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Development and Application of a Method for Real Time Motor Fault Detection

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Abstract

Predictive maintenance (PdM) has been widely used in manufacturing to reduce maintenance cost and unexpected downtime. A common element within manufacturing equipment/machines is a motor. This paper aims to detect motor faults by collecting and analyzing vibration data with wireless sensors. A cloud-based motor condition monitoring system is also built to detect motor faults by analyzing the data. An Artificial Intelligence (AI) model is trained using the collected vibration data, and principal component analysis (PCA) is utilized to detect abnormal behaviors of the motor. Hostelling's T^2 statistics and squared prediction error (SPE) statistics are then applied to clarify criterions for abnormal operations of the motor.

Keywords: Condition Monitoring; Smart Manufacturing; Predictive Maintenance (PdM); Artificial Intelligence (AI); Principal Component Analysis (PCA)

1. Introduction

Recently, the Internet of things (IoT) has accelerated the transformation of manufacturing industries from the conventional manufacturing system to smart and sustainable manufacturing. The advantages of smart manufacturing, such as reduced manufacturing costs and improved productivity, have attracted more and more manufacturers' attention to adopting it. With the innovative development of wireless sensors in higher availability and affordability, data acquisition and accessibility in cloud-based computing networks inspired manufacturers to move toward the highly interconnected manufacturing systems [1]. As a part of this change, a new production paradigm is offered where the cloud-based technologies play a vital role in the existing manufacturing industry. Artificial Intelligence (AI) is widely utilized in the manufacturing industry, that has an incredible impact on data characterization and prediction. As a subset of AI, machine learning (e.g., supervised learning and unsupervised learning) is one of the commonly used methods in machine condition diagnostics (e.g., predictive maintenance, prognostics, and health management). The application of machine learning in machine diagnostics can effectively predict the failure or abnormality of the machine in advance and further reduce maintenance costs and unexpected downtime.

Machine diagnostics can provide predictive maintenance solutions to a range of industries and have been broadly studied based on machine learning. To diagnose machine conditions, related data is often to be collected and analyzed. Currently, various types of data have been used for failure analysis such as acoustic data [2, 3, 4], acceleration data [5, 6, 7], infrared images [8, 9], and multi-sensor data fusion [10, 11, 12]. In a motor, each rotating component generates its own distinctive vibration pattern that can provide an explicit basis for the machine condition [13]. Hence, in condition-based maintenance of a motor, vibration monitoring and analysis are essential to the machine condition diagnostics. In addition, vibration analysis can provide imperative sensitivity and accuracy [14]. Therefore, the acceleration data is collected and analyzed in this study for abnormality detection of a motor.

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This work is built upon the collaboration with company partners where vibration sensors are deployed on the motors. A cloud-based motor condition monitoring system is then implemented where AI algorithm is trained with the collected data and principal component analysis (PCA), which refers an unsupervised learning method that can reduce the dimension of input data space for a reconfiguration of a data model, is utilized to detect the abnormality of the motor. The remaining sections of this paper are organized as follows. Section 2 describes the overall sensor networks for data acquisition and analysis using AI techniques for machine diagnosis. Section 3 presents the acceleration data and explains the concepts used for the feature extraction process from the data. Section 4 demonstrates Hotelling's T^2 and SPE statistics with the visualization of data to clarify abnormal operations of the motor.

2. A cloud-based motor condition monitoring system

In this work, continuously real-time observations on motors in manufacturing plants are conducted by developing an application of a cloud-based motor condition monitoring system. The overview of the system is shown in Fig. 1. In this system, tri-axial wireless vibration sensors are attached to the motors to measure acceleration data in 3-dimensional directions. Then, the measured data are transmitted to a sensor gateway via Bluetooth channel that can guarantee a stable connection in a short distance range. The sensor gateway is then connected to Wireless Local Area Network (WLAN) with IEEE 802.11 standards. Finally, the sampled data are collected and recorded in the cloud server that is accessible and visible online.

The feature extraction process and parameter manipulation are conducted for training an AI model. The model utilized in this work is trained to learn the data without pre-existing labels. The trained model then can detect the previously unknown abnormal patterns of the motors. Therefore, the outcomes of this system can provide machine diagnostics for the manufacturers to further optimize their maintenance plan. The verification of the AI model can be achieved by comparing data with the actual behavior of the observed motors. The explanation of the detailed procedure will be demonstrated in the following sections.

