Deviation Detection Using Feature Extraction in Industrial Rotary Machinery Diagnostics

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***Abstract*—The data sensing and communication technologies of Industrial Internet of Things (IIoT) enables monitoring technical state and utilization conditions for industrial rotary machinery. The monitoring system is based on multiple sensors that embed or surround machinery unit under the observation. The sensed data are used for diagnostics of the machinery operation and utilization processes. In this paper, we construct a digital profile for a given machinery. Its digital profile is constructed from the sensed data as information model evolving in time. Hence, detection of deviations in the digital profile provides basic information on possible faults and other incorrections in industrial rotary machinery. The NASA bearing dataset was used to evaluate the proposed model efficiency.**

I. INTRODUCTION

A. Background

According to the recent study [1], [2], an approach based on CNN and DNN for bearing health classification has limitations: feasibility study for datasets; model utilization. Moreover in [3] the CNN-based approach showed 99% accuracy on the test data. However, the unseen bearings in train stage, were misclassified in the test stage.

The accuracy evaluation on unseen test data shows that almost all the model configurations can detect a fault accurately [4], but with unsuccessful fault classification (healthy, inner, or outer ring defect). The best CNN model based on time-domain features showed max accuracy at 75%. NN-based pre-trained model utilization on open datasets does not guarantee the same accuracy, while each machinery unit is unique. To solve that problem transfer learning [5] is implemented.

Another technique for conditional state monitoring is deviation detection rather than classify defects or condition status. This approach allows detecting deviations in the machinery unit without a labeled dataset, just using unmarked sensory data.

The rest of the paper is organized as follows. Section II introduces our methodology for the deviation detection to apply further in industrial rotary machinery diagnostics. Section III describes our early experiments with the deviation detection model. Section IV summarizes the results of this paper.

II. DEVIATION DETECTION BASED ON DIGITAL PROFILE

A. Deviation detection approach utilization

The proposed deviation detection model is based on referring digital profiles of a unit [6]. The reference digital profile represents the technical state of the unit in normal operation mode. The technique is divided into the following two steps (modes).

1) Adaptation mode. The reference digital profile construction with data from various sensors while the equipment runs under normal conditions. This mode requires the utilization of machinery in all allowed operation modes, like a startup, running under load, etc. Data normalization is required in case data are presented as a feature vector.
2) Control mode. The model detects deviations by applying a comparison reference profile with the current observations where the last one had made from data obtained with the same sensors. Data normalization is required in case data are presented as a feature vector.

Additionally, let us introduce the ϵ coefficient. If the difference between current and reference profile is more than ϵ, we suppose, the machinery has deviations in the current state. In this way operator attention must be paid. The border ratio ϵ requires tuning for each machinery unit.

Technical conditional monitoring methods are based on digital profiles. In this case, the deviation detection uses matching the current data to the profile. No data markup is required. The process of digital profile construction and update goes automatically without staff and machinery halting.

Deviation detection model application showed in Fig. 1. There are two digital profiles are used: reference — for the healthy technical state, current — to compare with the reference profile and detect deviations in the machinery unit. Here, we extract a feature vector F [7] from heterogeneous data. These data are obtained from sensors and used to create a digital profile. The coefficient ϵ is applied to set detector limits.

Deviation detection digital profile-based method allows to modify reference profile (include new operation modes) without model stop and reconfiguration. There are several ways to create a digital profile:

- Autoencoders (deep, VAE) [8],
- Hopfield network provides patterns recognition [9] that could be used as digital profiles.
- Complex models can be used for feature vectors as an input, extracted from a raw signal.

