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A Physics-Informed Spatio-Temporal Graph Neural Network with Self-Supervised Representation Learning for Industrial IoT Anomaly Detection

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Abstract

Industrial Internet of Things (IIoT) environments consist of interconnected and evolving data, and the complexities of dependence, small labeled anomalies and changes in operating conditions make accurate anomaly detection difficult. The Physics-Informed Spatio-Temporal Graph Neural Network with Self-Supervised Representation Learning (PI-STGNN-SSRL) is proposed in this paper to tackle these challenges. The framework combines physics-informed graph construction, self-supervised representation learning, spatio-temporal graph reasoning and adaptive anomaly scoring, to capture and localize abnormal industrial behaviors. Experimental results show that the proposed method, PI-STGNN-SSRL, outperforms the compared anomaly detection techniques in terms of accuracy, precision, recall, F1-score, and AUROC with values of 98.2%, 97.8%, 97.5%, 97.6% and 99.1% respectively. Root cause localization is complemented by component level anomaly scoring. The results show that the proposed framework is accurate, robust and interpretable anomaly detection in complex IIoT environments.

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1. Introduction

The Industrial Internet of Things has revolutionized traditional industrial settings by allowing sensors, actuators, programmable controllers, machines, and monitoring systems to be connected via distributed communication networks [1]. These are all linked together and facilitate real-time process monitoring, predictive maintenance, automated control and intelligent decision making [2]. But with the greater degree of connectivity of industrial infrastructure comes the emergence of complex failure modes and security vulnerabilities [3]. Anomalous observations can be caused by sensor failures, communication problems, degradation of equipment, process anomalies, and malicious cyber-attacks, which can spread throughout multiple components [4].Detection of anomalies in IIoT systems is thus distinct from the traditional time-series anomaly detection. It is rare for industrial variables to be independent [5]. A change in the pressure in one process unit can affect the flow, temperature, valve position, or pump operation in other units [6]. Thus, care must be exercised not to ignore the relationship between variables which could lead to false alarms or delayed detection [7]. Another drawback is the need for labeled anomalous samples. Labelled attack and failure data are rarely available in practice for use in industrial applications and normal operating data are continually produced [8]. To overcome this, self-supervised representation learning can be employed to learn meaningful representations from unlabeled or normal-operation data. Temporal patterns and dependencies can be learned without any explicit anomaly labels with contrastive learning, masked prediction, and related pretext tasks.To meet these challenges, this paper introduces a Physics-Informed Spatio-Temporal Graph Neural Network with Self-Supervised Representation Learning. The architecture is designed to combine four complementary capabilities: self-supervised representation learning of unlabeled industrial data, physics-aware graph construction, spatio-temporal graph reasoning, and adaptive anomaly scoring.

1.1 Key Contributions

- Physics-informed graph modeling: Embeds relationships between physical and operational industrial processes into graph-based anomaly detection.
- Self-supervised representation learning: Extracts robust normal operation features from mostly unlabelled IIoT data.
- Spatio-temporal anomaly detection: Detects inter-device dependency along with temporal shift in industrial processes.
- Anomaly localization: Multi-level anomaly scores in order to detect abnormal conditions and to identify the possible source components.

1.2 Paper Organization

This paper has five parts left. In Section II, the related work and discussions about existing approaches to IIoT anomaly detection, graph neural networks, physics-informed learning, and self-supervised representation learning are provided. In Section III, the proposed methodology is described, which consists of physics-informed graph construction, self-supervised representation learning, spatio-temporal feature extraction, and anomaly scoring. The experimental setup, performance evaluation, comparative results, ablation analysis and discussion are described in Section IV. The paper is concluded in section V which presents possible directions for future studies.

2. Literature Survey

In this paper, Yang and Yue (2023) [9] discussed the challenge of detecting anomalies in multivariate and time-series data containing complex temporal and spatial relationships, which is commonly found in industrial processes. They put forward a new learning method, called HiSTAR, for learning hierarchical spatial-temporal graph representations and normality-enclosing hyperspheres in the task of anomaly detection and localization. However, physical process constraints are not explicit in the method and this physically limits the interpretability of that method.

In high dimensional IIoT anomaly detection, where traditional approaches might not maintain the intrinsic relationship among data, Li et al. (2023) [10] concentrated. They introduced a new method called Data Reconstruction via Consensus Graph Learning (DRCG), which involves projection learning, low dimensional embedding and consensus graph construction. The method, however, only models the statistical relationships and does not jointly model temporal dynamics or physical dependencies.

