THE JOURNAL OF APPLIED ENGINEERING AND TECHNOLOGIES
2026 Vol. 1, No. 3, ISSN (O): 3154-7877

Prototype Memory Control for Detecting Abnormal Operation Events in Industrial Robot Data Streams

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ARTICLE INFO

Keywords
Industrial robot monitoring
Data stream anomaly detection
Prototype memory control
Online clustering
Operation event streams
Mechanical degradation
Smart manufacturing

Published:
01 September 2026

ABSTRACT

Industrial robot systems produce continuous event streams from joint controllers, torque sensors, motion planners, safety interlocks, tool changers, servo drives, and production task logs. These streams evolve with product switching, task reprogramming, tool wear, maintenance cycles, and operator intervention. Standard streaming clustering methods may adapt too quickly to repeated abnormal motion events, especially when early mechanical degradation appears as small but persistent deviations. This study develops a prototype memory control method for detecting abnormal operation events in industrial robot data streams. The method maintains dynamic prototypes for normal operation states and introduces a memory-control coefficient to preserve rare deviation patterns across long production cycles. A multi-event representation module encodes joint deviation, torque fluctuation, cycle-time variation, emergency-stop frequency, tool-change irregularity, and controller warning sequences into stream vectors. Experiments are conducted on a robotic manufacturing dataset containing 1,140 industrial robots, 26 production cells, 52 operation variables, and 10-second records collected over 118 days. The dataset includes 364 million streaming event records and 2,960 annotated abnormal segments, including joint overload, servo instability, tool misalignment, abnormal cycle delay, and repeated safety-interlock triggers. The proposed method shortens median detection delay from 22.8 minutes to 6.2 minutes compared with CluStream. False alerts decrease to 1.8 cases per robot-month. The online engine processes 73,000 event vectors per second and stores 9,300 active operation prototypes with 1.08 GB memory usage. Prototype memory control preserves 2,110 low-frequency degradation patterns that are lost by fast-update clustering baselines. These findings indicate that controlled cluster memory can improve anomaly detection in non-stationary industrial robot event streams.

1. Introduction

Industrial robots are increasingly deployed in automated manufacturing lines for material

Citation: Sato, T., Yamamoto, H., & Nakamura, R. (2026). Prototype Memory Control for Detecting Abnormal Operation Events in Industrial Robot Data Streams. *The Journal of Applied Engineering and Technologies*, 1(3), 10-17.

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https://doi.org/10.64744/tjaet.2026.274.

handling, assembly, welding, machining, inspection, packaging, and other repetitive production tasks. Their operational reliability directly affects production safety, product quality, equipment utilization, and manufacturing continuity. Modern robotic systems continuously generate heterogeneous event streams from joint controllers, torque sensors, motion planners, servo drives, tool changers, safety interlocks, programmable logic controllers, and task-execution logs. These data provide valuable information for identifying abnormal operating conditions before they develop into serious equipment failures (Fu et al., 2020; Fylladitakis, 2025). However, robot event streams are highly dynamic because their statistical characteristics may change with product switching, task reprogramming, payload adjustment, tool wear, preventive maintenance, environmental variation, and operator intervention. Consequently, the same sensor pattern may indicate normal operation under one production condition but represent an abnormal state under another. Abnormal robot behavior does not always appear as an abrupt failure or a large sensor deviation. Early mechanical degradation, servo instability, excessive joint friction, tool misalignment, trajectory deviation, and repeated safety-interlock activation often emerge as weak but persistent changes distributed across multiple variables (Liang et al., 2025; Seid Ahmed & Amorim, 2025). These changes may propagate through mechanically or logically connected components, making it difficult to distinguish an initiating anomaly from its downstream effects. Recent multivariate time-series research has introduced causal inference to identify fine-grained dependencies among variables and separate primary abnormal factors from propagated responses, thereby improving anomaly localization and interpretability (Chen et al., 2025). Nevertheless, causal structures estimated from historical data may become less reliable when production tasks, control parameters, or robot configurations change. In addition, low-frequency degradation signals can be masked by normal cycle-to-cycle variation, temporary load changes, communication delays, and sensor noise (Yin et al., 2026; Lee et al., 2026). Reliable online monitoring therefore requires a method that can adapt to evolving operation states without eliminating rare but meaningful deviation patterns (Salboukh et al., 2025).

