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Application of sinusoidal analysis to feature extraction in rotating machine vibration signals

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Abstract. *Rotating machines as turbines, pumps, blowers, ventilators, and compressors are frequently subject to a wide range of severe operating conditions that induce mechanical faults and performance degradation. The extraction of relevant features of vibration signals from rotating machines has been the subject of intense research during the last few years. A fault signature can be seen as a set of characteristics related to a particular failure. These features should be extracted from specific vibration signals adequately. This paper presents a novel feature extraction method for fault diagnosis in rotating machines. The proposed method utilizes sinusoidal analysis, which comprises several methods traditionally employed in the audio signal processing field. This paper is the pioneer, up to the authors' knowledge, in utilizing such a family of methods to address pattern recognition problems encountered in industrial rotating machinery. The main goal of the paper is to differentiate isolated faults composed only by unbalance, vertical misalignment, and vertical misalignment from combined faults formed by unbalance associated with horizontal misalignment, unbalance associated with vertical misalignment, and horizontal misalignment associated with vertical misalignment.*
In this research, the vibration signals were described by the sinusoidal analysis, which aims to represent a vibration signal through a finite set of components formed by time-varying amplitude, phase, and frequency. After computing this novel time-frequency representation, the method extracts the main signal tracks, which contain the most relevant information about a signal. Some peculiar features are then obtained from these tracks, such as the birth frequency, the length of the largest track, the energy of the largest track, the variance of birth frequencies, among others.
The performed experiments revealed that such sinusoidal features can be beneficial for classification purposes. In the dataset utilized, one reaches a global accuracy of 86.35%, when such features are combined with OOBFI feature selection method and Random Forest algorithm as the pattern recognition method.
Further, the selection of the optimal number of features and the best classification algorithm capable of distinguishing fault patterns, through the recognition of sinusoidal features, are investigated.

Keywords: *sinusoidal analysis, feature selection, fault diagnosis, combined faults*

1. Introduction

Condition monitoring in rotating machines is an essential procedure to prevent mechanical failures and system performance degradation at early stages, bringing cost savings and establishing the best time of intervention (Martins *et al.*, 2021). Rotating machines, such as turbines, pumps, blowers, ventilators, and compressors, are frequently subject to a wide range of harsh conditions (Li *et al.*, 2020; Qian *et al.*, 2019). In this way, providing the system's effectiveness and reliability through an accurate fault diagnosis minimizes unexpected failures, additional costs, and system downtime (Yu *et al.*, 2019).

According to (Bai *et al.*, 2019), the most frequent failures occurring in rotating machines that directly affect their useful life are unbalance and misalignment. Misalignment is one of the main recurrent sources of faults, and it worsens with continuous operation, which requires then a periodical monitoring. A non-invasive technique applied to identify unbalance faults and misalignment is vibration analysis. The extraction of relevant features in the vibration signals has been the subject of intense efforts during the last few years. For instance, the work of (Pestana-Viana *et al.*, 2018) had successfully applied fault diagnosis Diesel engines by employing vibration response of the crankshaft and pressure curves variation inside cylinders. In (Klausen *et al.*, 2018), the authors proposed the use of two failure thresholds using acceleration vibration data.

Note that a fault signature can be seen as a set of characteristics related to a particular failure, and they should be extracted from specific vibration signals in an adequate manner (Pestana-Viana *et al.*, 2018). Therefore, to classify these fault signatures, it is necessary to apply stages of data acquisition, feature extraction, fault identification, and fault severity estimation (Martins *et al.*, 2018). In this work, a novel feature extraction method for fault diagnosis problems in rotating machines is proposed. This method utilizes sinusoidal analysis, which comprises several methods traditionally employed in the audio signal processing field. Up to the authors' knowledge, this paper is the pioneer in utilizing such a family of methods to address pattern recognition problems encountered in industrial rotating machinery.

As an example of application, in the work of Shirazi *et al.* (2008), the authors evaluated sinusoidal modeling of audio signals, where amplitude, frequency, and phase parameters of the sinusoidal model are used and compared as input features into an audio classifier system. Their results presented superiority of the amplitude parameters of the sinusoidal model. Another interesting application of the peak-matching approach is based on the sinusoidal model to detect tracks in the time-frequency (TF) plane. The authors obtained a new feature vector able to considerably improve the accuracy with low computational cost.

