Multiple regression analysis based approach for condition monitoring of industrial rotating machinery using multi-sensors

Xiaofeng Wang, Guoliang Lu, and Peng Yan
Key Laboratory of High Efficiency and Clean Mechanical Manufacturing of MOE
National Demonstration Center for Experimental Mechanical Engineering Education
School of Mechanical Engineering, Shandong University, Jinan, 250061, China
luguoliang@sdu.edu.cn

***Abstract*—Heterogeneous multi-sensors based change detection of machine running status is an important element to ensure the safety of industrial system. Considering the correlation between different sensors, this paper proposes a novel approach used for the detection of changes in machine condition. First, a prediction model is established using multiple regression, where a novel data description and prediction strategy is developed to make full use of the correlation. Residual analysis is then implemented to quantify the anomaly of investigated machinery. At last, decision making is made based on hypothesis testing. The proposed approach is evaluated by a representative condition monitoring application. Encouraging experimental results demonstrate that proposed approach has great potential in practical applications.**

Keywords*—machine condition monitoring; change detection; heterogeneous multi-sensors; multiple regression; statistical analysis

I. INTRODUCTION

Online condition monitoring (CM) has received considerable attention in industrial production where rotating machinery is the primary element. One of major steps is early change detection that can provide a reasonable starting point for further investigation such as fault diagnosis and life prediction. However, since the information collected by a single sensor may be incomplete, the detection system cannot make a reliable decision about the machine's operating state. Multi-sensors configuration can offset the information missing, which enables successful decision-making over a wider range of operating conditions [1,2].

Conventionally, the collected data from multi-sensors is in high dimensionality. In previous research, dimension reduction (DR) techniques(linear or nonlinear) have been widely used to reduce or deduct the number of dimension for a better description of machine condition, which utilizes the statistical characteristics of data [3,4]. However, this kind of methods cannot abstract information from multi-dimensional data collected form heterogeneous sensors. To overcome this shortcoming, feature-level fusion strategy was proposed. This kind of methods first extracts feature form the data collected by each sensor and then fuses them together to provide a comprehensive description of machine condition [5,6]. However, the major issue need to be considered is that the effectiveness and efficiency of this kind of approach for CM heavily relies on the process of feature extraction and creating new features may lose the physical meaning of original variables [7,8]. To overcome these deficiencies, time series prediction methods can serve as a good alternative, which uses residual as feature, i.e., the distance between real-time observation of sensor and the output of a defined prediction model [9,10].

Noticing the limitations of the existing methods and inspired by the time series modeling and prediction, this paper proposed a novel approach for the detection of changes in machine running status during continuous operation. Meanwhile, multiple regression technique (MRT) that is a powerful statistical technique to analyze multifactor data and is promising for the description of multi-sensors data whose different dimensions represent different factors [11] is adopted to utilize the hidden information among different sensors including collaboration, complementarity and/or competition

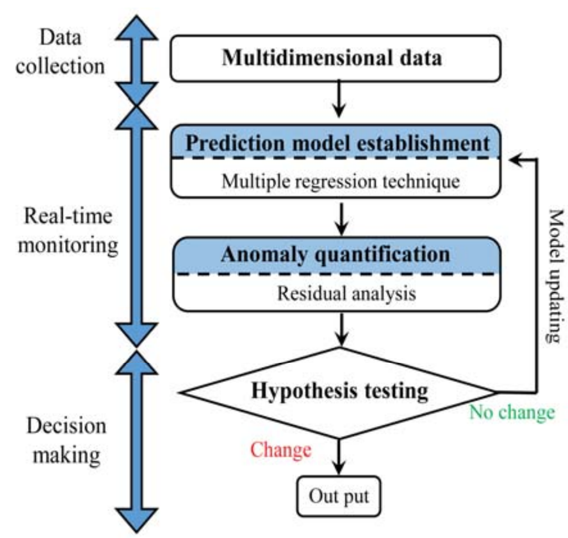

Figure 1. Proposed approach for change detection of machine runing status

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[12]. The detailed process can be seen in Fig. 1. On the basic of multidimensional data collected by different sensors, a prediction model is established using MRT. In particular, a novel data description and prediction strategy was proposed to utilize the relationship between different sensors. Then residual analysis is performed to quantify the anomaly of the machine being investigated. Followed by statistical analysis for final decision making, where a Gaussian distribution based hypothesis testing is implemented for newly-observed data. The proposed approach was evaluated by a representative condition monitoring application, and the promising results demonstrate its effectiveness in engineering applications.

