On Fault Classification in Rotating Machines using Fourier Domain Features and Neural Networks

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***Abstract*— The paper addresses the problem of classifying mechanical faults in rotating machines. In this context, three operational classes are considered, namely: normal (where the machine has no fault), unbalance (where the machine load has its weight not equally distributed), and misalignment (where the rotor and machine axes are dislocated from its natural concentric position). A large dataset consisting of 606 distinct scenarios is developed for system training and testing, along with a preprocessing strategy that improves data distribution among the three classes considered. A classifier based on an artificial neural network is described, achieving a global accuracy rate of 93.5%.**

I. Introduction

Recent technological advances in the areas of signal processing, circuit design, and computer science have benefited several engineering fields such as mechanical, civil, chemical, and so on. This work addresses the problem of mechanical-fault classification in rotating machines (pumps, motors, generators, and engines [1], [2]). In some cases, even a small malfunctioning of these devices can bring a large industrial process to a complete stop, leading to unrecoverable economical losses. To avoid this undesirable situation, monitoring and diagnosis techniques may be employed to assist the machine operators to detect or even predict such faults at early stages [1]–[7].

Traditional machine monitoring is often performed directly on time-domain signals collected from accelerometers. Such signals, however, tend to carry excessive information for a proper system classification, leading to the so-called *curse of dimensionality effect* [9]. Therefore, a successful fault classification greatly depends on the feature-extraction stage, which gathers enough discriminative information for the three classes of interest. The focus of this work is to describe an automatic fault classifier using an artificial neural network (ANN) capable of discriminating three kinds of operational classes: normal, unbalance and misalignment [2], [7], [8].

The organization of the paper is as follows: Section II presents the mechanical framework employed in this work, which includes a SpectraQuest RotorKit and three accelerometers for signal acquisition; In Section III, the feature extraction techniques are explained, including the rotating-frequency estimation, which is a key aspect of the system operating mode; In Section IV, the design and practical issues for developing a large signal database are described; Section V details the experimental results achieved by the ANN classifier, including the stages of system training and testing; Finally, Section VI concludes the paper summarizing its main contributions.

II. System Description

In order to obtain a controlled environment, all fault scenarios considered in this work were implemented on the SpectraQuest RotorKit depicted in Fig. 1.

Two operational faults were considered:

- System unbalancing: In this situation, the machine load is not equally distributed in the angular direction. In the SpectraQuest RotorKit, this fault is implemented by positioning an extra load in one of the peripheral holes of the disc shown in Fig. 2. Different unbalancing situations can be created for distinct rotating speeds or load weights. In this work, all unbalanced signals deployed only the

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Fig. 1. Rotorkit used in the fault simulation scenario.

center-hung position where the machine load is placed on the axis between two bearings.

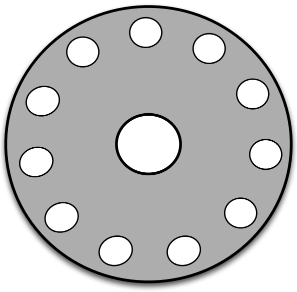

Fig. 2. Disc load used in the unbalance scenario. The central hole is where the disc fixed to the axis and peripheral holes are used to unbalance the disc weight.

- System misalignment: In this scenario, the rotor and machine axes are not concentric, as depicted in Fig. 3. Different misalignment scenarios can be created by distinct rotating speeds, shifts directions (horizontal or vertical), or shift amplitudes. In this work, the misalignment effect was implement by dislocating the rotor axis laterally or perpendicularly to the plane where it is fixed.

In each fault situation, vibration signals were acquired for 5.12 s using a $F_s = 800$ Hz sampling frequency, totaling 4096 samples in each signal. Following these conditions, in each machine configuration signals were acquired from three accelerometers positioned along the x (horizontal and along the machine axis), y (horizontal and orthogonal to the machine axis), and z (vertical) directions. The signals obtained from these sensors were labeled $s_x(n)$, $s_y(n)$, and $s_z(n)$, respectively, and a