The main goal of this work is to differentiate isolated faults composed by unbalance, vertical misalignment, and vertical misalignment from combined faults formed by unbalance associated with horizontal misalignment, unbalance associated with vertical misalignment, and horizontal misalignment associated with vertical misalignment. The vibration signals are described by the sinusoidal analysis to be represented by a finite set of components formed by time-varying amplitude, phase, and frequency. After computing this novel time-frequency representation, the method extracts the main signal tracks, which are responsible for containing the most relevant information about a signal. Then, peculiar features are obtained from these tracks (*i.e.*, the birth frequency, the length of the largest track, the energy of the largest track, the variance of birth frequencies, among others) to enhance the classification. Besides, this work also investigates the selection of the optimal number of features obtained through the sinusoidal representation by intelligent algorithms and the selection of the best classification algorithm model capable of distinguishing classes through the recognition of sinusoidal features patterns

2. Sinusoidal analysis

In the article McAulay and Quatieri (1986), a new procedure was proposed to carry out the analysis of voice signals in continuous time. This approach proved to be quite effective to perform the reconstruction of signals with low levels of error, using the amplitude, frequency, and phase information of the sinusoidal components from the original signals. The amplitude, frequency, and phase parameters are obtained by application of the short-time Fourier transform together with a peak detection algorithm.

The steps to carry out this representation are as follows: first, the signal of interest is sampled, then this signal is transformed into a two-dimensional representation of time-frequency and finally, the high energy parts of this signal are found, where the waveform inclination changes from positive to a negative value (Shirazi and Ghaemmaghami, 2008).

According to (McAulay and Quatieri, 1986), this representation technique can also be used in applications other than the study of voice signals. Following this idea, this technique was applied to the vibration signals of a rotating machine. Using this representation the signal is partitioned into F_r segments called frames as follow

$$s(n) = \sum_{k=1}^{F_r} \hat{s}\left(n - kN\right), \tag{1}$$

where N is the frame's length, k is the frame index and $\hat{s}$ is the sinusoids sum represented by

$$\hat{s}(n) = \sum_{j=1}^{L} A_j^k cos\left(2\pi f_j^k \frac{n}{F_s} + \phi_j^k\right), \tag{2}$$

where L is the order of sinusoids model, F_s is the sampling frequency of $s(n)$, A_j^k is the amplitude, f_j^k is the frequency and ϕ_j^k is the phase tracking of the j-th sine wave (Dubey *et al.*, 2020; Ramamohan and Dandapat, 2006). In this research, the order of sinusoids used was $L = 15$.

Analyzing a signal represented by the sinusoidal modeling technique, some peculiarities deserve to be highlighted: they are the birth of a trail, the duration of a track, the death of a track (Guerrero *et al.*, 2010). The birth of a new track occurs when the frequency of a peak in the current frame disappears in a given Δ range referring to the peak frequency of the previous frame. The death of a trail happens when a peak in the current frame is no longer tracked by another peak in a Δ range of the next frame.

The magnitudes verification of the peaks is essential to identify the adjacent peaks that belong to the same frequency and that present high magnitude differences. When this occurs, it indicates that these peaks belong to different tracks,

Table 1. Sinusoidal features.

F_1- Sum of track dimensions	F_{18}- Sum of track dimensions
F_2 Sum of birth frequencies	F_{19}- Mean power of LGT
F_3- Birth frequencies variance	F_{20}- Mean frequency of LGT
F_4- Maximum amplitude value	F_{21}- Std of the frequencies of the LGT
F_5- Second highest amplitude value	F_{22}- Std of first order derivative of frequencies of LGT
F_6- Third highest amplitude value	F_{23}- Std of second order derivative of frequencies of LGT
F_7- Frequency of F_4	F_{24}- Mean of first order derivative of frequencies of LGT
F_8- Frequency of F_5	F_{25}- Mean of second order derivative of frequencies of LGT
F_9- Frequency of F_6	F_{26}- Dimension of LFT
F_{10}- Maximum mean amplitude of all frames	F_{27}- Signal energy of LFT
F_{11}-Second highest mean amplitude of all frames	F_{28}- Mean power of LFT
F_{12}-Third highest mean amplitude of all frames	F_{29}- Mean frequency of LFT
F_{13}- Mean frequency of F_{10} frames	F_{30}- Std of the frequencies LFT
F_{14}-Mean frequency of F_{11} frames	F_{31}- Std of first order derivative of frequencies of LFT
F_{15}-Mean frequency of F_{12} frames	F_{32}-Mean of first order derivative of frequencies of LFT
F_{16}- Dimension of the LGT	F_{33}- Mean of second order derivative of frequencies of LFT
F_{17}- Signal energy of the LGT	

