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Dynamic classification method of fault indicators for bearings' monitoring

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Abstract – This paper introduces a dynamic classification method inspired by DBSCAN clustering method for machine condition monitoring in general and for bearings in particular. This method has been developed for two purposes; first to monitor the health condition of a bearing in real time and second to study the behavior of defected rolling element bearing. To fulfill those purposes, the temporal indicator RMS (Root Mean Square) has been chosen as an indicator of the bearing health condition; this indicator has been computed from signals extracted from an experimental bench by two piezoelectric sensors placed radially and axially. The decision upon the right classification method was taken after a comparative study between two classical of the clustering methods (K-means and Density Based Spatial Clustering of Applications with Noise DBSCAN), which led to the conclusion that DBSCAN is more adapted to vibratory signals. DBSCAN was re-adapted to follow any changing in bearings behavior.

Key words: Bearings / classification / monitoring / K-means / DBSCAN

1 Introduction

Rolling element bearings are essential components in domestic and industrial applications. Bearings, however, are generally considered as critical mechanical components since a defect not detected on time may cause catastrophic damages. Therefore, a correct and continuous monitoring of their health condition is vital for maintaining a smooth and interrupted functioning of the machine.

Different methods are used for detection and diagnosis of bearings' defects, most of which originate from vibratory analysis. Vibrations' analysis success is explained by its capacity to meet all the constraints needed to assure a strong and reliable monitoring strategy.

The main principle of vibratory analysis's detection techniques consists of extracting indicators capable of identifying the bearings' condition from a recorded signal in its temporal or frequency form. These scalar indicators, such as Kurtosis, crest factor, root mean square, magnitude of characteristic frequencies of defects, or others, can characterize the exact condition of a functioning machine [1,2]. The efficiency of these indicators increases for machines with relatively simple kinematics. In fact, these indicators are very sensitive to noise and to sensors' position. In addition to traditional tools of monitoring, classification methods can be used to detect the presence of one (or more) defect(s) in a mechanical component [3,4]. The time tracking of these indicators by a dynamic classification is useful to assess the severity of the defect and prognosis the failure.

In fact, the application of classification methods to detect flaws in mechanical components has attracted considerable interest in recent years. Despite that, all the used classification methods were static, many research questions remaining open, including the choice of a classification method, the selection of the optimal indicator for bearing health monitoring, the decision of static vs. dynamic classification schemes, and the behavior of the bearing once defected.

In this paper, we introduce a dynamic classification method of scalar indicators for machine monitoring in general and for bearing monitoring in particular. The main objective of this process is to predict the end of life of the followed component; this method is capable of classifying scalar indicators in real time, and it has been validated on a fatigue bench.

2 Classification methods

Classification is a widespread descriptive data mining technique, used to extract or find useful information that could be hidden in a large amount of data. This data processing technique gathers in a limited number of clusters, objects that are similar according to proximity or a

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resemblance criterion [5]. The criterion can be, for example, a distance or a correlation; and is chosen in general according to the properties that the objects share.

Static classification, however, omits the time changes exhibited by data and so the classes as well, which results in one inert distribution of data into static classes. Indeed a static classification of changing data couldn't be considered throughout representation of a real life system that naturally changes over time to switch from normal to abnormal functioning.

Static and dynamic classification use classifiers to distribute data to their classes or clusters. Classifiers can be either supervised or unsupervised. Supervised classifiers are usually used when the characteristics of the clusters are known beforehand; whereas unsupervised classifiers are used to find natural groupings of data [6], and they are used when no prior knowledge of the classes is available.

Unsupervised classifiers are more suitable for our purposes, since the prior knowledge of the system (bearings vibratory' behavior) is limited, if any, the choice of classifiers is narrowed down to unsupervised ones. The unsupervised classifiers will be used to study the evolution of scalar indicators over time, and group them into classes representing the bearing's degradation state.

Unsupervised classification is divided into three categories: partitioning, hierarchical, and mixed methods [7]. The choice of the right classifier has to be done according to the final application, the type data, the number of classes, the system dynamics, the number of dimensions, etc.

In this paper we introduce a dynamic classification method developed for bearings monitoring, the choice of the right classifier was done after a comparison of two standard unsupervised classification methods (K-means and DBSCAN), in which DBSCAN showed better adaptability to the nature of data and yield better performances in classification, as a result a dynamic classification method inspired by DSBCAN was developed for monitoring the condition of a bearing.

