DEVELOPMENT OF ROLLING BEARING HEALTH DIAGNOSIS AND PREDICTION SYSTEM USING MEMS ACCELEROMETER VIBRATION SENSING MODULE

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ABSTRACT

This work implements an ***in-house fabricated, cost-effective*** MEMS piezoelectric accelerometer module to acquire the vibration data for fault diagnosis of a rolling bearing in an electric motor. Choosing the right combination of data pre-processing method (Ensemble Empirical Mode Decomposition, EEMD) and machine learning model (Back Propagation Artificial Neural Network, BP-ANN) offers 99.61% accuracy in detecting the location and state of various bearing faults under varying motor speeds of 500, 1000, and 1500rpm, with fewer pre-processing steps. The developed module features excellent compatibility with industrial 4.0 intelligent manufacturing applications.

KEYWORDS

MEMS, vibration, microcontroller, machine learning, roller bearing, neural network.

INTRODUCTION

A large number of accidents caused due to machine equipment failure shifted the attention to mechanical fault diagnosis. Many fault diagnosis techniques have been developed since then to prevent any catastrophic breakdowns or machine failures. Roller bearing defects are considered to be one of the primary reasons for the rotary machine's degradation leading to various safety issues and expensive machine repair downtime. Bearings are responsible for supporting the functioning of the rotating shaft in the motor, thus maintaining the direction of motion. The condition of bearing components affects the life and processing quality of the machines to a great extent. Therefore, several methods of bearing fault detection have been developed to predict their health and lifetime.

Vibration data analysis is the most commonly used condition monitoring technique and is considered to be an accurate and reliable way to detect defects in an operating machine. The major elements that may cause bearing defects are the ball, inner race, outer race, and the holder. The main vibration sources of the ball bearings are the bearing rotation, rotation of the bearing connecting parts, vibration due to the rotating shaft, and environmental interference. When a bearing is operated under a certain load and at a specific motor speed, the faults generate the characteristics defect frequency components which provide fundamental information in bearing condition monitoring.

A piezoelectric accelerometer is most commonly used to analyze the vibration data due to its high sensitivity, signal-to-noise ratio (SNR), and simplicity [1]. But until now, a commercial accelerometer module has always been used for this purpose making fault detection an expensive solution. As a result, this work focuses on using a ***high performance-to-cost ratio accelerometer*** sensing module that integrates an in-house fabricated MEMS z-axis piezoelectric accelerometer, interface circuit, and a microcontroller as shown in Fig. 1. The unique contribution of this work is to develop an accelerometer vibration sensing module costing around 150USD, much lower than the commercial accelerometers (e.g., 3713D1FE3G from Piezotronics costs more than 880USD) used until now, saving more than five times of cost. Mass production of the proposed module would further bring the cost down, thus making it compatible with the industry 4.0 intelligent manufacturing applications.

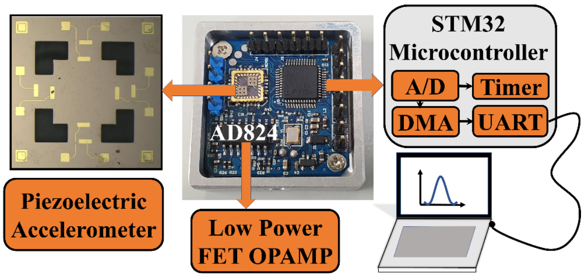

Figure 1: Integrated piezoelectric accelerometer module along with amplifier and microcontroller.

Refinement of various advanced signal processing techniques based on time-domain [2], frequency-domain [3], and time-frequency domain [4] analysis, along with the advancement of artificial learning methods have eased out the fault diagnosis process in different rotary machines. Ai *et al.* [5] diagnosed inner and outer ring defects in rolling bearings by combining EEMD with envelope spectrum analysis technique. This work has used a combination of EEMD and deep neural network (BP-ANN) to identify various bearing faults in an electric motor system provided by our industrial partner.

Our previous work builds on an in-house fabricated tri-axis piezoelectric accelerometer for predicting surface roughness in a CNC polishing machine [6]. This work shows the usage of a similarly designed accelerometer for detecting various motor-bearing faults under different rotation speeds (500, 1000, and 1500rpm).

In this work, fault detection is done for a total of 11 sets of bearings based on different locations (inner race, outer race), severity (0.4, 0.8, and 1.2mm wide cracks), and the number of faults (single and double cracks). The complete set of faulty input bearings is shown in Fig. 2.