II. PROBLEM DEFINITION

The data recorded by multi sensors can be represented by a matrix whose columns contain the time series measured by each sensor up to inspection time j. Let us assume there are i sensors totally, then the matrix can be constructed as,

$$\mathrm{X}_{1:j} = [\mathrm{x}^1, \mathrm{x}^2, \cdots \mathrm{x}^i] \ , \tag{1}$$

where $\mathrm{x}^i = [x_1^i, x_2^i, \cdots, x_j^i]^{\mathrm{T}}$ is the time series collected by i th sensor up to inspection time and $[\cdot]^{\mathrm{T}}$ is the transpose of matrix.

The first problem with multi-sensors data is correlation. Assuming there are 10 heterogeneous sensors and are labeled as $\mathrm{x}^1, \mathrm{x}^2, \cdots, \mathrm{x}^{10}$ respectively. Analyzing time series individually means ignoring the correlation of multi-sensors observations and performance promoting of multivariate approaches. The most intuitive representation of correlation is the covariance among them. In summary, there are 65 statistical indicators totally, i.e., 10 mean values, 10 variances and 45 covariances. If only 20 statistical indicators (mean value and variance) are inspected, the covariances which represent the correlation of different dimensions and account for 69.2% of the total parameters are not be considered. Consequently, the performance of machine condition monitoring will be terrible.

Another problem with multi-sensors data is redundancy. The properties of the matrix representation of multi-sensors data are closely related to the configuration of sensors (number, position or nature). In some particular configurations, the matrix exhibits multiple collinearity. In other words, there is an exact correlation or a high degree of correlation between different dimensions. A matrix like this causes the regression coefficients of linear regression model to be unsolved or meaningless.

Based on the foregoing discussion, the challenges of change detection in machine condition that monitored by heterogeneous multi-sensors are summarized as follows:

- To develop an appropriate strategy to utilize the correlation information of different sensors while minimizing data redundancy.

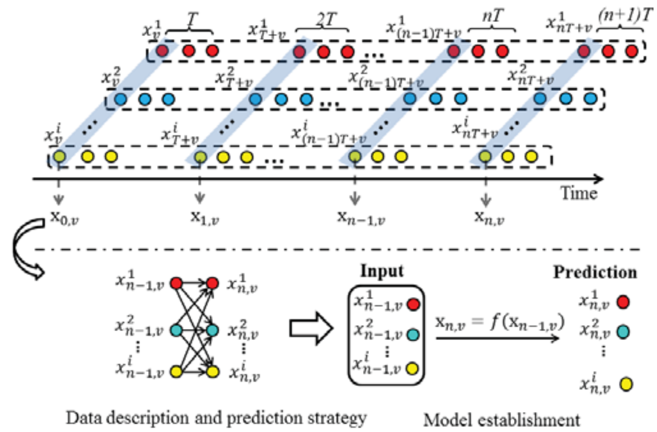

Figure 2. Proposed novel data description and prediction strategy

- To integrate the strategy into model establishment and apply the established model to real-time condition monitoring of rotating machinery.

III. METHIDOLOGY

In this section, a new approach is presented for multi-sensors based condition monitoring of rotating machinery. Specifically, the multivariate linear model is extended by a novel data description and prediction strategy to utilize the correlation among different sensors and accomplish the prediction task. Statistical analysis is then performed for decision making. The proposed approach mainly consists of three steps: (1) prediction model establishment; (2) anomaly quantification and (3) decision making. Detailed description is given in the following.

A. *Prediction model establishment*

Given a multidimensional time series $\mathrm{X}_{1:j}$ up to inspection time j, based upon the kinematics characteristics of rotating machinery [13] and the autoregressive integrated moving average (ARIMA) processes [14], it can be expressed in a periodic form,

$$\mathrm{X}_{1:j} = \left\{ \begin{matrix} \mathrm{x}_{0,1} & \mathrm{x}_{1,1} & \cdots & \mathrm{x}_{n,1} \\ \mathrm{x}_{0,2} & \mathrm{x}_{1,2} & \cdots & \mathrm{x}_{n,2} \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{x}_{0,v} & \mathrm{x}_{0,v} & \cdots & \mathrm{x}_{n,v} \end{matrix} \right\} \tag{2}$$

where inspection time j is transformed to periodic form, i.e., $j=nT+v$, the vth phase of n+1th cycle; T is periodicity length determined by algorithm proposed in [9]; v is the number of phase, $1 \le v \le T$; $\mathrm{x}_{n,v}$ is a series of observed values in the same phase v of n+1th cycle collected by different sensors, i.e., $\mathrm{x}_{n,v} = \left[x_{n\mathrm{T}+v}^1, x_{n\mathrm{T}+v}^2, \cdots x_{n\mathrm{T}+v}^i \right]^{\mathrm{T}}$ when there are i sensors in total.

