Fast Detection of Abnormal Data in IIoT with Segmented Linear Regression

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Abstract - Industrial IoT (IIoT) is considered as an important component of manufacturing system nowadays. By collecting the sensed data from the facilities with IIoT, the operation condition is properly analyzed and handled. Here abnormal data requires to be quickly detected for the safety and productivity of entire system. The existing threshold-based approach is not suitable for IIoT since it cannot detect any dormant error or abnormal behavior under the threshold. In this paper a novel approach for the detection of abnormal data is proposed which is based on segmented linear regression with predicted interval and priority-based scheduling. Computer simulation reveals that the proposed scheme is superior to the existing scheme employing threshold, typical linear regression, or FCFS policy in the speed of detecting abnormal data.

Keywords: IIoT, Machine learning, Packet scheduling, Emergency detection, Segmented linear regression

1 Introduction

Internet of Things (IoT) has been recognized as a crucial technology in the information and communication field for several years. In IoT environment, each object is connected using wired or wireless network so that the data can be effectively collected and analyzed to serve various end users. Numerous implementations based on IoT have been developed for real world problems. One of them is for applying to industrial manufacturing system, which is called industrial IoT (IIoT). In IIoT, sensors are placed in the production facilities to monitor the status of the equipment and surroundings. Then the sensed data are analyzed locally on the facility, and then globally on the centralized control system. As a result, the manufacturing facilities can be effectively monitored and controlled.

Since numerous sensors are deployed in the IIoT environment, effective ingestion of the data obtained from the sensors is a challenging problem. There have been various studies on monitoring the status of the nodes and processing the packets in IIoT. Especially, early identification of the loss of the sensor nodes which are in charge of critical facilities is of utmost importance since their loss can cause catastrophic damage to the entire premise. Therefore, it is imperative to quickly gather the data from the node of abnormal behavior and analyze them in the gateway (GW) before malfunctioning.

Two processes are involved in handling such node; detection and manipulation.

Threshold is usually employed to detect any emergency or abnormal condition of a sensor node or target object. The main shortcoming of this approach is that it cannot detect any abnormal data pattern under the threshold. Detecting such dormant abnormal data needs to use a dynamic approach such as predicting future data based on support vector machine (SVM) [1]. SVM has been considered as an efficient technique for the classification of data. However, a large volume of data need to be accumulated at the GW for a while to achieve a good quality classification, which is a big overhead to the resource limited GW. More importantly, slow operation is not acceptable to IIoT in which the connected nodes need to be handled in real-time according to the degree of the emergency. The GW sets the scheduling priority of the nodes, and a scheduling method based on the priority was proposed in [5] for local optimization. Here an effective scheme for detecting abnormal data in real-time in IIoT environment is required to be developed. In addition, the loss of the packets of other regular nodes due to increased processing rate of emergency node needs to be taken into account.

In this paper a novel approach for detecting emergency node connected to the GW is proposed, which generate abnormal data. It is achieved by employing the segmented linear regression technique with predicted interval. This can effectively solve the disadvantage of threshold-based approach which detects only the data exceeding the threshold. Segmented linear regression is an efficient technique for the regression of data between the breakpoints by detecting the inflection of regression, which is often used to determine the pattern of non-linear data. Since the data generated in IIoT environment is periodic, segmented linear regression is effective to analyze the regression of periodic data. The method controlling the priority of the packets processed in the GW is also proposed based on the multi-queue structure for quickly handling the emergency node. By increasing the priority of packet processing, the emergency data can be processed with high priority. The queuing theory is used to estimate the average waiting time, and the priority raise is limited not to overly delay other nodes. Computer simulation reveals that the proposed scheme can detect emergency node much faster than the existing schemes for various operational conditions. In addition, the emergency node is processed much faster than other regular nodes.
The rest of the paper is organized as follows. Section 2 discusses the work related to the proposed scheme. In Section 3, the proposed scheme is presented, and then its performance is evaluated in Section 4. The conclusion and future work are discussed in Section 5.