2.1 Classification method by partitioning: *K*-means

K-means is the most known partitioning method. This algorithm performs a strict partition ("hard"), which means that each object is assigned to only one cluster. The algorithm is iterative and its partitioning principle is very simple, consisting of classifying a set of elements $M = \{m_1, m_2 \dots m_n\}$ in a K number of clusters; K is specified by the user.

The final result of partitioning by K-means is made so that the elements within a cluster are as similar as possible, and the most distinct elements belong to other groups. The grouping is performed in two steps: first, we must define the K centroids or prototypes of each cluster (usually the initial choice of centers is arbitrary). Second each point or object is then assigned to the nearest center. Each grouping of points associated with a center becomes a cluster. The center of gravity of the newly formed class is updated at every iteration. Assignments and updates are repeated until the changes to the points do not cause changes in clusters or until the centroids no longer move.

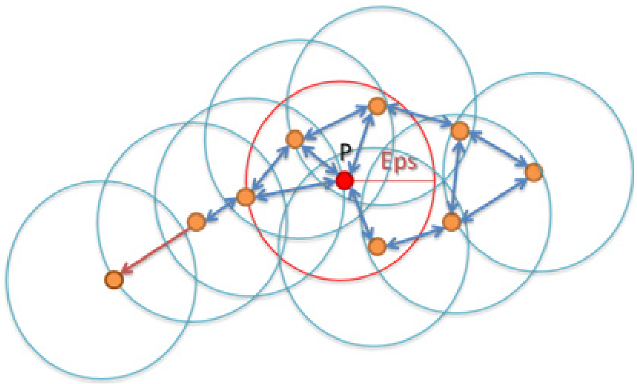

Fig. 1. Creation of a cluster by the DBSCAN algorithm.

The advantages of partitioning methods, especially K-means, are manifold. The complexity of this method is linear, i.e. its execution time is proportional to the number n of individuals, which makes it applicable to large amount of data. This method is easy to implement and the obtained clusters are challenged at each iteration. The K-means algorithm is however unstable; its final partitions depend essentially on the arbitrary choice of initial centers. It is unable to find clusters of a form other than the sphere, and the number K of classes must be known beforehand. If this number does not match the actual configuration of the cloud of individuals, the classification method does not give satisfactory results [6,7].

The K-means method has been used in the context of monitoring rotating machines. Yiakopoulos et al. [3] have used a modified version of K-means, combined with frequency-indicators to detect and locate bearing defects.

2.2 Agglomerative hierarchical clustering method: density estimation method DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

Density estimation methods are among the most likely methods to detect data clusters of complex shapes. These methods are borrowed from statistics, and their basic idea is to locate high density regions and separate them from each other with low density regions. Each region is a cluster defined as a densely connected component (Fig. 1).

The DBSCAN algorithm has the advantage of finding by itself the evolution of the number of clusters. It can also manage any type of data and consider outliers that are not assigned to any identified cluster [5,6]. Moreover, it has a few parameters to adjust and it is insensitive to noise [8,9].

Using DBSCAN requires defining two parameters: *Eps* and *MinPts*. *Eps* defines the neighbourhood radius or the maximum distance between two points of the same cluster. *Minpts* defines the density threshold that corresponds to the minimum number of objects in the neighbourhood of a point. The DBSCAN clustering is initialized by the arbitrary choice of a point p, then it performs a search for all items that are at a distance less than or equal to *Eps* so to form a cluster. If the number of items found is greater than or equal to *MinPts*, it will be considered as part of a cluster. It then goes through the neighbourhood step by step to find the set of points in the cluster.

3 Dynamic clustering method inspired by DBSCAN

Generally, the selection of the right classification method has to be realized according to the system on which the method is applied. However, DBSCAN is a standard classification method for this reason this dynamic method can be applied for other purposes.

The choice of DBSCAN as a classifier resides in the fact that DBSCAN uses the density as a separator and not just a simple distance; this is important because the data collected from bearings have several characteristics: first the indicators of similar health condition are naturally grouped in a cluster, second the density of each group of points (cluster) is different from the others, whenever the state of the bearing changes (such as increase of the fault surface) new clusters are created with a different density.

The basic idea of the proposed algorithm is to introduce the time concept into a static classification method (DBSCAN), so it would classify data (indicators) in real time. The originality of this algorithm lies in the concept of recursion and conditional events. The algorithm DBSCAN self-executes once new data arrives.

