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FAULT ANALYSIS IN A ROTOR SUPPORTED BY ROLLING BEARINGS USING CLUSTERING TECHNIQUES

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Abstract. *In this work, fault analysis in rolling bearings through unsupervised learning is explored. Different clustering methods were applied to vibration signals on a rotating machine with different faults inserted into the bearings. The objective was to evaluate the performance of the methods in detecting these faults. The clustering techniques applied were k-means, hierarchical clustering, and DBSCAN. It is also investigated the search for the ideal number of clusters considering only the detection of different types of faults, severity of the faults, and a general case with data of all types and severity of faults. The results were discussed and compared using an appropriate accuracy. It was found that the different methods showed similar performance for the detection of the faults. It was also possible to identify a similarity between the attributes of different groups, which interfered in the data clustering process.*

Keywords: *bearing fault identification, clustering, k-means, hierarchical clustering, DBSCAN*

1. INTRODUCTION

Bearings are essential elements for the operation of rotating machines, acting to support the rotor and, at the same time, allowing the rotation, providing low friction coefficient, and reducing mechanical losses. Rolling bearings are widely used in small to medium-sized machines, since they are low-cost elements with easy maintenance and highly available in the market.

The operation and maintenance of rotating machines are carried out in order to avoid unscheduled downtime, which generally leads to productive and financial losses. Thus, it is often chosen to health monitoring these machines, in order to detect faults in the components, such as the rolling bearings.

The fault identification in rotating machines can occur through several techniques, with very consolidated methods which are generally based on monitoring the machine's vibration signals, as presented in (Goyal and Pabla, 2016) and (Heng *et al.*, 2009). These methods are divided into two categories: physics-based models, related to finite element modeling and insertion of faulty component models into a mathematical equation, and data-driven methods, that are capable of extracting information from measurement data only. The last one stands out for its ease of calculation, quick adaptation in dealing with different analyses, often without the need for prior knowledge of the system, and takes into account the inherent characteristics of an experimental environment.

For rolling bearings, the analysis of vibration signals through the study of an envelope by Hilbert transform and the use of spectral kurtosis is one of the most notable ways to identify faults (Randall and Antoni, 2011). However, these methods are semi-automatic processes that still require further analysis of the results and prior knowledge. Thus, from the popularization of machine learning algorithms, several automatic methods began to be proposed to transform the faults detection into a completely automatic process. For that, signal processing techniques and parameter extraction are necessary together with efficient exploration algorithms (Goyal and Pabla, 2016), ranging from classifiers (Cerrada *et al.*, 2018) to deep networks (Liu *et al.*, 2018) and unsupervised learning techniques (Rai and Upadhyay, 2017; Wang *et al.*, 2020), to determine not only the fault presence in the elements of the bearing but also its location and severity. Unsupervised learning techniques have some advantages over classifiers and deep networks. These techniques work searching for patterns in the input data and, therefore, do not require labeled datasets to build a model or to train a network, which are difficult to obtain in practical applications due to the expensive and time-consuming procedures required to collect and label the data. Some researches were carried out in order to detect faults in rolling bearings with unsupervised learning techniques, more specifically clustering techniques. (Rai and Upadhyay, 2017) employed the k-medoids method in order to separate- the vibration data of a bearing test rig into normal state and failure state clusters. (Wang *et al.*, 2020), in turn, employed the k-means method to detect surge, rubbing and misalignment faults, achieving 94%, 100%, and 80% of accuracy for each fault, respectively.

The objective of this study is to verify the effectiveness of different clustering methods for the fault analysis on rolling element bearings, regarding the identification of the location of the fault, as well as the identification of its severity. In this work, the analyses are performed based on the vibration signals of an accelerometer positioned close to the electric motor of the rotating system and the clustering are carried out based on features extracted from the temporal sequences of these signals and merging techniques for identifying the number of clusters to assess the effects of different failure conditions on the clustering algorithms.

2. TOOLS AND METHODS

In this section, the database and the clustering methods are presented and, lastly, the methodology developed for the analyses is described.

2.1 Database

The data used in this work were taken from the database available at Case Western Reserve University (CWRU) (Case Western Reserve University, 2021). This database has test data from normal and faulty ball bearings. The experiments were carried out on a test rig (Figure 1) with a 2 HP electric motor, whose shaft is supported by rolling bearings and the accelerometers are fixed through magnetic bases in three positions: coupling, fan, and, in some cases, on the engine support base.

