*

Based on the SFFS method, ten features including mean, average amplitude, standard deviation, wave form, S, NC1, NC2, SD, AMLP and ASS are finally selected as the input.

The performance of the proposed BAS-SVM classifier and neural network algorithms are compared, including probability neural network (PNN), RBF neural network (RBFNN) and BP neural network (BPNN). Then the feature set used in this study and those used in other studies are input into the BAS-SVM classifier to calculate the recognition accuracy. Among them, the feature set used in reference [15] contains 12 features, and the feature set used in reference [16] contains 6 features. The results are listed in Table 2.

**Table 2.** Performance of different methods.

| Classifier | Input dimension | RA/% |
|------------|-----------------|------|
| BAS-SVM | 10 | 96.25 |
| PNN | 10 | 93.125 |
| RBFNN | 10 | 92.75 |
| BPNN | 10 | 95.5 |
| BAS-SVM | 12 | 89.375 |
| BAS-SVM | 6 | 92.875 |

It can be seen that compared with other methods, the classifier proposed in this study has the best classification performance, and the recognition accuracy is the highest when using the feature set in this study. Therefore, the CCP recognition method proposed in this study is more effective in the case of small sample with small amount of data.

*3.3. Model application*

Taking the quality control of the boring diesel injector hole process as an example. The data of injector hole diameter are obtained from production, and the change process after data transformation is shown in Figure 3.

The control chart observation window length in this study is 25. According to the recognition results, the production starts in normal pattern, while the control chart changes to upward shift pattern from the fourth observation window. Process settings, raw materials and processing personnel have not changed during the production process, so it can be judged that the possibility of machine parts failure is the greatest, which is consistent with the actual abnormal causes after inspection and analysis.
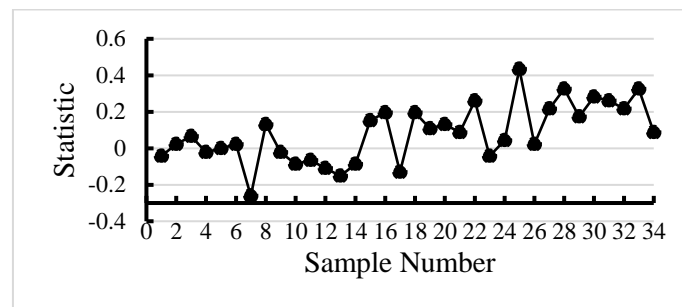
**Figure 3.** The change process of injector hole diameter after data transformation.

## 4. Conclusion

In this paper, the SFFS-BAS-SVM method is proposed to identify abnormal CCP in multi-variety and small batch production, and the causes of abnormal patterns are analyzed based on the recognition results. In the method, representative statistical and shape features of control chart are extracted first. Then, the optimal feature set is selected by SFFS and input into the multi-class SVM classifier optimized by BAS algorithm. The simulation results show that the SFFS-BAS-SVM method has a higher CCP recognition accuracy than other methods when the amount of data is small. Finally, the effectiveness of the pro-posed anomaly detection method is verified by an example.

An effective anomaly detection method in multi-variety and small batch production is proposed in this paper, which significantly improves the detection efficiency. In further work, the model can be extended to multivariate cases to expand the application.

## References
[1]    Li Q, Wei F and Zhou S 2017 Early warning systems for multi-variety and small batch manufacturing based on active learning *Journal of Intelligent & Fuzzy Systems* **33** 2945–52
[2]    Zhang G and Ran Y 2015 Typical Process Capability Analysis of Small-batch Production Based on Fuzzy Matter-element *Journal of Mechanical Engineering* **51** 116-22
[3]    Wu X, Miao R, Zhang X, et al 2015 A conjugate Bayesian approach to control chart for multi-batch and low volume production *International Journal of Production Research* **53** 2179-85
[4]    Wiederhold M, Greipel J, Ottone R, et al 2016 Clustering of similar processes for the application of statistical process control in small batch and job production *International Journal of Metrology and Quality Engineering* **7** 404-12
[5]    Gauri S K and Chakraborty S 2009 Recognition of control chart patterns using improved selection of features *Computers & Industrial Engineering* **56** 1577-88
[6]    Chen Z, Lu S and Lam S 2007 A hybrid system for SPC concurrent pattern recognition *Advanced Engineering Informatics* **21** 303-10
[7]    Addeh J, Ebrahimzadeh A, Azarbad M, et al 2014 Statistical process control using optimized neural networks: A case study *ISA Transaction* **53** 1489-99
[8]    Zhang Y and Lin X 2014 Recognition method for control chart patterns based on improved sequential forward selection and extreme learning machine *International Conference on Progress in Informatics and Computing* (New York: IEEE) pp 79–82
[9]    Shao YH 2016 Least squares recursive projection twin support vector machine for classification *International Journal of Machine Learning & Cybernetics* **7** 411-26
[10]   Wu C, Liu F and Zhu B 2015 Control chart pattern recognition using an integrated model based on binary-tree support vector machine *International Journal of Production Research* **53** 2026-40

[11] Kao LJ, Lee TS and Lu CJ 2016 A multi-stage control chart pattern recognition scheme based on independent component analysis and support vector machine *Journal of Intelligent Manufacturing* **27** 653-64

[12] Zhou Y, Zhou Y, Zhou T, et al 2017 Research on Improved Algorithm Based on The Sequential Floating Forward Selection *Computer Measurement & Control* **25** 294-7

[13] Zhu ZY, Zhang ZY, Man WS, et al 2018 A new beetle antennae search algorithm for multi-objective energy management in microgrid *13th IEEE Conference on Industrial Electronics and Applications Industrial Electronics and Applications* (New York: IEEE) pp 1599-603

[14] Hassan A, Baksh MSN, Shaharoun AM, et al 2003 Improved SPC chart pattern recognition using statistical features *International Journal of Production Research* **41** 1587-603

[15] Xiang Q, Xu L, Liu B, et al 2015 Processing anomaly detection based on rough set and support vector machine *Computer Integrated Manufacturing Systems* **21** 2467-74

[16] Addeh A, Khormali A and Golilarz NA 2018 Control chart pattern recognition using RBF neural network with new training algorithm and practical features *ISA Transactions* **79** 202-16

[17] Kecman V 2001 *Learning and Soft Computing: Support Vector Machines, Neural Networks, and Fuzzy Logic Models* (Cambridge: the MIT press) pp 121–5

[18] Manuel FD, Eva C and Senen B 2014 Do we Need Hundreds of Classifiers to Solve Real World Classification Problems *Journal of Machine Learning Research* **48** 3133-81

[19] Ranaee V and Ebrahimzadeh A 2011 Control Chart Pattern Recognition Using a Novel Hybrid Intelligent Method *Applied Soft Computing* **11** 2676–86

[20] Du S, Lv J and Xi L 2012 On-line Classifying Process Mean Shifts in Multivariate Control Charts Based on Multiclass Support Vector Machines *International Journal of Production Research* **50** 6288–310

[21] Fei B and Liu J 2006 Binary tree of SVM: A new fast multiclass training and classification algorithm *IEEE Transactions on Neural Networks* **17** 696-704

[22] Platt JC, Cristianini N and Shawe J 2000 Large margin DAG's for multiclass classification *Advances in Neural Information Processing Systems* **12** 547-53

[23] Hsu CW, Lin CJ 2002 A comparison of methods for multiclass support vector machines *Neural Netw* **13** 415-25