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FAULT DIAGNOSIS OF ROLLING BEARINGS USING UNSUPERVISED DYNAMIC TIME WARPING-AIDED ARTIFICIAL IMMUNE SYSTEM

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Abstract. Rotating machines heavily rely on an intricate network of interconnected sub-components, with bearing failures accounting for a substantial proportion (40% to 90%) of all such failures. To address this issue, intelligent algorithms have been developed to evaluate vibrational signals and accurately detect faults, thereby reducing the reliance on expert knowledge and lowering maintenance costs. Within the field of machine learning, Artificial Immune Systems (AIS) have exhibited notable potential, with applications ranging from malware detection in computer systems to fault detection in bearings, which is the primary focus of this study. In pursuit of this objective, we propose a novel procedure for detecting novel instances of anomalies in varying operating conditions, utilizing only the signals derived from the healthy state of the analyzed machine. Our approach incorporates AIS augmented by Dynamic Time Warping (DTW). The experimental outcomes demonstrate that the AIS-DTW method yields a considerable improvement in anomaly detection rates (up to 53.83%) compared to the conventional AIS. In summary, our findings indicate that our method represents a significant advancement in enhancing the resilience of AIS-based novelty detection, thereby bolstering the reliability of rotating machines and reducing the need for expertise in bearing fault detection.

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1. Introduction

The indispensability of rotating machines in today's industry is widely acknowledged. These machines comprise a complex network of interconnected and interdependent components, with bearings playing a pivotal role [14]. Notably,

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bearings have been implicated in 40% of failures observed in large machines, a figure that escalates to 90% when examining smaller machines [13, 21]. In essence, the malfunction of a bearing leads to a complete disruption of the machine's functionality, a scenario that frequently occurs. Consequently, extensive research efforts have been dedicated to the development of intelligent algorithms capable of robustly processing and detecting faults, with a particular emphasis on urgent situations such as real-time detection. These algorithms leverage vibrational signal analysis as a means of fault diagnosis [13, 19].

Traditionally, the detection of faults has been done through the use of costly experience and invaluable engineering expertise, by which, for an ever-growing automation in manufacturing processes, the need for intelligent and automatic systems of detection has become vital [15]. However, with the advent of smart and low-cost data acquisition systems, a huge volume of data (signals) has overwhelmed detection systems and created a whole new problem: the excess of useless information, which leads to two of the logical constraints for an intelligent system, which are to be able to filter unnecessary data and extract meaningful features [15].

As an addition to the aforementioned constraints, the detection system must also cope with varying working conditions [17]. That is, the operational parameters (e.g.: load and rotational speed) customarily change over time, as modifications to the production are requested. This, in turn, modifies the perception of available data, and the system should be able to promptly adapt [22]. Finally, one more constraint is that the data from the damaged state may simply not be available for training a model of detection. That can be a matter of cost, meaning that testing with an expensive machine might not be an optimal solution, or a matter of complexity or feasibility, when the damages pursued are not easily modeled or the model is not known [8]. In that case, the goal is to create a one-class classifier (healthy or nominal state), usually named as novelty detection, which is a topic that has lately attracted more research [8, 25].

Novelty detection (ND) is based on the idea that if an observation is found to be outside a limited subspace of reference (healthy state) within the feature space, then it is said that a novelty has occurred [10]. One of the main problems of ND is finding a proper threshold that distinguishes the novelty from the normal state [8]. To accomplish this, researchers usually apply the Euclidean or Mahalanobis distances as metrics for comparison [23] and, for example, [3] used the latter to set a novelty index for the detection of faults in wind turbine bearings.

However, it has been argued that the detection of faults in bearings could present particular challenges. The frequencies generated by the vibration of bearing spheres rolling over defects distribute their energy across a wide spectrum, which would remain hidden in traditional statistical analysis due to noise and low-frequency phenomena [24]. To cope with this and the constraints stated before, fault diagnosis of bearings became a hotspot of research in the artificial intelligence (AI) community [2, 11, 12].