ISSN 2305-7254

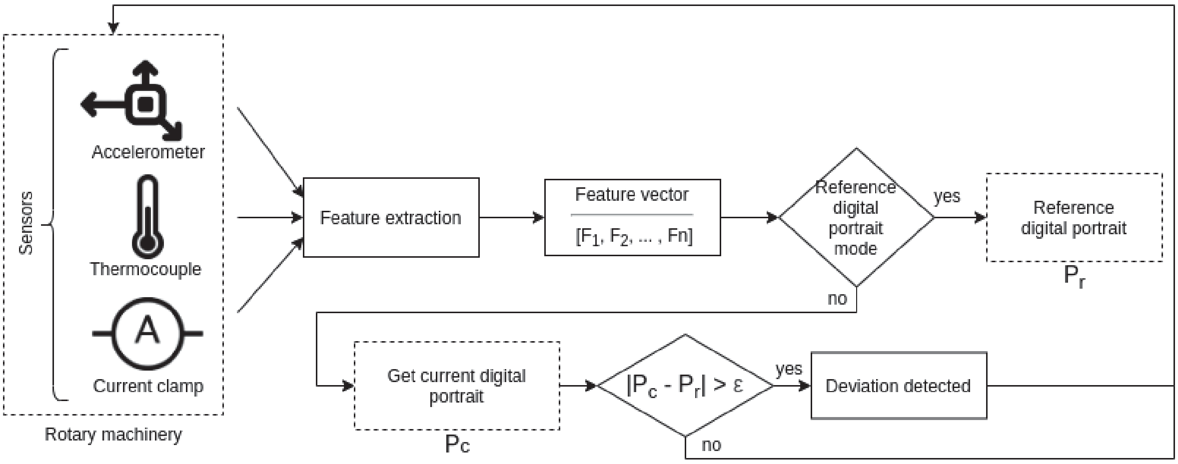

Fig. 1. Data flow diagram for a deviation detection model based on a feature vector

TABLE I. FEATURE VECTOR, EXTRACTED FROM A RAW SIGNAL

Feature name	Formula
Root mean square	$rms = \sqrt{\frac{1}{n}\sum_{i=0}^{i<n} x_i^2}$
Mean value	$mean = \frac{1}{n}\sum_{i=0}^{i<n} x_i$
Variance	$var = \frac{1}{n}\sum_{i=0}^{i<n}(x_i - mean)^2$
Maximum value	$max = max(x_i)$
Minimum value	$min = min(x_i)$
Kurtosis	$kurt = \frac{\sum_{i=0}^{i<n}(x_i - mean)^4}{n * var^2} - 3$
Line integral	$li = \sum_{i=0}^{i<n} \lvert x_{(i+1)} - x_i \rvert$
Skewness	$sk = \frac{\frac{1}{n}\sum_{i=0}^{i<n}(x_i - mean)^3}{\left(\sqrt{\frac{1}{n}\sum_{i=0}^{i<n}(x_i - mean)^2}\right)^3}$

B. Input data preparation

To evaluate model accuracy the feature vector with time-domain features was extracted from filtered vibration sensor signal from NASA bearing dataset [10]. For rolling machinery parts, like bearings, the data from the vibration sensor could be selected as a base to build the reference digital profile. The analog signal from vibration sensor was converted by ADC (analog-to-digital converter) into a_1, a_2, $\ldots$, a_m digital samples. Each n samples from digital signal are taken to extract N features x_1, x_2, $\ldots$, x_N, like RMS, mean, min and max values, crest factor, variance, etc. [7]. Finally, 8 features are presented in table I. Another approach of data preparation is using spectrogram as input data for making profiles [11].

When the adaptation mode is set a vector of features is extracted from a signal with n samples. We use this feature vector to build a reference digital profile in the adaptation mode.

In this study, each feature must be normalized by Equation 1

$$x_i = \frac{x_i - (Xmin_i - b)}{(Xmax_i + b) - (Xmin_i - b)} \tag{1}$$

Additionally, maximum and minimum feature values could be expanded by the b coefficient, with Equation 2. This is used in case $x_i > Xmax_i$, or $x_i < Xmin_i$. Here C — is an "expansion" coefficient (from 0 to 1).

$$b = C * (Fmax_i - Fmin_i)/2 \tag{2}$$

C. The proposed model description

Let us describe how the proposed model works. Firstly we must determine the number of features x_i in the feature vector F. After normalization, we denote all possible pairs n_{pairs} amount of the features in F with the following Equation 3:

$$n_{pairs} = \frac{(n_{features} - 1) * n_{features}}{2} \tag{3}$$

where $n_{features}$ — is a length of feature vector F.