In order to implement residual analysis, the first task is establishing a pre-defined mathematical model f which can predict the value $x_{n,v}$ from past observed data as

$$x_{n,v} = f(x_{n-1,v}) \ . \tag{3}$$

Considering the characteristics of signal, i.e., the values of different cycles at same phase present a certain development trend and the correlation among different dimension, a novel data description and prediction strategy was proposed as seen in Fig. 2. Furthermore, in order to improve computational efficiency, the multivariate linear model was extend to accomplish the task of prediction as,

$$x_{n,v} = \begin{bmatrix} x_{n-1,v}^{T} b^{1} \\ x_{n-1,v}^{T} b^{2} \\ \vdots \\ x_{n-1,v}^{T} b^{i} \end{bmatrix} + E \ , \tag{4}$$

where $b=[b_1, b_2, \cdots b_i]^T$ is an $i \times 1$ coefficient matrix and the values are different for different rows; $E=[\varepsilon_1, \varepsilon_2, \cdots \varepsilon_i]^T$ is an $i \times 1$ random error matrix where the members obey independent and identically distribution with zero mean.

To estimate the coefficients of different row and remove redundant information, Least Absolute Shrinkage and Selection Operator (LASSO) that is a commonly used sparse representation technique was employed. It uses regularization to limit the number of variables and achieve the selecting of information [15]. Essentially, the optimal coefficients are estimated by minimizing a costing function as,

$$b=\arg\min_{\hat{b}}(RSS(\hat{b})+\lambda\sum_{n=1}^{i}\left|\hat{b}_n\right|) \ , \tag{5}$$

where $RSS(\cdot)$ is the residual sum of squares; λ is penalty factor and the optimal value can be estimated by fold cross validation. The solution can be obtained efficiently using Alternate Direction Multiplier Method (ADMM) algorithm [16]. In the process of model training, a certain number of phase values before inspection time are adopted and the number is not greater than the number of sensors to give full play of the characteristics of LASSO.

B. Anomaly quantification

Assuming that $\{b^1, b^2, \cdots b^i\}$ has already been estimated, the prediction $\hat{x}_{n,v}$ of inspected cycle can be obtained by (4) subsequently. After that, the absolute cumulative deviation between prediction value and ground truth at n+1th cycle can be obtained using residual analysis. Moreover, in order to eliminate the effect of cycle length, the defined anomaly score Q_{n+1} which can quantify the deviation degree of machine from normal condition is calculated as,

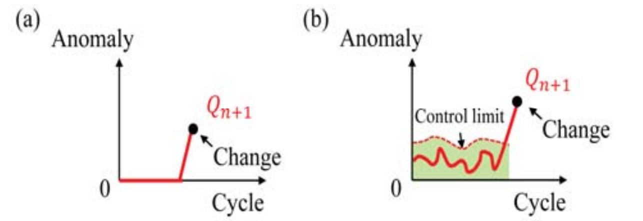

Figure 3. The fluctution of anomaly scores (a) stationary operating condition (b) non-stationary operating condition in practice

$$Q_{n+1} = \frac{1}{T}\sum_{v=1}^{T}\left|\hat{x}_{n,v} - x_{n,v}\right| . \tag{6}$$

C. Decision making

On the basis of recorded multidimensional data before inspection time n+1th cycle, a series of anomaly scores can be calculated by (6). Under the stationary operating condition, the anomaly scores are equal to zero. However, due to the machines are often running under non-stationary conditions (e.g., time-varying environment, wide range temperatures and lubrication, etc.), the effect of environmental factors is inevitable [17]. Moreover, considering the non-negative nature of anomaly scores, the anomaly scores fluctuate within a certain limit from zero as seen in Fig. 3. Here the commonly used 3σ control limit is employed.

