Convolutional Autoencoder-based Sensor Fault Classification

Jae-Wan Yang, Young-Doo Lee, In-Soo Koo
Dept. of Electrical Engineering
University of Ulsan
Ulsan, Republic of Korea
yjwan9308@ulsan.ac.kr, leeyd1004@naver.com, iskoo@ulsan.ac.kr

***Abstract*— Automation machines perform not only simple operations but also operations requiring high accuracy. Sensors are essential to carry out the delicate operations. Therefore, if there is a fault in sensors, the machine can malfunction and the process-line will be damaged. To prevent this, sensors should be monitored and diagnosed in real time. In the paper, we propose a convolutional autoencoder-based sensor fault classification scheme in which time-domain statistical features and convolutional autoencoder features of sensor data are both utilized to classify types of sensor faults. Through simulation, it is shown that the proposed scheme can improve classification performance of the sensor faults.

Keywords*— *Sensor faults; Fault detection; Time-domain statistical feature; Convolutional autoencoder; Support vector machine; Erratic fault; Drift fault; Hard-over fault; Spike fault; Stuck fault

I. Introduction

Recently, with the rapid development of digital conversion and machine equipment drive technologies, the number of automation machines used in production processes in the industrial field is increasing. As a result, the performance of automation machines has a paramount influence on the efficiency of the plant. To maximize the efficiency of an automated production process line, productive losses caused by defects in automated machines must be minimized. Therefore, there is a growing interest in the management and maintenance of automation machines. The sensors attached to automation machines and used for monitoring operation and detecting the amount of control are the key parts to control the speed and operation of the automation machine. Therefore, to prevent the economic loss caused by an abnormality in the sensor, a system for detecting the sensor fault in real time is significantly required[1].

Generally, signal processing analysis techniques and fuzzy theory have been used for fault detection of sensors and machines[2]. However, these methods are limited in their usability due to the complexity of the work environment and it is difficult to add or modify algorithms when new types of faults occur. To solve such problems, many machine learning techniques for classifying faults by analyzing patterns of fault signals have been applied. For the efficient use of machine learning in the case of a large amount of data or high-dimensional data, the features extracted from the obtained data are used for the machine learning algorithm[3]. In this paper, features extracted from sensor data using convolutional autoencoder (CAE) and statistical time-domain features are used to efficiently classify sensor fault types. Based on this, support vector machine(SVM) is used to classify sensor fault types.

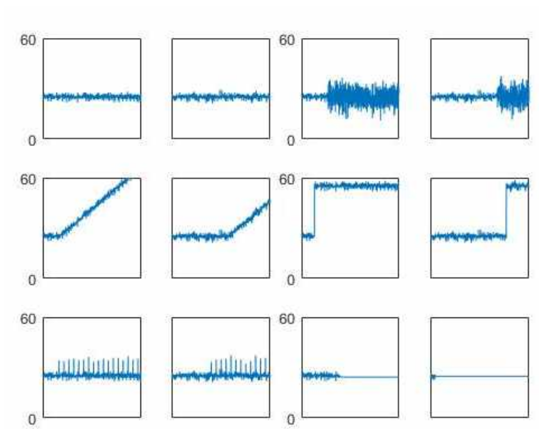

Fig. 1. Signal snap shots of Normal and faults at random points

II. Sensor Fault Data

The data used in this paper were obtained from a temperature sensor. one sample is comprised of 1,000 data points. The whole data consists of normal signal and five types of fault signals as follows: normal signal, drift fault signal, hard-over fault signal, erratic fault signal, spike fault signal and stuck fault signal. Figure 1 shows that the normal signal and the faults signal according to the detection point. In the case of sensor fault data measurement, the point where the fault occurs may appear differently depending on the detection time. Figure 1 shows signal snap shots of normal and faults. In this case, it is a matter of considerably how fast and accurate the fault is detected. The normal signal is measured from the temperature sensor and the remaining five fault signal data are obtained through the simulation[1].

