Control Chart Pattern Recognition using Optimized One- Dimensional Convolutional Neural Network under gamma distribution

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Abstract- In this study, the parameter optimization of one-dimensional convolutional neural network using the particle swarm algorithm and genetic algorithm on control chart pattern (CCP) recognition are proposed. The simulation studies exhibit the superior accuracy of CCP recognition for our proposed method, particularly when the underlying distribution follows a gamma distribution.

Keywords – Control Chart Pattern Recognition, Convolutional Neural Network, Particle Swarm Algorithm, Genetic Algorithm

I. INTRODUCTION

The control chart technique is an on-line statistical process control (SPC) approach that is widely applied for effectively detecting the occurrence of assignable causes. If the sample points fall outside the control limits of a control chart or exhibit a non-random pattern, then it is usually assumed that assignable causes might appear to result in the out-of-control state. When the process is running under an in-control state, the sample points always display a random pattern as the normal pattern. However, if assignable causes appear, the sample points on the control chart may present the non-random patterns as abnormal patterns. The common control chart patterns(CCP) include Natural Patterns (NP), Upward and Downward Shift Patterns (USP and DSP), Upward and Downward Trend Patterns (UTP and DTP), Cyclic Patterns (CP) and Systematic Patterns (SP) as shown in Fig. 1.

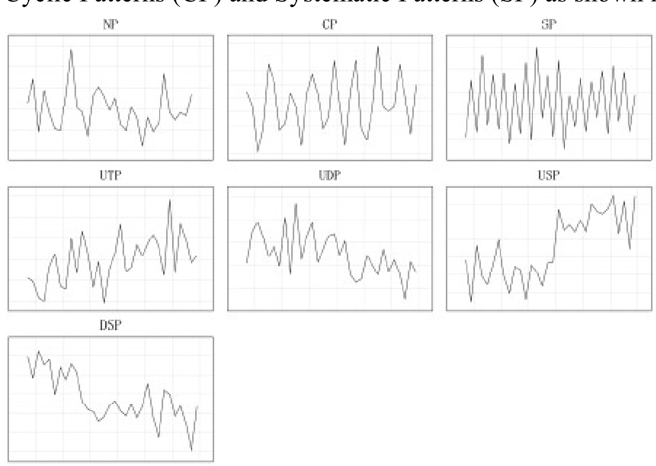

Figure 1. The Basic CCPs (Hong et al., 2019[1])

For many real world situations, the underlying distribution of the process characteristic may not be normally distributed. The gamma distribution is able to present a variety of probability distributions with a wide range of degrees of skewness and thence is able to comprehensively stand for the underlying distributions in many industrial cases. Therefore, the gamma distribution is often popularly employed to investigate the performance of control charts under non-normality.

Over the last several decades, many machine learning methods have been applied to the control chart pattern recognition (CCPR), and have obtained outstanding results. Hachicha and Ghorbel [2] reviewed more than 120 papers published on CCPR studies within 1991–2010 and found the majority of the reviewed articles use Artificial Neural Network (ANN) approach. Convolutional neural networks (CNNs), as a state-of-the-art deep machine learning approach, have been demonstrated remarkable performance in many machine learning fields.[3]

Different from the image task which uses two-dimension convolutional kernels, the input of the CPPs recognition model is one dimension, and so are the convolutional kernels. In this paper, two one-dimensional CNN (1D-CNN) models were built for CCPs recognition tasks. The optimal CNN parameters are obtained with Genetic Algorithm (GA-CNN) and Particle Swarm Optimization (PSO-CNN). Their performance is compared with the metrics of accuracy, precision, recall and F1-score.

II. Proposed Algorithm

A. *Simulation of Nonrandom Patterns*

In this study, the dataset for training and testing was simulated by a computer, and the 6 basic CCPs and 13 mixture CCPs were generated by the formula (1) and formula (2), respectively. The mixture CCPs are shown in Fig. 2

$$x(t) = \mu_0 + n(t) + d(t) \tag{1}$$

$$x(t) = \mu_0 + n(t) + d_1(t) + d_2(t) \tag{2}$$

where t is the time of sampling, x(t) is the value at time t , μ_0 is the process mean, n(t) is the value at time t which follows a gamma distribution $d_1(t)$ and $d_2(t)$ are the basic CCPs simulation formula. The formula d(t) of the basic control chart patterns and the parameters are shown in Table 1.

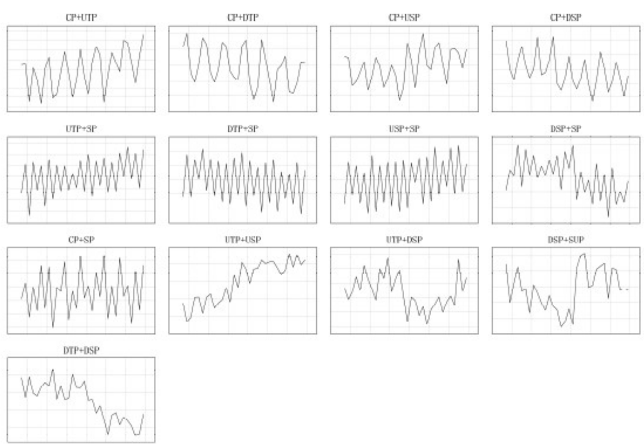

Figure 2. The Mixture CCPs (Hong et al., 2019[1])

Table 1. Parameters of the basic CCPs

Pattern type	Formula	Description	Parameter
UTP/DTP	$k*t$	k is the slope	UT: $0.1 \le k \le 0.26$ DT: $-0.26 \le k \le -0.1$
USP/DSP	$u(n)*s$	s is the shift magnitude	US: $1.0 \le s \le 3.0$ DS: $-3.0 \le s \le -1.0$
CP	$a \times \sin\frac{2\pi t}{\Omega}$	a is the cycle amplitude, Ω is the cycle period	$1.0 \le a \le 3.0$ $\Omega = 8$
SP	$g \times (-1)^t$	g is the magnitude of systematic	$1.0 \le g \le 3.0$

pattern

B. 1D-CNN Parameters Optimization with PSO

The major advantage of 1D-CNN is that a real-time and low-cost hardware implementation is feasible due to the simple and compact configuration of 1D-CNNs that perform only 1D convolutions (scalar multiplications and additions). The convolutional neural network consists of multiple types of layers: convolutional layers, pooling layers and fully connected layers. The general architecture of the convolutional neural network is shown in Fig. 3.