Consequently, a hypothesis testing can be implemented to inspect whether the machine condition changes or not in n+1th cycle,

$$\begin{aligned} H_0 &: Q_{n+1} - \bar{Q}_n > 3\sigma_0 , \\ H_1 &: Q_{n+1} - \bar{Q}_n \le 3\sigma_0 , \end{aligned} \tag{7}$$

where H_0 means that the change occurs in n+1th cycle, while if the change does not appear, H_1 will be satisfied. The parameters of control limit can be calculated respectively by

$$\bar{Q}_n = \frac{1}{n}\sum_{i=1}^{n} Q_i \ , \tag{8}$$

$$\sigma_0 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i - \bar{Q}_n)^2} \ . \tag{9}$$

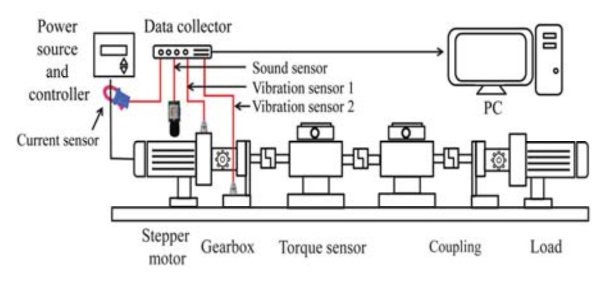

Figure 4. Schematic of experimental setup.

TABLE I. DETAILS OF EXPERIMENTAL SETUP

Component	Description
Drive motor	0.75kw, 230V three-phase AC, maximum speed: 3000rpm
Load moter	0.75kw, 230V three-phase AC, maximum torque: 86.4 N*m
Gearbox	Transmission ratio: 1:36
Data collector	16 Bit four-channel, AD convert synchronous sampling 1.25kHz
Vibration sensor 1	Acceleration, output voltage: 0-5V
Vibration sensor 2	Acceleration, output voltage: 0-50V
Sound sensor	AC/DC convert, output voltage: 0-5V
Current sensor	Output voltage: 0-5V
Torque sensor	Range: 0-100 N*m, accuracy 0.5%

IV. EXPERIMENT

To evaluate the effectiveness of proposed approach in real application, it was applied to the speed monitoring because the rotational speed fluctuates accordingly when the machine condition changes [18]. The layout of experimental setup is shown in Fig. 4, which mainly comprises drive source, gear reducer and load generator. In addition, considering the unavailability of speed sensor in some practical applications, three alternative measurements are employed, i.e., vibration signal, sound measurement and current signal. Detailed descriptions of system components are given in Table I.

The change of machine condition is simulated by the variation of speed. More specifically, the initial rotating speed v_0 is changed with Δv and the detail values are,

- $v_0=\{500,600,700,800\}$ and $\Delta v=\{100,200,\cdots,1000\}$ *rpm.*

Therefore, a total of 40 parameter combinations can be obtained with different speed changes. Note that in the experimental stage, the data is mapped to a range of 1 to-1 to eliminate the effect of sensor magnification.

Fig. 5 provides an example detected by proposed approach, which includes a 20% speed change 500→500+100 (rpm) in 21th cycle as seen in Fig. 5 (a). Fig. 5 (b) shows the detection result in which the detected change cycle is labeled. It can be seen that the change is detected successfully.

Fig. 6 exhibits another example of detection including 12.5% speed change 800→800+100 (rpm), and Fig. 7 gives another example including 14% speed change 700→700+100 (rpm). The changes are detected accurately as seen in Fig. 6 (b) and Fig. 7 (b) respectively. The promising experimental results demonstrated the proposed approach is robust to small fluctuations in speed, which indicates its great potentials for a wide range of operating conditions.

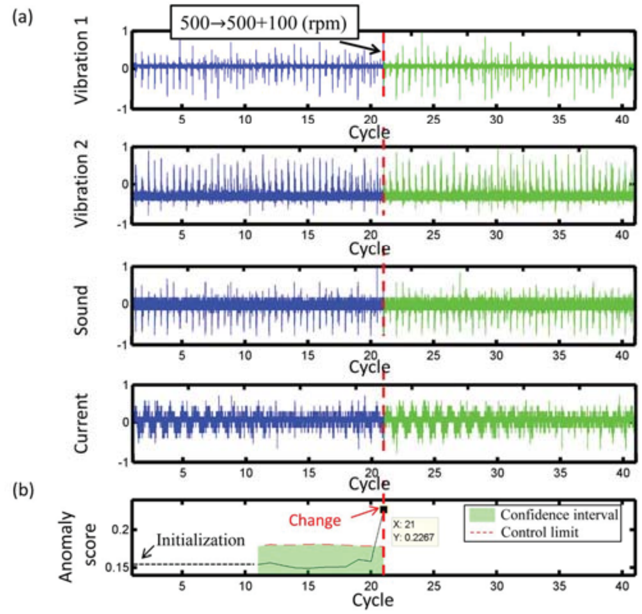

Figure 5. An example detected by proosed approach.