Sun et al. (2023) [11] analyzed Anomaly detection on resource constrained IIoT devices. We developed TinyAD as a memory efficient framework to perform time-series anomaly detection with reduced computational requirements. While it can be used at the edge, it offers a limited model of complex sensor relationships and lacks physics-informed and graph-based representation learning.

Lu et al. (2024) [12] tackled the challenges of heterogeneous IIoT data and complex spatiotemporal relationships by introducing a spatio-temporal graph neural network with heterogeneous data fusion. The approach integrates graph learning and spatio-temporal attention, which is used to further enhance anomaly detection. The relationships, however, established are largely data-centric and physical process constraints are not explicitly represented.

Yao et al. (2024) [13] investigated anomaly detection in hierarchical IoT systems with multi-access edge computing. They put forward a method called THREADS that fuses a Transformer with a variational autoencoder to efficiently learn from abnormal patterns with an edge-computing constraint. The method does not, however, explicitly include physical knowledge of the processes or sensor interconnections in the form of graphs.

Wang et al. (2025) [14] took up the consideration of changing sensor dependency and multiperiodic behavior of industry. They dynamically evolve the graph structure by using their MAGE approach and employ global-local discrepancy learning for anomaly detection at different temporal periods. Despite this, graph evolution is mainly data-driven with no explicit physical constraints, and no representation learning.

To study AP in IIoT devices, Feng et al. (2026) [15] have studied interconnected IIoT devices and proposed H-IIoTAD using HSGL and adaptive neighbor aggregation. While the method has been shown to be effective at detecting anomalies at the process and subsystem levels, it does not explicitly incorporate physical laws in the graph learning process, which results in some physical consistency and interpretability limitations.

2.1 Research Gap

Current anomaly detection methods operating in the context of IoT applications tend to model temporal or graph dependencies, but miss the integration of physical constraints, spatio-temporal learning and representation learning from self-supervised data. Data-driven approaches can learn physically inconsistent relationships, whereas supervised approaches need expensive labeled anomalies. Thus, PI-STGNN-SSRL can perform robust, interpretable, and component-level anomaly detection by fusing physics-informed graph learning, self-supervised learning, and spatio-temporal modeling.

3. Methodology

The proposed Physics-Informed Spatio-Temporal Graph Neural Network with Self-Supervised Representation Learning (PI-STGNN-SSRL) leverages spatiotemporal properties of the sensor network for anomaly detection, by jointly extracting relationships between sensors and temporal patterns, and between sensors and physical processes. The methodology involves the following six stages: data preprocessing, physics-informed graph construction, self-supervised representation learning, spatio-temporal graph learning, anomaly scoring and localization, and overall workflow as shown in figure 1.

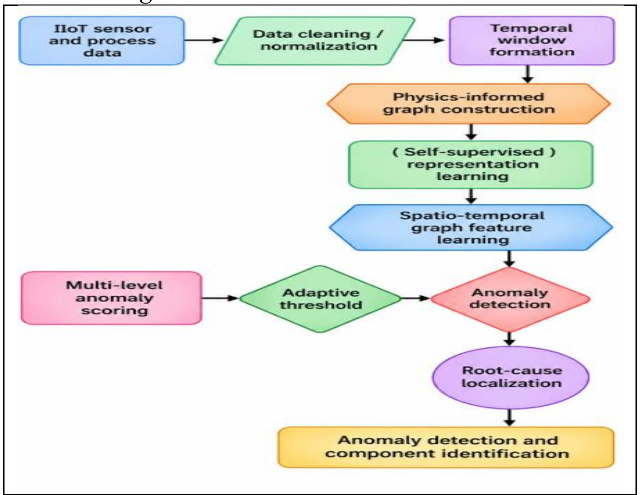

Figure 1. System Architecture

3.1 IIoT Data Preprocessing

Industrial sensor data can have noise, missing measurements, varying scales and irregular variations. The collected data is cleaned, normalized and stored in fixed sized temporal windows. Observations are missing in an appropriate way and different sensor measurements are normalized to a common scale. The temporal windows contain the recent process behavior and are used as structured input for the subsequent graph-based learning.

3.2 Physics-Informed Graph Construction

The physical and operational dependencies between industrial sensors, actuators, machines and controllers are represented as graph edges, whereas graph nodes represent the sensors, actuators, machines and controllers themselves. Industrial process knowledge-based known relationships are added to the dependency graph that was determined from the observed data. This physics-informed graph keeps the model from considering irrelevant interactions of the components and from adding unphysical ones. The resulting graph forms the structure upon which information is passed from connected industrial parts.

