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Review Article

Root Crack Incipient Gear fault detection using Machine Learning Algorithms

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A B S T R A C T

Rapid advancements in sensors and computing technology have motivated stupendous progress in evolving the next generation of Industry 4.0, where machines really speak about their health state in real time. Low-speed machinery, such as the churn gearbox in a chemical plant and the wind turbine main bearing, is considered to be the most difficult to analyse for incipient faults because these faults remain hidden in strong environmental noise during machine operation. Early detection of these faults at the incipient stage is paramount to increasing the overall availability of the whole plant and machinery. Vibration sensor-based fault diagnosis techniques were found to be the most popular among researchers working in the condition monitoring field as well as the most adopted framework in industries. However, acoustic analysis, a non-contact type of sensing technique, possesses huge potential in the fault diagnosis of rotating machinery. This article describes the framework for fault detection of a slow-speed gearbox working under variable speeds and loads using data fusion from vibration and acoustic signals at the statistical feature level. Maximal Overlap Discrete Wavelet Transform (MODWT) is used as the signal processing technique to remove the noise from the vibro-acoustic signals and extract the fault-related information. Feature monotonicity of the extracted features from MODWT-processed signals is considered as the selection criteria for selecting vibro-acoustic features containing maximum fault-related information. A performance comparison of sensor data fusion over vibration and acoustic sensors when used alone is also presented. To validate the performance of the proposed framework, five different artificial intelligence (AI) models have been used, and the results have been compared.

Keywords: Gears, Incipient Fault diagnosis, Rotating machines, Low speed machinery, Maximal Overlap Discrete Wavelet Transform, Artificial Intelligence

Introduction

With the advancement of manufacturing technologies, the complexity of machinery involved has also increased, which leads to arising maintenance challenges. In the last two decades, industries felt the urge to adopt the Industry 4.0 standard by digitising and digitalising the plant in order to stay competitive. Core machinery, such as the slow-speed churn gearbox in a chemical plant, the main bearing of a wind turbine, etc., needs more special maintenance attention than auxiliary machines, as downtime of these units leads to a huge financial loss.

Being slow-speed machines, the incipient faults that occurred in these machines remain undetected due to the presence of environmental noise in the sensor data. These incipient faults in slow-speed machines become more catastrophic under the cyclic loading conditions. Hence, it's a challenging task to accurately identify the health of machine components. Gear failure exhibits one of the most common failures in rotating machines [1]. General industrial practice for root cause analysis to identify the faults in the gears is mostly done by vibration analysis, acoustic analysis and thermography techniques [2,3]. However, implementation of acoustic-based detection is always used as a secondary technique in combination with vibration analysis [4,5].

Experimentation and Methodology

The setup for the experiments which is used in the present research work and the methodology used to extract relevant information from machine vibro-acoustic signals are presented in this section.

Design of Experiments

Experiments were carried out to create the robust model for gear fault diagnosis based on vibro-acoustic signals. Hence, a number of experiments were designed with varying input parameters such as speed, load and faults to capture root crack initial level faults in gears by using vibration and acoustic data. The input parameters and their respective ranges were fixed. The optimal position of the acoustic sensor was also fixed at 24 cm vertically from the base of the test rig based on the results presented in the research work [6,7]. The accelerometer was mounted on the bearing housing of the input shaft. Vibration and acoustic signals were captured simultaneously.

Experimentation setup

Gearbox Diagnostic Simulator (GDS) was used for simulation of faults in gears. The experimental setup is shown in figure 1, which was used for investigation. Four types of gears were taken into consideration, i.e., healthy gears and root crack faults of magnitudes 30%, 50% and 70%. Wire Electric Discharge Machining (EDM) was used to create these faults, as shown in Figure 2.

Methodology

The systematic methodology followed for obtaining fault signatures from machine vibration and acoustic signatures is given in figure 3. Data Acquisition To capture the vibration signal from the test rig, accelerometer PCB 356A32 was used and fixed on the input shaft's bearing housing. An acoustic signal was captured using a G.R.A.S. 46AE microphone with a frequency range of 5 Hz-20 kHz. Data Acquisition System (DAQ) from National Instruments (NI9234) was used with a signal sampling frequency of 25.6 kHz.

