Control Chart Pattern Recognition Using Preprocessing Based on DTW and 1D-CNN for Anomaly Equipment Detection

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Abstract

This study proposes a Control Chart Pattern Recognition (CCPR) model that integrates a Dynamic Time Warping (DTW)-based preprocessing method and a 1D-Convolutional Neural Network (1D-CNN). The model enhances anomaly detection by identifying unique patterns that deviate from similar equipment's behavior. Experimental results demonstrate its effectiveness in handling insufficient time-series data, achieving high classification accuracy, and reducing unnecessary alerts. This SPC-AI approach improves operational efficiency and reliability in complex production processes, such as display manufacturing.

Author Keywords

Control chart pattern recognition; Time-series classification; Anomaly Detection; Statistical Process Control; Convolutional neural network; Dynamic Time Warping

1. Introduction

Statistical Process Control (SPC) is a widely used method in industrial production for monitoring quality. However, its effectiveness often relies on engineer experience, making consistent quality management challenging. SPC employs rules such as the Western Electric and Nelson rules to set thresholds for anomaly detection, but their application is subjective and varies significantly. Furthermore, in sequential production processes, issues in earlier stages can cascade into later stages, causing unnecessary alerts and diverting attention from the root cause. Control Chart Pattern Recognition (CCPR) has emerged as a promising alternative to overcome some of SPC's limitations. By analyzing patterns in time-series data, CCPR enhances anomaly detection beyond rule-based systems. However, CCPR also faces challenges in securing sufficient time-series data and addressing cascading anomalies, common to both SPC and CCPR. This study proposes a practical quality monitoring methodology for manufacturing processes using CCPR. By incorporating time-series extension preprocessing and pattern comparisons across similar units, the proposed model enhances anomaly detection by identifying both traditional and previously undefined abnormal patterns. This approach provides (1) robust detection of unique patterns, (2) reduced false alert notifications, and (3) a focus on genuinely critical issues, improving efficiency in process management. This study validates the effectiveness of the CCPR model using defect rate data from display manufacturing, a field characterized by sequential and complex production processes. Patterns analyzed in the Methods and Results sections are based on real cases of abnormal equipment in display production.

2. Methods

Definition and Modeling of Abnormal Patterns: Typically, control chart patterns include a normal pattern (NOR) and six abnormal patterns originally defined by the Western Electric Company in 1958: Upward Trend (UT), Downward Trend (DT), Upward Shift (US), Downward Shift (DS), Cyclical Movement (CYC), and Systematic Movement (SYS). These patterns are usually generated based on formulas developed in foundational studies by Guh & Hsieh (1999) and Yang & Yang (2005).