One of the AI techniques that has increasingly attracted the attention of researchers is Artificial Immune Systems (AIS) [2]. An extensive review of AIS-based algorithms for fault diagnosis can be found in [2]. The basic concept of AIS is inspired by the action of T cells, a part of the human immune system, which possess surface receptors capable of detecting foreign particles after a censoring phase that prevents the immune system from reacting with the host body [9]. Initially, AIS was proposed to protect computers from foreign attacks such as viruses and malware [7]. Later, Dasgupta et al. [7] extended the basic algorithm from [9] to process time-series arrays. These ideas have led to the development of various algorithms, including fault diagnosis systems, which can be categorized into three groups: immune network-based, one-signal approach, and two-signal-based [2]. The present work focuses on the two-signal-based approach. In an AIS two-signal-based fault detection system, the first signal provides information to warn of a possible fault, and the second signal confirms it, thus reducing false positive alarms [2]. To enhance the detection accuracy, many authors have proposed modifications to AIS algorithm implementations. For instance, in [16], vibration signals undergo a wavelet transformation prior to the negative selection procedure and fault diagnosis. In [14], a method is proposed to optimize the number of antibodies (detectors) in the AIS system, using a multi-objective approach that maximizes the region covered by the antibodies in the feature space and minimizes their density by evenly distributing them. Furthermore, [1] suggests both an optimization of the detector set and a feature space-based AIS.

Finally, considering the aforementioned problems and constraints, and taking into account recent developments in the AIS community, we propose a new modification of AIS. Our approach is characterized as data-driven, requiring minimal expert knowledge, flexible enough to handle varying working conditions, and guided by the healthy state information only. Additionally, we present results indicating the optimization potential of our approach. Specifically, in this study, we utilize one of the procedures of Dynamic Time Warping (DTW) to assist in calculating the affinity rate, which is subsequently used for ND. The DTW algorithm compares two time-series inputs by calculating the point-by-point Euclidean distance and determining the comparison path that minimizes the overall distance between the series. A concise explanation of this method is provided in the following section. By applying this approach, we compare signals from a publicly available rolling bearing benchmark dataset [6] at different rotational speeds, extract the affinity rate between these signals, and implement a simple threshold scheme for ND. Additionally, in this work, we implement both the new AIS-DTW approach and the original AIS approach to compare the overall performance improvement of our method. Furthermore, we describe the preprocessing procedure, which utilizes Z-score normalization to mitigate bias caused by signal amplitude and mean. Unlike previous studies, we do not extract features from the signals; instead, the affinity rate provided by AIS serves as the feature itself for classification. In summary, this work introduces and tests a novel approach named AIS-DTW.

2. Methodology

2.1. Artificial Immune System. To address the issue of recognizing self and non-self information strings in computers, Forrest et al. [9] introduced a method known as Artificial Immune System (AIS). This algorithm takes inspiration from the biological immune process that takes place in the thymus, which detects system changes. Initially, the AIS was developed to address computer security concerns, as mentioned in Forrest's article. However, its applications have expanded, and its use in fault detection in machines has been reported [18, 19].

The basic algorithm of AIS involves two main phases. Firstly, a set of self-strings (S) is defined, which contains the information to be protected. This set serves as the basis for generating another set called detectors (D) during the censoring phase. In the second phase, known as monitoring, the set of detectors (D) is compared with new data to calculate an affinity rate [9]. Using expert knowledge, a threshold for the affinity rate is established, which is then used to classify each vector of the new data as either self or non-self. To handle real-valued time series, Dasgupta and Forrest [7] proposed a different matching criterion called the partial matching rule. In this study, we investigate the role of the affinity rate in the AIS algorithm, and its calculation can be performed according to [4, 16], as follows:

$$t_{af} = A_n/A \tag{1}$$

here A_n is the number of matches obtained through the comparison of a vector and one of the detectors in (D), and A_t is the total length of each vector. This comparison is made with regards to a matching criterion which, as given in Outa et al. [18], can be written as:

$$d_{i,k} - dev < S_k < d_{i,k} + dev \tag{2}$$

where $d_{i,k}$ is the value of the ith detector vector at the kth position, S_k is the value at the kth position of the analyzed vector, and dev is a tolerance which is calculated or given by prior knowledge. In other words, if the value of the analyzed vector in a certain position falls in the interval given by Eq. 2, that position is said to have matched and will add a unity in A_n in Eq. 1.