2 Related Work

2.1 Detection of Abnormality

With the growth of IoT, a plenty of researches have been conducted, aiming to monitor and handle any emergency situation in the system. Especially, highly reliable technique is needed for the detection of abnormal situation to minimize the damage in the IIoT environment. Figure 1 shows the structure of IIoT. Most existing schemes employ threshold to detect any malfunctioning of the target object. The threshold-based approach has an advantage of simple implementation. However, any abnormal data within the threshold cannot be detected which may eventually cause an emergency situation. In addition, considering the diversity of IIoT, adjusting the threshold for each different type of facilities will be quite cumbersome. Therefore, there have been various researches on accurate and adaptive detection of abnormalities in IIoT environment.

For example, a method predicting and controlling the stability of a power system based on the voltage and velocity of generator was proposed in [1]. This is done by analyzing the existing data and predicting the future data using SVM. It predicts the time approaching to instability by 95% of accuracy. In [2], they focused on the classification of noise data with a new approach of Support Vector Data Description (SVDD) for singular classification. This approach adopts $\varepsilon$-insensitive function with distance-based local density and negative sample to reduce the noise of data which in turn increases the accuracy of detecting abnormal data. A method using 3-parameter Weibull distribution for the Harmonic current data was proposed to classify abnormal data by properly setting the threshold value [3]. Reference [4] proposed the operation criterion for compound relay protection which is based on the law of current and classification algorithm for detecting abnormal data. They classify abnormal data by detecting discontinuous wave point among continuous wave of current data. The existing methods are for detecting abnormal data from huge amount of sensed data. However, they are not effective to be implemented on resource limited IIoT GW requiring real time operation on small amount of data. Therefore, in this paper, an efficient classification approach is proposed for identifying abnormal data in IIoT environment.

2.2 Priority-based Scheduling

After detecting an emergency node, the data from the node has to be processed with high priority. The purpose to detect emergency node is to handle urgent situation. For this, the central manager, whether it is human or computer, requires enough data to correctly analyze the situation. Therefore, the data from emergency node has to be rapidly sent to the manager and accumulated. In the GW operating with the FCFS policy, the data from different sources are not able to be processed according to its priority.

To effectively handle urgent data, various priority-based scheduling schemes have been proposed. Figure 2 shows the operational flow of priority-based scheduling. Reference [5] proposed an emergency scheduling method based on priority and local optimization for smart grid. The proposed scheme exchanges the location information of the nodes to reduce the number of hops and distance between the sink and source node. Then, based on the emergency information, the destination node decides the sequence of packet scheduling to minimize packet loss, waiting time, and latency.

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The Two-Ford mechanism [7] achieves QoS during the process of new load by arranging the loads based on the characteristics of the first packet and delay requirement. Reference [8] considers the latency occurring in the aggregation of data to reduce the power consumption of M2M devices. The M/G/1 queueing model is utilized to analyze the priority for the data aggregation in the M2M gateway. As a result, the system latency and power efficiency were improved based on the priority.

Various scheduling schemes employing multi-queue structure have also been proposed. Reference [9] proposed a scheme with dynamic job selection based on burst time for cloud computing. In [10] the Round robin scheduling based on time-sliding was combined with the priority-based scheduling to reduce the waiting of the tasks. The existing schemes focus on load balancing or efficient utilization of resources, with less concern on efficient handling of emergency situation. In this paper the multi-queue structure is adopted along with priority for proper treatment of emergency node.

3 The Proposed Scheme

3.1 Detection of Abnormality

Linear regression is an efficient technique used to analyze the trend of the target data, which is done by minimizing the error between the data and a linear function. Due to simple calculation, linear regression is suitable to be implemented in IIoT GW. However, the data generated in IIoT environment do not often display linearity, and therefore regression for inflected data is required. Regardless of the data type in IIoT environment such as temperature, vibration, and pressure, the emergency node generates abnormal data during its operation period. Note that the typical IIoT sensors operate with a fixed cycle in monitoring the environment. Therefore, it is important to compare the pattern of the data collected in each cycle and the regression of the data has to be applied to them.

