Cyclic Pattern-based Anomaly Detection in Smart Manufacturing Systems using Contrastive Learning

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***Abstract*— In the manufacturing industry, the environment for collecting sensor data has expanded through Industry 4.0, but labeling is difficult, and there is relatively little faulty data, making it challenging to apply conventional supervised learning-based anomaly detection methods. Specifically, anomalies that occur in sensor data with cyclic patterns are difficult to detect with traditional methods. This study proposes an unsupervised anomaly detection approach using contrastive learning to address these challenges. The method segments sensor data based on cyclic patterns, which are identified through autocorrelation coefficients. Fast Fourier transform (FFT) is then applied to focus on low-frequency bands where anomalies frequently occur. The model learns normal and abnormal behaviors by comparing similar and dissimilar data segments without relying on labeled data. Experimental results show that cyclic pattern-based anomaly detection is effective for anomaly detection in manufacturing environments and could be useful for real-time monitoring.**

Keywords—Anomaly detection, Cyclic pattern segmentation, Contrastive learning, Time-series data, Autocorrelation

I. INTRODUCTION

The manufacturing industry is undergoing significant transformation through the implementation of Industry 4.0, which drives digital transformation (DX) with advanced technologies such as smart factories, the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics. These advancements are facilitating automation and enhancing operational efficiency, with a strong emphasis on real-time data collection from various sensors embedded in production systems [1]. Such sensor data, including critical information like power, current, and energy consumption, is collected in time-series format and plays a key role in monitoring machine health, identifying operational anomalies, and improving overall process efficiency.

Among the various applications of time-series data, anomaly detection is crucial for predictive maintenance, as it enables the identification of potential equipment failures before they lead to system downtime [2]. Time-series data is inherently variable, and detecting abnormal patterns or signs of impending failures is essential for effective decision-making in manufacturing environments. Timely anomaly detection helps manufacturers minimize downtime, reduce maintenance costs, and maintain consistent product quality [3].

Despite its critical importance, anomaly detection in manufacturing faces several challenges that must be addressed to fully leverage its potential benefits. While normal data is abundant, labeled anomaly data is severely limited, making it difficult to accurately detect and classify anomalies. Manufacturing processes often exhibit repetitive patterns and noisy data, which complicates the task of distinguishing between normal fluctuations and actual anomalies. Additionally, labeling data is not only costly but also labor-intensive, making it challenging to apply in real-world environments. Moreover, aside from experimental data, anomaly data is significantly scarce in practice. Therefore, developing advanced anomaly detection methods based on unsupervised learning that can operate effectively in environments with limited or no labeled data is essential.

While methods like sliding windows and fast Fourier transform (FFT) have been widely used for feature extraction, they face significant limitations in capturing the intricate periodic behaviors and complex interactions typical in manufacturing systems. These limitations highlight the need for an alternative approach, such as pattern-based learning, which can better represent the unique characteristics of manufacturing data. One of the key challenges is the difficulty of accurately capturing periodicity and variability in the data [4]. To address these limitations, pattern-based learning offers a promising approach to better represent the unique characteristics of manufacturing data.

This paper proposes a novel anomaly detection method focused on pattern-based learning. The proposed method aims to minimize information loss, reduce computational costs, and more effectively capture the periodic characteristics of manufacturing processes. A key innovation of this approach is the utilization of contrastive learning, which enables unsupervised learning in the absence of labeled data. This allows the method to effectively detect anomalies even in environments where labeled anomaly data is scarce.