3. Dynamic Time Warping

The AIS algorithm, as seen in Eq. 2, is directly applied to vectors using the same indexes on both for the matching criterion to calculate the affinity rate. However, variations (e.g., amplitude, phase, and mean) of the signal due to rotational speed might influence the comparison between a given signal and a detector, which could result in a biased amount of false positives or negatives. To tackle this problem, the Dynamic Time Warping Algorithm is proposed to make a more proper path of comparison between signals applied at the AIS. A graphical representation of DTW applied to two series extracted from sinusoids at different frequencies is shown in Fig. 1. In this figure, the difference between the regular Euclidean path (Fig. 1(a)) and the one calculated by the DTW (Fig. 1(b)) algorithm becomes clear if the reader focuses their attention on the maxima of both curves.

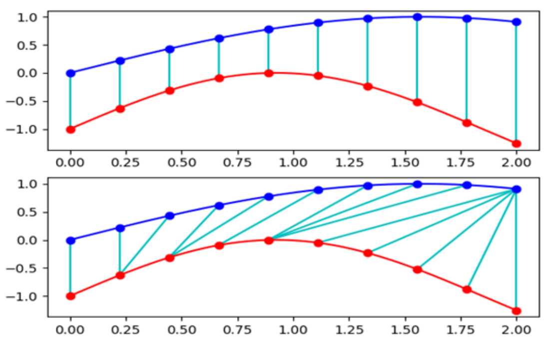

FIGURE 1. A graphical representation of the path of comparison using Euclidean distance (a) and the one calculated by the DTW algorithm (b).

This algorithm takes two time series inputs, $X = x_i$ for $i = 1, \ldots, N$ and $Y = y_j$ for $j = 1, \ldots, M$, where M and N are the lengths of the series X and Y, respectively. Then, a matrix D, usually named as the DTW distance matrix, has its elements $d(x_i, y_j)$ calculated by [20]:

$$d(x_i, y_i) = \sqrt{(x_i - y_i)^2} \tag{3}$$

The matrix D is then analysed through dynamic programming in order to find the warping path that minimizes the cumulative distance $\gamma(i, j)$ between the two compared signals, using the following expression (with a starting point at $\gamma(1, 1)$):

$$\gamma(i, j) = d(x_i, y_i) + min\{\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)\} \tag{4}$$

When the iteration process controlled by Eq. 4 ends, the warping path used to obtain the minimum cumulative distance is then applied to the AIS algorithm. Other authors usually use the DTW cumulative distance as a feature for comparison [20]. However, in this work, we propose using a different calculation of the affinity rate, which would only require the path and not the distance returned by the DTW algorithm.

4. Z-score Normalization

The AIS algorithm applied to raw vibration data is logically directly sensitive to the mean and variance of the signals, as observed in Eq. 2. In other words, depending on the difference of the mean between the antigen and the antibody, the calculated affinity rate can become heavily biased. To avoid this effect, we have chosen to apply the Z-score normalization by using the following equation:

$$z_i = \frac{x_i - \underline{x}}{\sigma} \tag{5}$$

where $\underline{x}$ and σ are the mean and the standard deviation of the vibration signal being normalized. Doing so provided a fair comparison between signals for the application of the AIS algorithm, unbiased from variations of rotational speed and amplitude due to faults on the bearings.

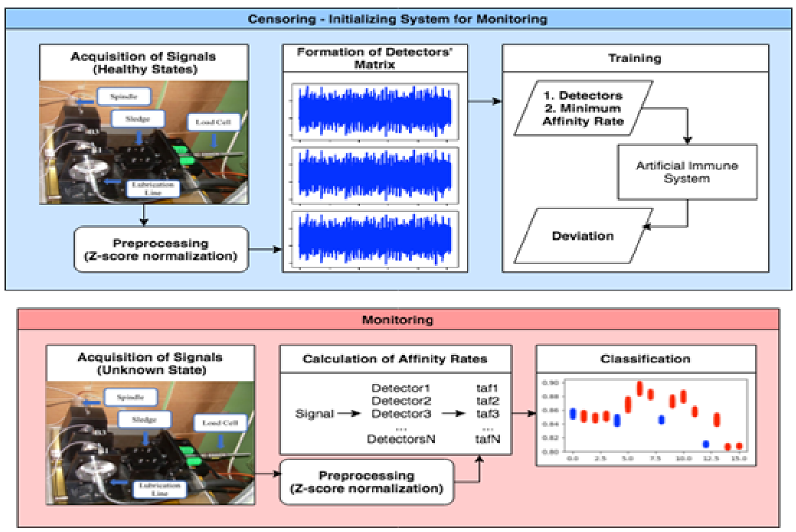

FIGURE 2. Proposed framework for the novelty detection of faults in bearings separated in two phases.