Deep learning, statistical process monitoring, and stream clustering have been widely investigated for industrial anomaly detection. Autoencoders, recurrent neural networks, Transformer architectures, and graph-based models can learn nonlinear relationships among multiple sensor variables and identify complex temporal patterns (Zhang et al., 2026; Zhang, 2026). However, many of these methods rely on offline model training, stable data distributions, substantial computing resources, or sufficiently large labeled fault datasets. These requirements limit their application in manufacturing environments where robot tasks are frequently modified and labeled degradation events are scarce. Retraining a complex model whenever a production condition changes may also interrupt real-time monitoring and increase system maintenance costs (Su & Zhang, n.d.; Garcia et al., 2025). Moreover, highly accurate offline results do not necessarily guarantee stable performance in continuously evolving event streams. Statistical monitoring methods provide clearer decision rules and are generally easier to implement, but fixed thresholds and stationary distribution assumptions may produce excessive false alarms when robot speed, payload, trajectory, or cycle requirements change (Qi & Qiao, 2026; Du et al., 2026). Adaptive thresholds can reduce some unnecessary alerts, yet they may gradually shift toward persistent abnormal observations and consequently treat degradation as normal behavior. Online clustering algorithms, including CluStream-based methods, offer an alternative by incrementally updating compact summaries of incoming data (Shukla et al., 2025; Xiong et al., 2026). Their limited memory consumption and continuous updating capability make them suitable for high-volume industrial streams (Qi & Qiao, 2026; De Barrena et al., 2025). However, rapid cluster adaptation creates a potential pattern-absorption problem. When an abnormal motion or warning pattern occurs repeatedly over a long production cycle, the clustering model may gradually incorporate it into a normal-state cluster. Rare degradation information can then disappear from the retained summaries, reducing sensitivity to slowly developing failures (Zhang et al., 2025; Kumar & Sharma, 2026). Existing industrial robot monitoring studies also remain limited in data scale, fault diversity, and evaluation design. Many experiments are conducted using individual machines, laboratory testbeds, short observation periods, or artificially injected faults (Su & Dong, 2026; Du et al., 2026). Such settings may not adequately represent large manufacturing systems containing multiple robot models, production cells, task programs, and operating regimes. Performance is also frequently reported using conventional classification measures such as accuracy, precision, recall, and F1-score. Although these indicators are useful, they do not fully reflect operational requirements. In practical deployment, a monitoring system must identify anomalies with minimal delay, maintain a low number of false alerts for each robot, process incoming events at production speed, and operate within limited memory and computational resources (Sarmas et al., 2026; Hong et al., 2026). The ability to preserve low-frequency degradation evidence over long monitoring periods is equally important because early warning often depends on patterns that occur only occasionally.

This study develops a prototype memory control method for the online detection of abnormal operation events in industrial robot data streams. The proposed method maintains dynamic prototypes representing normal operating states while introducing a memory-control coefficient to regulate prototype updates and retain rare deviation patterns. A multi-event representation module integrates joint-position deviation, torque fluctuation, cycle-time variation, emergency-stop frequency, irregular tool-changing behavior, and controller warnings into unified stream vectors. The method is evaluated using a large-scale robotic manufacturing dataset containing 1,140 robots from 26 production cells, 52 operation variables, and approximately 364 million records collected over 118 days. The study examines whether controlled prototype updating can prevent persistent abnormal patterns from being prematurely absorbed into normal clusters while maintaining adaptation to legitimate production changes. Its main purpose is to reduce anomaly-detection delay, decrease false alerts at the robot level, preserve low-frequency degradation information, and satisfy real-time throughput and memory constraints. By addressing the conflict between rapid adaptation and long-term anomaly retention, the study provides a practical online monitoring approach for improving robot reliability, maintenance planning, production continuity, and operational safety in smart manufacturing environments.

