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Control Chart Patterns Detection Using COA Based Trained MLP Neural Network and Shape Features

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Keywords

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Abstract

Statistical process control (SPC) is widely applied as a potent tool to measure, recognize, analyze and interpret process data to enhance the quality of products and service by detecting instabilities and justifying possible causes. In this paper, fast and accurate system is proposed to detect the control chart patterns (CCP). The proposed method includes three main parts: the feature extraction, classifier and training parts. In the feature extraction part, we used shape features as effective inputs. The dimension of input vector is reduced from 60 to eight by using these features. In the classifier part, we used multilayer Perceptron neural network (MLPNN). In order to improve the MLPNN performance, we used cuckoo optimization algorithm (COA) to train the network. In test stage, 10-fold cross validation method was applied to the synthetic control chart time series dataset to evaluate the proposed system accuracy. The recognition accuracy of proposed system is 99.21%. This research demonstrated that the proposed hybrid system can be used to obtain fast automatic detecting systems for control chart patterns.

1. Introduction

Control charts, in statistical process control are gadgets used to determine if a producing process is in a state of statistical control. If study of the control chart points that the producing process is under control, then no corrections to process control parameters are necessary or desired. Furthermore, data from the process can be applied to forecast the future performance of the process. If the control chart points that the studied process is not in control, investigation of the control chart may help determine the sources of faults, as this will result in degraded process performance [1- 3].

During the last years, CCP recognition has been studied by many researchers. In [4- 5], authors used support vector machine (SVM) to CCP recognition. Using SVM is the new tool that is receiving increasing attention, with significant performance. However, the performance of an SVM is dependent on the optimal selection of kernel function and the control parameters such as margin of the hyper plane, penalty factor and etc. Failure to determine the best control parameters for a SVM model decrease its accuracy [6].

In related works, some approaches have been proposed using fuzzy logic to CCP recognition [7, 8].The fuzzy systems have good performance in pattern recognition problems, but they suffers from the computational burden related to handling a large number of initially generated inappropriate and sometimes wrong fuzzy rules [9].

Artificial neural networks (ANN) have been widely used to CCP recognition [10- 12]. The ANNs offer a number of benefits, such as ability to recognize indirect nonlinear relationships among dependent and independent variables and ability to recognize all feasible interactions among predictor variables. In ANNs training phase, the widely used training algorithm is the back propagation algorithm that is a gradient-based method. Therefore multiple natural problems existing in back propagation algorithm are also frequently encountered in the application of this training algorithm. The main inability of back propagation algorithm is that it will easily get trapped in local minima especially in nonlinear complex pattern recognition problems [13, 14], therefore this algorithm may lead to defeat in finding a global optimal solution. Furthermore, the convergent speed of the back propagation algorithm is very slow.

The recognition of unnatural patterns is a important subject in SPC. In this paper we proposed a fast and accurate system for CCP recognition. The following of paper is organized as follow. In next section, the studied dataset is described. The third section presents the proposed method.

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The forth section presents some simulation results and finally section fifth concludes the paper.

2. CCPs

The main goal of process quality control is to obtain and maintain an admissible level of the sought process quality characteristic consistently. The CCPs can be divided to normal and abnormal patterns. The main significance of a normal pattern is that it points a process under control. An abnormal pattern identifies a producing process when it is out of control. The abnormal patterns sometimes contain worth information relevant to process parameters and process variation. Once the source of assignable causes are correctly detected as early as possible, quality practitioners can dispel them and bring the abnormal process back to the normal situation. Abnormal patterns of control chart are as follow: Cyclic, increasing trend, decreasing trend, upward shift, and downward shift. The associated causes of abnormal patterns are described below

Cyclic pattern: This pattern can be observed by a serial of peaks and troughs occurred in the producing process. Common causes are the cyclic rotation of operators, systematic environmental changes or fluctuation in the production tools.

Trend pattern: This pattern can be defined as a continuous motion in either positive or negative orientation. Common reasons are equipment wear, operator fatigue, tool deterioration, and other causes.

Shift pattern: This pattern can be defined as an abrupt change above or below the average of the process. This shift can be caused by an alternation in process setting, substitution of raw materials, minor failure of machine sections, or introduction of new personnel, and so forth. Figure 1 shows the CCPs.