5. Proposed Framework

Figure 2 above depicts the framework used to extract the AIS-DTW features of the signals, and it is explained as follows. Firstly, vibration signals at a singular rotational speed from the healthy state of a machine are collected and normalized using the Z-score procedure (these will compose the detectors matrix of the AIS algorithm). A threshold for the affinity rate is chosen, which is 70% in the present work, as proposed in [16]. Then, through an iterative process, the basic AIS algorithm is applied to the detectors themselves to extract a deviation value that provides the chosen minimum affinity rate between all signals within the detectors' matrix. This process guarantees that the AIS can detect its own (healthy) signals with enough confidence (minimum affinity rate). This entire explanation summarizes the initialization of the system.

After initializing the system, the monitoring phase begins. Vibrational signals are acquired from an indeterminate state of the machine and subsequently compared to each signal in the matrix of detectors. Each comparison yields an affinity rate value, associating each analyzed signal with an array of affinity rates equivalent in size to the number of signals in the detectors' matrix.

6. Experimental Procedure

As a means to provide a solid foundation for comparison with other works, we have chosen to apply the present methodology to "The Politecnico di Torino" rolling bearings test rig [5]. This publicly and freely accessible experiment consists of a large amount of vibrational signals and is divided into two distinct investigations: 1. Different working conditions (rotational velocity and radial load) and damage severities, and 2. Endurance test with a single faulty bearing. This work focuses on the former investigation since it clearly distinguishes between healthy and faulty states of the machine.

The testing rig comprises three high-speed aeronautical rolling bearings, with two supporting the shaft and a larger one (B2) in the middle specifically supporting the applied load (when present). Two triaxial accelerometers were installed. For simplicity, we chose to apply the present methodology to the signals obtained from channel 2 (radial direction), which is closest to the damaged bearing, with no load applied to bearing B2. Furthermore, two types of damage were induced using a Rockwell tool, differentiated by the location on the bearing: 1. Inner ring and 2. Roller. The working conditions and damage severities analyzed in this work are summarized in Table 1. To investigate the use of a signal taken from a healthy condition and different working conditions than the ones analyzed, the detectors' matrix consists only of healthy signals from the 100 Hz rotational speed.

7. Results

7.1. Artificial Immune System. The AIS algorithm has been utilized in various studies to detect faults in machines by analyzing vibration signals, as mentioned earlier. To enable a comparison with the proposed method, the initial set of results is presented in Fig. 3. These results aim to showcase the potential performance of the Artificial Immune System when applied to POLITO's Dataset without utilizing DTW (the original proposition of the AIS). Each plot in this figure corresponds to a rotational speed, and each point represents the average affinity rate calculated from the array of affinity rates obtained for each analyzed signal, compared with all signals in the detectors' matrix of the AIS algorithm. It is important to note that not all values of the array of affinity rates are displayed due to its high dimensionality ($n = 100$, which represents the number of signals in the detectors' matrix). However, the mean value has proven to be a precise representation of the array of affinity rates. Finally, the x-axis represents the labeled state corresponding to each of the healthy and damaged states outlined in Table 1.

TABLE 1. Labels of each damaged situation, their extension and rotational speed.

Condition	**Label**	**Severity [μm]**	**Rotational Speed [Hz]**				
Healthy	0	**No Damage**	100	200	300	400	500
Damage Inner Ring	1	150					
	2	250		200	300	400	500
	3	450					
Damaged Roller	4	150					
	5	250		200	300	400	500
	6	450					

Fig. 3(a) - (d) represent the rotational speed from 200 to 500 Hz, respectively. It can be seen that the mean affinity rate, interpreted as a feature of the signal, becomes more sensitive to the damage as the rotational speed increases. This sensitivity does not show a correlation between the size of the damage and the value of the mean affinity rate. However, even in Fig. 3(a), corresponding to 200 Hz, a clear distinction between the healthy state and label 6 (roller with a 450 μm damage) is observed. Another observation is that the lowest degrees of damage (inner ring and roller with 150 μm damage, labels 1 and 4, respectively) showed a complete separation from the healthy state at 400 and 500 Hz velocities, which seems especially relevant considering that the operation of the machine could become more critical at higher velocities.