As shown in Figure 1, the sensor data collected from equipment under normal operation (a) contrasts with the data obtained just before failure (b), where abnormal behavior starts to emerge. These patterns suggest that, as the equipment nears failure, the operational patterns change, and abnormal data is increasingly observed. Identifying these abnormal patterns in advance is crucial for implementing predictive maintenance. By capturing these anomalies early,

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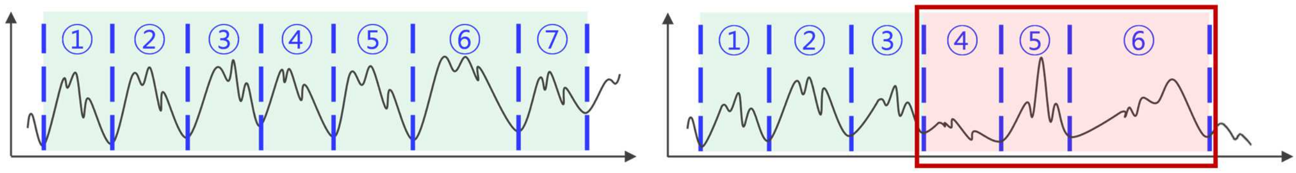

(a) Normal State (b) Abnormal State

Fig. 1 Time-series data of equipment

maintenance actions can be taken to prevent failures and avoid unplanned downtime.

The ability to detect abnormal data patterns before equipment failure is critical for maintaining and optimizing manufacturing systems. Predictive maintenance not only prevents system failures but also ensures production quality and efficiency. Since sensor data inherently reflects machinery operations, recurring patterns in the data can provide valuable insights into the status and behavior of equipment. By effectively learning these patterns, abnormalities can be detected early, enabling timely interventions that prevent unplanned breakdowns and reduce operational downtime. To achieve this, cyclic pattern-based analysis is essential. By segmenting time-series data into cycles, early warning signs of equipment anomalies can be identified, ensuring that equipment remains in optimal working condition and productivity is maximized.

To address these challenges, the proposed method introduces the following key contributions:

- Cyclic Pattern-based Learning: Moving beyond traditional sliding window methods, the data is segmented into cycles based on repeating patterns. This better captures the periodic characteristics of manufacturing processes.
- Minimized Information Loss: The combination of FFT processing and contrastive learning minimizes information loss and efficiently handles data with varying cycle lengths.
- Contrastive Learning: This approach learns meaningful representations of normal data, enabling robust unsupervised anomaly detection with limited labeled data.

The proposed methodology enables unsupervised learning even in the absence of labeled data, making it highly effective in environments with limited labeled examples. The integration of contrastive learning and FFT-based feature extraction allows for more accurate and efficient anomaly detection in complex and dynamic manufacturing environments. In particular, contrastive learning is especially useful when labeled data is scarce, providing a robust solution for anomaly detection in real-world manufacturing processes. This paper aims to address the challenges of anomaly detection in manufacturing by introducing a novel method that combines cyclic pattern-based learning, FFT processing, and contrastive learning. This approach ensures accurate anomaly detection in complex and dynamic manufacturing environments, even when labeled data is scarce. This paper introduces a novel anomaly detection method that combines cyclic pattern-based learning, FFT processing, and contrastive learning to address the challenges of detecting anomalies in manufacturing environments.

II. METHODOLOGY

The framework of the proposed methodology is illustrated in Fig. 2.

A. *Problem Definition*

In this study, the sensor data collected for anomaly detection is univariate time series data, represented as $\mathbf{X} = [x_1, x_2, \ldots, x_T] \in \mathbb{R}^T$, where T denotes the total length of the time series. Anomaly detection in this context aims to identify abnormal behavior by learning from the patterns of normal operating conditions. Since the data does not contain labels for anomalies, this paper focuses on unsupervised anomaly detection using cyclic pattern-based segmentation and contrastive learning. The exact time when the anomaly occurred is unknown, and the data collection interrupted due to an equipment anomaly. Therefore, the initial part of the data is assumed to be normal, and the latter part is assumed to be anomalous. This assumption enables the application of unsupervised learning methods. The goal is to detect deviations in the system's behavior by leveraging the inherent periodicity in the time series and optimizing representations of the data using a vector space approach.