METHODOLOGY

The time-frequency analysis method, for the extraction and analysis of sensor vibration data, is combined with the neural network training to establish the overall fault diagnosis system. The flow chart in Fig. 3 depicts the strategy used for the detection of the faulty bearings in the motor system. It accommodates three main stages: data acquisition, data pre-processing, and machine learning.

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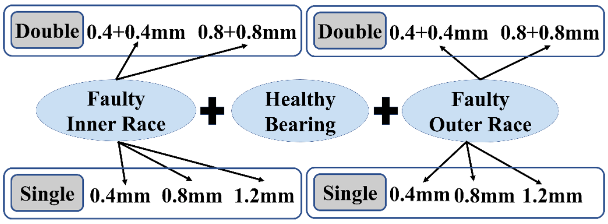

Figure 2: Set of inputs provided for the machine learning based on different states and locations (inner defect, outer defect, and health) of bearings.

Time Series Segmentation

Fault detection is done for a total of 11 sets of bearings with single and multipoint faults at both inner and outer raceways with grooves having 0.4, 0.8, and 1.2mm widths, under different motor speeds (500, 1000, and 1500rpm) as shown in Fig. 2. Each degree of damage has a total of 2,250,000 acceleration data points with 12,500 samples/segment. For 33 different input combinations, with z-axis measurement data, overall 1791 time sequences are generated for further processing.

Data Preprocessing

The Empirical Mode Decomposition (EMD) method was a breakthrough in the vibration analysis of the bearings [7]. Unlike the conventional Fast Fourier Transform (FFT) technique, it poses a special advantage of being able to process even the non-stationary and non-linear signals. In the EMD technique, all the local maxima points of the original data are collected to first form the upper envelope and local minima points for the lower envelope. The mean value of the local maxima and minima is then subtracted from the original signal to obtain another time sequence signal which, after following a certain set of conditions, becomes an intrinsic mode function (IMF). IMFs are further decomposed into various components until the residual value obtained by subtracting each IMF component from the original signal is a monotonic function.

$$x(t) = r_n + \sum_{i=1}^{n} c_i(t) \quad (1)$$

Here, $x(t)$ is the original signal, $c_i(t)$ is the IMF component, and r_n is the residual value.

It is possible that while decomposing IMF components, the same IMF contains extremely different time-scale features or similar time-scale features are distributed in different IMFs, causing mode-aliasing. To avoid this, Wu and Huang *et al.* [8] proposed Ensemble Empirical Mode Decomposition, EEMD, in 2009. By adding Gaussian noise to the signal and using the average of the selected signals, EEMD eliminates the problems of mode-aliasing, substantially reducing the pre-processing time and steps.

$$x_i'(t) = x(t) + w_i(t) \quad (2)$$

Here, $w_i(t)$ is the white noise, generated by Gaussian distribution on random number function, *randn(t)*, multiplied by the weight (NSTD) and the waveform standard deviation (YSTD). *m* groups of IMF components are obtained by adding the white noise to different sequences each time. Finally, a new IMF component ($c_j'(t)$) is generated from the average IMF obtained from the previous EMD technique.

$$c_j'(t) = \frac{\sum_{i=1}^{m} c_{ij}(t)}{m} \quad (3)$$

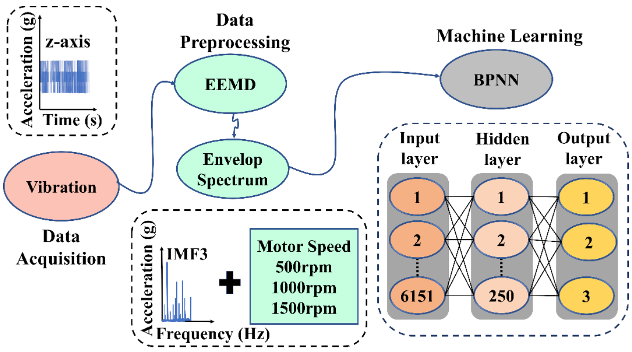

Figure 3: Flowchart for the bearing fault diagnosis of the industrial motor system.

Machine Learning

Many mature algorithm models are present in machine learning. Supervised Back Propagation Artificial Neural Network (BP-ANN) is used here as a machine learning algorithm. The program uses the high-end API Keras suite of Python Tensorflow.