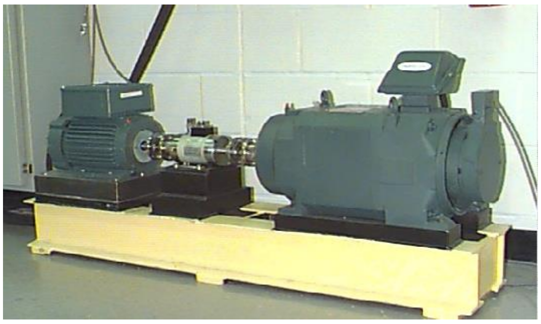


Figure 1. Test rig used for CWRU rolling bearings' database.

Measurements were made for three types of faults in the bearings: fault in the inner race, fault in the outer race, and fault in the rolling element (ball). In addition, the faults in the external race are located in three different positions, according to its orientation regarding the location for load application (for this work no data was used with the loading application). Each of these faults has different severities, specified through the diameter and depth of the fault. The data were collected with sampling frequencies of 12 kHz. This database is available to the public (Case Western Reserve University, 2021).

2.2 Clustering

Clustering is a type of unsupervised learning that aims to separate a given set of data, using some measures of similarity, into groups called clusters. These groups are expected to have some homogeneity or internal regularity, indicating that clustering methods can reveal a natural structure existing in the dataset or group it according to the similarities between the data.

To study the feasibility of employing the clustering in the detection of bearing faults, three clustering methods were selected: k-means, hierarchical, and a density-based approach known as DBSCAN (Ester *et al.*, 1996).

The k-means method is based on the hypothesis that the distances between points belonging to the same cluster must be less than the distances concerning points outside that cluster (Pedregosa *et al.*, 2011). It is interesting to note that, when using this method, it is necessary to previously define the number of clusters present in the dataset.

Hierarchical clustering is a general family of algorithms that build hierarchical clusters by grouping or dividing them successively. This hierarchy of clusters is represented as a dendrogram, in which the similarities between features are calculated from a proximity matrix, and an agglomerative clustering of data. In this type of representation, initially with the number of clusters equal to the number of data, close (similar) clusters are successively joined until all are grouped under a single cluster.

The DBSCAN algorithm considers clusters as areas of high density separated by areas of low density. Because of this, the clusters found by DBSCAN can have any shape, unlike k-means, which assumes that the clusters have a convex shape (Pedregosa *et al.*, 2011). The DBSCAN consists of two stages: in the first stage, each sample is labeled as a central point, a border point, or noise. In the second one, the central and border points are grouped into clusters according to a distance metric. A central point is a sample in the dataset so that there are a minimum number of samples within radius value, which are defined as neighbors (boundary) of the main sample. The cluster will then become the junction between central and boundary samples that can recursively be linked.

2.3 Methodology

Based on the objectives of this work, the first step was to select and extract the features of the vibration signals that carry information about the faults present in the machine's bearings. This step was performed by reviewing the literature on faults detection and evaluating the features extracted from the signals available in the database (Randall and Antoni, 2011; Janssens *et al.*, 2016; Neupane and Seok, 2020).

Moreover, it was necessary to define which vibration signals would be suitable for the fault's identification. This choice was done by comparing the results of initial tests with the clustering methods. With all the features of the selected signals, the most appropriate number of clusters was selected for the methods that require this information a priori.

In following, three clustering methods were applied to check if it would be possible to detect each of the faults present in the bearings. The metric for evaluating the results was the accuracy. Since learning is unsupervised, the definition of accuracy for supervised learning with classification cannot be considered. Accuracy (Acc) for clustering involves finding the best combination between the known labels and the labels obtained with the clustering, being defined as presented in Eq. (1) (Morbieu, 2021):

$$Acc(y,\hat{y}) = \max_{pem\in P} \frac{1}{n}\sum_{i=0}^{n-1} 1(perm(\hat{y}_i) = y_i) \tag{1}$$

where P is the combination of all permutations in $[1, K]$, with K being the number of clusters.

After the ability to identify the faults was evaluated, different severities of the same fault were tested. Then, all data (different faults with different severities) were tested to verify the ability of the methods to separate faults and different severities into separate groups.

3. RESULTS

The database has vibration signals from three different accelerometers, however, the accelerometer positioned on the base of the test rig was not used for all classes of faults. In order to define the most appropriate signals of the database, some tests were carried out using the k-means method. After a previous analysis, it was verified that the data of the sensor positioned in the coupling (near the electric motor) present well-defined clusters, considering that the bearing is closer to this sensor than the others. To simplify the analysis, only the coupling sensor data was used.