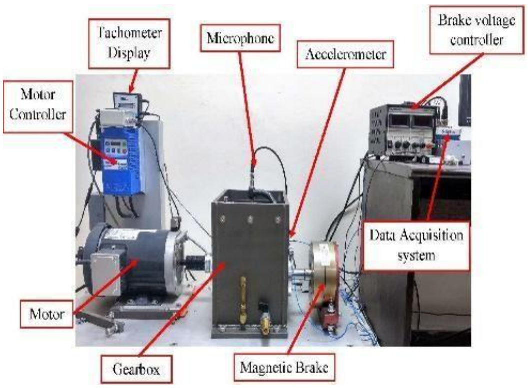

Figure 1. Test rig used for the experiment

Figure 2. Gears with different conditions

Twenty-five repetitions were taken for gear condition at 420 rpm in order to have sufficient data for testing and training. The raw vibration and acoustic signals were then bandpass filtered between 8 Hz and 1200 Hz so that components having low frequency can be filtered out, which usually detect faults such as misalignment. But this research is particular to gear fault, so the raw data is filtered up to 3X of gear mesh frequency.

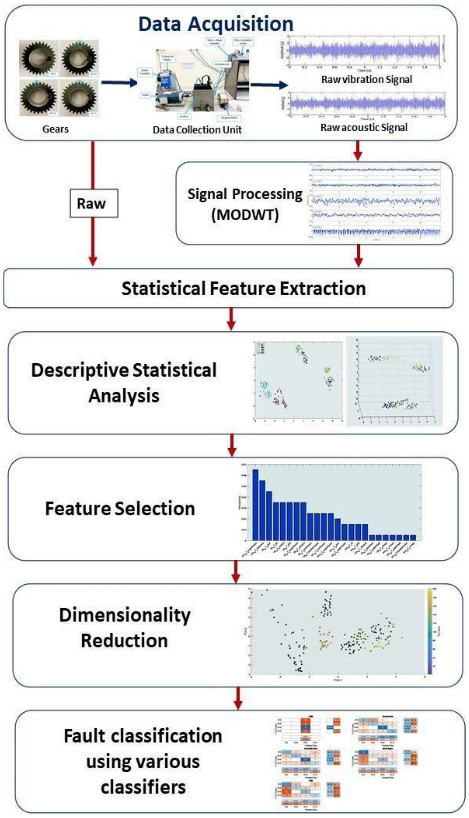

Figure 3. Experimental Methodology

The level of decomposition selected was 4 because the theoretical gear mesh frequency and its harmonics fall in the range of the selected decomposition level. The mother wavelet chosen both for vibration and acoustic was ‘sym 4’. The same mother wavelet was chosen for all captured signals under variable speed and loading conditions. Hence, if there is any change detected in the amplitude of the extracted signature, it directly indicates the change in the gear's health condition. The complete signal processing part was done in Matlab Version 2020.

Feature Extraction

The feature processing stage is the most critical part of determining the health status of rotating components. Different types of features are extracted, including time domain, frequency domain, and time-frequency domain features. In this study, 24 statistical features were extracted (12 for vibration and 12 for acoustic signals) for both raw and de-noised signals using MODWT.

Descriptive statistical analysis

Descriptive statistical analysis is used to visualise the spread of data in space, and it can be done by using t-Distributed Stochastic Neighbour Embedding (t-SNE). t-SNE graphs for all faulty stages are generated and compared for variable speed and loading conditions. These graphs help the reader to visually separate and identify gear fault conditions.

Feature Selection

Feature selection means selecting the sensitive features by feature selection methods to detect the heath condition of machine. Out of 24 time domain statistical features (12 features for vibration signal and 12 for acoustic signal) the most prominent features were selected based on value of monotonicity. As the fault progresses in component statistical feature trend should show a monotonic trend (either increasing or decreasing). Hence the features or parameters which shows monotonic trend are only selected. These parameters can be considered as the best indicators for detection of faults and can be used for further processing.

Dimensionality Reduction

There are some features that provide meaningless information or same information, so after feature selection dimensionality reduction method is used. It preserves the maximum statistical information by reducing the dimensions of the data set. Dimensionality reduction method can be linear and non-linear. Linear methods includes Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for dimensionality reduction. In this research PCA which is unsupervised algorithm is used for dimensionality reduction. Data having many variables can be replaced with the single new variable. PCA generates new set of variables known as principal components and these components are nothing but combination of original variables. Redundant information is not present in principle components which are orthogonal to each other. First principal component is represented on one axis and second principal component on other axis. These features are then input to artificial intelligence algorithms.