called partials. Based on this magnitude condition, a process is carried out to combine each frequency in frame t with some frequency in frame $t+1$ using interpolation (Guerrero *et al.*, 2010).

2.1 Feature extraction

To carry out this step, a literature search was made to find promising sinusoidal features for this application. Features used in classification problems of audio signals (Taniguchi *et al.*, 2008; Shirazi and Ghaemmaghami, 2008, 2010; Xie *et al.*, 2020), electroencephalogram signals (Guerrero-Mosquera and Vazquez, 2009; Guerrero *et al.*, 2010), and handwriting recognition (Choudhury and Prasanna, 2019) were used, to verify whether these features are also effective to differentiate types of failures in rotating machines.

To reduce the amount of information to be processed in this step, the first 15 tracks for each accelerometer were considered. The extracted features are shown in Table 1, these were extracted for each of the 3 directions: axial, horizontal, and vertical in the internal and external bearings. Thus, the feature vector formed has 198 positions.

In Table 1, F_0 is the fundamental frequency of the machine rotational speed, Std is the standard deviation, LGT is the largest global track and LFT is the largest F_0 track.

3. Feature selection

Feature selection techniques are employed to choose a subset of features that are capable of effectively representing the original features (Ahmed and Nandi, 2018). Feature selection is a useful step in pattern classification problems when the feature space has a high cardinality. Because when the set of features has high cardinality and is used as input to the classifier, there is a decrease in computational efficiency (Zhang *et al.*, 2018).

The use of feature selection must be carried out carefully to avoid relevant features that are considered unnecessary and are removed from the set of features to be employed (Urbanowicz *et al.*, 2018). Several algorithms perform the feature selection task. For this paper, the RELIEFF and Out of bag feature importance (OOBFI) methods were chosen.

3.1 RELIEFF

In this paper, RELIEFF was used, which is an upgrade from the original version of the RELIEF. RELIEFF was developed to be applied to classification problems with more than two classes, as is the case of this research. The main purpose of this algorithm is to increase the accuracy of the classification, overcoming the problem generated by the use of irrelevant, redundant, or noisy features (Munirathinam and Ranganadhan, 2019).

The RELIEF algorithm is a widely used filtering feature selection method due to its effectiveness and simplicity (Sun, 2007). This algorithm evaluates the relevance of a certain feature comparing to the other features. RELIEF is non-parametric because doesn't concern assumptions of sample size or population distribution. It analyzes the weight of each feature and selects the most relevant features in order to form a new smaller subset of features than the original set (Zhang *et al.*, 2018).

First, an instance x is randomly chosen then two closest neighbors to x are chosen, one from the same class of x and the other from a different class of x. The last step is to update the weight of each of the features. Features that show a distinct value between the target instance and the nearest miss support the hypothesis that they are relevant to the outcome, so the quality estimation weight of feature x is raised (Urbanowicz *et al.*, 2018). The feature weight measure W_i of example i is given by:

$$W_i = W_i - (x_i - H_i)^2 - (x_i - M_i)^2, \tag{3}$$

where x_i is the randomly chosen example, H_i is the nearest hit example and M_i represents the nearest miss example (Munirathinam and Ranganadhan, 2019).

3.2 Out of bag feature importance

A great advantage regarding the use of Random Forest is the facility to measure the relative importance of each feature in the prediction, through the measurement of out-of-bag (OBB) error (Saraswat and Arya, 2014). Providing an excellent tool for this, which measures the importance of the feature by analyzing how many nodes of the trees, which use a given feature, reduce the general impurity of the forest. This value is calculated automatically for each feature after training and normalizing the results so that the sum of all amounts is equal to 1 (Genuer *et al.*, 2010; Guyon and Elisseeff, 2003).

