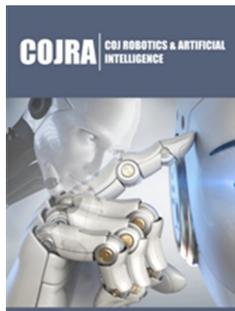


Wavelets-based Features Infusion for Machine Learning Classification; Towards a Holistic Rotate Vector (RV) Reducer Fault Detection and Diagnosis system for an Industrial Robot

Rohan A*, Raouf Iand Kim HS

Department of Mechanical, Robotics and Energy Engineering, South Korea

ISSN: 2832-4463



*Corresponding author: Rohan A, Department of Mechanical, Robotics and Energy Engineering, South Korea

Submission: 📅 November 25, 2020

Published: 📅 December 16, 2020

Volume 1 - Issue 3

How to cite this article: Rohan A, Raouf Iand Kim HS. Wavelets-based Features Infusion for Machine Learning Classification; Towards a Holistic Rotate Vector (RV) Reducer Fault Detection and Diagnosis system for an Industrial Robot. COJ Rob Artificial Intel. 1(3). COJRA. 000511. 2020.
DOI: [10.31031/COJRA.2020.01.000511](https://doi.org/10.31031/COJRA.2020.01.000511)

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Abstract

The feature extraction and selection are the most important part of any fault detection and diagnosis system. Especially when it comes to the Machine Learning (ML), improper feature extraction and selection can cause poor classification accuracy. ML's key challenge is the tedious process of manually extracting the features which require expert knowledge, and it is time-consuming. ML-based classifier might be less accurate than Deep Learning (DL) without proper discriminant feature extraction and selection. However, if the extraction and selection of the features are performed correctly with the knowledge about the type of input data being utilized, greater classification accuracy can be achieved.

In this work, we adopt an approach where we extract two types of features from the decomposed wavelets of the original current signals recorded from a robot test bench. The first type of features is solely based on the wavelet characteristics and it focuses on the wavelet domain whereas the second type of features is extracted based on the statistical analysis. The reason to extract different types of features is that in typical analysis methodologies either the first type of feature is utilized or the second type. Also, it is dependent on the type of fault being diagnosed. In the case of Rotate Vector (RV) reducer fault detection and diagnosis, due to the high sensitivity of the fault, the typical feature extraction methodologies fail to provide higher classification accuracy. Therefore, we developed a method where we extract features based on both of the above-mentioned types and implement deterministic feature selection to choose the most prominent features among them. Doing so provides the power to utilize the properties of wavelet and statistical domain simultaneously in an efficacious way. The proposed approach showed satisfying results regarding the fault detection and diagnosis for RV reducer with a classification accuracy of 96.7%.

Methodology

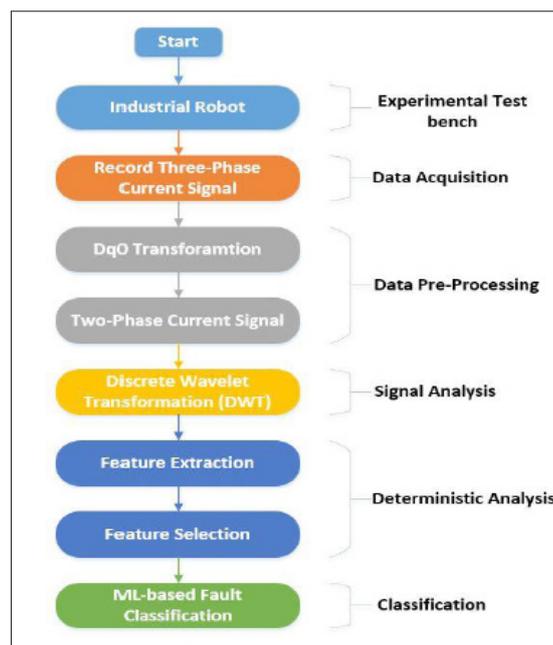


Figure 1: Flow chart of the proposed methodology.

The flow chart of the proposed methodology of this study is shown in Figures 1 & 2. To implement the proposed method an experimental test bench based on an industrial robot was used. Initially, the data is recorded employing current sensors installed at each of the electric motors' three-phases. Data is recorded for each motor installed at a specific point of the industrial robot [1]. The current signals data in three-phase is pre-processed and data dimension reduction is performed to compress the data. The reduction of the data dimension is accomplished using the DQ0 transformation. The DQ0 transformation converts the three-phase current signals to the two-phase current signals without losing any

useful information. Using Discrete Wavelet Transformation (DWT), the two-phase current signals are further analyzed in the time-frequency domain. DWT breaks down the signals into wavelets which are further used to extract features [2]. Several features are extracted from the wavelets based on wavelet characteristics, and statistics. Then these features are analyzed using feature selection algorithms to select the most prominent and deterministic features. Upon determining the prominent features among the extracted features, ML-based classifiers are trained to categorize among the various classes of faults (Figure 1).