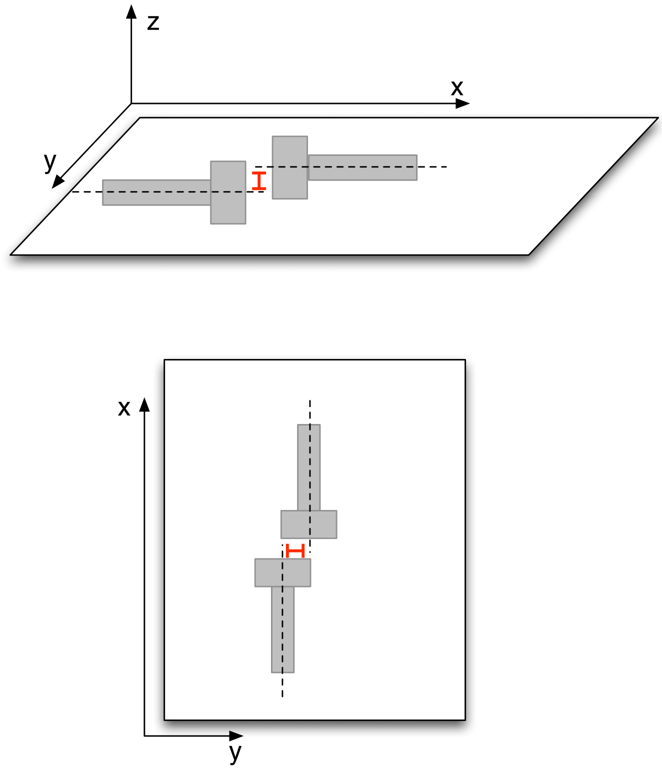

Fig. 3. Misalignment explanation. The upper and the lower part show the vertical and the horizontal misalignment, respectively. The solid "hammer"-shape objects represent the rotor and axis to be connected, where the "hammer" head is the connection between them.

fourth $s_t(n)$ trigger signal was also acquired allowing a direct rotating-speed estimation, as detailed below.

III. Feature Extraction

A. Rotating Frequency Estimation

The rotating speed can be estimated from the N-point discrete Fourier transform (DFT) $S_t(k)$ of the trigger signal $s_t(n)$. In some cases, however, the machine failure can introduce spectral peaks with more energy than the peak associated to the fundamental frequency of $s_t(n)$. Therefore, to cope with this problem, a two-step estimation algorithm was considered.

An initial frequency estimate is determined as

$$f_a = \frac{k_a F_s}{N} \text{ Hz}, \tag{1}$$

where k_a is the frequency index associated to the most significant peak of $|S_t(k)|$. Once such a peak is detected, then the values of $S_t(k)$ are set to zero for $(k_a - 3) \leq k \leq (k_a + 3)$. This procedure of peak detection-and-removal is repeated four times, generating four frequency candidates, namely f_a, f_b, f_c, and f_d. Based on these values, the final rotating-speed estimate R_f is chosen as

$$R_f = \min\{f_a, f_b, f_c, f_d\}. \quad (2)$$

B. Extracted Data Feature

The extracted features of interest are obtained from the three accelerometer signals $s_x(n)$, $s_y(n)$, and $s_z(n)$, and, for the machine faults considered here, are heavily dependent on the rotating frequency R_f [8].

Once the rotating speed is estimated, as detailed above, we then determine the magnitude of the spectrum of the three accelerometer signals at the frequencies R_f, $2R_f$ and $3R_f$.

The complete feature vector also incorporates the value of R_f, totaling only 10 features to describe the complete machine setup. This dimensionality reduction is very useful to remove excessive data which does not carry discriminating information for the classification problem at hand. In addition, by reducing the amount of input data one also reduces the overall computational complexity associated to the classifier learning process.

IV. Database

An important step on the designing process of a given classifier is the database development. Such database must represent the process of interest on a faithful and consistent manner, containing enough information to characterize each of the classes of interest.

The database deployed in this work considered the following machine operating conditions:

- Normal: In this class, 34 different rotating speeds were considered within the interval $9.98 \leq R_f \leq 59.76$ Hz.
- Unbalance: In this class, several scenarios with load weights $[4, 10, 15, 20, 24, 30, 35]$ g were considered, each with $[34, 34, 33, 33, 30, 34, 34]$ different rotating speeds, respectively, totaling 232 unbalance signals.
- Misalignment: In this class, both vertically and horizontally shifts were considered. In particular, vertically misaligned signals included distance shifts of $[0.36, 0.83, 1.31, 1.59, 1.86, 2.36]$ mm with 34 different speeds each, providing a total of 204 signals; meanwhile, the horizontally misaligned signals included only 4 different distances, $[0.5, 1, 1.5, 2]$ mm, all of them also with 34 frequencies, generating 136 data signals.

Therefore, the whole database includes a total of 606 distinct scenarios, 34 of which from the normal class, 232 from the unbalancing class, and 340 from the misalignment class. Each scenario, as mentioned above, has one trigger and three accelerometer signals, acquired at a 800 Hz sampling frequency along 5.12 s.

V. Experimental Results

A. Rotating Frequency Estimation

Validation of the automatic approach for the rotating-frequency estimator described in Section III-A is performed comparing the actual (as measured by a frequency analyzer during signal acquisition) and the estimated rotating frequencies, R_f. Results are as observed in Fig. 4, which indicates the high accuracy achieved by the proposed method that yields a mean squared error (MSE) of only 0.15 Hz^2, with an error variance of $\sigma^2 = 0.02$ Hz^2.