2. Materials and Methods

2.1 Sample and Study Object Description

The study used a dataset collected from an industrial robotic manufacturing platform over 118 days. It included 1,140 robots across 26 production cells and 52 operational variables, such as joint positions, torque, cycle times, tool changes, and safety-interlock events. Metrics were recorded every 10 seconds, resulting in 364 million event records. A total of 2,960 abnormal segments were labeled, including joint overload, servo instability, tool misalignment, abnormal cycle delays, and repeated safety-interlock triggers. Each event stream was treated as a separate data unit. Sensitive operational details were removed to ensure privacy. The dataset captured both normal operations and rare deviations, providing a realistic basis for evaluating anomaly detection.

2.2 Experimental Design and Control Experiments

The experiment compared the proposed memory-controlled method with two baseline methods: streaming k-means and CluStream. The memory-controlled method retained low-frequency deviations in prototypes, while streaming k-means updated clusters continuously without memory, and CluStream used fixed-window micro-clusters. The first 80 days were used to build initial clusters and tune parameters. The remaining 38 days were reserved for online evaluation. All methods processed events in time order without using future data. This setup allowed direct comparison of detection delay, false-alert rate, cluster stability, and memory use across methods.

2.3 Measurement Methods and Quality Control

Operational variables were grouped into four categories: joint performance, torque control, cycle timing, and safety indicators. Joint metrics included deviations from target positions and speed fluctuations. Torque metrics captured overloads and instability events. Cycle timing measured abnormal delays. Safety indicators included emergency-stop frequency and tool-change irregularities. Quality control removed duplicates, invalid timestamps, incomplete sequences, and impossible event orders. Sessions with fewer than two valid events were excluded. Feature values were winsorized at the 0.5th and 99.5th percentiles. Abnormal segments were cross-checked against maintenance logs and operator reports to ensure reliability.

2.4 Data Processing and Model Formula

Event records were converted into time-ordered vectors and normalized using median and interquartile scaling. Categorical variables, such as tool type or robot model, were encoded numerically. For each event vector x_t, the distance to the nearest prototype p_j was calculated as:

$$D_t = \min_j \sqrt{\sum_{k=1}^{p} w_k \left(x_{t,k} - p_{j,k}\right)^2}$$

where p is the number of features and w_k is the feature weight. Prototype updates were controlled by a memory coefficient m_t to retain rare anomalies:

$$p_j^{(t+1)} = p_j^{(t)} + \eta(1-m_t)(x_t - p_j^{(t)})$$

where η is the learning rate. Larger m_t reduces updates for repeated rare deviations. The final anomaly score combined prototype distance D_t and event-sequence deviation S_t:

$$A_t = \alpha D_t + (1-\alpha) S_t$$

where α balances cluster-level deviation and sequence-level anomaly contribution.

2.5 Model Evaluation and Statistical Analysis

Performance metrics included median detection delay, false-alert rate, memory usage, number of active prototypes, and cluster stability. Detection delay measured the time from the first abnormal event to the first alert. False alerts were reported as investigation cases per robot-month. Memory usage tracked the size and number of active prototypes. Cluster stability evaluated the method's ability to adapt to normal operational changes without losing sensitivity to rare events. Confidence intervals were computed using day-level block bootstrap to preserve temporal structure. Paired comparisons across daily blocks evaluated whether the memory-controlled method consistently outperformed the baselines under normal and abnormal operation periods (Xiong et al., 2026; Hong et al., 2026).

3. Results and Discussion

3.1 Detection Delay Compared with Baselines

The prototype memory control method reduced detection delay compared with the CluStream baseline. Across all labeled abnormal segments, the median delay dropped from 22.8 minutes to 6.2 minutes. Fig. 1 shows that the memory control method raised alarms earlier than CluStream for both frequent and rare faults. Previous studies also noted that methods without mechanisms to retain past abnormal patterns often detect faults late or miss them when operational metrics change over time (Hong et al., 2026; Mayilsamy, 2025).

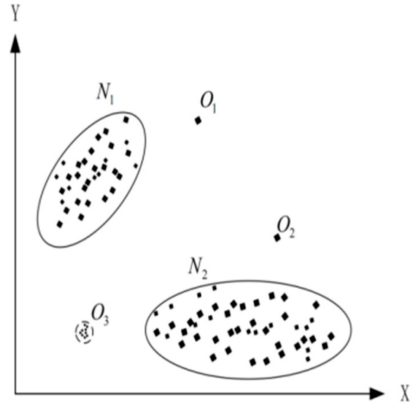

Fig. 1. Median detection delay of the memory-controlled method and baseline models, showing faster fault detection.