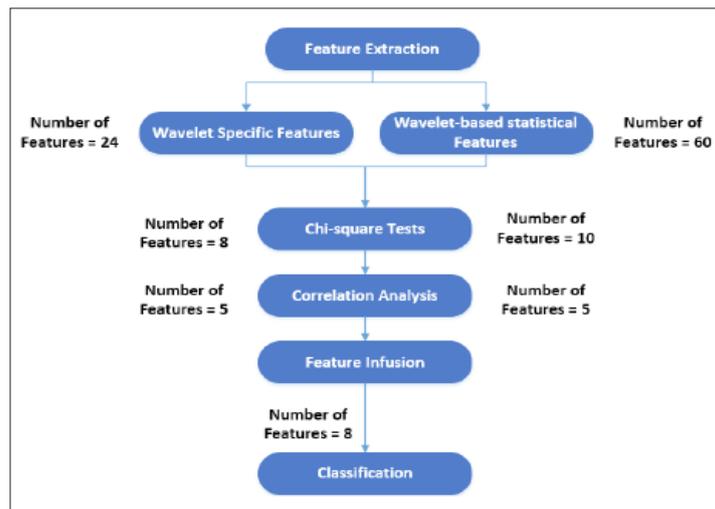


Figure 2: Feature Infusion scheme.

Computational Results

Data acquisition

The data is recorded simultaneously for each motor under different fault scenarios. In the first scenario, RV reducer eccentric bearing fault was inserted in the reducer coupled with the 4th axis

motor. Whereas, in the second scenario, the fault was inserted by replacing the RV reducer with the deteriorated one. The data was recorded for a total of three classes i.e Normal, Faulty (RV reducer eccentric bearing fault), Faulty Aged (RV reducer aging fault). Figure 3 shows the location of the fault in the Hyundai Robot with a detailed conceptual view [3].

Feature extraction and infusion

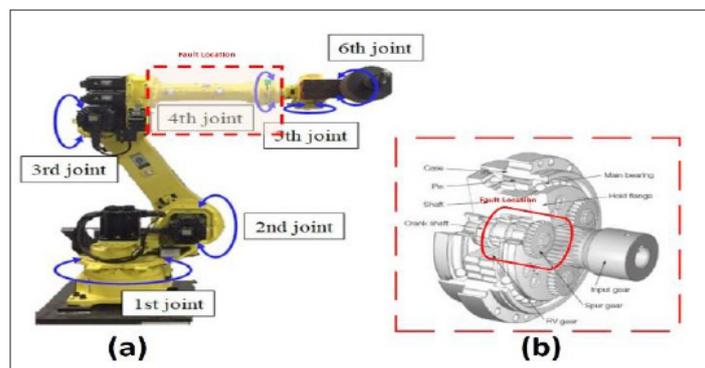


Figure 3: Location of the fault;

- Robot
- Detailed conceptual view.

As shown in Figure 2, two types of features were extracted from the current signal data. These types had a different number of features. 24 features were based on the specific characteristics of the wavelet and these were Wavelet Energy and Entropy. 60 features were extracted based on statistical analysis, these were Mean, Standard Deviation, Variance, Kurtosis, and Skewness. All of these features were extracted for 6 decomposed wavelet coefficients of the current signals. Then we reduced the features by using chi-square tests, and correlation analysis is used to further infuse the features. Finally, we get 8 prominent features that provided high

classification accuracy for fault detection [4,5].

Performance evaluation by using machine learning

Table 1 summarizes the results of SVM, k-NN, LDA, and Naïve Bayes algorithm. The table provides a detailed comparison regarding the classification accuracy for each type of feature and the proposed infused feature. The proposed scheme performed well to classify the faults; the maximum accuracy achieved was 96.7 using LDA for classification. The second best was 93.3% for K-NN. Also, the number of features were just 8 as compared to the wavelet specific (24), and wavelet-based statistical features (60) [6].

Table 1: Performance evaluation and comparison of accuracies.

Algorithms	Wavelet Specific Features	Wavelet-based Statistical Features	Proposed Feature Infusion Scheme
	Classification accuracy (%)	Classification accuracy (%)	Classification accuracy (%)
SVM	83.3	53.3	86.7
k-NN	46.7	53.3	93.3
NB	43.3	36.7	63.3
LDA	93.3	46.7	96.7
Average Accuracy (%)	66.65	47.5	85

Conclusion

This study proposes a wavelet-based feature infusion scheme for ML-based classification of the RV reducer fault in a robot system. The proposed scheme has shown a clear advantage when it comes to the amount of the features and the classification accuracy. The number of features was reduced to 8 from a total of 86 features by carefully infusing the prominent features. The results proved that the proposed scheme provides better results, and it can be used in real-time due to the less computational cost.

Acknowledgment

This research was financially supported by the Ministry of Trade, Industry, and Energy (MOTIE) and Korea Institute for Advancement of Technology (KIAT) through the International Cooperative R&D program. (Project No. P059500003).

References

1. Lee J, Wu F, Zhao W, Ghaffari M, Liao L, et al. (2014) Prognostics and health management design for rotary machinery systems-Reviews,

methodology, and applications. *Mechanical Systems and Signal Processing* 42(1-2): 314-334.

2. Vichare NM, Pecht MG (2006) Prognostics and health management of electronics. *IEEE Transactions on Components and Packaging Technologies* 29(1): 222-229.
3. Bittencourt CA (2012) On modeling and diagnosis of friction and wear in industrial robots. Thesis.
4. Voisin AA, Jung B (2012) Bottom-up capacities inference for health indicator fusion within multi-level industrial systems. *IEEE Conference on Prognostics and Health Management*, Detroit, USA.
5. Sheppard JW, Kaufman MA, Wilmering TJ (2009) IEEE standards for prognostics and health management. *IEEE Aerospace and Electronic Systems Magazine* 24(9): 34-41.
6. Swiercz M, Mroczkowska H (2020) Multiway PCA for early leak detection in a pipeline system of a steam boiler-selected case studies. *Sensors* 20(6): 1561.

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