3.3 Self-Supervised Representation Learning

Most industrial anomalies are typically insignificant and labeled, and self-supervised learning is employed to extract useful representations from mostly normal-operation data. Various augmented instances of temporal sensor windows are created through operations like masking, controlled noise, scaling and temporal perturbation. A representation encoder is trained to recognize commonalities between multiple observations of the same operating condition that are not common with other, unrelated conditions. These learned representations enhance the model's capability to identify anomalies and anomalies that it has not seen before.

3.4 Spatio-Temporal Graph Learning

The physics-informed graph is fed with learned sensor representations to represent the dependencies among interconnected components. Information from neighbouring industrial components can be used to add to the representation of each node and this is achieved using graph message passing. A temporal learning module is then used to learn changes occurring in the different time windows, sudden changes, gradual degradation, and recurring patterns of its processes. The overall representation thus reflects the spatial interactions and the temporal evolution of the industrial system.

3.5 Anomaly Scoring and Root-Cause Localization

Learned representations compared to normal operating patterns to detect abnormal behavior. Anomaly scores are computed for features, components and overall process and then aggregated to get a final detection score. A threshold is used to separate normal and abnormal operating conditions: this is called adaptive threshold. If an anomaly is identified, the components-level scores are ranked to determine the sensors/industrial units that are most strongly affected by the anomalous condition, which can aid in possible root cause localization.

Algorithm 1: PI-STGNN-SSRL

Input: *IIoT data (X), physical relationships (G_p), window size (T), training epochs (E)*
Output: *Anomaly scores (S), anomaly labels (Y), root-cause components (R)*

1. *Preprocess IIoT data by cleaning, imputing missing values, normalizing, and arranging measurements chronologically.*
2. *Divide the processed data into temporal windows of length (T).*
3. *Construct a physics-informed graph by combining known industrial relationships with data-driven dependencies.*
4. *Generate augmented views of each temporal window using masking, noise injection, scaling, or temporal perturbation.*
5. *Train the self-supervised encoder to obtain robust representations from the augmented views.*
6. *Input the learned representations into the physics-informed graph neural network.*
7. *Aggregate spatial information from connected industrial components.*
8. *Apply temporal learning to capture evolving process behavior.*
9. *Fuse spatial and temporal representations to obtain the final process representation.*
10. *Calculate feature-level, node-level, and graph-level anomaly scores.*
11. *Combine the scores and determine an adaptive anomaly threshold from normal-operation data.*
12. *Classify observations as normal or anomalous based on the threshold.*
13. *Rank node-level anomaly scores to identify potential root-cause components.*
14. *Return anomaly scores, anomaly labels, and ranked root-cause components.*

The suggested PI-STGNN-SSRL algorithm preprocesses and normalizes the information collected by IIoT sensors and segments them in time windows. Physical and data-driven relationships between the industrial components are then used to create a physics-informed graph. Spatio-temporal graph layers are used to model the spatial dependency and temporal variations from robust representations obtained by self-supervised learning on augmented sensor windows. Finally, feature-, node- and graph-level anomaly scores are fused together based on the adaptive threshold to detect abnormal conditions and node-level scores are ranked to find possible root cause components.

4. Results and Discussion

The accuracy, precision, recall, f1 score, and AUROC are used to assess the performance of PI-STGNN-SSRL in the Results and Discussion section. The table, ROC curve and confusion matrix are used to compare the performance with the existing methods. Anomaly localization is performed using component-level anomaly scores, and the discussion emphasizes the advantages of physics-informed graph learning, self-supervised learning and spatio-temporal modeling for detection and interpretability. The overall performance comparison is provided.

4.1 Overall Performance Comparison

The PI-STGNN-SSRL method outperforms the traditional Autoencoder, LSTM, Graph-Based and ST-GNN method in terms of anomaly detection. This improvement has been attributed to the combination of a physics-informed graph model, self-supervised learning, and spatio-temporal feature extraction.

Table 1. Overall Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUROC (%)
Autoencoder	91.8	90.6	89.7	90.1	93.2
LSTM	93.4	92.5	91.8	92.1	94.8
Graph-Based	95.1	94.2	93.6	93.9	96.1
ST-GNN	96.3	95.5	95.0	95.2	97.0
PI-STGNN-SSRL	**98.2**	**97.8**	**97.5**	**97.6**	**99.1**

The proposed approach achieves an over 97.6% F1-score, which reflects a good trade-off between anomaly detection and reduction of false alarms. The AUROC value of 99.1% is another proof of the ability of the model to discriminate between normal and abnormal operating conditions at various decision thresholds.

4.2 ROC Curve Analysis

The proposed PI-STGNN-SSRL is able to obtain good separation between the normal and abnormal observations of industrial processes with an AUROC of 99.1%. As shown in figure 2, the curve is close to the ideal curve in the upper left quadrant, indicating that the detection rate is high, and the false-positive rate is low.