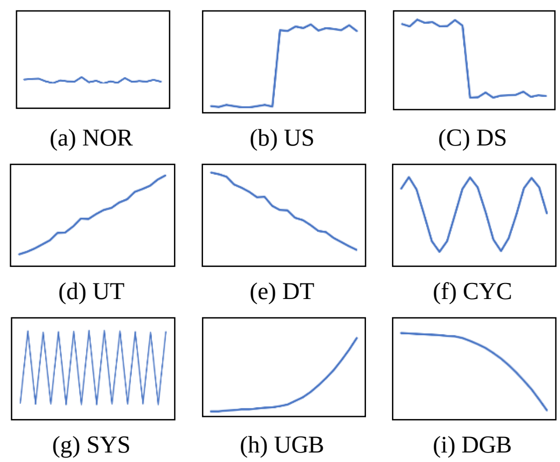

Figure 1. Unnatural Control Chart Patterns

Table 1. Equations for each pattern

Patterns	Traditional Equations	Applied Equations
(a) Normal (NOR)	$y(t) = x(t)$	$y(t) = x'(t)$
(b) Upward Shift (US)	$y(t) = x(t) + \tau d$	$y(t) = x'(t) + \tau(t)d$
(c) Downward Shift (DS)	$y(t) = x(t) - \tau d$	$y(t) = x'(t) - \tau(t)d$
(d) Upward Trend (UT)	$y(t) = x(t) + dt$	$y(t) = x'(t) + \tau(t)dt$
(e) Downward Trend (DT)	$y(t) = x(t) - dt$	$y(t) = x'(t) - \tau(t)dt$
(f) Cyclic (CYC)	$y(t) = x(t) + d\, sin\frac{2\pi t}{\omega}$	$y(t) = x'(t) + \tau(t)d\, sin\frac{2\pi t}{\omega}$
(g) Systematic (SYS)	$y(t) = x(t) + (-1)^t d$	$y(t) = x'(t) + \tau(t)(-1)^t d$
(h) Upward Gradient Boosting (UGB)	Undefined	$y(t) = x'(t) + \tau(t-3)dt + \tau(t)dt^2$
(i) Downward Gradient Boosting (DGB)	Undefined	$y(t) = x'(t) - \tau(t-3)dt - \tau(t)dt^2$

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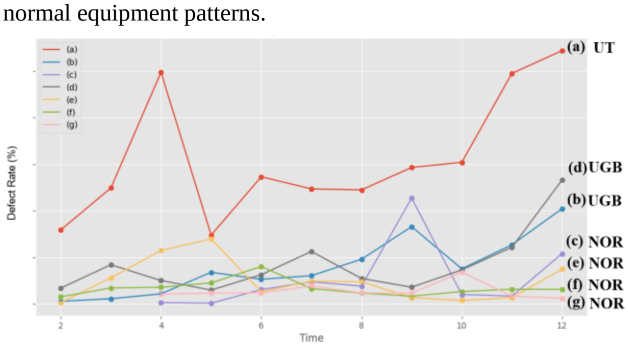
Table 2. Parameters for equations

Parameter	value	description
$x(t)$		N (0.002,0.01^2)
$x'(t)$		Replace values generated form $x(t)$ that are less than 0 with 0
$\tau(t)$	$\tau = \begin{cases} 0 & before\ certain\ timing \\ 1 & after\ certain\ timing \end{cases}$	Time of abnormal pattern occurrence UT/DT: 1–10 US/DS: 8 UGB/DGB: 10 CYC/SYS: 1, 8
d	US/DS: 0.01–0.13 UT/DT: 0.003–0.009 UGB/DGB: 0.005–0.012 CYC/SYS: 0.01–0.03	
c	CYC/SYS: 0.03–0.09	Adjust to prevent negative values due to amplitude
ω	CYC: 4–6	

However, real-world data from display manufacturing reveals limitations in these traditional 7 patterns definitions. In Figure 2, equipment (a) was confirmed as abnormal. With the 7 patterns classification, it was difficult to distinguish equipment (a) from similar equipment with upward trends, such as (b) and (d). However, the 9-pattern model, incorporating the Upward Gradient Boosting (UGB) pattern, grouped equipment (b) and (d) separately due to their steeper, accelerating slopes. UGB, a newly defined pattern, represents a steep, progressively accelerating upward trend in defect rates and addresses the limitations of traditional classifications. This differentiation enabled accurate isolation of the abnormal equipment (a), demonstrating that the 9-class approach effectively distinguishes between abnormal and normal equipment patterns.



Training Patterns	(a)	(b)	(c)	(d)	(e)	(f)	(g)
7 Patterns	UT	UT	NOR	UT	NOR	NOR	NOR
9 Patterns	UT	UGB	NOR	UGB	NOR	NOR	NOR

Figure 2. Actual Case Requiring UGB Pattern Definition and Result Differences by Training Patterns

To better simulate actual production scenarios, this study incorporates the time-based transition variable τ(t), inspired by Ünlü and Ramazan (2021). Previously applied only to patterns like Upward Shift (US) and Downward Shift (DS), τ(t) is now extended to all defined patterns, enhancing detection capabilities. This variable transitions between 0 and 1 to reflect real conditions where equipment initially operates normally but later develops issues. Details, including the mathematical definitions of patterns, are presented in Tables 1 and 2.