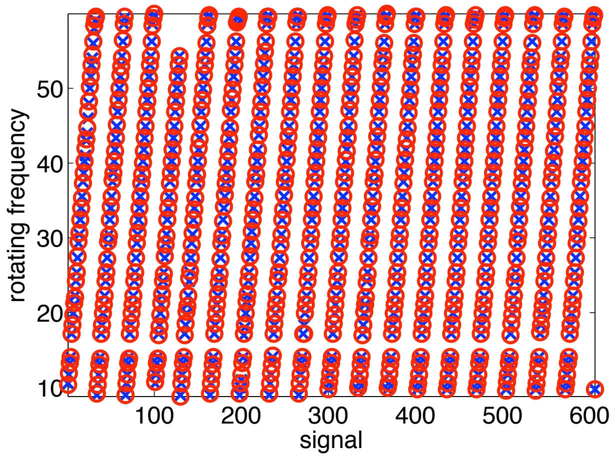

Fig. 4. Comparison between the actual (○) and automatically estimated (×) rotating frequencies.

B. Fault Classification

A multi-layer perceptron ANN classifier was devised with an input layer of dimensionality 10, the same as the feature vector, a 10-neuron hidden layer, and an output layer with 3 neurons using the hyperbolic-tangent sigmoid as activation function. Each neuron in the output layer represents one class to be recognized.

The whole 606-signal database was separated in three disjoint sets with approximately 70% signals for training, 10% for validation, and 20% for test. The validation subset is employed to avoid overtraining, that is, to avoid the ANN to become excessively specialized on the training signals thus loosing its generalization capability. The ANN learning process, also called training, was performed with the so-called backpropagation algorithm.

The initial test results presented in Table I indicate an overall classification performance of 92.7%. This overall rate, however, overshadows the fact that the no signal from the 'normal' class was correctly classified, most certainly due to the small number of signals (only 34 in the test database) associated to this class in comparison to the classes (there are 232 unbalanced and 340 misaligned signals within the test database, for instance). In such a case, the classifier system tends to overlook the under-represented class, without penalizing much the overall classification rate, as noticed here. Very similar overall and class-specific results were observed also for the training and validation databases where the 'normal' class is also misrepresented.

TABLE I
CLASSIFICATION PERFORMANCE X/Y FOR THE TEST DATABASE WITH CLASSIFIER TRAINED WITH ORIGINAL TRAINING DATABASE. IN THIS TABLE, X IS THE NUMBER OF RECOGNIZED SIGNALS AND Y IS TOTAL NUMBER OF SIGNALS FOR THE TARGET CLASS UNDER ANALYSIS.

Output Class	Target Class		
	Normal	Unbalance	Misalignment
Normal	0/6	0/42	0/62
Unbalance	3/6	41/42	1/62
Misalignment	3/6	1/42	61/62

In order to avoid this class-dependent performance one must reduce the difference in class representation in each of the database subsets. In this work, we opted to divide the 4096-sample normal signals into 8 smaller 512-sample signals, modifying the database to include 272 'normal', 232 'unbalanced', and 340 'misaligned' operating scenarios.

TABLE II
CLASSIFICATION PERFORMANCE X/Y FOR THE TEST DATABASE WITH CLASSIFIER TRAINED WITH THE INCREASED 'NORMAL' CLASS. IN THIS TABLE, X IS THE NUMBER OF RECOGNIZED SIGNALS AND Y IS TOTAL NUMBER OF SIGNALS FOR THE TARGET CLASS UNDER ANALYSIS.

Output Class	Target Class		
	Normal	Unbalance	Misalignment
Normal	31/34	3/42	1/62
Unbalance	3/34	38/42	1/62
Misalignment	0/34	1/42	60/62

Table II presents the results for the classifier trained with the increased 'normal' class. Although the final system performance, 93.5%, did not improve significantly compared to the previously tested classifier, the normal class efficiency increased to 91.2%, while the unbalance and misalignment decreased a little bit to 90.5% and 96.8%, respectively.

VI. CONCLUSION

This paper addressed the problem of classification of rotating-machine failures, including unbalanced loads and misaligned axes. A robust algorithm for rotating speed, R_f estimation was described and validated. Feature extraction considered the spectrum magnitude at R_f, $2R_f$ and $3R_f$ along three accelerometer signals along x, y, and z coordinate axes. A complete 606-signal database was developed including 34 'normal', 232 'unbalanced', and 340 'misaligned' machine setups. A 3-layer ANN-based classifier was designed, which achieved a 93% recognition accuracy after balancing the dataset of each class within the ANN training stage.

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