To numerically evaluate this progression, a simple fault detection method was implemented: if the mean affinity rate of a given signal falls between the maximum and minimum values of the mean affinity rate of the healthy state, the signal is classified as healthy; otherwise, it is classified as faulty. In this approach, we assume that the healthy state of the machine is known, which is typically the only available case in industrial practice and is characteristic of the ND approach [8]. By following this method, Table 2 is generated, which demonstrates an observed increase in detection performance as the rotational speed increases (100% would be ideal, similar to detecting 600 signals of faulty states). The percentages shown in the table do not include the healthy states, as they are properly detected based on the classification method that utilizes the maximum and minimum affinity rate among all signals labeled as healthy.

7.2. AIS-DTW. To the best knowledge of the authors, only one paper used DTW in conjunction with AIS for fault detection [6]. That paper, however, has some major differences with ours. Firstly, they analyzed time-series of variables

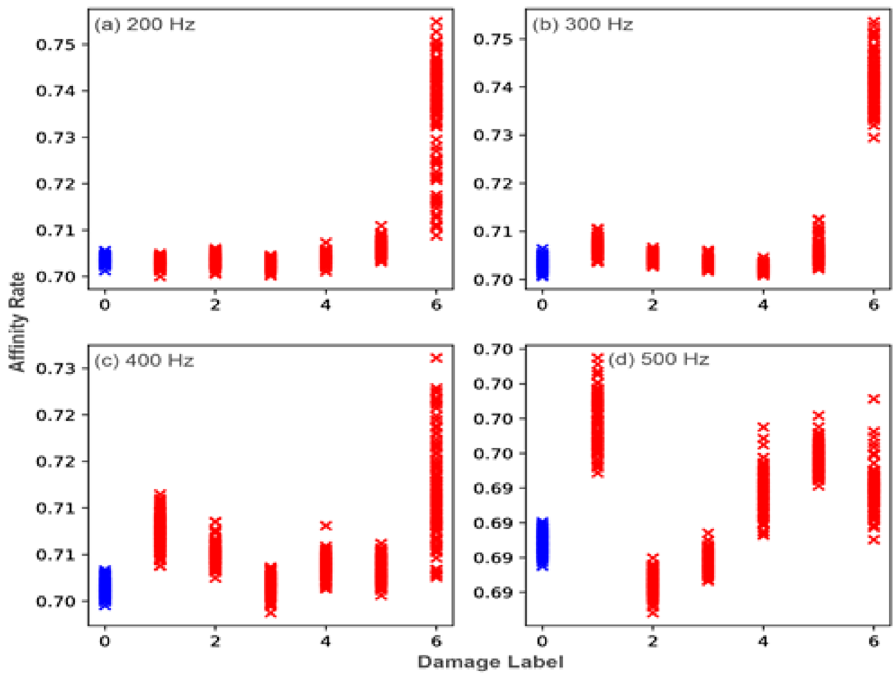

FIGURE 3. Affinity rate of the original AIS implementation for each damage label.

TABLE 2. Novelty detection percentage of the original AIS.

	200 Hz	300 Hz	400 Hz	500 Hz
Percentage of Detection	32.17%	31.17%	68.67%	85.5%

pertinent to batch chemical processes, which are not periodical phenomena. Secondly, the DTW algorithm was used to calculate a proper distance between an antibody and an antigen, which differs from our implementation because we are using the path calculated from DTW, not the distance. Lastly, their work was a classification problem with multi-categories, whereas the current work is within an ND paradigm. The uniqueness of our study relies on the unification of DTW and AIS algorithms, in a pursuit to extract the meaningful aspects from each of those methodologies, adapt and apply them to the context of fault diagnosis of bearings.