Preprocessing: Despite extensive research on CCPR, practical applications face a key challenge: existing studies have often assumed sufficient time-series data is available to meet learning requirements. In practice, however, securing enough time-series data can be difficult, especially for new products or novel defect types, making it challenging for AI to classify patterns accurately. This data scarcity limitation has generally been overlooked in CCPR research. To address this, a Dynamic Time Warping (DTW)-based preprocessing method is applied, as shown in Figure 3. Unlike simpler methods such as padding or duplication, DTW optimally stretches time series segments to preserve essential temporal relationships, enabling the model to handle variable-length input data more effectively and improving classification performance. The approach extends the time series length while maintaining DTW similarity by recording and adjusting variations that occur during DTW calculations to align with a reference series. In this study, the reference time series has a length of 12 and a defect rate of zero, which causes the extended series to include segments with low defect rates. This configuration is particularly effective in replicating realistic scenarios where normal conditions shift to abnormal ones, highlighting potential issues during this transition.

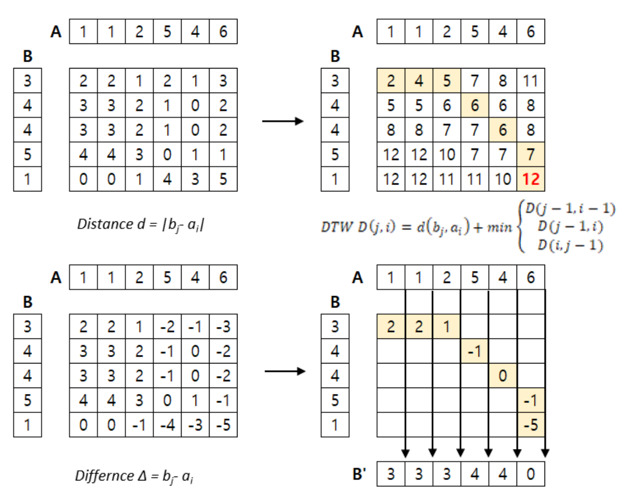


Figure 3. Example of DTW-Based Series Transformation

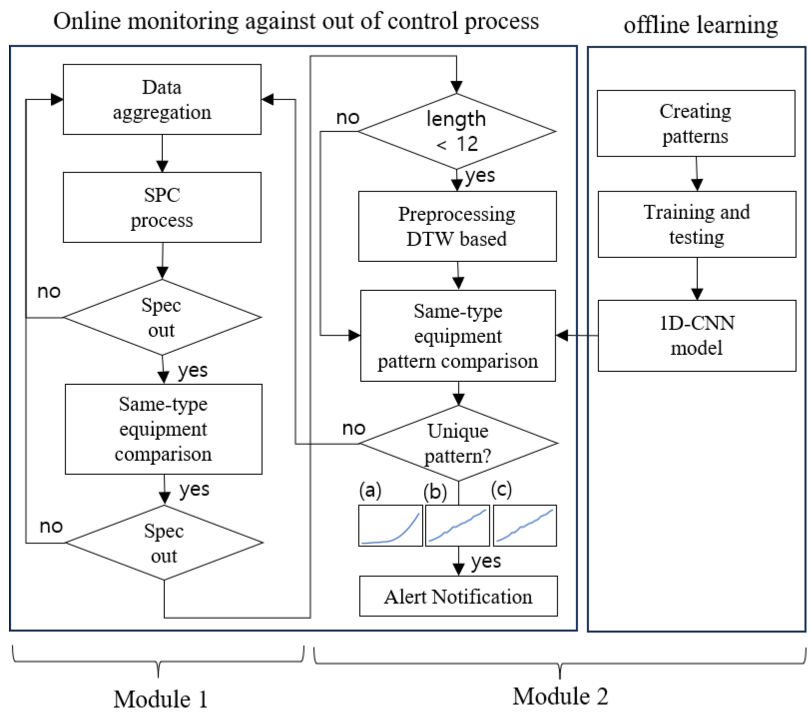


Figure 4. The Structure of the Anomaly Detection System Using Online Monitoring and Offline Learning