Defects with a diameter of 0.007in were selected to verify the capacity of the methods for fault identification, thus resulting in 5 groups (fault in the inner race, faults in the three different positions of the outer race, and fault in the ball). Defects in the inner race with diameters of 0.007in, 0.014in, 0.021in and 0.028in were selected to verify the ability of the methods on the identification of the severity, resulting in 4 groups. To verify the capacity of the methods for general identification, different severities of all available faults were selected, resulting in 15 groups. All the sets were also combined with features obtained from rolling bearings signals under heathy conditions.

3.1 Features

The chosen temporal features were RMS value (Root Mean Square), kurtosis, the difference between maximum and minimum, Peak-magnitude-to-RMS ratio, and asymmetry (skewness). These features were considered because they are sensitive to faults and characterize the degradation process of rotating machines, in addition to being well known and used in other works available in the literature (Rai and Upadhyay, 2017; Cerrada *et al.*, 2018; Wang *et al.*, 2020).

To assess whether these features would be suitable for the database used in this work, they were computed for vibration signals in normal conditions and with defects of the same severity in the rolling element (ball), in the inner race, and in the outer race, in the load application position, in the position orthogonal to the load application and in the opposite position to the load application, resulting in 6 clusters.

Figure 2 (a) shows the values of the features extracted from each vibration signal. All values were standardized, that is, average values were extracted and divided by the standard deviation to facilitate the performance of the algorithms.

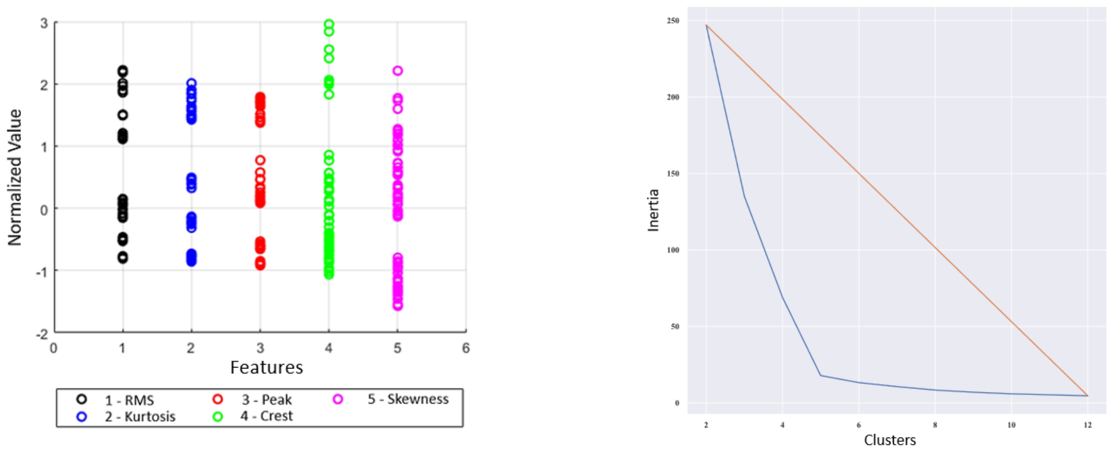
Moreover,

Figure 2 (a) shows the identification of several groups with similar RMS, peak, and kurtosis values. As for the crest and asymmetry features, there is some division, but it is not so clear. The formation of these groups with different values of the same feature is important because the distance between these values is a measure of similarity used in some methods of clustering, among them the k-means, which will be used in this study.

3.2 Number of Clusters

In the previous analyses, the number of clusters was selected based on the classifications already existing in the database. In the analyses performed in this section, the number of clusters will be defined based on three evaluation metrics, being the Silhouette coefficient, the Davies-Bouldin index (DB), and the Elbow method. For this, 100 tests were carried out evaluating all the criteria. For the Elbow criterion, in which the ideal number of clusters is conventionally defined qualitatively, a way to automate the results is proposed. Based on the equation that defines the distance between a point and a line, it is assumed that the best number of clusters will be that which results the longest distance. In this procedure, the sum values of the square distances of each sample to the nearest cluster center, here named as inertia, are evaluated from a pre-defined interval of clusters number. As can be seen in Figure 2 (b), the red line represents the connection between the starting and ending number considered for the cluster numbers in the data and the blue line represents the inertia values obtained in each cluster iteration.

Figure 2 (b) illustrates the procedure adopted for the Elbow criterion. The data used for the illustration were those with different defects of same severity. Note that the optimum value obtained was 5, but, for this case, there are 6 groups (defect in the inner race, defect in the rolling element, 3 defects in the external race - in different locations - and data for the healthy bearing).