B. *Cycle Segmentation using Autocorrelation*

To capture the periodic patterns in the time series data, autocorrelation is employed to identify the periodicity [5]. Autocorrelation measures the similarity between a time series and its lagged version, helping to identify repetitive cycles in the data. The cycle boundaries are then determined based on the significant peaks in the autocorrelation function. The autocorrelation formula is defined as follows:

$$ACF(k) = \frac{\sum_{t=1}^{T-k}(x_t - \mu)(x_{t+1} - \mu)}{\sum_{t=1}^{T}(x_t - \mu)^2} \quad (1)$$

Where $ACF(k)$ is the autocorrelation at lag k, x_t is represents the time-series data at time t, μ is the mean of the data, T is the length of the time series.

By examining the autocorrelation function, the time series is divided into meaningful cycles, where similar patterns repeat over time.

C. *FFT Processing for Cycle Segmentation*

Once the data is segmented into cycles, ttttt is applied to convert the time-domain signals into the frequency domain. FFT is particularly useful in detecting anomalies in low-frequency bands, as equipment anomalies often manifest in specific frequency ranges. The length of the cycle l is adjusted based on the frequency characteristics of the data. The FFT formula is given by follows:

$$X(f) = \sum_{t=0}^{N-1} x_t e^{-i2\pi f t/N} \quad (2)$$

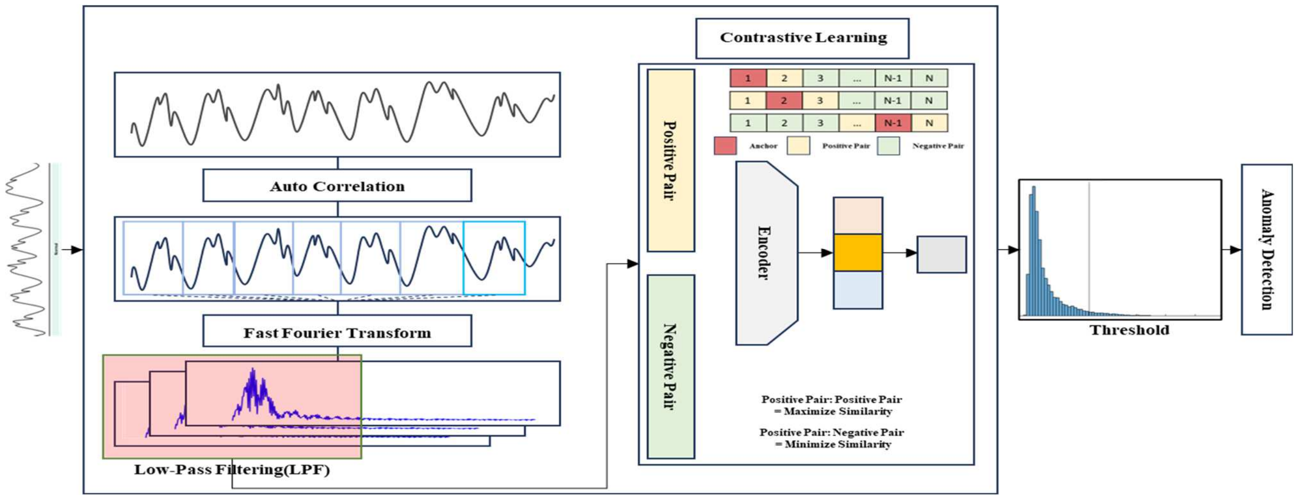

Fig. 2 Proposed Framework

Where $X(f)$ is the frequency-domain representation, x_t is the time-series data at time t, N is the number of data points, f is the frequency.

By applying FFT to each segmented cycle, the frequency components are extracted, with particular focus on low-frequency components that correspond to equipment failures or anomalies.

D. Contrastive Learning for Feature Extraction

After obtaining the frequency-domain representation via FFT, contrastive learning [6] is used to extract discriminative features. Contrastive learning enables the model to distinguish between normal and anomalous cycles without relying on labeled data [7].