System Structure: The anomaly detection system, depicted in Figure 4, consists of two main modules: Module 1 (SPC) and Module 2 (AI). In Module 1, the SPC process monitors defect rates for each product, process, equipment, and defect type three times daily. If any equipment's defect rate exceeds specified limits, it is flagged as a potential abnormal candidate. Additional logic compares the defect rates and production volumes of the flagged equipment with similar equipment. If the flagged equipment does not exceed predefined thresholds for these comparisons, it does not proceed to Module 2. This logic, absent in traditional SPC systems, has been previously implemented to effectively reduce false alarms. In Module 2, a preprocessing method inspired by DTW is applied to adjust the time series length when the flagged equipment's data is too short for analysis. This method modifies the time series while preserving essential temporal relationships, enabling the system to process variable-length data effectively. If the time series already meets these criteria, no additional preprocessing is performed, and the system directly conducts pattern classification using a 1D-CNN. The suspect equipment's pattern is then compared to those of similar equipment. An alert notification is triggered only if the suspect equipment exhibits a unique abnormal pattern that does not appear in similar equipment. This approach enhances SPC reliability by minimizing unnecessary alerts and enabling engineers to focus on genuine process deviations.

3. Results

Classifier Performance Comparison: In this study, The time series length was set to 12, as defect rates are calculated three times a day, reflecting the trend over a 4-day period. Two scenarios were tested: one with a time series length of 12, and another with a shorter time series length of 6 (half of 12). When the time series length was 12, no preprocessing was applied, as the data met the model's required input length. When the time series length was 6, it was expanded to 12 through preprocessing. Three methods were applied for this expansion: first, padding with the average value; second, stretching each existing value by duplication (for example, a sequence like 1, 2, 3 would become 1, 1, 2, 2, 3, 3); and third, using DTW-based time series transformation. The training dataset consisted of 800 rows per pattern for each of the nine patterns, totaling 7,200 rows used to train the model. Table 3 summarizes the classification accuracy across various models. As shown in Table 3, while the improvement was not substantial in each case, the 1D-CNN model achieved slightly higher accuracy overall, making it the most reliable choice among the tested classifiers. Details on the hyperparameter configurations for SVM, MLP, XGBoost and 1D-CNN are provided in the Appendix. Each scenario was repeated three times, and the average accuracy of these three repetitions is presented. These scenarios included four classifiers tested without preprocessing for time series of length 12 and with the three preprocessing methods for time series of length 6. When the training and testing data had the same time series lengths (both 12), classification accuracy reached approximately 99% without preprocessing. However, when testing with a time series length of 6, accuracy improved significantly when DTW-based preprocessing was applied to extend the data length to 12. Based on these results, the combination of DTW-based preprocessing and the 1D-CNN model was ultimately selected for this study.

Table 3. Classification Test Results (Accuracy)

Test length	Pre processing	SVM	XGBOOST	MLP	1D-CNN
12	None	0.987	0.989	0.984	0.991
6	Padding	0.473	0.596	0.537	0.646
6	Stretching	0.573	0.551	0.563	0.573
6	DTW-based	0.910	0.914	0.920	0.930

Anomaly Detection Case Studies: Figures 5 and 6 illustrate representative cases handled by the proposed system. In Figure 5, equipment (a) was confirmed to be problematic and is identified as abnormal due to its unique pattern, which is not present in any other similar equipment. This distinctive abnormal pattern triggers an alert notification, since equipment (a) is the only unit among similar equipment exhibiting this pattern. In contrast, Figure 6 shows a case where both equipment (a) and (b) exhibit abnormal patterns; however, since their patterns are identical, the alert is filtered out. This suggests that the issue likely originates from an earlier process, rather than from individual equipment.