3.2 False Alerts and Operational Workload

The number of false alerts was lower with the memory control method than with the baselines. In our experiments, alerts averaged 1.8 cases per robot-month, whereas streaming k-means and CluStream produced more alerts. This indicates that retaining rare abnormal patterns helps prevent normal fluctuations from being classified as faults. Without memory control, clusters quickly adapt to slowly evolving abnormal events, increasing false alerts. Similar observations were reported in previous studies, highlighting that memory span and handling of changing operational patterns affect false-positive rates in streaming anomaly detection (Hong et al., 2026; Mayilsamy, 2025).

3.3 Prototype Stability under Changing Operations

Prototype stability was assessed during task changes and maintenance cycles. The memory control method kept prototype positions stable even as normal operational metrics varied. Fig. 2 shows that this method limited shifts in prototype positions, while baselines with faster updates exhibited larger changes. Maintaining stable clusters is important for separating true faults from normal variations. Prior work emphasizes that methods must handle changing data streams to provide reliable real-time anomaly detection (Zhang et al., 2026; Mayilsamy, 2025).

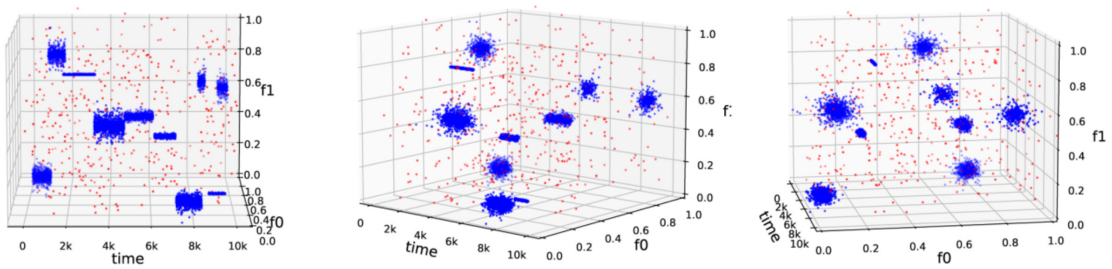

Fig. 2. Prototype displacement during dynamic operations, illustrating stable cluster behavior with memory control.

3.4 Comparison with Previous Studies and Implications

Compared with conventional streaming clustering, the memory control method produced faster detection, fewer false alerts, and more stable clusters. Standard methods update clusters quickly, which can absorb repeated abnormal events into normal clusters. Memory control retains information about rare events, improving detection over long sequences. This aligns with literature emphasizing the need to balance adaptation and memory retention for reliable streaming anomaly detection. However, this study has limitations. The evaluation used data from a single platform, so results may differ in other manufacturing environments. Additionally, tuning the memory coefficient may require adjustment for different robot types and production conditions. Future work should explore cross-platform testing and automated memory parameter tuning to improve robustness and usability.

4. Conclusion

This study presented a prototype memory control method for detecting abnormal operation events in industrial robot data streams. The method uses dynamic operation prototypes and a memory-control coefficient to keep rare fault patterns during long production cycles. Experiments on 1,140 industrial robots, 26 production cells, and 364 million event records showed that the method reduced the median detection delay from 22.8 minutes to 6.2 minutes compared with CluStream. False alerts were reduced to 1.8 cases per robot-month. The online engine also maintained 9,300 active operation prototypes with 1.08 GB of memory use. These results show that controlled prototype memory improves the detection of joint overload, servo instability, tool misalignment, abnormal cycle delay, and repeated safety-interlock triggers. The main contribution is a clear clustering method that balances fast model update with the retention of low-frequency degradation patterns. This method can be used for real-time robot monitoring, early fault warning, predictive maintenance, and production safety control in smart manufacturing. However, the study used data from one robotic manufacturing platform, and parameter settings may need adjustment for different robot models, production tasks, and sensor layouts. Future studies should test the method on other platforms and build automatic parameter tuning for wider use.

Acknowledgments

We are grateful to all respondents who participated in this study.

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