In the adaptation mode, for each feature pair in F, the two-dimensional array $B_1, \ldots, B_{n_{pairs}}$ is created with size $m * m$, where m determinates by available RAM, and required precision (optimal value is 100). Each B_i array — is a table representation of two-variable function 4:

$$n_{cases} = f(x_i, x_j) \tag{4}$$

where x_i and x_j — a pair of two normalized features from F, n_{cases} — indicates how many times a pair of x_i and x_j features occured in total during all uptime in the adaptation mode. Normalized feature values are used as indices for array B_k. The number of B arrays equals n_{pairs}: $B_1, \ldots, B_{n_{pairs}}$. All cells in B_k must be initiated with a zero value.

The adaptation mode aims to record normalized feature pairs. This is implemented by incrementing the value in the appropriate cell of B_k array with indices x_i and x_j. For each feature pair x_i and x_j new case records as follows 5:

$$B_k[x_i][x_j] = B_k[x_i][x_j] + 1 \tag{5}$$

The B_i array can be visualized as a surface and shown in Fig. 2

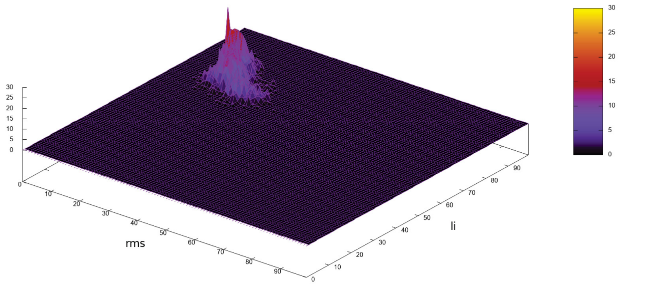

Fig. 2. Visualization of the array B_k for pair of features “RMS” and “line integral”

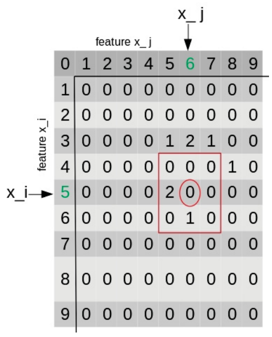

Fig. 3. Processing array B_k for pair of features $x_i = 5$ and $x_j = 6$, with $3 * 3$ kernel

In the adaptation mode, the machinery unit is operated under normal conditions in different modes, except breakdown. This is used to gather as much data as we can about the normal condition.

When the model is fit enough for some time, it sets by staff into the control mode (applying a comparison reference profile with the current observation). In this control mode, the feature vector F is calculated, likewise in the adaptation mode. After that, all feature pairs n_{pairs} were denoted. Then all $B_1, \ldots, B_{n_{pairs}}$ arrays are observed. Example of processing B_k array for some feature pair x_i and x_j shown on the Fig. 3.

In the control mode, we analyze the B_k array, with search kernel $n * n$. If inside the kernel $n * n$ with a center in $B_k[x_i, x_j]$ found a value that bigger or equal P-border (this value must be defined by the user), the “check” was successful. Otherwise, the $counter_{failed}$, increases by one. After analysis of all $B_1, \ldots, B_{n_{pairs}}$ for all pairs in F, we calculate the metrics M by the following equation 6:

$$M = \frac{counter_{failed}}{n_{pairs}} \tag{6}$$

If the metrics M is nearby zero value, the technical state represents a good condition, otherwise, $M \to 1$ indicates deviations in normal operation mode. Introduced early coefficient ϵ clearly shows deviations for the case: $M > \epsilon$.