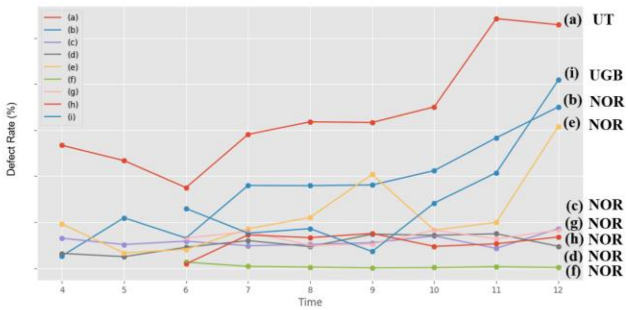


Figure 5. Unique Abnormal Pattern Triggering an Alert

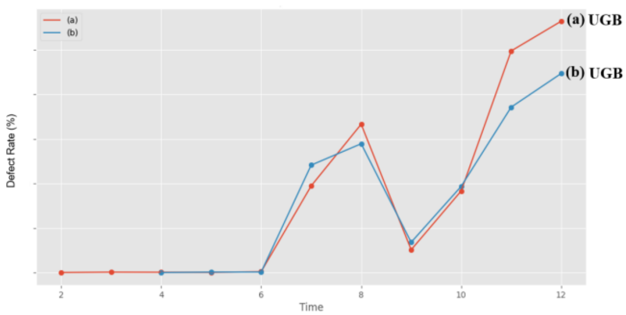


Figure 6. Identical Patterns Leading to Alert Filtering

In traditional SPC systems, pattern classification or comparison with similar equipment was not possible, so any control limit violation would automatically trigger an alert notification. Figure 7 shows how defects from one facility can impact subsequent processes, causing a chain of unnecessary alerts from a single root cause, like Equipment 1. Existing CCPR studies share this limitation, focusing only on individual time series and ignoring interconnected processes. The proposed system addresses these issues by introducing pattern comparison across similar equipment, filtering non-critical cases as false positives and distinguishing true anomalies from propagated alerts. This approach reduces unnecessary alerts and is ideal for complex, sequential production environments.

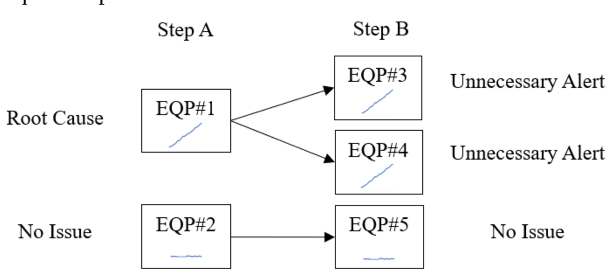


Figure 7. Root Cause and Unnecessary Alerts in Sequential Processes

4. Conclusion

In this study, we developed a novel Control Chart Pattern Recognition (CCPR) model for anomaly detection in manufacturing processes, combining DTW-based time series extension preprocessing with a 1D-CNN classifier. This model addresses a significant limitation in traditional SPC systems by achieving high classification accuracy even with limited data. By comparing patterns across similar equipment, the system effectively detects unique abnormal patterns while minimizing unnecessary alerts, allowing engineers to focus on critical issues. The integrated SPC-AI system demonstrated reliable filtering of non-critical alerts, achieving a 100% Negative Predictive Value (NPV) for false positives. This automatic filtering capability reduced the number of alert notifications by approximately 60% compared to previous systems, significantly enhancing operational efficiency. Currently, this study focuses on a single scale, specifically defect rates. However, SPC is not limited to defect rate monitoring; it is widely applied to various measurement items with different scales. Some of these items require upper limit control, while others involve target-centered or lower limit management. Extending the CCPR model to handle multiple scales and diverse types of measurement values is a crucial area for future work. By adapting CCPR for broader applications, the system can be practically implemented for comprehensive monitoring across various metrics, enhancing its utility in real-world SPC environments.

5. References

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6. Appendix

The following summarizes the hyperparameter tuning results for the four classifiers used in this study:

1. SVM: C=10, gamma='auto', kernel='rbf'

2. XGBoost: colsample_bytree = 0.923, max_depth = 5, subsample = 0.924

3. MLP: Dense units = [448, 320, 416, 64]

4. 1D-CNN: Conv filters = [256, 256, 384], Dense units = 352