Algorithm:

```
Input:
Minpts; // minimum number of items in a cluster.
Eps ; // neighborhood radius.
Outputs:
K={k1,k2,….,kn};
Start:
  M={ }; // Set of unclassified items (initially empty) .
  K=0 ; // Initialization of the number of clusters
  C = {} ; // Set of clusters
    Do
        If ( event= true) then // If a new signal is recorded
            Update ( M,nv) ; // Update M
              For i=1 to n do // n : Number of M elements
                  If (mi doesn't belong to any cluster) then
                      X={mi / |mj-mi|<Eps};
                       If card(X)>MinPts then
                          K=K+1;
                          Ck=X;
    While (running)
End
```

The algorithm is a two phases' process; classification, and updating.

When the new signal is received, the indicators are extracted, and then the set of elements to classify is updated to include the new set of points belonging to the new signal **nv**. Once the updating is over, the classification is done normally for the updated set of points.

The classification is done normally by DBSCAN whenever a new signal is arriving, each new signal is represented by a set of points $m = 1, 2, 3, \ldots s$, with s the number of points representing the signal.

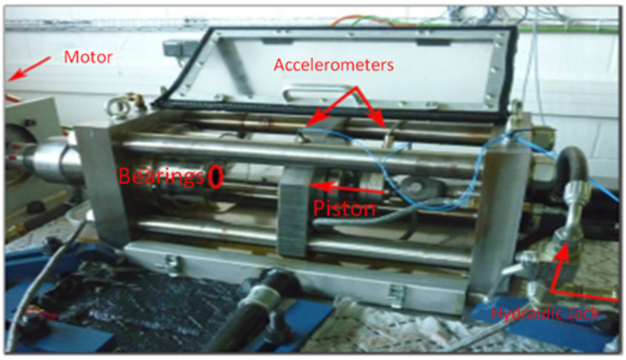

Fig. 2. Experimental bench.

Fig. 3. Thrust bearings single direction (SNR 51207), with the spalling highlighted.

The condition of creation of a new cluster depends on the fulfillment of two conditions; if the current point m_i can't be attribute to any former cluster and if the number of elements of X (the set of points found in the neighbourhood of m_i) is superior than *Minpts* then a new cluster is created, the number of classes K is incremented, and the set C of clusters is updated to include the new cluster with its points (X).

4 Experimental device

The proposed techniques have been implemented on an experimental bench (Fig. 2) consisting of a motor driving the shaft in rotation at 1800 rpm, a bearing hosting one of the two tested thrust ball bearing's raceway, a piston on which the other raceway is placed, and a hydraulic jack for exerting the preload by means of the piston. Two piezoelectric accelerometers are placed radially and axially on the frame that is holding the race of the thrust ball bearing.

The operation consists of placing one race of the thrust ball on the fixed landing, and the other race with the balls on the loose bearing. The plunger is then actuated to turn the assembly of the races in contact. Pressure is adjusted to obtain a load of 30 000 N. The system is rotated through the engine until the occurrence of a spalling defect on the track of the thrust ball (noise characteristic). At this stage, we carried out a visual inspection of the defect size scaling steadily (Fig. 3). After the inspection,

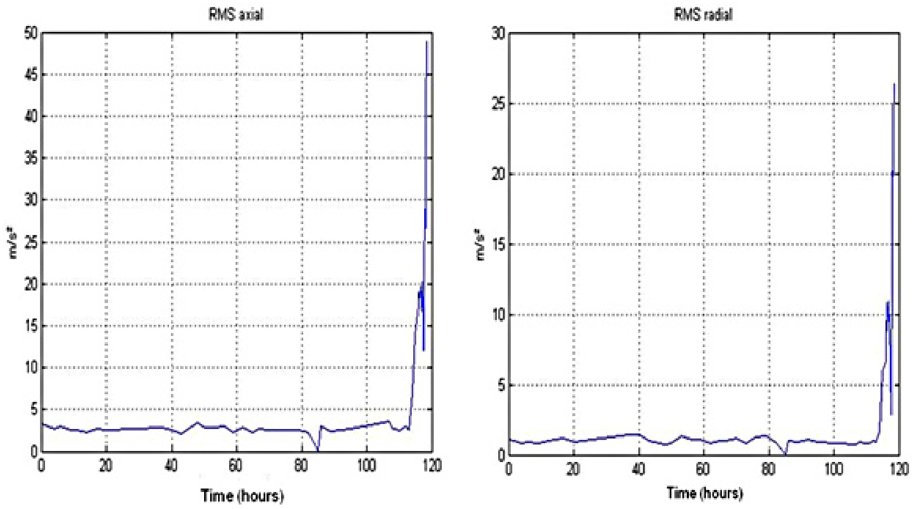

Fig. 4. The evolution of the RMS value over time.

the thrust ball bearing is returned to its place and the system is reset. This is repeated until one considers that the fault becomes too large, or the thrust ball is ruined. The tested thrust ball bearing is a thrust ball bearing single direction SNR51207 reference. It has 12 balls and a dynamic load capacity ISO C of 39 000 N (Fig. 3).