3. Principal component analysis of acceleration data

Raw acceleration signals are plotted using MATLAB and shown in Fig. 2. Fig. 2(a) shows the average and peak to peak acceleration value of each axis. Fig. 2(b) illustrates acceleration signals which a noise reduction technique is applied following normalization with zero mean and unit variance. 6 features (i.e., root mean square and range of each axis) are selected and generated with different central tendencies and dispersions. PCA is then applied to coordinate multi-dimensional dataset to new axes in a reduced dimension. The principal components (PCs) are generated from the feature datasets, while the interdependency between variables is minimized. Simultaneously, the most variation of the dataset is preserved to make it easier to distinguish abnormal data. During the training process, sample data under normal operating conditions are used and the covariance matrix of the data is obtained, which indicates the correlation of the training dataset.

The PCs can then be identified after eigen decomposition of the covariance matrix. That is, the covariance matrix is decomposed into its eigenvectors and eigenvalues. The eigenvector of the covariance matrix, which has the largest variance, is called the first PC and the eigenvector with the second largest variance is called the second PC. Since the dimensions of original data are reduced, the number of PCs needs to be carefully selected, ensuring that the new PC domain conserves the information of original data. One way to determine the number of PCs is to use the percentage of explained variance, which has been routinely used in PCA. Explained variance indicates how far each data point in the dataset is from the mean. This value determines how much information from the existing data will be retained. The explained variance can be calculated by the ratio between the variance of the selected PCs and the variation of all PCs as shown in the following Eq. (1).

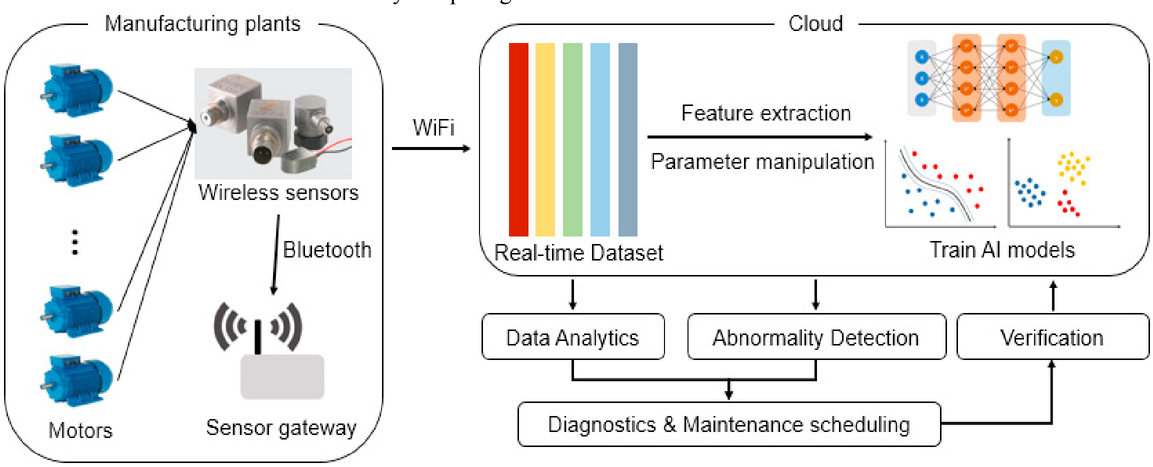

Fig. 1. Cloud-based motor condition monitoring system.

$$Explained\,Variance(\%) = \sum_{i=1}^{p}\lambda_i \,/\, \sum_{i=1}^{n}\lambda_i \quad (1)$$

where λ_i represents i^{th} principal component and p, n denote the number of selected principal components and the number of all principal components, respectively. It is common to select the explained variance value between 70% to 95% to minimize loss of information due to dimension degradation of data [15]. In this research, two PCs are selected to ensure that the explained variance exceeded 90%, which indicates the PCs have more than 90 % associativity with the original data. The training data are projected on the new PC domain to obtain the retained PCs. The training and testing data utilized in this work are continuously sampled for one month and 2 weeks, respectively. The data are sampled at 1 data point per minute. In total, 43,200 sampled data and 21,600 data are utilized to train and test the AI model, respectively. The AI model can be further improved by sampling more data or sampling at a higher rate.