(a) (b)

Figure 2. Features extract from the time signal considering the same severity (a) and how is determined the optimal number of clusters using the elbow method (b).

The ideal number of clusters was determined using the cited criteria varying from 1 to 12 clusters for sets containing different defects of same severity (Location Set) and containing different severities for the same defect (Severity Set), in which should ideally result 6 and 5 clusters, respectively. For the set containing different defects with different severities (Location and Severity Set), which should result 16 clusters, the number of clusters tested was varied from 1 to 20.

Table 1 shows the number of clusters with the highest occurrence in the tests, as well as the number of times that it was estimated as the best value by the evaluation metrics.

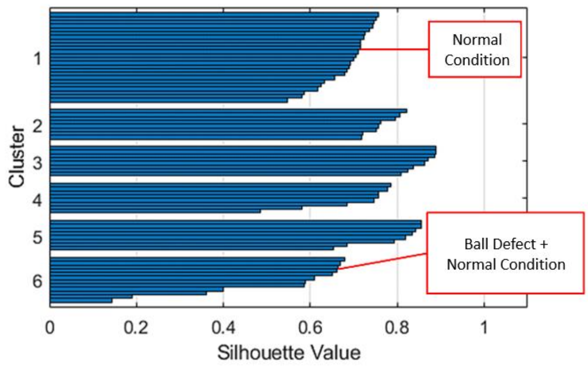
Table 1. Estimated number of clusters and its occurrence in the 100 tests performed.

Set	Number of Cluster	*Silhouette*	*Davies-Bouldin*	*Elbow*
Location	6	5 (74)	7 (59)	5 (78)
Severity	5	5 (98)	5 (98)	5 (93)
Location and Severity	16	15 (25)	15 (20)	15 (14)

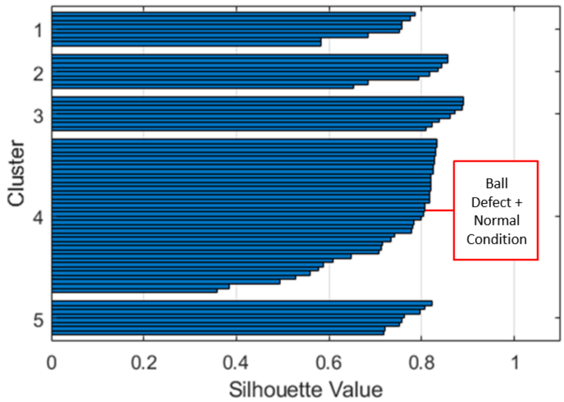
For the Severity Set, all metrics indicated the correct number of clusters present in the data (5), whose accuracies vary between 93% and 98%. For the Location Set, the correct number of clusters (6) was not mostly indicated by any of the metrics, which indicated different values between them. And for the Location and Severity Set, all metrics indicated the number of clusters as being 15, however, the correct number of clusters is 16.

These results indicate that there are groups of faults with similar characteristics that end up being either identified as a single cluster by clustering methods or that the amount of data used to perform clustering by the k-means method is not sufficient.

To illustrate what happened in more detail, the graphs of the Silhouette coefficient are presented for the Location Set. From this index, it is noticed that the clusters formed by the data of the normal condition and the defect in the rolling element have the lowest Silhouette coefficients. Thus, the cluster 6 presents data from these two different groups (Figure (a)). However, when only 5 clusters are used, these two sets come together to form a single cluster (Figure 3 (b)).



(a)



(b)

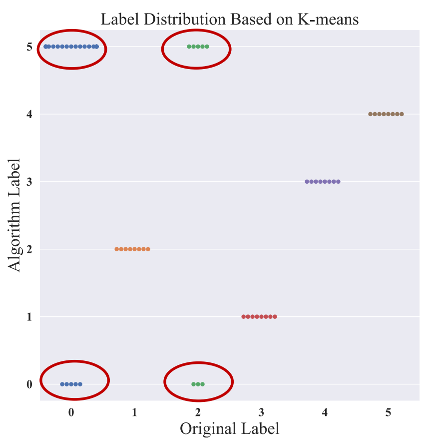
Figure 3. Silhouette coefficient of fault clustering considering 6 clusters (a) and Silhouette coefficient of fault clustering considering 5 clusters (b).