To implement the classification methods, we were particularly interested in a trial that lasted 120 h.

As we have already mentioned, there are several types of indicators used for fault detection. We focus on scalar indicators given their simplicity and popularity in industry. From the vibration signals recorded at different times, several indicators were calculated (RMS, peak to peak factor, Kurtosis). After analyzing these indicators, it appeared that the RMS indicator was the most relevant. The specificity of the bench does not allow the use of other indicators.

The RMS (Root Mean Square) value is the most commonly used scalar indicator. It measures the average energy of the signal, and it is used to detect abnormally high energy dissipation accompanying the birth of a defect. The RMS is the root of the mean square of the signal $x(t)$.

$$V_{\mathrm{rms}} = \sqrt{\frac{1}{T} \int_{t}^{t+T} x^2(t)\mathrm{d}t}$$

T represents the recording time of the signal.

5 Results and discussion

Figure 4 shows the evolution of the axial RMS (sensor placed axially) and radial RMS (sensor placed radially) as a function of time (hours).

In Figure 5, we can see a change in RMS values around $t = 114$ h. This change corresponds to a bearing failure (2.7 mm^2 spalling on the race). These RMS values increase up to $t = 116$ h, then decrease until $t = 117$ h, and then rise again from $t = 117$ h. The decrease corresponds to the simultaneous passage of two balls in the defect with the length corresponding to the surface covering two balls (60 mm^2 spalling).

The graphical representation of the radial RMS in function of the axial RMS clearly shows the evolution of the ruin of the bearing (Fig. 6). We observe that the points (RMS radial/axial) are grouped into seven clouds separated from each other. The first cloud is around the value of 0 m/s^2, the latest lies between the values 16 m/s^2 and 30 m/s^2 (radial RMS). The formation of these seven clouds corresponds to changes in the average energy of the signal due to the increase of the surface defect; these changes are visible only if we display the RMS radial/RMS axial. To better study the reasons behind the formation of these clouds, we were oriented toward the classification method.

Our first choice of a classification method was K-means for its simplicity and its history in the field of rotating machinery diagnosis. We set K-means so it would find the same clusters distinguished with the naked eye (Fig. 7).

The clusters found by K-means do not correspond to the clouds discerned with the naked eye. Partitioning with K-means can achieve an error rate of 45% point/class. This is explained by the fact that K-means is better suited to clusters that have a spherical shape, while clusters of the recorded signals are of irregular shapes.

Our second choice was the DBSCAN algorithm because it can recognize classes of irregular shape, it does not require a priori knowledge of the number of classes, it used the density as a separator, and since in Figure 6 we can see clearly that the density of clusters changes from one cluster to another. The application of DBSCAN on our indicators (Fig. 8) gave better results compared to K-means, and it could discern the correct clusters with a success rate of 100%.

The DBSCAN parameters *Eps* and *Minpts* were set to 10 and 4 respectively.

The dynamic method inspired by DBSCAN was applied to the same data to which K-means and DBSCAN were applied. The results of this method are shown in Figure 9.