Segmented linear regression is an efficient technique for the regression of data between the breakpoints by detecting the inflection of regression, which is often used to determine the pattern of non-linear data. Since the data generated in IIoT environment is periodic, segmented linear regression is effective to analyze the regression of periodic data. In the proposed scheme, predicted interval is used to get the range of normal data based on the result of regression. The models of the proposed scheme are as follows.

Linear regression is a model predicting a dependent variable, y, from an independent variable, x, by analyzing the linearity of the data. The training process models the relationship between x and y for the given data set \{y_i, x_{i1}, ..., x_{ip}\}. The model is as follows.

\[
y_i = \beta_0 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i \quad i = 1, \ldots, n
\]  
\[
x_{ip} + m = X^T \beta + m \quad i = 1, \ldots, n
\]

In the equations above, \(\beta_p\) is a coefficient of independent variable and \(p\) is the number of parameters assumed by linear regression. Also, \(X_i\) is a transposed form of \(X_i\), and \(X^T \beta\) is inner product of \(X_i\) and \(\beta\). As a result, the linear regression model is formed as a linear function, \(Y = Ax + B\).

With segmented linear regression data are divided into several segments along x-axis, and linear regression is applied to each segment. Assume that the data set is divided into two segments. With linear regression, there would be only one segment of a line. However, two linear functions are obtained with segmented linear regression as follows.

\[
Y = \begin{cases} 
A_1 x + K_1, & x \leq P_B \\
A_2 x + K_2, & x > P_B 
\end{cases}
\]  

where \(P_B\) is the breakpoint at which the regression result is inflected. If the independent variable \(x\) is lower than \(P_B\), \(Y\) is determined by the first linear function. Otherwise, the other function determines \(Y\).

The breakpoint signifies the reference point which divides the data set. It is determined as Eq. (4).

\[
P_B = \min_{x \in X} \sum (y - Y_r)^2
\]  

where \(y\) is the data value and \(Y_r\) is predicted regression result for the given \(x\). \((y - Y_r)^2\) is called loss function. Therefore, the breakpoint, \(P_B\), is an \(x\) value which minimizes the loss function.

After the segmented linear regression is applied, the predicted interval of each segment is obtained to get the boundaries of normal data. The predicted interval is obtained as follows.

\[
\gamma = P(l < X < u) = \int \left( \frac{l - \mu}{\sigma} < \frac{X - \mu}{\sigma} < \frac{u - \mu}{\sigma} \right)
\]  

where \(\sigma\) is standard deviation of the given data set and \(\mu\) is mean value. \(l\) and \(u\) are the minimum and maximum value, respectively. It can be derived as follows.

\[
l - \mu = -z
\]  
\[
u - \mu = z
\]

Here \(z\) is \(z\)-score value. Then, \(l\) and \(u\) can be expressed as follows.

\[
l = \mu - z\delta
\]  
\[
u = \mu + z\delta
\]

When the sensed data are started to be sent from the nodes, the GW decides the period of the data. Then it searches the breakpoints where the data rapidly changes. With them, linear regression and predicted interval of the data between the breakpoints are obtained. The predicted intervals are treated as boundaries of normal data. After this setup, the GW gets the sensed data from the nodes and their data are compared with the normal boundary of the data cycle. The overall procedure of the detection of emergency node is shown below.
Procedure 1. Detection of emergency node

Input: Node connected to GW, \( N_i \)
Controller resource capacity, \( M \)
Input data, \( D \)

Begin
1: \( X_s, Y_s \rightarrow \) Segmented linear regression model
2: \( Y_{\text{high}} \rightarrow \) Predicted interval of \( X_s, Y_s \)
3: for input data \( d (d \in D) \) do
5: if \((d_{\text{value}} > Y_{\text{high}})\) then
6: \( \text{Emergency_count} \rightarrow \text{Emergency_count} + 1 \)
7: \( \text{If (Emergency_count > Emergency_threshold) then} \)
9: \( N_i \rightarrow \) Emergency node
10: \( \text{End if} \)
12: \( \text{End for} \)
End

The GW is able to identify abnormal data by just comparing the value of the data and boundary. Figure 3 shows the process of abnormal data detection.