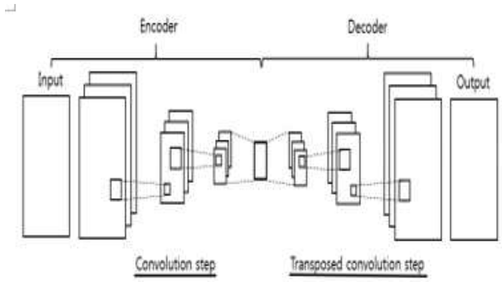

Fig. 2. Convolutional autoencoder structure for sensor data feature extraction

III. Feature Extraction from Sensor Data

A. The time-domain statistical features

In general, when classifying data by using machine learning such as SVM, the features are extracted from the data rather than using the data itself. Time-domain statistical features have been frequently used as input data in machine learning training and have shown nice performances[4]. In this paper, time-domain statistical features are extracted from measured sensor output signals and used as inputs of SVM. For a total of 6 signal types, 600 samples are used where 100 samples are for each signal type. The features used are as follows: root mean square (RMS), kurtosis value (KV), peak-to-peak value (PPV), impulse factor (SF), square root of the amplitude (SRA) skewness value (SV), crest factor (CF), kurtosis factor (KF), and mean, central moment (CM).

B. Convolutional Autoencoder(CAE)

Autoencoder is one of the unsupervised learning methods that extracts the features of data using only input values in machine learning, and its learning components are comprised of encoder and decoder which are a symmetrical connection structure[5]. The input data is reduced in dimension through the encoder, and the data features are obtained in this process. In the decoder, it targets the same value with the input data fed to the encoder. In this study, we use the convolutional autoencoder (CAE), which is a combination of the autoencoder and the convolution layer, to extract the features from the sensor data. CAE consists of a convolution layer, a fully connected layer, and a transposed convolution layer. Figure 2 shows the structure of CAE used in feature extraction in this study[6]. The encoder is composed of three convolution layers with 3×3 filters and ReLU activation. The number of feature maps for encoders is 50, 100 and 150. After passing the encoder, the dimension is reduced to 20 nodes. The decoder is set up symmetrically with the encoder network structure. The hyperparameters of CAE are set to minimize the mean square error. The data obtained from the sensor is scaled between 0 and 1, then transformed into the image form of the 2D matrix and learned by CAE. One data sample is used in the form of a two-dimensional image. In CAE, 100 samples are used for each type of sensor data, and hence a total of 600 data samples are used for CAE feature extraction. Two-dimensional images are fed as input to the CAE and reconstructed again through the transposed convolution layer. Figure 3 shows the input data image and the restored data image for the whole signal types. Through this process, the mean squared error value was 0.00368 and the reduced 20-dimensional features were obtained from the sensor data.

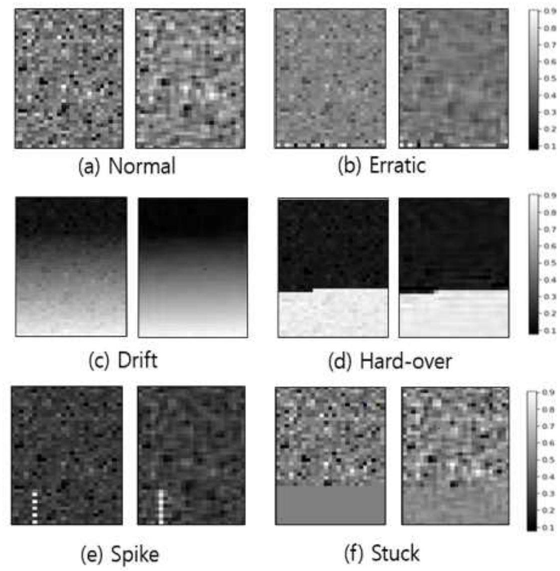

Fig. 3. Input data(right) and reconstructed data(left)

IV. SVM-Based Sensor Fault Classification

SVM basically deals with binary classification problems and is based on statistical learning theory. SVM is mainly used in pattern recognition by supervised learning, but it has been applied to various fields such as voice recognition, image recognition, financial data analysis, brain signal processing, and shown excellent performance[3][4][7]. In this paper, SVM is used for sensor fault diagnosis and classification.

SVM finds the maximum distance hyperplane defined by the support vector nearest to the decision boundary to classify the training data. Since SVM can classify data using only the support vector, it is advantageous in that the classification time is less and the overfitting can be avoided compared with the algorithms using all the data. SVM often classifies data with nonlinear characteristics. Therefore, kernel functions are used to classify data having linear characteristics as well as data having nonlinear characteristics. In this study, three kinds of kernel functions, linear, RBF, and polynomial, are used for SVM learning[8].