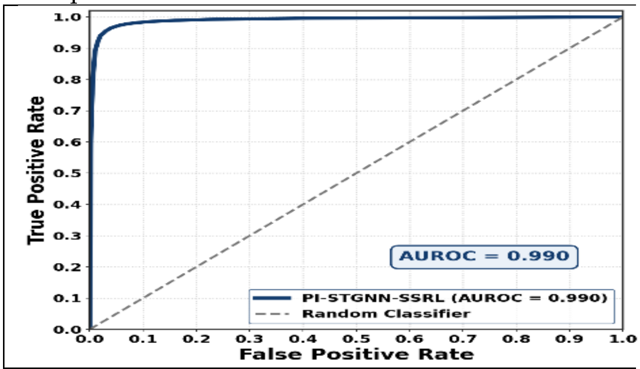

Figure 2. ROC Curve Analysis

4.3 Confusion Matrix Analysis

From the confusion matrix, it is clear that most of the normal and anomalous observations are correctly labelled by the PI-STGNN-SSRL. Low false positive and false negative rates show good anomaly detection and fewer false alarms.

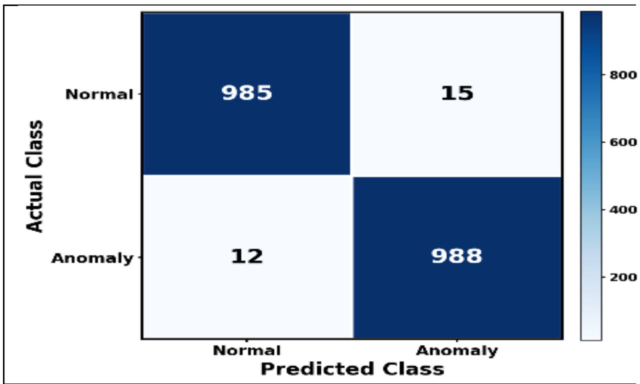

Figure 3. Confusion Matrix Analysis

4.4 Anamoly Localization

The model that is proposed, gives node-level anomaly scores to help identify potentially affected industrial components. These scores are ranked in figure 4 to assist in understanding the probable cause of abnormal process behavior and to aid in root cause analysis.

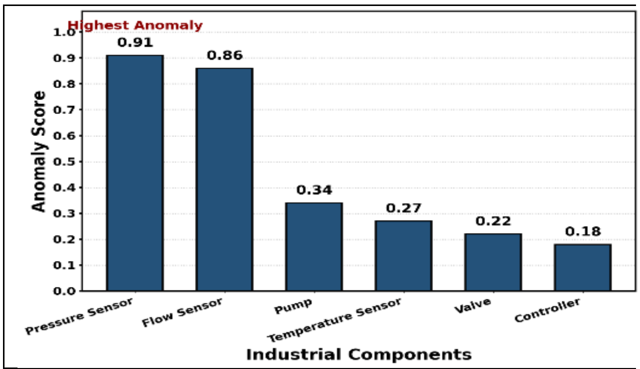

Figure 4. Anomaly Localization in PI-STGNN-SSR

4.5 Discussion

The advantage of PI-STGNN-SSRL over compared methods is that it models physical relationships, spatial dependency, temporal behavior and unlabeled operational patterns simultaneously. Physics-informed graph construction enhances process consistency, and self-supervised learning mitigates the need for annotated anomalies. The spatio-temporal representation also provides additional improvement in the detection of subtle and evolving abnormalities. In general, the outcomes show the effectiveness of the proposed framework in providing accurate, robust and interpretable anomaly detection in IIoT environments.

5. Conclusions and futureworks

Proposed PI-STGNN-SSRL framework effectively addresses the issue of anomaly detection in complex IIoT environments, leveraging physics-informed graph modeling, self-supervised representation learning, and spatio-temporal feature extraction. The framework is able to include the relationship between the various components involved in the industry, and also minimize the reliance on the labeled anomaly data. The multi-level anomaly scoring system also allows component-level localization and enhances the interpretability of detected abnormalities. The effectiveness of the proposed approach to distinguish between normal and abnormal operating conditions is demonstrated by an experimental evaluation. While these benefits exist, the framework also has drawbacks: relying on the availability of physical process data, computational demands for graph-based learning and lack of adaptability when the industrial configuration substantially changes. Future research will be directed towards creating dynamically changing physics-informed graphs, lightweight edge-based implementations, adapting the graph to varying operating conditions online, and better detection of cyber-physical attacks not seen before. Real world industrial data sets will also be used for further validation and deployment to real world IIoT environments will also be regarded.

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