In typical contrastive learning, data augmentation is commonly performed to create positive and negative pairs. However, in Ts2vec [8], augmentation is not applied. Instead, overlapping windows are treated as positive pairs, meaning that adjacent cycles in time are paired together as positive examples for the contrastive learning process.

This approach constructs positive pairs by minimizing the distance between similar samples (e.g., normal cycles that are adjacent in time) and negative pairs by maximizing the distance between dissimilar samples (e.g., anomalous cycles or non-adjacent cycles). The model learns to map adjacent data to similar representations and distant data to separate representations. Cosine similarity is used to measure the similarity between two vectors, where higher values indicate similarity and lower values indicate dissimilarity.

The cosine similarity between two vectors **x** and **y** is defined as follows:

$$S(x, y) = \frac{x \cdot y}{\|x\|\|y\|} \tag{3}$$

The contrastive loss function can be defined as follows:

$$L_{contrastive} = \frac{1}{2} y \cdot (1 - S(x_1, x_2))^2 + \frac{1}{2}(1 - y) \cdot \max(0, m - 1 - S(x_1, x_2))^2 \tag{4}$$

Where y is the label (0 for adjacent, 1 for non-adjacent), S is the cosine similarity between the feature vectors of the two samples, and m is the margin that defines the minimum distance for non-adjacent pairs.

This step allows the model to learn representations that effectively capture both normal and anomalous behaviors, even in the absence of explicit labels.

E. Anomaly Detection

Finally, the features (latent vectors) extracted from the contrastive learning step are used for anomaly detection [9]. In contrastive learning, time-adjacent data are learned to have similar embeddings, while time-distant data are learned to be separated. It can be assumed that the data showing anomalies is farther from the initial normal pattern and closer to the anomalous patterns. The point of failure may occur when there is a sharp increase in the embedding difference between the normal and anomalous patterns, and if the model is trained correctly, it should be able to detect these sharp changes. Additionally, when anomalous data appears, multiple anomalous patterns may tend to cluster in similar directions in the embedding space. The model learns these anomalous patterns and can infer the point of failure. If the model has been trained well, time-adjacent normal samples should be mapped to close embeddings, and anomalous cases should be learned to be sufficiently far from the normal pattern.

The anomaly detection process starts with the assumption that the initial normal pattern, learned through contrastive learning, represents the typical behavior of the system. After training is completed, the learned representations of new test samples are compared with this normal pattern. The anomaly score is calculated by measuring the distance between the feature vector of the test sample and the initial normal representation.

The anomaly score (score) for each test sample is calculated as the Euclidean distance between the test sample's feature vector $\hat{x}_t$ and the learned feature representation of the initial normal pattern $\hat{x}_0$:

$$Score = \|x_t - \hat{x}_0\| \tag{5}$$

After the anomaly score (score) is calculated, the threshold is set based on the distribution of the dataset assumed to be normal, which helps in distinguishing between normal and anomalous data. If the anomaly scores of normal samples mostly fall within a certain range, the threshold is set within

TABLE I. PILOT EXPERIMENTAL RESULTS

	RAW			Cycle		
DATASET	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
ECG5000	0.868	**0.994**	**0.927**	**0.893**	0.912	0.902
ECGFiveDays	**0.923**	0.755	0.831	0.837	**0.832**	**0.834**

that range. Any anomaly score that exceeds the threshold is classified as anomalous, while scores below the threshold are classified as normal.

III. Experiments

A. Dataset

In this study, we aim to develop a cyclic pattern-based anomaly detection model for manufacturing processes. Since no benchmark datasets exist for manufacturing data that are both labeled and exhibit periodicity, a key characteristic of manufacturing processes, we selected ECG datasets for the experiments. These datasets were chosen due to their labeled nature and periodic characteristics, which resemble the periodic patterns found in manufacturing processes.