By inspecting the importance of the features, it is possible to decide which features to leave out of the model, as they do not contribute enough or nothing to the prediction process. This is important, as a general rule in machine learning is that the more features you have, the more likely your model will suffer from overfitting (Fan and Li, 2001).

In addition to providing an estimate for the generalization error, OOB data can be used to calculate the importance of variables and proximity of observations (Genuer *et al.*, 2010). First, the importance measure is very useful in the presence of many predictor variables. The importance of the variable is given by the difference between the accuracy or the Gini index when the variable's values and the original data are randomly exchanged, this keeping the values of the other variables fixed. The measure captures the sensitivity of the model for each predictor, the more sensitive, the more important the variable for the performance of the model (Breiman, 2001).

The studies by (Breiman, 1996) point out that the error calculated with the OOB observations is an unbiased and consistent estimator of the prediction error. The OOB error is defined as:

$$\mathrm{err}^{\mathrm{oob}} = \frac{1}{O}\sum_{i=1}^{O} I(\hat{f}^{\mathrm{bag}}(x) \neq y_i^{\mathrm{oob}}), \tag{4}$$

where O represents the number of observations that were not selected in the bootstrap sampling, where $O \approx \frac{1}{3}$ of samples that were not used in the training step. The term $\hat{f}^{\mathrm{bag}}(x)$ considers the classifier together with all trees adjusted to the samples, the term y_i^{oob} represents the actual classification of observation i. $I(\cdot)$ Represents the indicator function, that is, it assumes a value of 1 when the condition is satisfied and 0 otherwise. Therefore, the $\mathrm{err}^{\mathrm{oob}}$ calculates the proportion of times that the classifications were erroneously performed given the aggregation of O decision trees.

4. Random Forest

Random Forest (RF) is an ensemble supervised machine learning algorithm that can be used for classification and regression tasks (Breiman, 2001). This algorithm is formed by simple predictor elements, that is, decision trees. An ensemble classifier is often more powerful than the individual predictors that are forming it (Yang *et al.*, 2008). Random Forest provides excellent results when used in fault detection and prediction (Martins *et al.*, 2018), (Pestana-Viana *et al.*, 2018). In this work, this algorithm is used in the classification task.

The decision trees that form the Random Forest algorithm are unstable predictors, that is, small changes in the training set are capable of causing significant differences in the classifier results, so the bagging method is used to mitigate this problem (Altmann *et al.*, 2010). Bagging increases prediction performance compared to a single tree by decreasing the forecast variance. The bootstrap method can generate samples by inserting a random component into the tree formation process resulting in a tree distribution and, therefore a distribution of predicted values for each sample (Yang *et al.*, 2008). The trees grouped according to the bagging method are not totally independent of each other since the original predictors are used in the tree divisions, as can be seen in (Breiman, 1996).

The training algorithm for random forests applies the general technique of bootstrap aggregating, or bagging, to tree learners. Given a training set $X = x_1, \cdots, x_n$ with responses $Y = y_1, ..., y_n$, bagging repeatedly (B times) selects a random sample with replacement of the training set and fits trees to these samples:

for $b = 1$ **to** B **do**
  1. Sample with replacement n training examples from X, Y and call them X_b, Y_b;
  2. Train a classification tree f_b on X_b, Y_b.
end

After training, predictions for unseen samples x' can be made by taking the majority vote in the case of classification trees on x':

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b(x'). \tag{5}$$

This bootstrapping procedure leads to better model performance because it decreases the variance of the model, without increasing the bias. This means that while the predictions of a single tree are highly sensitive to noise in its training set, the average of many trees is not, as long as the trees are not correlated (Altmann *et al.*, 2010).

5. Dataset

The Alignment Balance Vibration Trainer (ABVT) simulation bench, also known as RotorKit, was used to generate the operating scenarios of the rotating machine. Through this equipment, it is possible to analyze fault problems in rotating machines in a controlled environment. The acceleration signals were acquired in three perpendicular directions to each other. Two different measurement locations were used, as shown in Figure 1, the internal and external bearing pedestals.