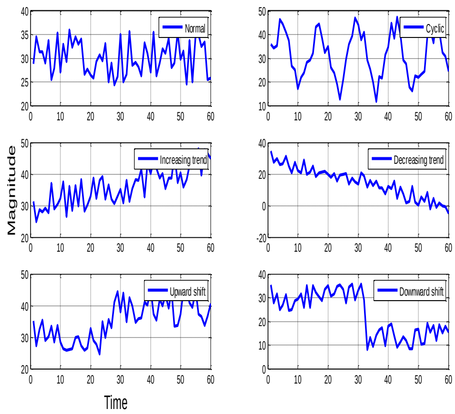

Figure 1. CCPs

3. Proposed Method

Figure 2 shows the main structure of the proposed method. The proposed method includes three main parts: the feature extraction part, classifier part and training part. In the feature extraction part, we used shape features as effective inputs. The use of row CCP data has two problems: 1) The amount of data to be processed by the classifier is large and 2) The training task of the classifier is difficult and more time consuming.

One solution to enhance the accuracy of a classifier is to use smaller input vectors. This task will reduce the classifier size and training time. If the new input vectors represent the shape of the patterns explicitly and if their arrays are reproducible with the process conditions, the classifier's classification rate will increase significantly. In this paper we used shape features that are introduced in [15]. These features are (1) S: the slope of the least-square line, (2) NC1: the number of mean crossings, (3) NC2: the number of least-square line crossings, (4) AS: the average slope of the line segments, (5) SD: the slope difference between the least-square line and the line segments, (6) APML: the area between the pattern and the mean line, (7) APSL: the area between the pattern and its least-square line, (8) ASS: the area between the least-square line and the line segments. More details about these features can be found in [15]. The value of these feature for CCPs are shown in Figure 3.

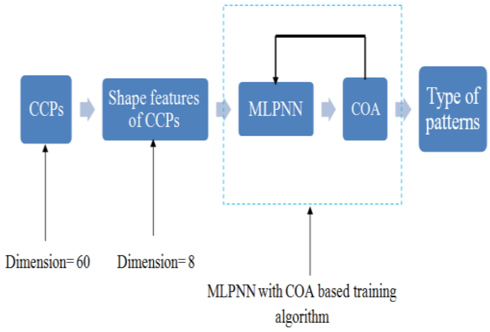

Figure 2. The main structure of the proposed method

In the classifier part, we used MLPNN. The MLPNN is composed of an input layer, one or more hidden layers and an output layer. The CCPs recognition consists of two main phases: training and testing. In the training phase, weights and biases are computed using training algorithm. The issue of training algorithm and its speed is very important for the MLPNN. As mentioned, back propagation is the most used training algorithm in MLPNN that has some serious drawbacks. To overcome these drawbacks, in this paper we proposed the application of COA to train the MLPNN [16].

In this method, each cuckoo represents all weights of a MLPNN structure. For example, for the MLPNN with the structure of 2–2–1 (two neuron in input layer, two neuron in hidden layer and one neuron in output layer), the corresponding encoding style for each cuckoo can be represented as

$$Cuckoo(i) = [w_{11}, w_{21}, w_{12}, w_{22}, b_1, b_2, v_{11}, v_{21}, b_3]$$

$$W = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix}$$

$$B_1 = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \tag{1}$$

$$V = \begin{bmatrix} v_{11} \\ v_{21} \end{bmatrix}$$

$$B_2 = [b_3]$$

where W and B_1 are the hidden layer weight matrices, and V and B_2 are the output layer weight matrices.