III. Early Experiments

We used NASA bearing dataset to evaluate model performance in the deviation detection task. This dataset consists of three experiments for rolling bearings and describes a test-to-failure experiment. The second bearing with the first ADC channel was selected as input data. Bearing failure was occurred after exceeding the designed lifetime of the bearing which is more than 100 million revolutions. The dataset for this bearing consists of individual files. These files are 1-second vibration signal snapshots recorded at specific intervals. Each file consists of 20,480 points with the sampling rate set at 20 kHz. Eight features from every 984 files were extracted: $F_1, \ldots, F_{984}$ with I. After that, we used $F_1, \ldots, F_{49}$ vectors to evaluate the minimum and maximum values for each feature in F_i. Other $F_{50}, \ldots, F_{349}$ feature vectors were used to fit the model in the adaptation mode. The last $F_{350}, \ldots, F_{984}$ were applied in the control mode to evaluate metrics M. The results of the model test presented in Fig. 4.

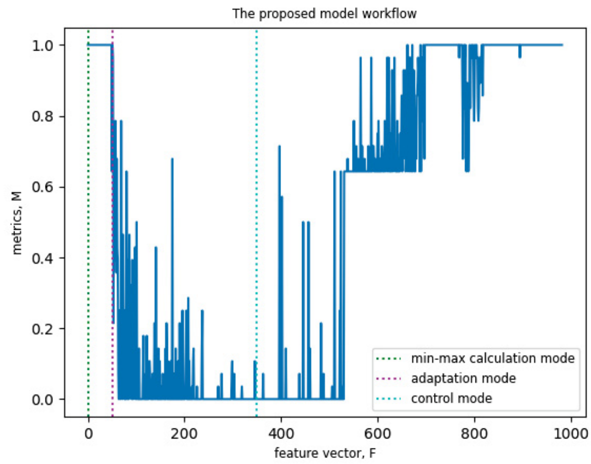

Fig. 4. Deviation detector test on NASA bearing dataset

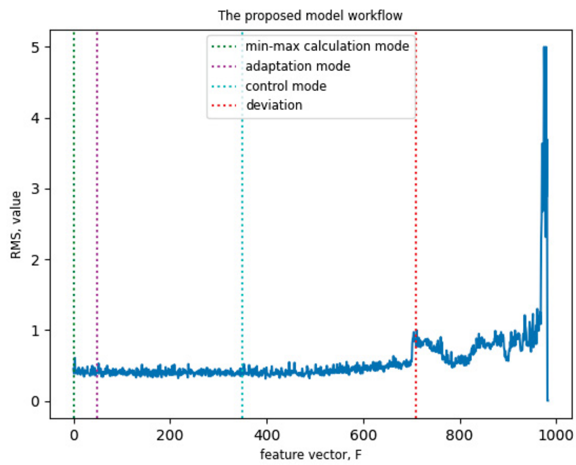

Fig. 5. “RMS” value from each feature vector F

RMS and Kurtosis feature values were selected as a reference from the feature vector F in Fig. 5 and Fig. 6.

Here red dotted lines visualize deviations on the feature value plots. It can be noticed that the proposed model for the first time detected deviation at the 540-th file (F_{540}), otherwise according to feature value plots deviations could be detected

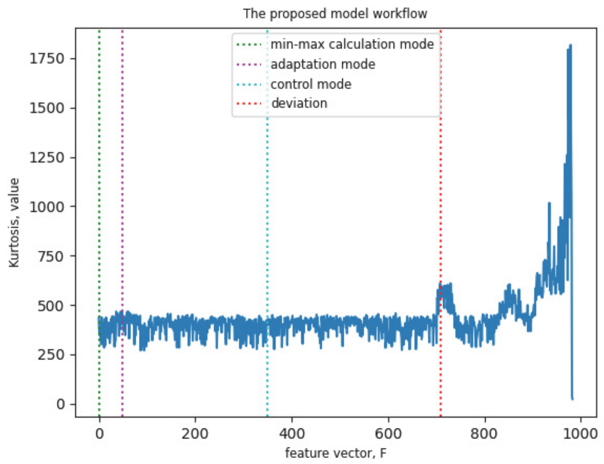

Fig. 6. "Kurtosis" value from each feature vector F

more lately. The technique based on the pair feature analysis can detect deviations more earlier.