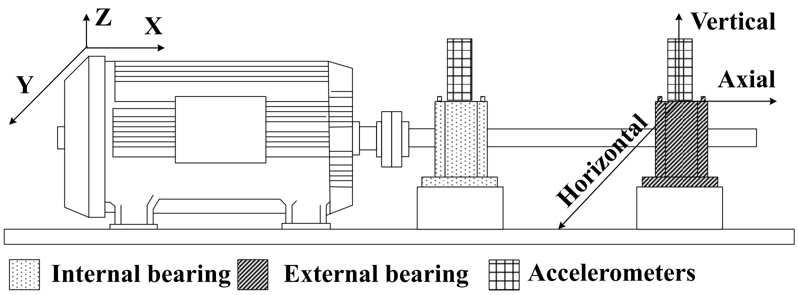


Figure 1. Test apparatus and accelerometers' location.

The dataset used in this paper has 2,162 vibration signals referring to seven operating conditions of the rotating machine simulator divided as follows: 245 normal operation examples, 336 unbalance examples, 195 horizontal misalignment examples, 243 vertical misalignment examples, 351 combined unbalance with horizontal misalignment examples, 351 examples of combined unbalance with vertical misalignment examples and 441 horizontal misalignments combined with vertical misalignment examples.

The vibration signals were acquired with a sampling rate $f_s = 50$ kHz and for 5 seconds. Therefore, each entry of the dataset contains 250,000 samples. Different values of the motor rotation speed (in the interval [12,60] Hz) were recorded, with an increment of approximately 1 Hz.

6. Results and Discussion

To evaluate the feasibility of implementing sinusoidal analysis to identify combined failures in rotating machines, five steps were performed as shown in Figure 2. In the first step, vibration acquisition signals were made, then the sinusoidal representation of these signals was performed, in the third stage the features of the first 15 tracks were extracted, then the selection of the most relevant features was carried out, and finally, in the fifth stage, the classification task was performed.

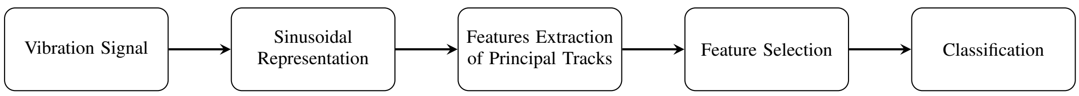
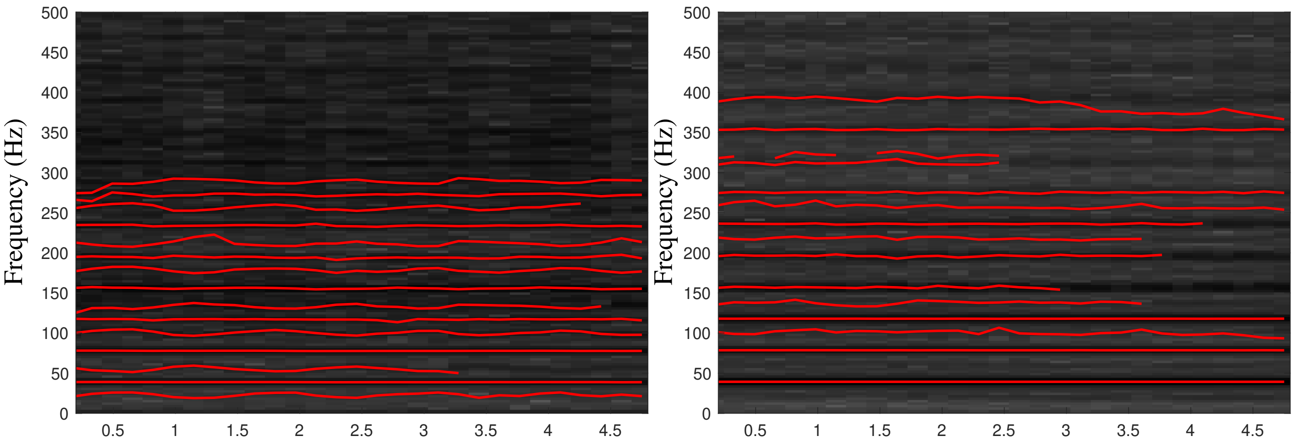


Figure 2. Process block diagram.

After the data acquisition, the second step of the process consists of representing each vibration signal through the sinusoidal analysis. In this research, the first 15 tracks were used to represent each of the signals to decrease the amount of information to be processed in the next step.

