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Fault Detection and Classification of Time Series Data Using Support Vector Regression and Inception-v3

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***Abstract*:** *It is important to detect and classify the cause of abnormalities by monitoring the abnormal status of the periodic signal generated by the equipment of the process system in real time. We propose research methods, support vector regression (SVR), and Inception-v3 to effectively detect and classify outlier data of periodic signals measured at process system facilities. Therefore, in this study, outliers are detected as SVR method and apply the models classified as normal and abnormal to the Inception-v3 model. The real-time process monitoring result graph is predicted as normal or Abnormal through Inception model.*

Keywords: *Fault Detection and Classification, FDC, SVR, CNN, Inception*

1. Introduction

Management of process equipment is necessary continuously for efficient operation in semiconductor process. To reduce the defects in the process and increase the yield, periodic signals are used to confirm the abnormality of the process. With the emergence of the Smart Factory and the Big Data era, data from various sensors such as temperature and pressure generated in the process can be measured. Through the data mining technique, we extract useful information from complex data and find meaningful rules. With Pattern Analysis and Novelty detection method, reliability and stability to the facility system can be influenced early and complement the quality. By monitoring in real time, it is possible to analyze the pattern of the cause and save enormous cost and time. In this paper, we propose a novelty detection method using periodic signal data generated in CVD (Chemical Vapor Deposition) semiconductor process equipment through data mining technique. Novelty detection is a method of judging whether a new observation is an ordinary cognitive defect when compared with an existing data pattern. As a detection method, there are basic statistical methods and Machine Learning method such as SPC, Hotelling's T2, PCA, kNNDD, Neural Network and CNN [3,9]. Lee et al. proposed FDC-CNN-based multivariate sensor fault classification and fault diagnosis methods. [8]. Park et al. proposed an efficient monitoring chart using principal curves [7]. R. Isermann proposed various error detection methods by extracting feature values from the measured signals [1]. However, many companies basically use SPC control charts. A control chart is a statistical tool that can be used to determine how a process changes over time in a process [2]. SPC (Statistical Process Control) is a method of modeling data of a time series process using Upper Control Limit and Lower Control Limit. There is a problem that the management limit line is amplified when the value change is large. Therefore, in this study, to solve these problems, an abnormality occurring in the nonlinear system is detected by using the SVR (Support Vector Regression) method, Using the Inception-v3 model, real time periodic signals are determined to be normal and abnormal. The composition of this paper is as follows. Section 2 describes the data description, experimental method, Support Vector Regression (SVR), Inception-v3 method, and experimental results. Section 3 discusses the conclusion and future research topics.

2. Data and Method Model

2.1. Data

The data is periodic signal sensor data generated in CVD (Chemical Vapor Deposition) semiconductor equipment. The data used in the study is time-series data not being labeled, and using the K-means clustering method, assuming that plural are normal data, the remaining data are labeled with defects.

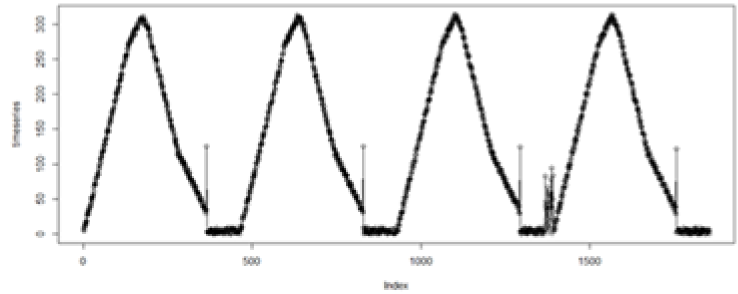

Fig. 1 Timeseries Data

2.2. Experimental Method

The order of experiments is Data Preprocessing, SVR Fault detection, Inception-v3. Data is obtained from the A system company and is unlabeled data. For the detection method, SVR (Support Vector Regression) is used to form a master pattern for normal labeling data, and margins were set as UCL and LCL of the control chart. In addition, we classify the image of data which is labeled with normal and abnormal as divided into three classification models into Inception model and classify the sensor data generated in process monitoring process in real time. For the tool, R-programming 3.4 and Python 3.5 are used.