Continuing, we applied the DTW algorithm to calculate the path that would minimize the distance between the two time-series, as explained before, and used that path as a guide for calculating each affinity rate between a given signal and the signals in the detectors' matrix. Our modification essentially alters the application of Eq. 2, resulting in the following new inequality:

$$d_{i,k'} - dev < S_{k''} < d_{i,k'} + dev \tag{6}$$

where we changed the kth positions on both vectors to k'th and k"th, which are the positions calculated by the DTW, which denote the positions of each vector connect-ed by the cyan lines in Fig. 1 that will be effectively compared in Eq. 6. In this novel approach, the affinity rate can be found to be higher than unity, that is due to the path, calculated by the DTW, possibly being longer than the number of points in a given signal, as in affinity rate's definition (Eq. 1). Nevertheless, the same denomina-tor was used in all cases, which maintains the equality of procedure among all states and signals being analyzed.

Table 3. Novelty detection percentage of the proposed AIS-DTW and a comparison with the original algorithm.

	200 Hz	300 Hz	400 Hz	500 Hz
AIS	32.17%	31.17%	68.67%	85.5%
AIS-DTW	43.83%	85.00%	93.83%	94.00%
Absolute Difference	+11.66%	+53.83%	+25.16%	+8.5%

Figure 4 depicts the results from the proposed method. Each plot of said figure corresponds to a rotational speed and their y and x-axis represent the mean affinity rate and its label, respectively, as done in Fig. 3. A great distinction between healthy and damaged states, compared to the AIS method, is most clearly noticed on the rotational speeds of 300 and 400 Hz. Similarly, at 500 Hz, however not entirely comparable to Fig. 3, that difference remained, with a perceptible separation from the healthy state.

By utilizing the same fault detection method as in section 3.1, in combination with the results from Table 2, we present Table 3. This table exhibits a similar behavior to Table 2 regarding the increase in the detection percentage as the rotational speed rises. However, each percentage demonstrates a significant improvement compared to the standard AIS across all rotational speeds. The largest disparity between the two methods was observed at 300 Hz, while the smallest was at 500 Hz. It is important to note that these percentages do not measure the number of healthy signals detected, but rather only the damaged ones. This is due to the definition of the implemented method, which ensures the detection of all healthy signals.

7.3. Time Consumption and Percentage of Detection. The AIS algorithm utilized in this work compares two signals of the same length by computing the ratio between the number of points that fall within a specific interval (as shown in Eq. 2) and the length of both signals. Hence, the comparison path can be interpreted as a sequence of positions from both time-series denoted by

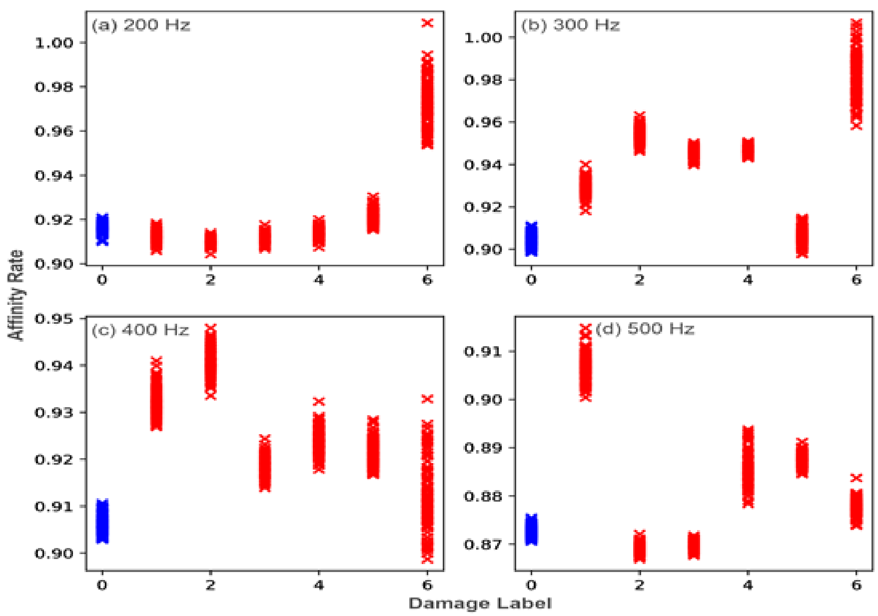

FIGURE 4. Affinity rate of the AIS-DTW for each damage label.