4. Data visualization and abnormality detection

The first and second PCs determined by the PCA are visualized in Fig. 3. Different colors are applied to the data points for each day to help identify the abnormal operation of a specific day. The PCA dimension reduction automatically realizes data clustering as is evident in Fig. 3. Similar data points are grouped together, and the data that have different properties are segregated from one another while revealing underlying data patterns or outliers. However, this may not provide a clear interpretation of the motor condition. To clarify this ambiguity, further data interpretation through the

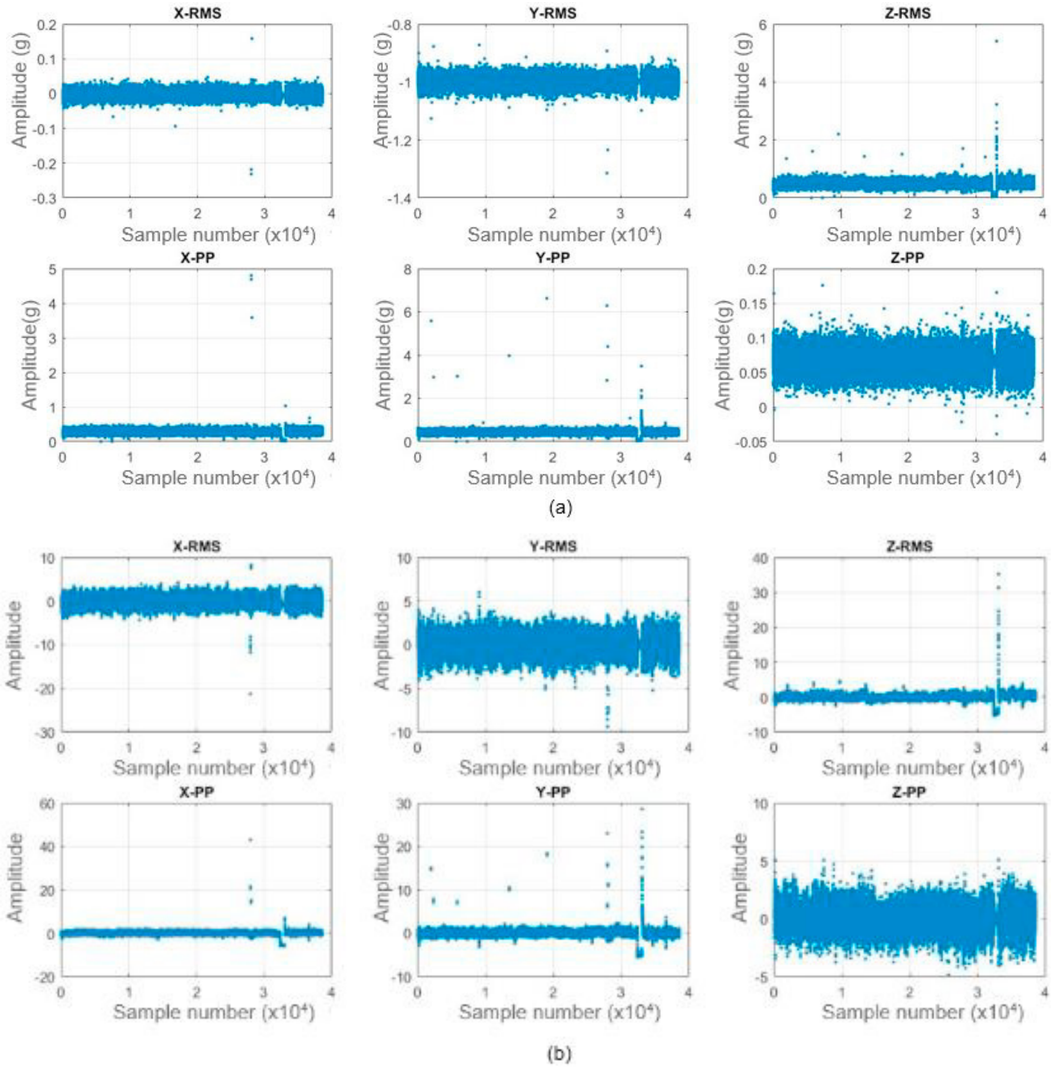

Fig. 2. (a) Raw acceleration signal plot; (b) Normalized acceleration signal plot.

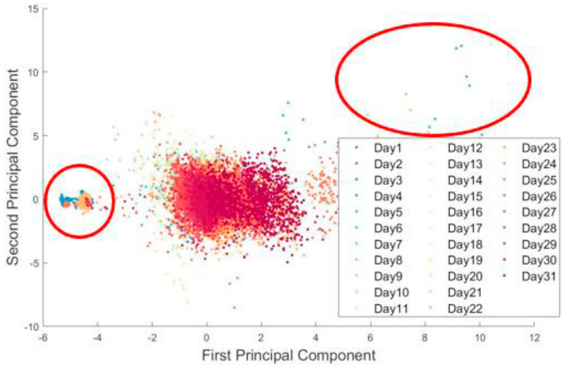

Fig. 3. Illustration of PC data points using two PCs.