The ECG5000 dataset, derived from the MIT-BIH Arrhythmia Database, contains 5000 ECG signals in time-series format, labeled into five classes: one normal class and four abnormal classes. Similarly, the ECGFiveDays dataset, provided by the UCR Time Series Classification Archive, consists of 884 samples, labeled into two classes: normal and abnormal. Both datasets exhibit periodic patterns in heart rhythms, making them suitable for evaluating the proposed cyclic pattern-based anomaly detection methodology.

By using these ECG datasets, which share similar periodic characteristics with manufacturing processes, we can effectively assess the model’s ability to detect anomalies based on cyclical behavior in data.

B. Evaluation metric

The performance of anomaly prediction was evaluated using three metrics: Precision, Recall, and F1-Score. These metrics were calculated using the following equations, as shown in the formulas:

Precision is calculated as:

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Recall is calculated as:

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

F1-Score is calculated as:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

C. Result

A pilot experiment was conducted to verify the feasibility of cyclic pattern-based anomaly detection. In this experiment, segments separated based on the cyclic pattern-based approach were used to train an autoencoder and reconstruct the data. The evaluation was performed using dynamic time warping (DTW)-based labeled values, and the performance metrics (Precision, Recall, F1-score) were calculated based on the formulas outlined in section B: evaluation metrics. The results, as shown in table I, demonstrate that the performance achieved with this method is comparable to models trained with labeled data. Specifically, for the ECG5000 dataset, the cyclic pattern-based approach achieved 0.893 precision, 0.912 recall, and 0.902 F1-score, which is similar to the performance of the raw method. Similarly, for the ECGFiveDays dataset, the cyclic pattern-based approach achieved 0.837 precision, 0.832 recall, and 0.834 F1-score, showing significant improvement over the raw method. These results confirm that cyclic pattern-based anomaly detection is indeed feasible.

IV. Conculsion

This study presents a novel methodology for cyclic pattern-based anomaly detection in manufacturing processes. In real industrial environments, sensor data often exhibits variability due to external environmental changes and equipment anomalies, making accurate anomaly detection a critical challenge. To address this, the study proposes segmenting the data into cycles and accurately detecting recurring patterns through autocorrelation. The features extracted during this process are then effectively learned using contrastive learning, aiding in the detection of abnormal patterns.

The proposed methodology provides an effective solution for real-world environments where anomaly data is imbalanced and labeled data is scarce. While experiments were conducted using ECG data, further experiments with real-world manufacturing datasets are necessary to evaluate the model’s applicability in more practical scenarios. Future work will focus on applying cyclic pattern-based anomaly detection to manufacturing processes, allowing for the tracking of anomalies occurring during the production of products or components. By linking these insights with quality data, it will be possible to improve both process efficiency and final product quality.

Future work will focus on applying cyclic pattern-based anomaly detection to manufacturing processes, allowing for the tracking of anomalies occurring during the production of products or components. In this context, soft contrastive techniques will be applied in the pair construction process, enabling more flexible definitions of positive pairs and negative pairs [10]. This will help improve the model's ability to detect anomalies more effectively. By linking these insights with quality data, it will be possible to enhance both process efficiency and final product quality.

Additionally, the computational complexity of the model will be evaluated, with a focus on analyzing the efficiency of the cyclic pattern-based anomaly detection method in real-world environments. In such environments, where the scale of data and detection speed are crucial, a detailed assessment of the model's computational cost will ensure its feasibility for large-scale deployment. This will help establish the model's accuracy and efficiency for practical applications in manufacturing processes.

DATA AVAILABILITY STATEMENT

The ECG5000 Data is available at http://www.timeseriesclassification.com/description.php?Dataset=ECG5000 and The ECGFiveDays is available at https://www.timeseriesclassification.com/description.php?Dataset=ECGFiveDays

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