2.3. Support Vector Regression

SVM (Support Vector Machine) is a binary classification method used for classification or regression analysis. SVR (Support Vector Regression) is a function of ε-insensitive loss function to SVM so that any real value can be predicted [10]. In this study, the presence or absence of abnormality of the periodic signal was confirmed using SVR which is a nonlinear regression technique [4].

$$f(x) = \langle \omega, x \rangle + b, \omega \in X, b \in \mathbb{R} \tag{1}$$

$$\min \frac{1}{2} \left\| \omega \right\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{2}$$

$$\textbf{Subject to} \quad \begin{aligned} & y_i - \langle \omega, x_i \rangle - b \le \varepsilon + \xi_i \\ & \langle \omega, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \ge 0 \end{aligned} \tag{3}$$

The reason for using SVR is to use Master (CL) for the cycle signal of the repeated process and apply median value of the value of equation of the periodic signal [10]. The kernel functions used in SVR are RBF (Radial Basis Function) and Laplacian, and Laplacian (7) function is used considering the characteristics of time series data. As shown in Fig. 1, the marginal line is set to the UCL(5) and the LCL(6) by applying the standard deviation to the values of data per t seconds.

$$CL = Median(f(X_t)) \tag{4}$$

$$UCL = CL + 6 * \sqrt{E(X_t^2) - (E(X_t))^2} \tag{5}$$

$$LCL = CL - 6 * \sqrt{E(X_t^2) - (E(X_t))^2} \tag{6}$$

$$k(x, x') = \exp\left(-\left\| x - x' \right\| / \sigma\right) \tag{7}$$

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2.4. Inception-v3

One of the CNN models is Conv-Net image recognition model. Figure 2 shows the Inception-v3 model, in which multiple convolutions of small size are stacked instead of Convolution Layer [5,6]. Through the structure called inception, it is possible to reduce the number of connections in the neural network and perform dense operations by the method of matrix multiplication 1 1. Inception-v3 model is used to pre-study process cycle signals and classify them when a new cycle signal emerges through the learned model and check whether one cycle signal is normal in real-time process monitoring.

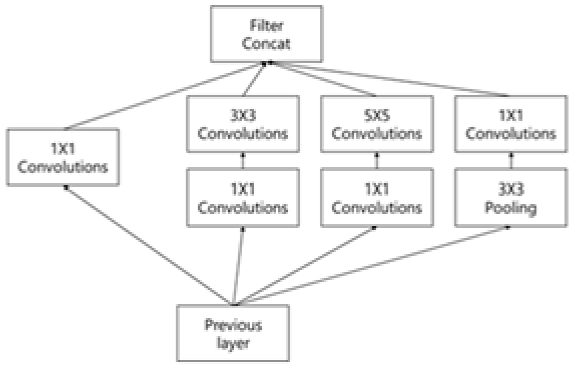

Fig. 2 Inception Module with dimension reductions

3. Experiment Result

3.1. SVR Result

Detection results of periodic signals using Support Vector Regression model are as follows. The table 1 and figure below show the detection results of periodic signals. Fig. 3 shows the X-bar chart of the control chart and Fig. 4 shows the result of applying the proposed model. Compared with Fig. 3, the proposed method is effective for detection. UCL and LCL have limitations in detecting abnormal values at 139 and 131, respectively. As a result, Fig. 4 is the data that is labeled as normal and belongs to the marginal line, and the periodic signal is normal. Fig. 5 is abnormally detected over 400 seconds as abnormal model 1, and there was an abnormal value in the periodic signal. Fig. 5 is abnormally detected over 400 seconds as abnormal model 1, and there is an abnormal value in the periodic signal. The table 1 shows that Fault_Num 0, Fault_Ratio 0 is normal in Original Cycle , Fault_Num 17 is abnormal in New Cycle 1, and Fault_ratio is abnormal in 3.6%. New Cycle 2 has 344 Fault_Num and 74.4% Fault_ratio.