Figure 3 shows two vibration signals referring to two different operating conditions of the machine at a rotation speed of 40 Hz. Figure 3 (a) shows the signal spectrogram with the first 15 tracks of the radial direction referring to the normal operating machine's condition. While Figure 3 (b) shows the signal spectrogram with the first 15 tracks of the radial direction refers to unbalanced (30 grams) combined with 1.91 mm vertical misalignment operating machine's condition.

The third step consisted of extracting the features listed in Table 1 for each accelerometer signal, thus resulting in a 198 dimension vector.



(a) Time (s)   (b) Time (s)

Figure 3. Examples of signals: (a) Spectrogram of radial direction signal referring to normal condition. (b) Spectrogram of radial direction signal referring to unbalance (30 grams) combined to vertical misalignment (1.91 mm) condition.

The fourth step of the process was to apply two selection methods to obtain the most relevant features for the combined failures' diagnosis. Finally, the best model of the Random Forest algorithm was selected to perform the classification step.

The performance of the Random Forest algorithm was evaluated in 3 different cases: I) using all 198 extracted sinusoidal features, II) applying the OOBFI algorithm for features selection, and III) using the RELIEFF (REL) algorithm for feature selection.

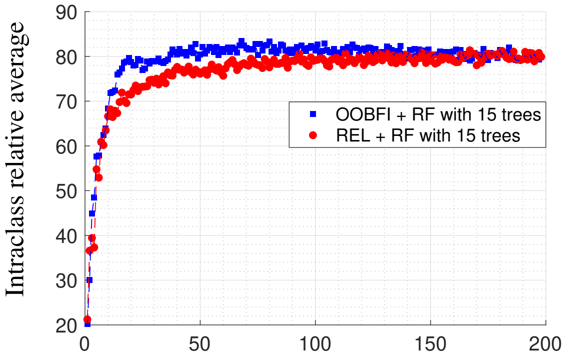
The evaluation metric used to measure the classifier performance was the intraclass average relative accuracy. This metric can be calculated as follows: sum the accuracy values of each scenario (class) divided by the number of classes. To reduce bias in the classification stage, the K-fold cross-validation technique with 5 partitions was used. In this technique, the dataset is divided into 5 partitions, 1 of which is used in the test stage, while the 4 remainings are used for the training stage. Five rounds are performed to obtain the fold accuracy values and, finally, the fold accuracy averages are obtained.

In Figure 4, it is possible to observe that initially, the increase of features number improves the performance of the classifier, however, in a given number of features the performance of the classifier remains at a certain level until it reaches the point that the addition of features slightly changes the classifier performance. From the graphs, it can be seen that the OOBFI performs better than the RELIEFF for selecting the most relevant features to differentiate the types of rotating machine failures. Table 2 presents the baseline results using Random Forest with three different numbers of trees (15, 30, 45) to compare the best results of the OOBFI and REL features selection techniques. In Table 2 the trees number column indicates the number of trees that form the algorithm, the features number column shows the number of features used by the model, the time column represents the processing time of the algorithm for classifying an example and the intraclass relative average column is the measure of the classifier's performance.

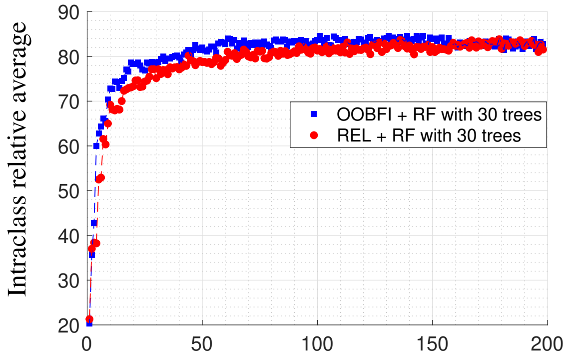
From the results presented in Table 2, it is noted that the use of the two methods of reducing features improved the classifier performance. It is observed that the OOBFI method surpassed the performance of the REL method reaching the best accuracy for the three configurations of the number of trees used. The use of the OOBFI method also made it possible to decrease the number of features used, thus decreasing the response time of the algorithm. Comparing the results presented in Table 2, it is verified that the method with the best performance is OOBFI + RF. Taking into account the baseline with employing RF with 45 trees, the OOBFI + RF method presents an increase in the accuracy of the classifier of 2.21%, reduces by more than 1/3 the number of features used, and decreases the processing time of the algorithm by 0.14 s. The results show that OOBFI + RF with 45 trees is the best method.