Hotelling's T^2 and SPE analysis is conducted based on kernel density estimation (KDE), which refers to a data-driven technique for the non-parametric estimation of density functions [16]. The Hotelling's T^2 statistics is a mathematical procedure to estimate model interior data change so that it reflects the change in variables by counting the fluctuation of the PCs. The SPE statistics is the estimation of model exterior data change, and it shows the deviation of the current measured variable to the PCA model [17]. The Hotelling's T^2 and SPE statistics are expressed in the following Eq. (2) and (3) [18, 19].

$$T_i^2 = X_i P_k \lambda^{-1} P_k^T X_i^T \tag{2}$$

$$SPE_i = X_i (I - P_k P_k^T) X_i^T \tag{3}$$

where $\mathbf{X}_i$ is the i^{th} row of the input matrix **X,** and **I** is a unit matrix and P_k is the kth principal component of loading matrix **P** and λ is a diagonal matrix of the eigenvalues corresponding to the selected principal components. $\mathbf{T}_i$ and $\mathbf{SPE}_i$ represent i^{th} row element of the statistic matrices. KDE is obtained by the following probability density function (PDF) as shown in Eq. (4) [17].

$$f(x,H) = \frac{1}{n}\sum_{i=1}^{w} K(H^{-1}(x - x_i)) \tag{4}$$

where x is an input feature matrix, K is a kernel function, H is the bandwidth, and w is the number of samples. The Gaussian distribution function is a widely-used kernel function, where an appropriate bandwidth matrix is chosen based on the estimated standard deviation of sample data. The Gaussian kernel function is expressed in Eq. (5).

$$K(x) = \frac{\exp(-x^2/2)}{\sqrt{2\pi}} \tag{5}$$

For a given confidence level, (i.e., 95%, 99%, and 99.9% as the first control limit, second control limit and action limit, respectively), the probability of a point falling beyond the control limit is calculated based on the kernel function to indicate whether the process is "in control" or "out of control." Often, the control limits for T^2 and SPE control charts are computed using F and χ2 distributions, respectively. This computation is typically performed upon the assumption that the original data is temporal independence and follows a multivariate Gaussian distribution [20]. Since such an assumption may not be valid for this study, the control limits are established using KDE. The corresponding control limits based on KDE is calculated using the kernel density estimator, as shown in Eq. (6).

$$P(x < c_l) = \int_{-\infty}^{c_l} f(x, H \mid T^2 orQ)dx \tag{6}$$

where $P(x)$ indicates the probability that a data point exceeds the control limit and c_l is an upper bound of the control limit. This probability is then compared with the given confidence levels to provide a warning action and diagnosis of the motor operating condition. The SPE, which is also known as Q residual, and Hotelling's T^2 control limits, are illustrated in the control charts shown in Fig. 4. The first control limit is emphasized in the yellow line, and the second control limit is highlighted by the red line. These control charts clearly show the abnormal operations exceeding control limits that are indicated in the dotted circle. The established control limits are then used for machine condition monitoring in actual manufacturing plants. The verification of this model is accomplished by comparing the analysis results with the real operation of the motor.

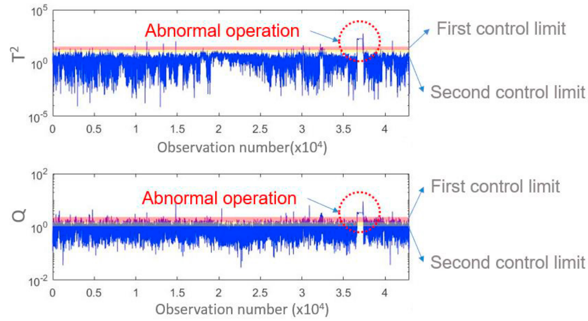

Fig. 4. Hotelling's T2 and SPE control charts.

5. Conclusions

In this work, a cloud-based motor condition monitoring system was implemented to detect abnormal operations of motors. Tri-axial vibration sensors were utilized to collect acceleration data. The acceleration data were recorded in the cloud server for sending and receiving the data. PCA technique was then applied for the feature extraction and analysis of the sampled data. In this research, two PCs were selected based on KDE to ensure the preservation of original information. Also, Hotelling's T^2 and SPE statistics were used to provide explicit criteria for abnormality detection. The analyzed data were then visualized in Hotelling's T^2 and SPE control charts. Relevant equations were explained to demonstrate the relationship between KDE and control limits of the two statistics. The confidence levels at 95%, 99%, and 99.9% were used to determine the control limits and illustrated in the control charts. The Hotelling's T^2 and SPE control charts presented the data exceeding the control limits to distinguish the abnormal operation of the motors from the normal operation. In future research, more sophisticated sensors will be applied to collect data at a higher frequency that can further improve the AI/PCA model.

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