The neural network architecture consists of an input layer, multiple hidden layers (Deep Neural Network), and an output layer, each consisting of several neurons. The link between the layers (synapses) carries a weight value, and its usage calculates the gradient of the loss function. These weight values are continually updated using the gradient descent method, to minimize the loss.

The bearing conditions are classified based on Onehot Encoding: [1,0,0], [0,1,0], and [0,0,1] for normal, inner race damaged and outer race damaged bearings, respectively. The data can therefore be binarized and each classification becomes independent of the other.

A well-trained model gradually converges to an optimal solution through a large number of time-consuming iterations. To improve the training speed of the model, a mini-batch gradient descent method is implemented followed by an adaptive learning rate method called Adam optimization. Overfitting can occur in an ill-trained model due to several reasons like a greater number of layers or more neurons in the model, uneven data distribution between training and validation data sets, and insufficient training resource set. To avoid these overfitting problems, regularization and batch standardization methods are followed. To indicate the efficacy of the model, its F1-score is calculated which is predicted based on the number of results predicted to be true (or false) that were considered to be true (or false).

EXPERIMENTAL SETUP

The motor fault diagnosis system provided by Delta Electronics Inc. has been used as a test vehicle as shown in Fig. 4(a). The main shaft is a chrome-plated spindle with a diameter of 12mm. The spindle transmits the torque generated by the motor through the coupler, and the load is loaded on the spindle as the radial force generated by the workpiece to the spindle and the bearing. Bearings are responsible for supporting the spindle. Fig. 4(b) illustrates two examples of the bearings used with a double crack of 0.8mm width at the inner race (left) and a single crack of 1.2mm width at the outer race (right) created using Electric Discharge Machining (EDM).

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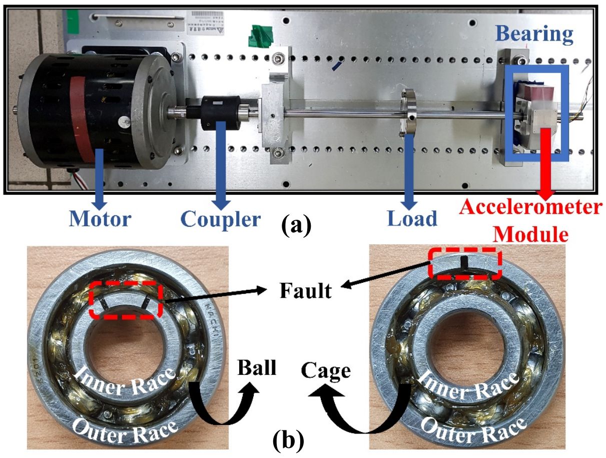

Figure 4: (a) Motor fault diagnosis test platform. (b) Pictorial view of two of the bearings used with 0.8mm double and 1.2mm single fault at inner and outer race, respectively.

Piezoelectric Sensing Module

The z-axis piezoelectric MEMS sensing module is an amalgamation of MEMS accelerometer, amplifier circuit, and microcontroller for analog to digital conversion. The signal generated by the accelerometer is amplified using a charge amplifier and filtered using a low-pass filter (LPF). The output is then fed to the microcontroller. The microcontroller used is STM32F373CCT6 with the ARM 32-bit Cortex-M4 having a 12-bit SAR (Successive Approximation Register) and three 16-bit sigma-delta ADC (Analog-to-Digital Converter), providing high-resolution analog to digital conversion. The firmware compilation software is the development platform Keil. After the firmware is compiled, the program is input into the microcontroller using ST-LINK. Digital filtering of the signal is carried out using an infinite impulse response (IIR) LPF to set the cut-off frequency at 6250Hz. The external wires of the module are connected to the USB-UART conversion module. UART digital signal is received by the USB end of the computer. The collected CSV file is entered into MATLAB for data consolidation and EMD pre-processing. The data after processing is used for feature extraction, data regularization, cutting training, and validation data set for machine learning model training.