![Figure 3. The process of detecting abnormal data.](image)

### 3.2 Priority Control with Multiple Queues

To implement priority for each node, multi-queue structure is employed. The packet from each node is handled by separate waiting queue of the GW. Figure 4 shows the structure of the proposed multi-queue scheduling for the GW.

![Figure 4. The structure of multi queue scheduling.](image)

In normal state the packet processing sequence is decided according to the number of packets in each queue. The processing rate of Node-\(i\), \( \mu_i \), in a period of \( T \) is as follows.

\[
\mu_i = \frac{P_i}{T} \tag{10}
\]

Here \( P_i \) represents the number of packets to process for Node-\(i\). Then the service rate of GW for it becomes \( \mu_i \) since it is the processing rate. The number of packets of Node-\(i\), \( N_i \), at steady state is as below.

\[
N_i = \sum_{k=0}^{\infty} k \pi_{ik} = (1 - \frac{\lambda_i}{\mu_i}) \sum_{k=0}^{\infty} k \left( \frac{\lambda_i}{\mu_i} \right)^k \tag{11}
\]

where \( \pi_{ik} \) is \( k \)-th steady state probability of Node-\(i\), while the state is defined as the number of packets. \( \rho_i \) is the service utilization which is the average number of packets to be processed. The average wait time, \( T_Q \), is the time for a packet to wait to be processed.

\[
T_Q = \frac{1}{n} \sum_{i=1}^{n} \frac{N_i}{\mu_i} \tag{12}
\]

The emergency node is given higher priority as follows. Note that each sensor node generates and sends packets to a queue associated with it in the GW. The GW allocates the processing time of each queue in proportion to the input rate. Assume that three nodes send the packets to the GW (hence three queues), and the input rate of Queue-1,2, and 3 are 5, 3, and 2 packets/sec, respectively. Then the GW processes the packets of the queues in circular fashion, from Queue-1 to Queue-3, in regular operation condition, with 50%, 30%, and 20% of processing time for the three queues, respectively. Assume that the node sending packets to Queue-1 is detected as an emergency node when a packet of Queue-1 has just been processed. Then another packet of Queue-1 is processed instead of processing that of Queue-2. Then the average waiting time of the nodes is calculated. If it is still lower than the threshold, the packet of Queue-1 is processed repeatedly until the moment when the average waiting time becomes larger than the threshold. Then the packets from other queues are processed in the original circular sequence. This approach allows to handle the packets of emergency node more rapidly than the other nodes, while avoiding excessive delay of other nodes.

### 4 Performance Evaluation

#### 4.1 Simulation Setup

The experiments were conducted on a PC consisting of 8GB memory and Intel i5-7500 CPU based on Windows OS, and the scheme was implemented using Python language. In order to evaluate the effectiveness of the proposed scheme, it is compared with the emergency node detection scheme using linear regression, threshold, or FCFS policy in terms of processing time in different operational conditions.

#### 4.2 Simulation Results

In order to evaluate the performance of the schemes, a network consisting of six nodes is built. The data generated
from the nodes and the results of predicted interval of the proposed segmented linear regression and linear regression are shown in Figure 5.

Figure 5. The result of regression with the data.

It is assumed that each node senses a specific data of the manufacturing facilities. When the facility is on the rest, the sensed value is 30 as shown in the figure. When it operates, the value rapidly grows to about 80 and decreases to the default value of 30. Notice form the figure that the emergency node gets malfunctioning from the third period, and becomes totally abnormal from the fourth period. The predicted interval of each regression is shown in Figure 6. Since it is modeled for the data of each period, the model is separately applied to each period. As the figure reveals, the upper boundary of the predicted interval of linear regression follows the trend of the data to a certain degree. However, the difference from the actual data is about 10 in average. On the other hand, the predicted interval of the proposed segmented linear regression match the inflection point. Therefore, the change in the trend can be accurately inferred. As a result, the model of the proposed scheme well fits the data, and thus it is possible to accurately detect the abnormal data.