Although CNN are very powerful, performance or accuracy of CNN directly depends upon the parameter selection. The selection of network parameters affects the classification accuracy.[4][5] A Particle Swarm Optimization (PSO) based CNN approach developed by Sinha et al. [6] was adopted as shown in Fig. 4 for optimal parameter selection to achieve highest classification accuracy.

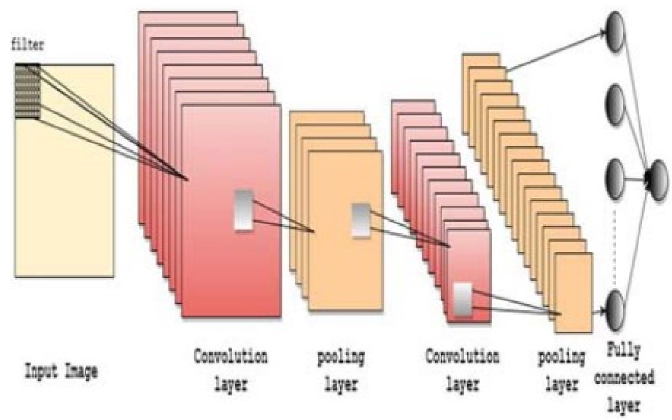

Figure 3. General architecture of CNN

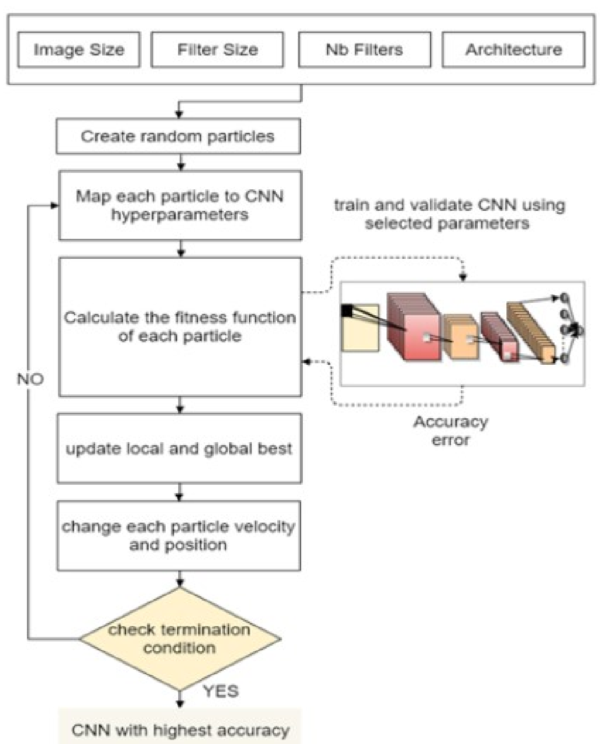

Figure 4.PSO-CNN approach developed by Sinha et al. [6]

C. Performance Metrics

Four metrics are used in this paper, including accuracy, precision, recall, and F1-score. The calculation formula for the above metrics are as follows:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

$$precision = \frac{TP}{TP+FP} \tag{4}$$

$$recall = \frac{TP}{TP+FN} \tag{5}$$

$$F1-score = \frac{2*precision*recall}{precision+recall} \tag{6}$$

where TP is the true positive, FP is the false positive, TN is the true negative, and FN is the false negative. The CCPs recognition is a multi-class classification problem. The metrics mentioned above are suitable for binary classification tasks.

III. Experiment and Result

The simulation results of PSO-CNN and GA-CNN with a different convolutional layers of 3, 4, and 5 under a gamma distribution with a shape parameter of 8 and a scale parameter of 0.01 are shown in Table 2. The 3-layer models perform slightly better than the others. PSO-CNN models are superior to GA-CNN models in all four metrics. There are 0.25% CCP misclassification including misclassifying UT to UT+SYS, UT+US/UT+DS to UT, and DS+SYS to SYS.

IV.CONCLUSION

In this paper, two one-dimensional CNN (1D-CNN) models were built for CCPs recognition tasks. The optimal CNN parameters are obtained with Genetic Algorithm and Particle Swarm Optimization. Our proposed model PSO-CNN on CCPs classification of 6 basic CCPs and 13 mixture CCPs reveals very high accuracy. The PSO-CNN performance is also superior to GA-CNN in all four metrics.

Table 2. Metrics of GA-CNN and PSO-CNN with layers 3, 4, 5

Model\Metric	*Precision*	*Accuracy*	*Recall*	*F1-score*
GA-CNN-3	99.70%	99.70%	99.70%	99.70%
GA-CNN-4	99.62%	99.63%	99.62%	99.63%
GA-CNN-5	99.09%	99.14%	99.09%	99.09%
PSO-CNN-3	99.95%	99.95%	99.95%	99.95%
PSO-CNN-4	99.84%	99.84%	99.84%	99.84%
PSO-CNN-5	99.50%	99.51%	99.50%	0.9950

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