The analyses of the k-means method will be carried out with both the correct and estimated number of clusters. In this way, it will be possible to separately verify the capacity of the k-means method to perform the fault identification and the capacity of the entire identification process, considering the definition of the number of clusters by any of the methods presented as part of this process.

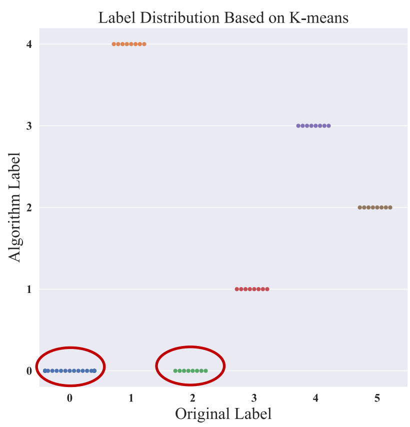
In addition, the results obtained by the DBSCAN and hierarchical clustering will also be presented. These algorithms are based on different metrics to perform data separation and, therefore, may behave differently from the traditional k-means, depending on the layout of the data.

3.3 Fault Identification

Figure 4 (a) and Figure 4 (b) show the results of the k-means method when applied to the Location Set. Figure 4 (a) was obtained using the known number of labels as the number of clusters. Figure 4 (b) was obtained using the estimated number of clusters, as shown in the previous section. In Figure 4 (a), it can be seen that the bearing data in the normal condition (label 0) and the bearing data with defect in the rolling element (label 2) are distributed between the clusters 0 and 5. When the number of clusters is reduced to 5 (Figure 4 (b)), it is precisely these two groups that are grouped to form a single cluster. This again indicates a similarity between the features of these two groups.



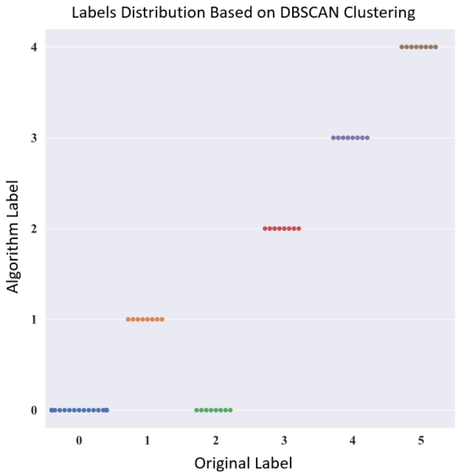
(a)



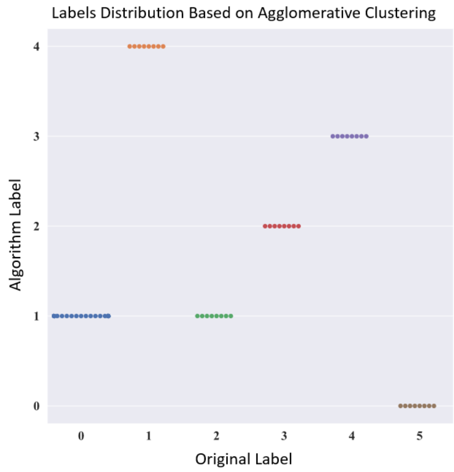
(b)

Figure 4. K-means clustering considering 6 clusters (a) and 5 clusters (b).

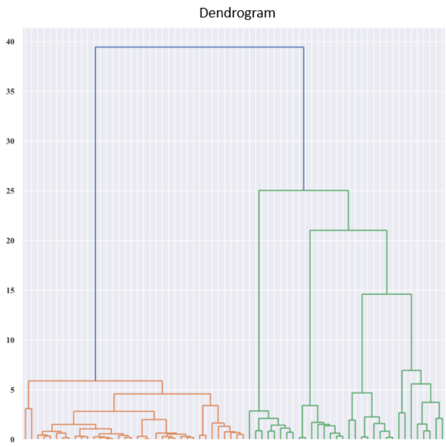
The k-means assessment metric assumes that the clusters are convex and isotropic, which is not always the case. It tends to generate poor results in elongated or irregularly shaped spaces. Considering a sufficient simulation time, the convergence of k-means is guaranteed, however, this can be for a local minimum, making it strongly dependent on the centroid initialization. As a way of improving the classification of features, bypassing these disadvantages, the way of unsupervised learning was varied with the other two methods mentioned in the previous section, DBSCAN (Figure 5 (a)) and hierarchical clustering (Figure 5 (b) and Figure 5 (c)).



(a)



(b)



(c)

Figure 5. DBSCAN clustering (a), Agglomerative clustering (b) and Dendrogram (c) for faults identification.