Additionally, the model can be improved by normalizing features with machinery shaft RPM. Moreover we cat use function $f = M(t)$ to analyze time-series sequences. In this case, a one-shot rise for M could be marked as fake and will not be take into account. The model accuracy can be improved by using more feature pairs or use feature by three, instead of two.

IV. Conclusion

This short paper considered the opportunities of technical conditional monitoring methods for rotary machinery diagnostics. We identified the basic research problems for selecting a digital profile construction method, transforming raw sensed data, and applying the deviation detection model. We proposed a new deviation detection model based on feature extraction. Testing results showed the ability of the model to detect abnormal conditions during normal operation mode.

Acknowledgment

This research is implemented in Petrozavodsk State University (PetrSU) with financial support by the Ministry of Science and Higher Education of Russia within Agreement no. 075-11-2019-088 of 20.12.2019 on the topic "Creating the high-tech production of mobile microprocessor computing modules based on SiP and PoP technology for smart data collection, mining, and interaction with surrounding sources". This research is supported by RFBR (research project # 19-07-01027) in part of network communication and processing models for efficient data transfer from sensors. The work is implemented within the Government Program of Flagship University Development for Petrozavodsk State University (PetrSU) in 2017–2021.

References

[1] V. Ermakov, K. Rudkovskiy, and D. Korzun, "Deviation detection in industrial rotary machinery diagnostics," in *2019 25th Conference of Open Innovations Association (FRUCT)*, 2020.

[2] G. Singh Chadha, M. Krishnamoorthy, and A. Schwung, "Time series based fault detection in industrial processes using convolutional neural networks," in *IECON 2019 — 45th Annual Conference of the IEEE Industrial Electronics Society*, vol. 1, 2019, pp. 173–178.

[3] V. Pandhare, J. Singh, and J. Lee, "Convolutional neural network based rolling-element bearing fault diagnosis for naturally occurring and progressing defects using time-frequency domain features," in *2019 Prognostics and System Health Management Conference (PHM-Paris)*. IEEE, 2019, pp. 320–326.

[4] S. Langarica, C. Rüffelmacher, and F. Núñez, "An industrial internet application for real-time fault diagnosis in industrial motors," *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 1, pp. 284–295, 2020.

[5] L. Guo, Y. Lei, S. Xing, T. Yan, and N. Li, "Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 9, pp. 7316–7325, 2018.

[6] C. Raghavendra and C. Sanjay, "Deep learning for anomaly detection: A survey," *arXiv preprint arXiv:1901.03407*, 2019.

[7] J. K. Kimotho and W. Sextro, "An approach for feature extraction and selection from non-trending data for machinery prognosis," in *Proceedings of the second european conference of the prognostics and health management society*, vol. 5, no. 4, 2014, pp. 1–8.

[8] Y. K. N. Zijian and W. Xiaofei, "Lstm-based vae-gan for time-series anomaly detection," *Sensors*, vol. 20, no. 13, p. 3738, 2020.

[9] P. Dabas and U. Kumar, "Pattern recognition using artificial neural network," *International Journal of Computer Applications Technology and Research*, vol. 3, no. 6, pp. 358–360, 2014.

[10] J. Lee, H. Qiu, G. Yu, J. Lin *et al.*, "Bearing data set," *IMS, University of Cincinnati, NASA Ames Prognostics Data Repository, Rexnord Technical Services*, 2007.

[11] M. T. Pham, J.-M. Kim, and C. H. Kim, "Accurate bearing fault diagnosis under variable shaft speed using convolutional neural networks and vibration spectrogram," *Applied Sciences*, vol. 10, no. 18, p. 6385, 2020.