EXPERIMENTAL RESULTS

The performance of the standalone accelerometer along with the amplifier circuit is summarized in Table 1. The modified dynamic response of the z-axis piezoelectric accelerometer using a shaker depicting 5kHz bandwidth is represented in Fig. 5(a). Due to the shaker limitation, it could only be measured until 5kHz but, in actual the accelerometer can support bandwidth up to 6250Hz. R^2 is found to be 0.995 from the linearity graph plotted under 2.5kHz of excitation frequency as shown in Fig. 5(b). The experiment time and the digital output sampling rate of the accelerometer module are set to be 3mins and 12,500 samples/second, respectively. Vibration performance of the z-axis accelerometer with inner and outer 0.4mm faulty bearing (Model 6201) is shown for a motor speed of 500rpm in Fig. 6(a). The inner race faulty bearing shows a

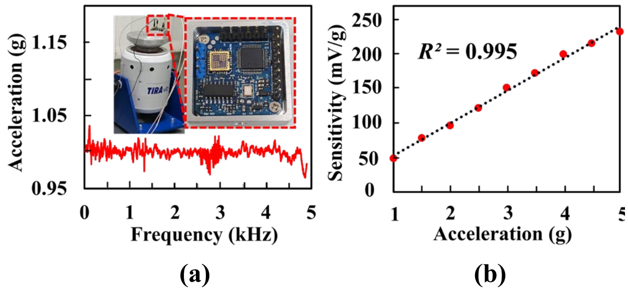

Figure 5: (a) Frequency response of the proposed piezoelectric z-axis accelerometer. (b) Linearity at 2.5kHz excitation frequency.

periodic vibration compared to the outer race damaged bearing, with significant influence under z-axis acceleration. EEMD decomposition is carried out on all the time sequences to acquire their IMF components.

Seven IMFs are selected to be decomposed. The IMFs are converted using the Hilbert transform, followed by the conversion of the envelope signal using FFT. Selection of an appropriate IMF component is a critical step for subsequent envelope analysis and it is done by matching their inner and outer defect characteristic frequency as follows:

$$F_{BPI} = \frac{N}{2} \cdot F_s \left(1 + \frac{BD}{PD} cos\varphi\right) \quad (4)$$

$$F_{BPO} = \frac{N}{2} \cdot F_s \left(1 - \frac{BD}{PD} cos\varphi\right) \quad (5)$$

F_{BPI} and F_{BPO} in the above equations signify the frequency of a point where the ball passes through the inner ring and outer ring track, respectively. For the motor speed of 500rpm, N=7 (number of balls), ball diameter, BD=5.54mm, pitch diameter, PD=22mm, and the contact angle between ball and inner/outer race, φ=0°, F_{BPI}, and F_{BPO} are found to be 36.5Hz and 21.83Hz, respectively. Out of all the seven IMFs, the IMF3 envelope spectrum is chosen as it matches the characteristics defect frequency corresponding to the inner and outer race single and double faults as shown in Fig. 6(b). Even in the case of 1000rpm motor speed, it is verified that the characteristic frequencies of inner and outer ring defects can be obtained simultaneously by choosing IMF3 as the input data set for the subsequent neural network.

Neural Network Model Training

After acquiring the decomposed IMF3 component, the neural network model is trained and the results of the model with the different number of neurons are compared to finalize the number of neurons. After all the testing and verification, 250 neurons are finally used in the hidden layer. Data of 11 sets of bearings are cut into training and testing sets. Training data is used to train the neural network and testing data is then input into the trained model to test the results. To prevent the model over-fitting issues,

Table 1. Specification of the designed z-axis accelerometer.

	Bandwidth	Sensitivity	R^2
Performance	5-6250Hz	16mV/g	0.995

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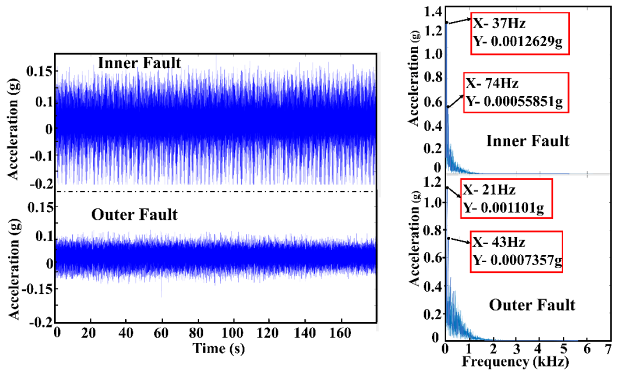


(a) (b)

Figure 6: (a) Experimental vibration data of z-axis acceleration for bearing with inner race and outer race 0.4mm fault under 500rpm motor speed. (b) Selected IMF3 representing defect frequency corresponding to the inner and outer race single and double faults.

training data is further cut into a validation set, randomly extracting 30% of the training data. In case of over-fitting, the parameters are adjusted based on the validation data results.