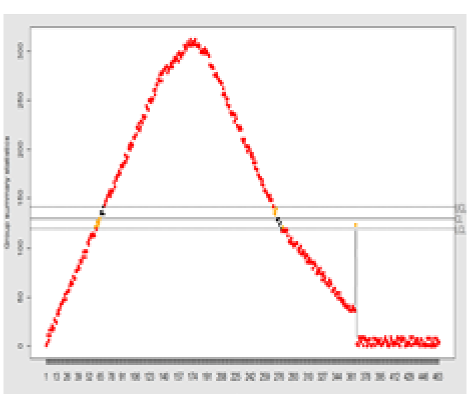

Fig. 2 X-bar Chart Result

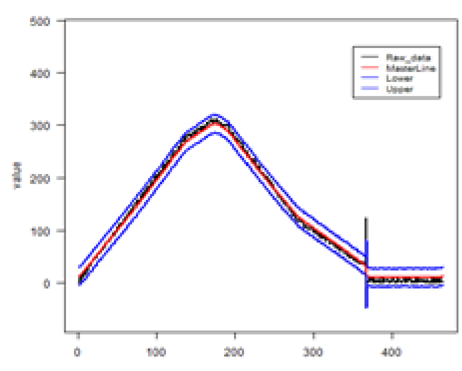

Fig. 3 Original Data Detection Result

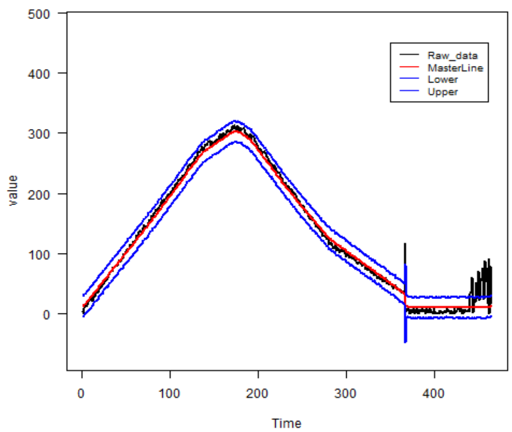

Fig. 4 New Cycle 1 Data Detection Result

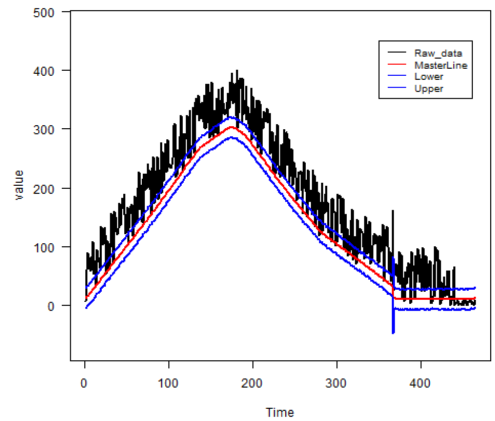

Fig. 5 New Cycle 2 Data Detection Result

Table I New Cycle Detection Result

Cycle	Fault _Num	Fault _Ratio (%)	Result
Original Cycle	0	0	normal
New Cycle1	17	3.66	abnormal
New Cycle2	344	74.4	abnormal

3.2. Inception Model Result

To apply the Inception-v3 model, we made the image for all cycle signals based on the result of the classified model above. Inception-v3 model is used to find out which classification belongs to process monitoring period signal data when a new periodic signal was generated. Assuming that the data in Fig. 5 and Fig. 6 are monitored in the process, the classification accuracy is as follows. Normal is normal model data, Abnormal is above Model 1, Abnormal Model 2, Other Signal contains data of other Signal and learned. New Cycle 1 Image shows an accuracy of 81% in abnormal model and New Cycle 2 Image model shows 99% accuracy in Abnormal. Although it showed high accuracy in the Image 2 model, it can be confirmed that Image 1 has reduced accuracy with a probability of 18%. In the relatively abnormal value remarkable model, the accuracy of the Inception model was confirmed to be high, the accuracy of New Cycle 1 data was low.

Table II Inception -v3 Accuracy

	Iteration	Normal	Abnorma1	Other Signal	Result
Original Cycle		0.9213	0.0775	0.0011	Normal
New Cycle 1 Image Accuracy	1000	0.1804	0.8143	0.0016	Abnormal
New Cycle 2 Image Accuracy		0.00003	0.9997	0.00027	Abnormal

4. Conclusion

In this research, we have used SVR (Support Vector Regression) and Inception-v3 model to detect abnormal values of sensor data periodic signals of semiconductor devices and proposed models classified by learned models. Control Chart was not successfully detected, and the model proposed in the research was effectively detected when the periodic signal was abnormal. Future research will require analysis of data in the Margin range. It is defined as a form to check the data that deviates from the area by setting the margin interval, but analysis of the information about the data that is missing is required. In addition, it is necessary to apply CNN model in addition to Inception-v3 model for more precise performance comparison study.

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