(i, i), where $i = 1, 2, \ldots, N$, and N represents the length of both signals. Interestingly, this comparison path does not require any additional calculations. On the contrary, the path obtained through DTW necessitates signal comparison utilizing the Euclidean distance, as explained in Section 1.2. This process involves numerous simple calculations (Eq. 1).

Therefore, the time spent effectively using a given path to compare two signals is nearly the same in AIS and AIS-DTW. The main distinction between these algorithms lies in the time spent calculating the path, which is negligible in AIS (as previously explained), but not the case with AIS-DTW. Each analyzed signal will have a specific DTW path of comparison with every signal in the detectors' matrix. The time required for one signal to be analyzed by the complete set of detectors (consisting of 100 healthy signals from a rotational speed of 100 Hz) is 111.13 ± 4.70s (mean $\pm$ SD), based on a sample of 50 analyzed signals using a GPU-accelerated computer routine (NVIDIA TESLA K80).

The time required for calculating DTW's path, however, can be reduced by decreasing the number of signals in the detectors' matrix. Table 4 demonstrates the relationship between the number of detectors and the total time taken in seconds by the proposed method to calculate the array of affinity rates for a single analyzed signal. Each value represents the mean from a sample of 10 signals, with the standard deviation shown in parentheses. A significant reduction in time is observed as the number of signals in the detectors' matrix decreases.

Although a smaller number of detectors leads to a shorter array of affinity rates calculated by the AIS algorithm, it also introduces more uncertainty, as indicated by the increased standard deviation in Table 5. This uncertainty could be attributed to the inherent variance of the signal throughout the entire acquisition period, as evident from the distribution of affinity rates for the healthy states depicted in Figures 4 and 5. The aforementioned table presents the detection percentage (using the previously explained simple detection method) as a function of the number of signals in the detectors' matrix. The values in the table represent the mean and standard deviation derived from a series of 1000 random classifications. This implies that the signals comprising the detectors' matrix were randomly selected from the initial dataset containing 100 available signals.

Table 5 reveals that reducing the number of detectors results in a decrease in detection performance, indicating that more signals from the damaged conditions exhibit affinity rates closer to those of the healthy conditions. The most significant loss of detection was observed at a rotational speed of 500 Hz (94.00% to 50.54%), while the lowest loss occurred at 300 Hz (85.00% to 83.68%). In addition to this loss, an increase in standard deviation is observed as the number of detectors decreases. However, this trend becomes noticeable only when the number of signals falls below 80.

Table 4. Time spent in seconds and their standard deviation for the processing of a single signal versus number of signals in detectors.

Number of Detectors	100	80	60	40	20
Time in Seconds	111.13 (4.70)	103.00 (5.11)	77.92 (4.06)	50.18 (1.20)	25.30 (0.96)
Number of Detectors	15	10	5	1	-
Time in Seconds	23.70 (0.82)	21.67 (0.73)	20.32 (0.46)	18.88 (0.04)	-

7.4. Discussion. Novelty or anomaly detection methods primarily rely on extracting features to tackle the two-class (healthy and faulty) classification problem. It has been shown that AIS is one of the possible machine learning algorithms that could address this issue by applying a direct comparison between signals from an unknown state and a baseline state which, in the present work, corresponds to the healthy state of the analyzed machine working at 100 Hz and characterizes the novelty detection technique [8]. Furthermore, the AIS algorithm translates the comparison between two signals into a value called the affinity rate. Differently from other works, here we interpret this rate as a feature of a given signal when it is compared to an array of signals (the detectors' matrix). By doing so, each analyzed signal can be objectively compared to those that are from the healthy state in a given working condition.

The first set of results shows that the AIS could reach at least 31.17% of detection of faulty states from the 300 Hz run and, with our implementation of said algorithm, a maximum of 85.5%. This difference suggests that both simulated damages (inner ring and roller indentation) seem to show a pronounced effect on the dynamics of the system on higher velocities which resulted in a clear distinction between the mean affinity rate of the healthy and damaged states.

Table 5. Percentage of detection versus number of signals in the detectors' matrix (1000 runs).