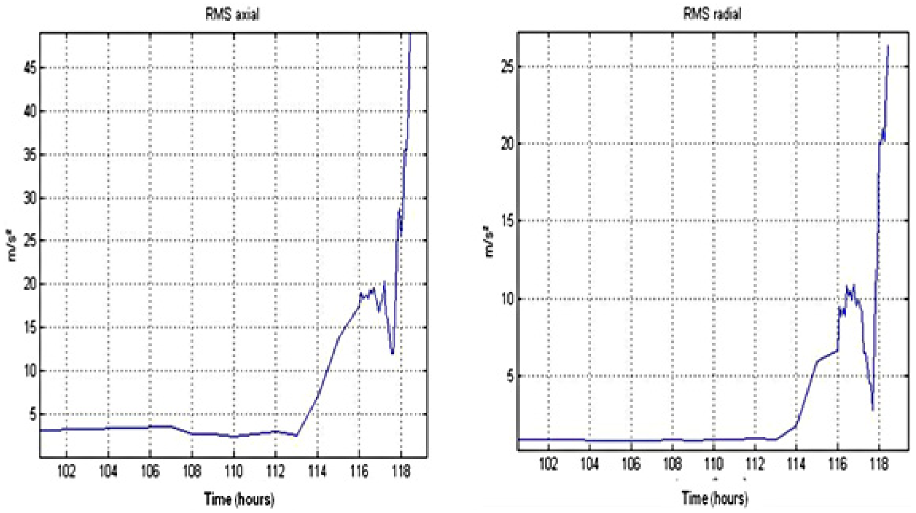

Fig. 5. Evolution of the RMS values between 100 h and 120 h.

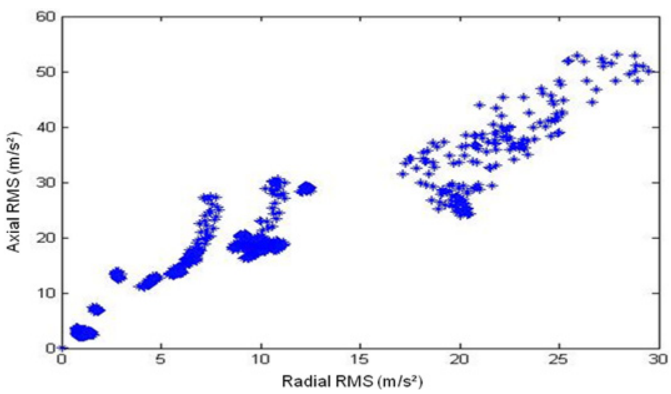

Fig. 6. Radial RMS and axial RMS.

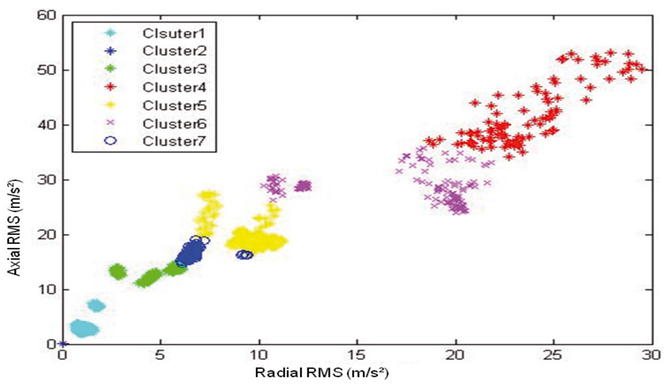

Fig. 7. The different clusters formed by K-means.

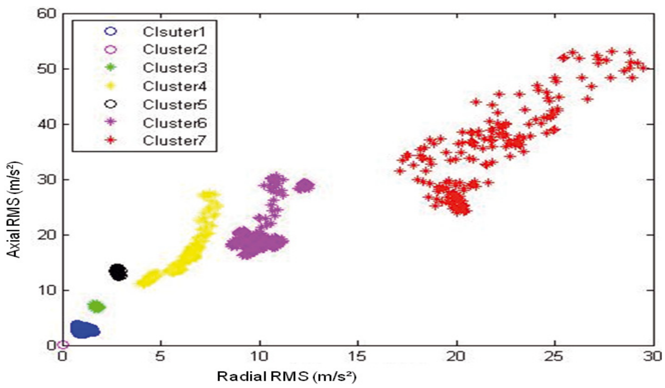

Fig. 8. The clusters found by DBSCAN.

The correspondence between the clusters determined by the dynamic classification (Fig. 9) and the surface of the defect showed that each appearance of a new class corresponds to a new state of degradation of the bearing; the 7 clusters correspond to different fault dimensions, the first cluster correspond to a healthy bearing, the second one to a bearing with a fault surface less than 2 mm^2, the third one to a fault' surface between 27 mm^2 and 22 mm^2, the fourth one is representing a bearing with a fault surface between 22 mm^2 and 65 mm^2, the fifth one of 66 mm^2 and 83 mm^2, the sixth 83 and 127 mm^2, and the last cluster is for a fault surface superior than 127 mm^2. This correspondence showed the health state of the bearing can be characterized also by the cluster's characteristics such as its density, its surface, its spatial localization, its form, etc.