Using the best-selected model OOBFI + RF with 45 trees, the performance of identifying the scenarios through the ROC (Receiver Operating Characteristic) curve was investigated. The Area under the ROC curve (AUC) is a performance metric used to evaluate the ratio of true positives to the rate of false positives, its value is in the range of [0,1]. This metric is widely used in the field of rotating machines fault diagnosis (He *et al.*, 2016; Rauber *et al.*, 2013; Purohit *et al.*, 2019). True positive corresponds to an example of the scenario of interest that was correctly classified, while False-positive corresponds to an example of the scenario of interest incorrectly classified (Saidi *et al.*, 2015).

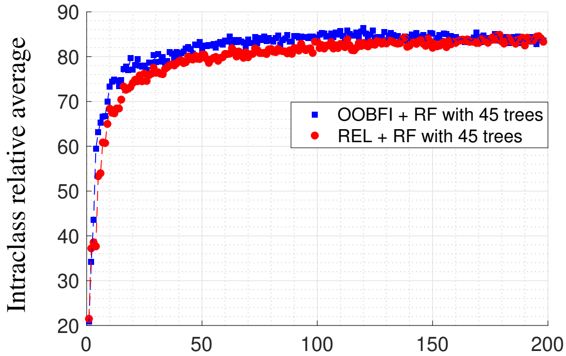
Through Figure 5, it is possible to verify the classifier's performance concerning the identification of each of the 7 scenarios studied in this research. The closer the curve is to the left and upper edges, the better the classifier will perform for this scenario and higher is the AUC value. The best-identified scenarios were the normal (AUC=0.993) and the vertical misalignment associated with horizontal misalignment (AUC=0.991). While the classes that had the lowest AUC values were unbalance associated with the horizontal misalignment (AUC=0.968) and the horizontal misalignment (AUC=0.969).



(a) Number of features



(b) Number of features



(c) Number of features

Figure 4. Comparison of the methods.

Table 2. Methods Comparison.

Method	Trees number	Features number	Time	Intraclass relative average
RF	15	198	0.33 s	80.28%
OOBFI +RF	15	68	0.21 s	83.45%
REL + RF	15	167	0.25 s	81.38%
RF	30	198	0.56 s	82.07%
OOBFI +RF	30	101	0.55 s	84.61%
REL +RF	30	179	0.64 s	83.85%
RF	45	198	0.76 s	84.14%
OOBFI + RF	45	120	0.62 s	86.35%
REL + RF	45	179	1.17 s	84.88%

7. Conclusions and Future Work

Research in other areas of knowledge has already used sinusoidal analysis as a pre-processing step and obtained good results in tasks of classification of audio signals, electroencephalogram signals, and handwriting recognition. However, this approach has not yet been applied to the recognition of combined failures in rotating machinery from vibration signals. In this work, the use of sinusoidal analysis in vibration signals were evaluated as a pre-processing step and the selection of the most relevant features from the RELIEFF and OOBFI algorithms. The objective was to perform fault classification in a rotating machine, differentiating simple faults from combined faults.

Through the results presented in this paper, it can be seen that the technique of feature extraction by sinusoidal analysis associated with the feature selection technique OOBFI and Random Forest classifier is effective for the classification task of diagnosis combined faults in rotating machines reaching an accuracy of 86.35%, reducing the number of features used by more than 1/3 and decreasing the processing time. Using the ROC curves, it was seen that the classifier performed well in the recognition of combined failures.