Figure 4 shows a framework of the model applied for sensor fault detection in this study. The time-domain statistical features and CAE features are extracted from the following data obtained from each type of sensor fault, and the features are used as learning and test data of SVM. A total of 600 samples are used for the SVM, 300 samples for learning, and 300 for testing.

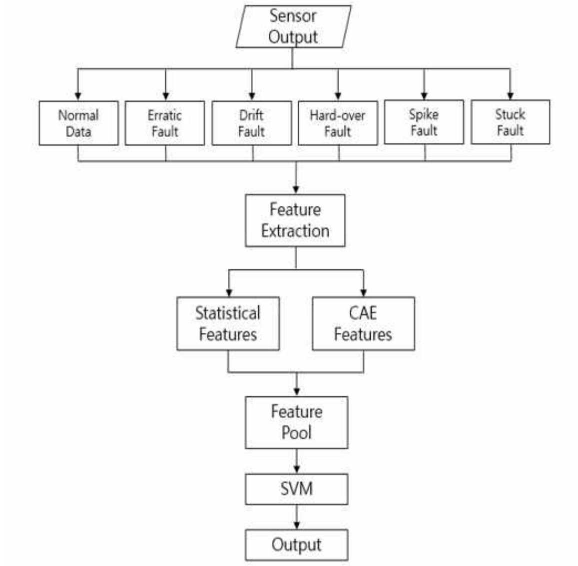

Fig. 4. Framework of the model applied for sensor fault detection.

TABLE I
ACCURACY OF SVM USING TIME-DOMAIN STATISTICAL FEATURES(%)

Kernel Function	Time-domain statistical features					
	0	1	2	3	4	5
Linear	86	100	87.33	95.33	97.33	88.67
RBF	91.67	100	97	99.33	99.33	93
Polynomial	93.33	99.33	96.67	100	99.67	93.67

TABLE II
ACCURACY OF SVM USING CAE FEATURES(%)

Kernel Function	CAE features					
	0	1	2	3	4	5
Linear	89.33	96.33	95.33	97	98.67	95.33
RBF	83.33	83.33	97	94.33	99.67	83.33
Polynomial	86.33	96.67	97	99.33	100	90.67

TABLE III
ACCURACY OF SVM USING TIME-DOMAIN STATISTICAL FEATURES AND CAE FEATURES(%)

Kernel Function	Time-domain statistical features and CAE features					
	0	1	2	3	4	5
Linear	93	100	97	100	99.33	96.67
RBF	83.33	83.33	97	92.67	99.33	83.33
Polynomial	92.33	100	97.33	100	99.33	94.67

In this paper, the one-versus-rest method is used in training SVM to classify each fault type and the results are shown in TABLE 1, 2, and 3, respectively. The numbers from 0 to 5 in the tables denote the classes of normal, erratic, drift, hard-over, spike, and stuck faults, respectively. TABLE 1 shows the classification results based on time-domain statistical features. 1 (erratic) class is more accurate than comparatively different sensor fault classes and the accuracy of 0 (normal) and 5 (stuck) classes is relatively low. On the average, polynomial kernel function case showed the highest accuracy of 97.11% in classification based on time-domain statistical features. TABLE 2 shows the results of sensor faults classification using CAE features. 0 (normal) and 5 (stuck) classes had the lowest accuracy in classification based on CAE features as well as based on time-domain statistical features. In the classification results based on CAE features, the linear kernel function showed the highest accuracy with an average of 95.33%. TABLE 3 shows the classification results based on all the features extracted from the sensor data. Using the linear kernel function in SVM based on all the features, the highest accuracy was obtained with an average of 97.67%. It can be identified that the classification results of 0 (normal) and 5 (stuck) classes are improved more than the case of using one kind of data feature.

V. CONCLUSION

In this paper, features were extracted from faulty signals such as erratic, drift, hard-over, spike and stuck for sensor fault classification, and classified using SVM. Two main feature extraction methods were used, in time-domain statistical and from CAE. The accuracy of SVM classification was higher. When both of the feature extraction methods were used together than separately. Future work is further to enhance the classification accuracy by selecting only the features needed by performing feature selection

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