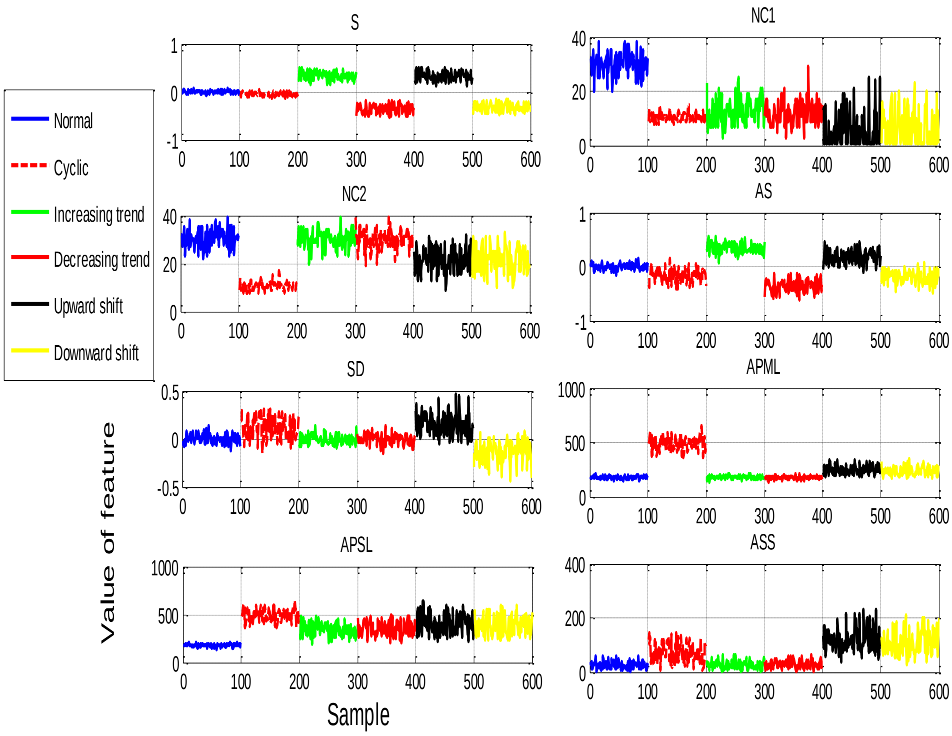

Figure 3. Shape features

4. Simulation Results

In this section, the performance of the proposed system is examined. The computational experiments for this section were done by a PC with Intel core 2 Duo with 4 GB RAM using ASUS computer. The computer program was performed on MATLAB (version 7.8.0.347 (R2009)) environment by using the neural networks toolbox. In order to compare the accuracy of proposed system, the *k*-fold cross validation technique is used. The *k*-fold cross validation technique was employed in the experiments, with $k = 10$. The data set was thus divided into 10 portions, with each part of the data sharing the same proportion of each class of data. 9 data portion were used in the learning phase, while the remaining part was applied in test phase. The MLPNN-training methods were run 10 times to permit each part of the data to take turn as a testing data. The recognition accuracy rate is computed by summing the individual accuracy rate for each run of testing, and then dividing of the total by 10. All the obtained results are the average of 50 independent runs.

4.1. Performance of Traditional MLPNN

In this experiment, we have used MLPNN with traditional training algorithm. The control parameters of applied MLPNN are listed in Table 1. The obtained results are listed in Tables 2 and 3. The number of neurons in hidden layer (NNHL) is determined based on trial and error and after extensive simulations. It can be seen that the use of shape features can improve the recognition accuracy (AR) significantly.

Table 1. MLPNN parameters

Network structure	Value of parameters
Number of layers	2
Number of neurons in output layer	6
	RPROP
	LM
Training algorithm	SCG
	CGBFR
	BFGSQB
	OSS
Initial weights	Random
Transfer function in hidden layer	Tangent-sigmoid
Transfer function in output layer	Linear

4.2. Performance of Proposed Method

In next step, we apply COA for finding the optimum weights and biases of MLPNN. Table 4 shows the coefficient values in the COA.These values obtained after several experiments. Also, Table 5 shows the obtained results. It can be seen that the proposed method has much better accuracy rather than traditional MLPNN.

Table 2. Performance of traditional MLPNN with row data

Training algorithm	NNHL	RA (%)
RPROP	14	92.65
LM	18	93.54
SCG	22	92.43
CGBFR	16	90.29
BFGSQB	19	92.51
OSS	10	91.43

Table 3. Performance of traditional MLPNN with shape features

Training algorithm	NNHL	RA (%)
RPROP	9	98.26
LM	6	98.42
SCG	10	97.52
CGBFR	14	98.19
BFGSQB	7	97.87
OSS	6	97.36

Table 4. Coefficient values in the COA

Number of Cuckoos	40
Minimum number of eggs	2
Maximum number Of eggs	5
Number of clusters	4
Maximum number Of Cuckoos	150
α	30
λ	0.2
Maximum iteration	50

Table 5. Performance of proposed method

Input	NNHL	RA (%)
Row data	23	95.63
Shape features	11	99.21

5. Conclusions

Accurate recognition of CCPs is very important for producing high-quality products. This study has investigated the design of an automatic and accurate system for recognition of CCPs. This study presents methods for improving MLP performance in two aspects: feature extraction and learning algorithm. The results showed that the proposed model was effective in finding the optimal weight and biases of back propagation, and that it improved recognition accuracy. The simulation results indicate that the proposed method has high classification accuracy (99.21%).

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