Both in Figure 5 (a) and Figure 5 (b), the algorithms presented the same difficulty observed by k-means in separating the labels 0 and 2. For DBSCAN, successive hyperparameters were defined, consolidating the results with values of 2 for radius and 5 minimum samples. As for the agglomerative algorithm, the final hyperparameters were based on the Manhattan distance and single linkage, since this type of configuration in higher dimensional data is preferable (Aggarwal, Hinneburg and Keim, 2001). With the dendrogram (Figure 5 (c)), it is also possible to perceive the difficulty of division from order 5, leading to the conclusion that the three forms of analysis of the features are equivalent for this case.

These analyses can be extended to the two subsequent cases: analyzing the severity of a defect (Severity Set) and, later, evaluating the entire dataset (Severity and Location Set).

3.4 Severity Identification

Analyzing the severity of the defect, the data can be initially divided into 5 categories. The application of the k-means, DBSCAN and hierarchical (agglomerative clustering and dendogram) methods can be seen in Figure 6.

Figure 6 (a) demonstrates that k-means was able to fully classify the data, with 100% accuracy for the analyzed data, as well as the agglomerative clustering presented in Figure 6 (c). Regarding the DBSCAN, although to correctly separate the data into 5 labels, two features were classified as noise because they were unable to meet the connection requirements and connection number defined for the function.