For future work, we intend to test the use of sinusoidal features in other classification algorithms, such as a Support vector machine, the K nearest neighbors, and the artificial neural networks to improve the performance of the fault identification task. In addition, it is also intended to use deep learning algorithms to learn features from the sinusoidal

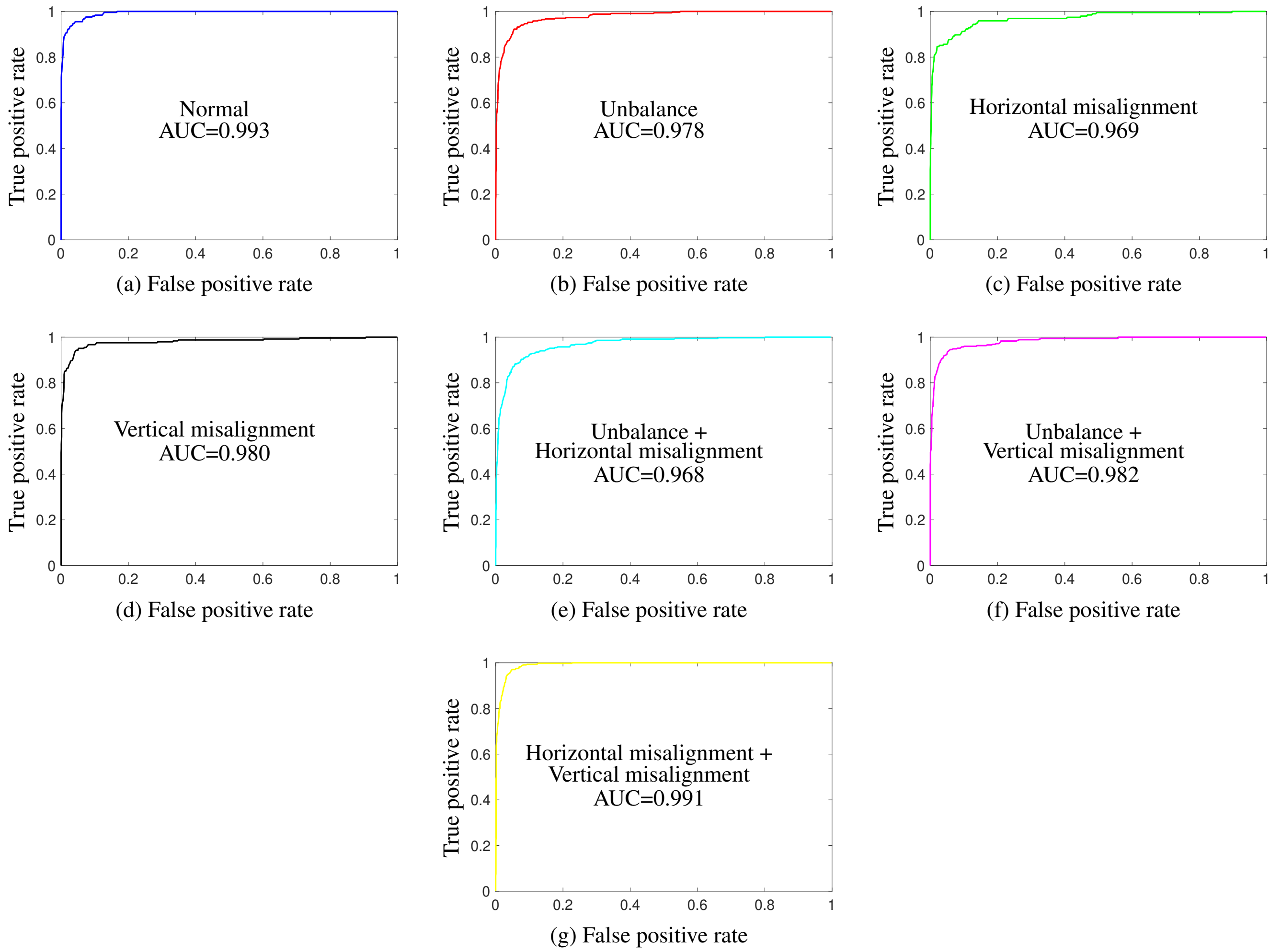


Figure 5. ROC curves: (a) Normal scenario; (b) Unbalance scenario; (c) Horizontal misalignment scenario; (d) Vertical misalignment scenario; (e) Unbalance + Horizontal misalignment scenario; (f) Unbalance + Vertical misalignment scenario; and (g) Horizontal misalignment + Vertical misalignment scenario.

representation of the vibration signals in an automatic way without use further information and then use these features in the classification step to verify whether the performance of the classifiers will increase by applying this approach. In addition, the intention is to use data augmentation techniques in order to increase the efficiency of classification in horizontal misalignment scenario.

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