	100	80	60	40	20	15	10	5	1
200	43.83 (0.00)	43.83 (0.00)	43.83 (0.07)	43.74 (0.36)	43.17 (1.34)	42.64 (1.94)	41.90 (2.73)	38.98 (4.66)	28.12 (8.22)
300	85.00 (0.00)	85.00 (0.00)	85.00 (0.00)	85.00 (0.02)	84.98 (0.08)	84.96 (0.11)	84.91 (0.19)	84.75 (0.38)	83.68 (1.40)
400	93.83 (0.00)	93.83 (0.00)	93.82 (0.07)	93.71 (0.28)	93.34 (0.80)	93.13 (1.01)	92.48 (1.91)	90.17 (6.43)	73.38 (22.21)
500	94.00 (0.00)	94.00 (0.00)	93.83 (0.83)	93.09 (2.54)	88.47 (7.79)	85.89 (9.63)	81.45 (11.25)	74.96 (12.90)	50.54 (17.87)

To further enhance the efficiency of the AIS as a novelty detection algorithm, the DTW algorithm was implemented to aid the comparison path of the AIS routine. With this modification, all the mean values of every affinity rate array increased. This increase was expected since the path calculated by the DTW can have greater lengths than those of the signals. However, this does not affect the comparison between the healthy and damaged states, as the healthy state of each tested speed also had the same increase.

The important finding of this investigation is that the implementation of DTW made the difference between the healthy and damaged states clearer. This is supported by the fact that the AIS-DTW showed a considerable increase in detection compared to the simple algorithm explained earlier. The lowest percentage of anomaly detection was found to be 43.83% at 200 Hz, while the highest was 94.00% at 500 Hz.

Surprisingly, the velocity with the lowest percentage of detection (300 Hz) in the standard AIS showed the largest increase, rising from 31.17% to 85.00% with the use of AIS-DTW. Overall, the absolute differences in detection between AIS and AIS-DTW suggest that the 300 Hz run is a limiting case, indicating that damages start to have a noticeable effect after that velocity. Further analysis with additional signal features could be explored, but it is beyond the scope of the present work.

Finally, a time consumption analysis was conducted using the same computer setup. It was observed that the total time required to analyze a single signal is 111.13 s. However, this could be reduced to 18.88 s by decreasing the number of detectors in the detectors' matrix. Nonetheless, as expected, this reduction in time consumption was accompanied by a decrease in the detection percentage.

The largest drop in detection was observed at 500 Hz, while the smallest drop was at 300 Hz.

Moreover, the detection percentage at 300 Hz was found to be 83.68% with a standard deviation of only 1.40% when using a single signal in the detectors' matrix. This suggests that the machine used for the tests has a velocity at which the effects of damages on the vibrational signal become more pronounced with a further increase in velocity. Additionally, there might be an ideal velocity for detection, one that yields the clearest distinction between healthy and faulty states, as observed at 300 Hz using the affinity rates calculated by the AIS-DTW.

8. Conclusion

A new modification to the standard AIS algorithm, utilizing the path of comparison calculated by the DTW algorithm, is presented in this paper. The detectors' matrix used in this work consists of signals from a single rotational speed (100 Hz). The z-score normalization technique is explained and employed to enable this comparison. Our novel approach allows for the detection of faults in rolling bearings by analyzing vibrational signals from various rotational speeds, requiring minimal expert knowledge. We compared our new approach with the standard AIS, demonstrating an improvement in novelty detection (i.e., fault detection) performance through an experiment using a publicly available dataset. The increase in detection ranged from a minimum of 8.50% (from 85.50% to 94.00% fault detection at 500 Hz) to a maximum of 53.83% (from 31.17% to 85.00% at 300 Hz). Additionally, we investigated the time consumption required to analyze a single signal within our framework by varying the number of signals in the detectors' matrix. Reducing the number of signals from 100 to 80 resulted in a negligible loss of detection and a reduction of 8.13 s in time consumption (from a total of 111.13 s). In the extreme case of only one signal in the detectors' matrix, our algorithm takes 18.88 s to analyze a single signal. However, the detection rates decreased from 94.00% to 50.54% at 500 Hz and from 85.00% to 83.68% at 300 Hz, suggesting an ideal rotational speed for detection using our approach with The Politecnico di Torino's public dataset of vibrational signals. Overall, our approach has demonstrated the ability to detect faults by analyzing vibrational signals from different rotational speeds.

Conflicts of interest : The authors declare no conflict of interest.

Data availability : Not applicable

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