Classification and Performance Evaluation With the advancement of technology there is growing need of Artificial Intelligence (AI) to solve the problems of machines and its components. To predict the faults based on AI various Machine Learning (ML) algorithms are used.

The most common ML algorithms used in this research are SVM, Decision tree, Ensemble tree, Naive Bayes, and k-NN. The principle components for raw data and MODWT data are input to these ML algorithms. For training 70% data and for testing 30% data was used by Holdout cross-validation method. Bayesian optimization was used as an optimization approach as the hyperparameters can be efficiently tuned of the model. Overfitting and underfitting of the model can be prevented by hyperparameters which the model precise and robust. Best performance can be achieved by automating the selection of hyperparameter by hyperparameter-optimization. For all classifiers the number of iterations was set to 30 for the minimum classification error plot. The kernel function used in SVM is the radial basis function. Minimum classification error plots along with confusion matrix were plotted to evaluate and compare the performance of the different classifiers.

Results and Discussion

Descriptive statistical analysis: t-SNE results

The t-SNE graphs for raw vibro-acoustic signatures at speed of 420 rpm. There are four different label of gears i.e healthy, root crack 30% (RC30), root crack 50% (RC50) and root crack 70% (RC70) which are represented in form of points in 2-D space. The data labels are widely dispersed and not clustered in space for all gear running conditions, and there is evident overlap between points, indicating a low potential for classification. As a result is shown in figure 4, the raw feature dataset is inadequate in identifying the health status of the machine and its components. Furthermore, the raw signal from components running at low speeds is obstructed by substantial environmental noise, rendering fault signatures indistinguishable. Consequently, t- SNE is incapable of predicting labels for different faults under specific speed and loading conditions.

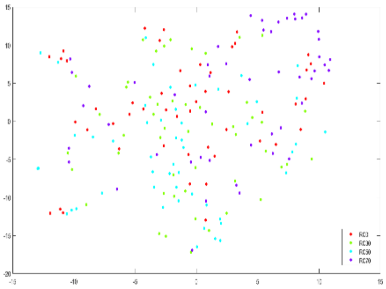

Figure 4. t-SNE data representation for raw vibro-acoustics data at 420 rpm

However, t-SNE graphs for MODWT proceed vibro-acoustic signatures as shown in figure 5 shows some exciting clusters. It is clear that not only are all four gear conditions distinctly clustered, but the loading conditions are also accurately classified. Hence, MODWT based signal processing extracts and separate the vibro-acoustic features to accurately identify the faults which were not detected in the raw form.

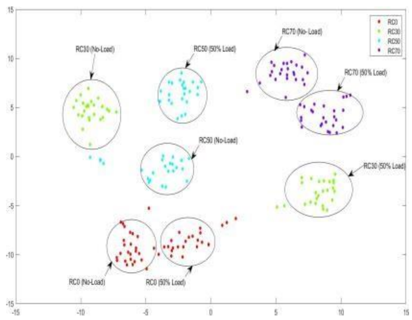

Figure 5. t-SNE data representation for MODWT processed vibro-acoustics data at 420 rpm

Monotonicity Results

The feature selection method used in this study is monotonicity, which helps identify sensitive features that contain useful information. Monotonicity values for both the raw data set and the MODWT data set are shown in figures 6 and figures 7 for different speeds respectively. Features with values greater than 0.03 are selected for further processing, and different speeds require different features (both vibration and acoustic).

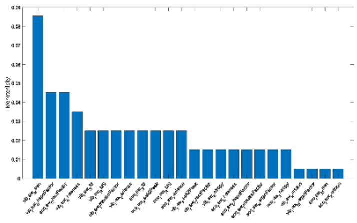

Figure 6. Monotonicity of raw feature data at 420 rpm

For example, at 420 rpm raw data, four features were selected, including vibration mean, vibration shape factor, acoustic crest factor, and vibration skewness. factor, acoustic peak2peak, vibration crest factor, and vibration impulse factor. These selected features are sufficient to detect faults in machine components, rather than selecting all features.

In the case of MODWT feature data at 420 rpm, eight features were selected, including acoustic shape factor, acoustic skewness, vibration mean, vibration standard deviation, vibration kurtosis, vibration rms, vibration shape factor, and vibration variance. Among all these, the acoustic signal after de-noising with MODWT contains maximum information to detect faults in low-speed machinery.