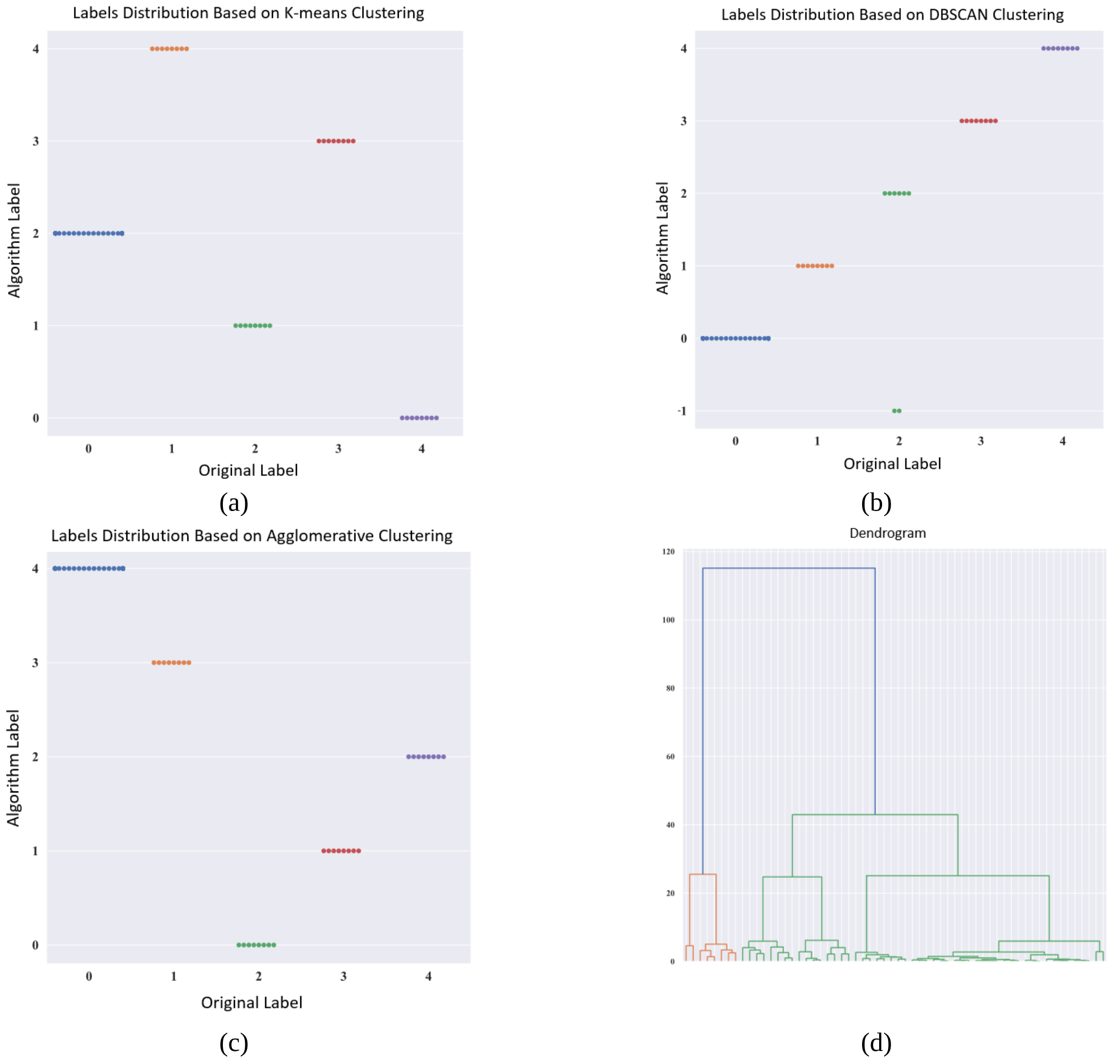


Figure 6. K-means (a), DBSCAN (b), and agglomerative clustering (c), and Dendrogram (d) for severity identification.

3.5 General case

In this last analysis, the entire database was considered, including the data of different severity and location of defects (Severity and Location Set). Thus, several challenges can be found for the subdivision of features. According to Figure 7, the algorithms performed a great effort to completely classify the database.

Analyzing Figure 7 (a), Figure 7 (c) and Figure 7 (d), it is possible to note the similarity of the estimated number of clusters using the k-means and hierarchical (agglomerative clustering) methods, and also by the analysis of the dendrogram, since the subdivisions become small for values greater than 15, indicating that the methods would return data classified more diffusely with a greater number of clusters. In these conditions, the DBSCAN method was able to separate the data in the same number of true labels, as can be seen in Figure 7 (b). However, for this to occur, the hyperparameters of the algorithm were severely modified (radius of 1 and 2 minimum samples), generating a large number of features labeled as noise (label -1), in addition to subdividing equal groups of defects (for example, true label 2). Thus, despite the correct number of labels, its performance was inferior when compared to the k-means and the hierarchical methods, as its final classification is very different from the original classification.