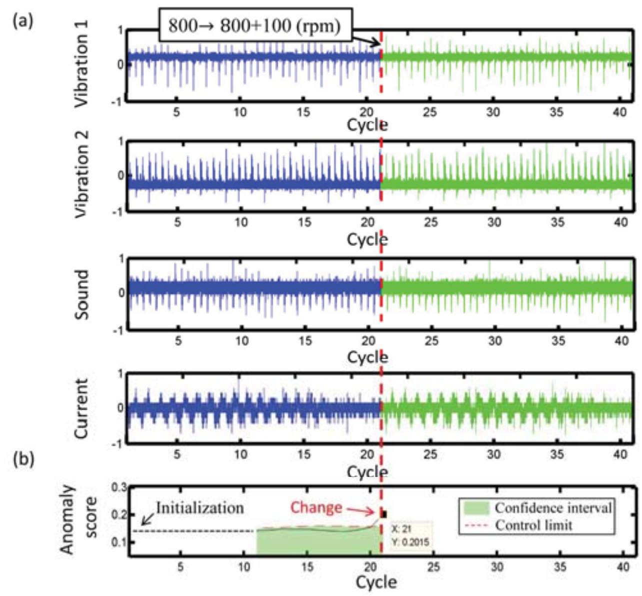

Figure 6. An example of 12.5% speed change detection.

To comprehensively evaluate the effectiveness of proposed approach, three statistical indicators are employed including Precision, Recall and F_{score} which are defined respectively as follows,

$$\text{Precision}=\text{TP} / (\text{TP}+\text{FP}) , \quad (10)$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) , \quad (11)$$

$$F_{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}} , \quad (12)$$

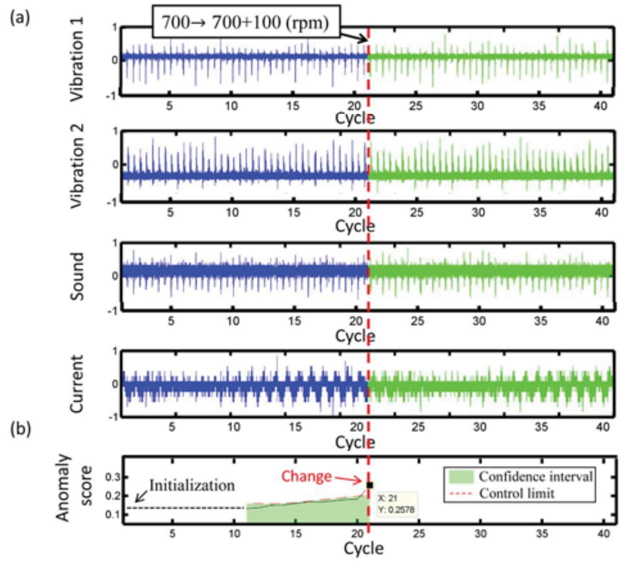

Figure 7. An example of 14% speed change detection

TABLE II. DETECTION RESULTS OF SPEED CHANGE DETECTION

Method	**Statistical indicator**		
	Precision	***Recall***	***F_{score}***
Proposed approach	100%	100%	100%

where TP is true positive; FP is false positive and FN is false negative. From the summarized results (Table II), it can be seen that the proposed approach exhibits great performance in the condition monitoring of rotating machinery.

V. CONCUSIONE

This paper presents a novel approach for condition monitoring of rotating machinery using multi-sensors. In this approach, a prediction model is established based on multiple regression, where the correlation among heterogeneous multi-sensors is formulated by a novel strategy. Anomaly quantification is then performed by the way of residual analysis, followed by statistical analysis for decision making. In the experimental stage, the proposed approach is applied to rotational speed monitoring with different speed fluctuations. The experimental results demonstrated the effectiveness of proposed approach, which indicates its great potentials in real engineering applications.

Further investigation based on the detected change(e.g., fault diagnosis and life prediction) and comparison with the state-of-the-art methods are future extensions of this study.

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