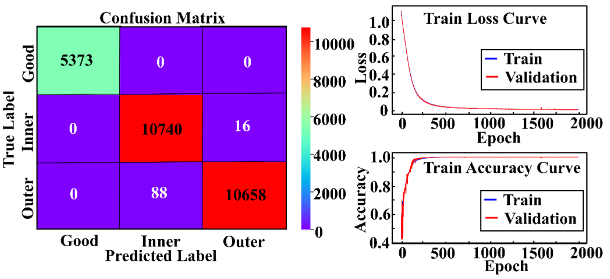
Feature Fusion

As observed from equations (4) and (5), the characteristics defect frequency of the ball bearing mainly depends on the motor rotation speed as all other factors (BD, PD, and φ) are constant for a total of N=6201 open ball bearings. Thus, it is necessary to fuse the motor spindle speed with the envelope frequency spectrum of IMF3 after EEMD decomposition.

Model Identification Capability Result

While training the neural network model, various parameters, for instance, learning rate, number of hidden layers, number of neurons in the hidden layer, number of training iterations, etc., need to be adjusted and optimized. The optimized learning rate parameter and number of neurons in the hidden layer are chosen to be 0.00001 and 250, respectively to obtain the best test results. The confusion matrix, loss, and accuracy curve of the best test model are plotted in Fig. 7(a) and Fig. 7(b).

The confusion matrix shows that 88 cases of bearing with outer ring defects are misjudged as inner ring defects, 16 cases of bearing with inner defects are misjudged as outer defects, whereas, others are correctly predicted, and the final F-1 score reaches 0.9961. The training and the verification accuracy are found close to 100%. Table 2 concludes the best test results of the trained neural network.



(a) (b)

Figure 7: (a) Confusion Matrix. (b) Best model training loss and accuracy curve.

Table 2: Neural network best test results.

	Loss	Precision	Recall	F1-Score
Model Testing	**0.02**	0.9961	0.9961	**0.9961**

CONCLUSION

Motor roller bearing health diagnosis and prediction system implements an in-house fabricated, cost-effective, and high bandwidth z-axis piezoelectric accelerometer, *for the first time*. By choosing a combination of the EEMD algorithm and BP-ANN as the machine learning step, this study achieves the best accuracy with a few steps of pre-processing. Fault detection is done for different locations and states of the bearings under different motor speeds. The identification rate of the method used reaches 99.61% after the neural network validation and testing, thus verifying the applicability of the cost-effective accelerometer module as well as the feasibility of the proposed method in the study.

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REFERENCES

[1] W. Wang and O. A. Jianu, "A smart sensing unit for vibration measurement and monitoring," *IEEE Trans. Mechatronics*, vol. 15, no. 1, pp. 70-78, Feb. 2010.

[2] S.-C. Du, T. Liu, D.-L. Huang, and G.-L. Li, "An optimal ensemble empirical mode decomposition method for vibration signal decomposition," *Journal of Vibration and Acoustics*, vol. 139, no. 3, pages 031003, June 2017.

[3] B. Li, M. Y. Chow, Y. Tipsuwan, and J. C. Hung, "Neural-network-based motor rolling bearing fault diagnosis," *IEEE Transactions on Instrumentation Measurement*, vol. 47, no. 5, pp. 1060-1069, 2000.

[4] D. Ho and R. B. Randall, "Optimisation of bearing diagnostic techniques using simulated and actual bearing fault signals," *Mechanical Systems and Signal Processing*, vol. 14, no. 5, pp. 763-788. Sep. 2000.

[5] S. Ai, H. Li, and Y. Zhang, "Condition monitoring for bearing using envelope spectrum of EEMD," 2009 International Conference on Measuring Technology and Mechatronics Automation, 2009, pp. 190-193.

[6] S. Trivedi, T. Shen, C. Chang, P. Huang, and S.-S. Li, "Design of piezoelectric MEMS accelerometer module and its application in surface roughness prediction of fused silica substrate," *IEEE Sensors Journal,* vol. 21, no. 19, pp. 21979-21988, Oct. 2021.

[7] N. E. Huang, Z. Shen, and S. R. Long, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. R. Soc. London A,* vol. 454, pp.903-995, 1998.

[8] Z. Wu and N. Huang, "Ensemble empirical mode decomposition: a noise-assisted data analysis method," *Advances in Adaptive Data Analysis*, vol. 1. pp. 1-41. Jan. 2009.

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