DBSCAN as any other method requiring the initialization of parameters, its classification' results depend on the initialization of *Eps* and *Minpts*, and specially of *Eps*, however there is an heuristic that can help to find the right value of *Eps* called K-distance graph [10].

The DBSCAN clustering method allows dynamic real-time monitoring of bearing condition and assesses the severity of the defect. It also enables the automation of monitoring indicators, which will facilitate its integration into a monitoring system that is similar to an expert system.

6 Conclusion and perspectives

A classification method based on dynamic DBSCAN has been presented for monitoring indicators bearing

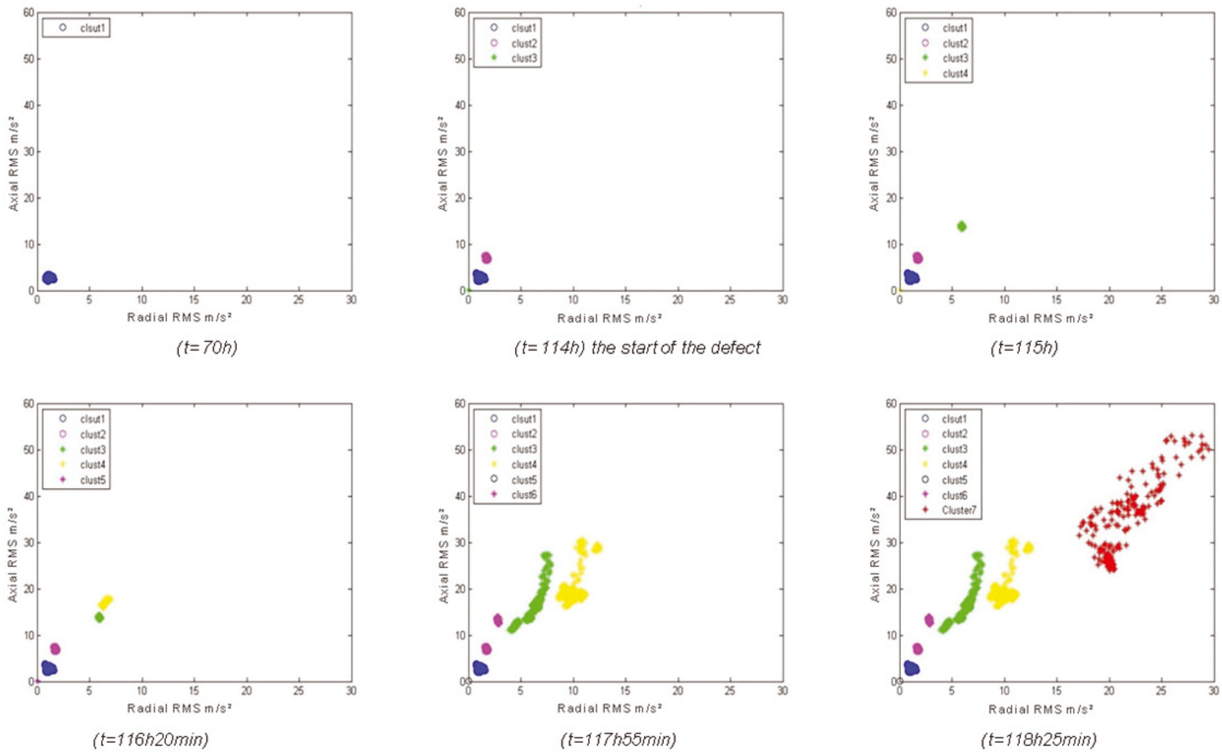

Fig. 9. Dynamic classification of RMS values by the proposed algorithm.

defects; its originality lies in its dynamic aspect that incorporates the concept of time.

The comparative study of unsupervised classification methods showed the performance of the method DBSCAN compared to K-means for vibration signals. We have adopted the principle of density as a criterion for partitioning the dynamic clustering method.

This method has been tested and validated on real signals taken from a trial bench. We also compared the results with those of the static DBSCAN method.

The proposed approach achieves a dynamic classification of RMS axial/radial. This partitioning clearly illustrates the progression of the state of degradation of the bearing over time.

We are currently working on the application of this classification method with other indicators of defect by exploiting cyclostationarity bearing vibration signatures [11,12]. We are trying to exploit the clusters characteristics to enhance the monitoring process. Moreover, we investigate the possibility of using this method of classification in the context of a predictive maintenance strategy.

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