Figure 6 compares the accumulated processing times of the emergency packet with different schemes. In this simulation the average rate of each node is 70 packets/sec and the processing rate of the GW is 500 packets/sec. The threshold for the delay in controlling the priority of emergency node is 0.5 sec, and the confidence level of the predicted interval is 95%. In the figure the processing time linearly increases with the growth of the number of processed packets. Then it bends at the point when the GW detects the emergency node. After the detection, the priority of emergency node gets higher than the other nodes. As a result, the processing rate of emergency packets gets higher and the gradient becomes lower. For the FCFS case, the priority is not changed, and therefore the slope does not change. Observe from Figure 7 that the proposed scheme using segmented linear regression detects the emergency node much earlier than the scheme with linear regression, at about 160th packet compared to 190th packet. It is because the proposed scheme accurately models the upper bound of the data. Therefore, if an emergency node gets malfunctioning and exceeds normal data, the proposed scheme immediately detects it. However, the scheme with linear regression or threshold requires more time to hit the boundary of normal range.

Figure 6. The comparison of processing times of emergency packet. (Confidence level = 95%)

Figure 7 is the case 90% confidence level. When the confidence level is decreased, the boundary of the data which affects the regression model gets narrow. It means that the upper bound of the predicted interval becomes closer to the data. Therefore, detecting abnormal data becomes more sensitive than with higher confidence level. As the figure shows, the proposed scheme detects the emergency node at about 110th packet. It is also faster than the other schemes. In addition, unlike with Figure 6, the difference in the detection time between the linear regression and threshold technique gets bigger. This is because the predicted interval of linear regression becomes narrower as the confidence level decreases while that with threshold does not change.

Figure 7. The comparison of processing times of emergency packet. (Confidence level = 90%)

Figure 8 shows the comparison of processing times for 300 packets generated from an emergency node with different input rates. As the input rate increases, the processing time decreases because the processing rate is much higher than input rate. As shown in the figure, the time becomes flat after 80 packets/sec since the capacity of GW meets the transmission rate from all the nodes. Meanwhile, the processing time of the proposed scheme is always smaller than the scheme with linear regression and threshold. It means that
if there exists surplus capacity in the GW, the proposed scheme can serve more emergency data.

**Figure 8. The comparison of processing times with varying input rate.**

Figure 9 shows the comparison of the processing times with different service rates. Similar to input rate, the processing time gradually decreases as the service rate increases. Notice that the proposed scheme of segmented linear regression consistently performs better than the other schemes.

**Figure 9. The comparison of processing times with varying service rate.**

Table 1 presents the processing ratio of emergency node. The number of emergency packets over entire packets is measured with 70 packets/sec of input rate and 500 packets/sec of processing rate. The FCFS scheme processes emergency packets equally as other packets. Since there are six nodes, the packets from each node are processed equally likely at about 16%. However, with the proposed scheme, the GW handles about 2% more packets from the emergency node than other nodes.

**Table 1. The comparison of processing ratios.**

<table>
<thead>
<tr>
<th>Time(s)</th>
<th>Processing ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Proposed</td>
</tr>
<tr>
<td>5</td>
<td>18.707</td>
</tr>
<tr>
<td>50</td>
<td>18.518</td>
</tr>
<tr>
<td>500</td>
<td>18.866</td>
</tr>
</tbody>
</table>

**5 Conclusion**

In this paper we have proposed a scheme based on the predicted interval of segmented linear regression to quickly detect emergency node in IIoT environment. The proposed scheme compares the sensed data with the upper bound data in the predicted interval to quickly detect abnormal data. Also, a priority control scheme has been proposed to handle the emergency node preferentially. The control scheme is based on multi-queue structure, and queuing theory is adopted not to overly degrade the normal nodes. Computer simulation reveals that the proposed scheme is superior to the existing threshold-based, linear regression, and FCFS scheme in the speed of detecting abnormal data. Also, the data from emergency node can be processed at the GW with higher rate than the others.

Future research includes the study on the optimal setting of the threshold and waiting time since they are important parameters for the detection and management of emergency node. A formal modeling and experiment will be conducted to systematically decide the values showing the best performance in various IIoT environments. Also, the proposed scheme will be enhanced to support different pattern of operation of the nodes, data distributions, etc.

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**7 References**