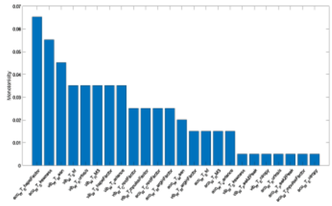

Figure 7. Monotonicity of modwt feature data at 420 rpm

Standard deviation, vibration rms, vibration variance, acoustic kurtosis, vibration kurtosis, vibration skewness, vibration crest factor, vibration impulse factor, and acoustic mean.

In summary, it can be concluded that at low speeds, acoustic de- noised signals contain useful information, while under high speeds, vibration de-noised signals contain the most valuable information for the detection of faults in the machine.

Classification Results

Minimum Classification error plot and Confusion matrix

Figures 8, 9 and 10 illustrate the combined minimum classification error plot for all the classifiers in both raw and MODWT denoised cases at different 420 rpm. The results indicate that the Ensemble tree demonstrated the lowest classification error for both raw and MODWT cases across all speeds, with the minimum classification error observed at 420 rpm in Figure 9 for raw and Figure 10 for MODWT.

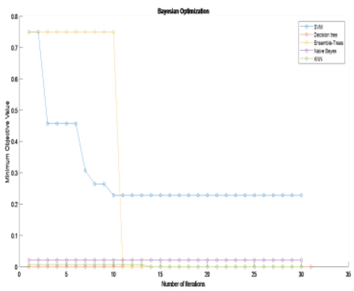

Figure 8. Combined minimum classification error plot for raw data at 420 rpm

After hyperparameter tuning, the optimized model was tested, and the results obtained from the classifiers were displayed as a confusion matrix. The confusion matrix for raw data at 420 rpm for all five classifiers is presented in Figure 10. Similarly, the confusion matrix for MODWT denoised data at 420 rpm for all classifiers is displayed in Figure11.

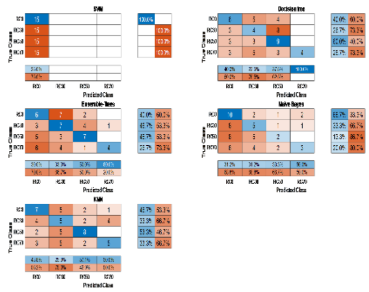

Figure 9. Combined minimum classification error plot for MODWT data at 420

In the case of raw data, the Ensemble tree and Decision tree misclassified RC30 as healthy, which is highly dangerous and can lead to catastrophic failure and severe accidents. Furthermore, these classifiers misclassified some healthy conditions as faulty, which is not hazardous since healthy gears can be replaced with new ones. However, in the case of MODWT, the Ensemble tree
and Decision tree classified healthy conditions as healthy and faulty conditions as faulty only..

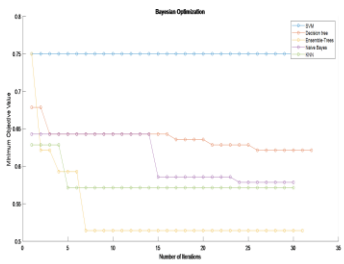

Figure 10. Confusion matrix of different classifiers for raw data classification at 420 rpm

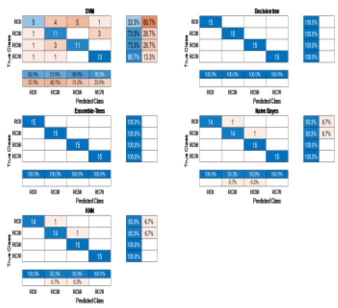

Figure 11. Confusion matrix of different classifiers for MODWT data classification at 420 rpm

Conclusion

This research paper outlines a methodology for diagnosing initial level faults in low speed gearboxes using a hybrid intelligent approach that combines vibro-acoustic analysis and advanced signal processing algorithms. The method involves preprocessing the raw vibration and acoustic signatures using the Maximal overlap discrete wavelet transform (MODWT) algorithm, followed by the extraction of time domain statistical features. The statistical features are selected based on their monotonic behavior, which ensures that changes in the feature values correspond to changes in the gearbox condition. The selected features are then fed as input to state-of-the-art classifiers, such as SVM, Decision Tree, Ensemble Tree, Naive Bayes, and k-NN, to evaluate their performance. The results show that the proposed methodology improves fault classification accuracy and can uncover initial level faults that were hidden in the raw vibration and acoustic data of low-speed machinery.

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