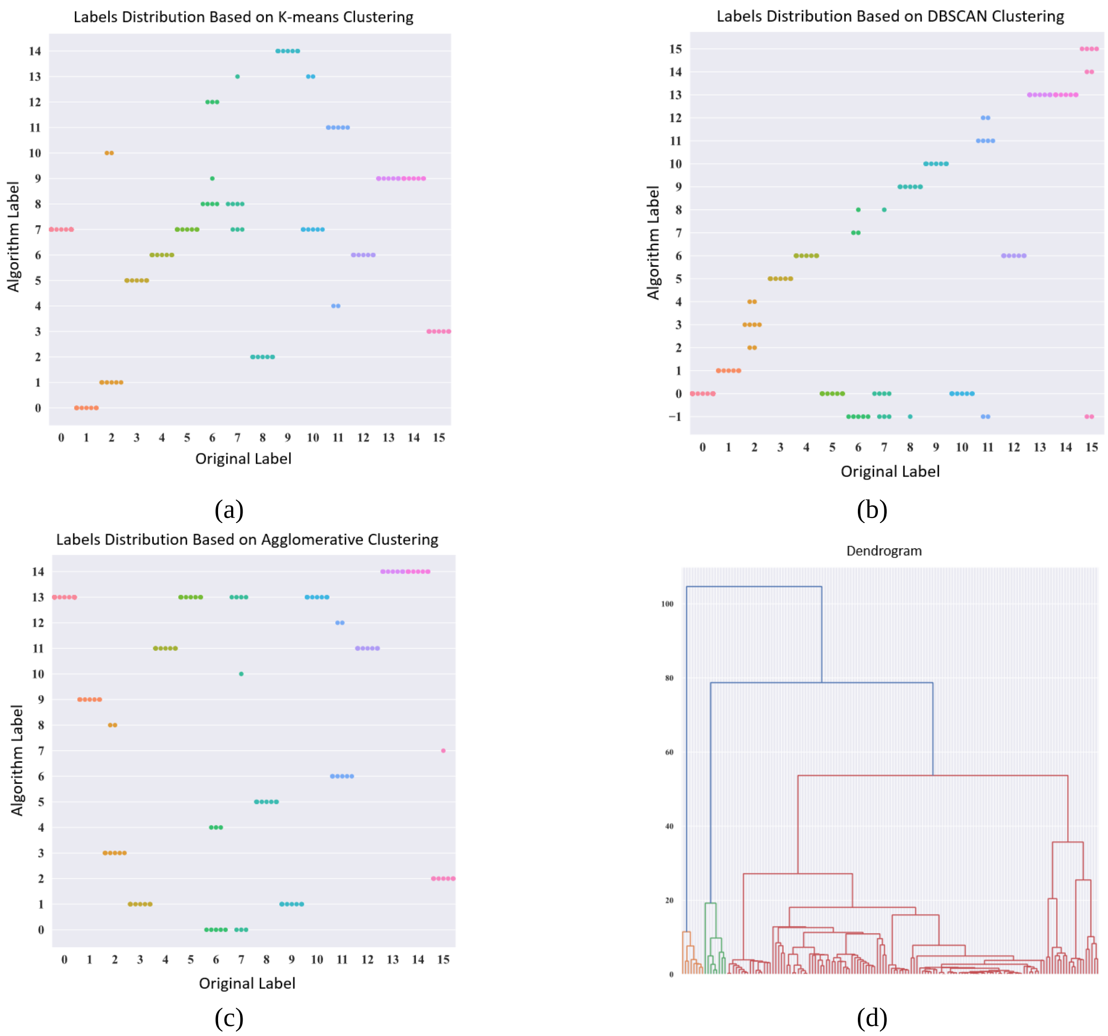


Figure 7. K-means (a), DBSCAN (b), and agglomerative clustering (c), and Dendrogram (d) for the general case.

3.6 Accuracy

For the k-means method, 100 tests were performed and the accuracy of the identification was calculated for each test. The mean and standard deviation of the accuracy are shown in Table 2 and Table 3, respectively. Considering that the DBSCAN and agglomerative algorithms are deterministic, only one test was performed to compute the accuracy. The results are also shown in Table 2.

Table 2. Average accuracy for the fault identification in the 100 tests.

Method	Location	Severity	General
K-means with correct number of clusters	92.5%	99.6%	77.7%
K-means with estimated number of clusters	86.8%	99.6%	77.5%
DBSCAN	88.2%	99.6%	62.8%
Hierarchical	88.2%	100.0%	62.8%

Table 3. Standard deviation of the accuracy for the fault identification in the 100 tests.

Method	Location	Severity	General
K-means with known number of clusters	0.044	0.022	0.055
K-means with estimated number of clusters	0.025	0.022	0.051

As seen in the tables, the differences between the accuracy with the correct value and the estimated number of clusters were minimal. Even using the number of data labels as the number of clusters, there is no 100% accuracy. This shows that there are cases in which data belonging to the same label ends up being separated. This phenomenon can occur due two reasons: the existence of a similarity between the features for these cases or the existence of some uncertainty in the k-means method, caused, for example, by the initialization of centroids.

The major difference was observed in the Location Set. The occurrence of this result, accompanied by high values for the standard deviation, may indicate that the extra uncertainty is due to the similarity between features. This phenomenon was also verified in the analyses of the Silhouette coefficient.

Finally, comparing the accuracy of the different sets, all have presented high values. However, there is a slight decrease in accuracy and an increase in the standard deviation of the set containing all the data (Severity and Location Set). This happens for all methods and may suggest a relative complexity of this set of features.

The k-means method was the one that achieved the best results for the Location Set and Severity and Location Set, but for the Location Set, the superior performance depends on previous knowledge of the number of clusters. For the Severity Set, the best result was obtained with hierarchical method (agglomerative clustering).

4. CONCLUSIONS

In this paper, three unsupervised learning methods were evaluated to classify a database of acceleration signals of bearing with different location and severity of faults.

The three methods (k-means, hierarchical and DBSCAN) were chosen because they tend to behave quite different depending on the disposition of the features, as shown in literature. The k-means and hierarchical methods require an initial number of clusters, which was determined from three different metrics: Silhouette, Davies-Bouldin, and Elbow. Finally, the techniques to estimate the number of clusters and the clustering algorithms for fault identification were applied to three sets extracted from the database.

Based on the CWRU database, the results showed that the metrics to determine the number of clusters are equivalent, since they generated close results. With the numbers of clusters determined, the data clustering was evaluated according to the accuracy in each set. The results showed that the k-means method, one of the simplest and most common methods of clustering, was the one that best performed to separate the data. Equally, the agglomerative algorithm (hierarchical method) achieved performance and results similar to k-means. Regarding the DBSCAN method, despite determining the correct number of labels for the general case, it associated several different labels, impairing its accuracy.

Finally, the results obtained in this paper indicate that these methods of unsupervised learning represent a promising tool for bearing fault analysis. The potential is evidenced by clustering the data under different conditions and by small interaction required, becoming more advantageous for application on real machines. These positive aspects encourage the development of specific techniques, in order to obtain more robust and accurate results for fault identification in rotating machines.

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