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Research Article

Shannon Entropy and K-Means Method for Automatic Diagnosis of Broken Rotor Bars in Induction Motors Using Vibration Signals

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For industry, the induction motors are essential elements in production chains. Despite the robustness of induction motors, they are susceptible to failures. The broken rotor bar (BRB) fault in induction motors has received special attention since one of its characteristics is that the motor can continue operating with apparent normality; however, at certain point the fault may cause severe damage to the motor. In this work, a methodology to detect BRBs using vibration signals is proposed. The methodology uses the Shannon entropy to quantify the amount of information provided by the vibration signals, which changes due to the presence of new frequency components associated with the fault. For automatic diagnosis, the K-means cluster algorithm and a decision-making unit that looks for the nearest cluster through the Euclidian distance are applied. Unlike other reported works, the proposal can diagnose the BRB condition during startup transient and steady state regimes of operation. Additionally, the proposal is also implemented into a field programmable gate array in order to offer a low-cost and low-complex online monitoring system. The obtained results demonstrate the proposal effectiveness to diagnose half, one, and two BRBs.

1. Introduction

Inductions motors are widely used in many applications because of their easy maintenance, ruggedness, low cost, versatility, and ease control [1]. During their service life, they are subject to unavoidable failures as a result of mechanical, environmental, thermal, and electrical stresses [2]. These faults such as bearing faults, air gap eccentricity, and broken rotor bars (BRBs) can yield a reduction on production, product quality, and an increase on costs, besides being a hazard for people and machinery [3]. Among the different faults that can occur in induction machines, BRB is a silent failure that allows operating the motor with apparent normality, but it can cause an excessive vibration, a change in current consumption, and higher thermal stress with catastrophic consequences if the situation is not solved at early stages [4, 5]. In this regard, condition monitoring equipment has become an essential tool in many industrial areas. Yet, this task is very challenging because depending on the application the motor may be subject to transient and/or steady (nominal) regimes of operation, which changes its mechanical and electrical conditions by affecting and limiting the performance of equipment that only operates in a specific regime. From this point of view, an online and real-time monitoring system for an early detection of BRB in transient and steady regimes is a needed equipment in many industrial areas, since it will allow

scheduling maintenance operations in order to minimize its negative impact as well as saving time and money.

During the last decade, several vibration and current analysis-based processing techniques for BRB detection have been proposed. The conventional signal processing technique used to perform this task is the fast Fourier transform (FFT) [6–8]. However, it is limited in its capability for extracting features from signals that exhibit nonlinear and nonstationary characteristics, besides being susceptible to noise, making a correct identification of features related to the BRB fault difficult [9]. More recently, other powerful signal processing techniques, such as multiple signal classification (MUSIC) algorithm [10, 11], wavelet transform (WT) [9, 12–16], Empirical mode decomposition combined with Hilbert transform known as Hilbert-Huang transform (HHT) [16], and Wigner-Ville distribution (WVD) [17], have been used for BRB detection. Nevertheless, although prominent results have been obtained, the aforementioned signal processing techniques present some unresolved difficulties. For instance, MUSIC requires *a priori* knowledge of the interest frequencies and consumes significant computational resources [11]. The WT capabilities are significantly degraded in noisy signals, and the mother wavelet has to be appropriately chosen to obtain reliable results [4]. On the other hand, the WVD introduces cross-term interference in the estimated signal components, which inhibits the efficient estimation of the instantaneous frequencies, besides suffering aliasing problem [18]. The HHT suffers from the mode mixing effect, which means that waves with the same frequency are assigned to different intrinsic mode functions, affecting the accurate estimation of the instantaneous frequencies. In general, many advantages and disadvantages of the aforementioned techniques may be further discussed; yet, from a monitoring equipment viewpoint, two aspects become important. The first one is the performance capabilities; it means that the equipment does not degrade its performance when it analyzes transient or stationary signals. This desirable feature may be achieved either using a nonsusceptible signal processing technique or using different techniques for each scenario. The second one is the complexity since it may compromise the online analysis if low-end digital signal processors are used. In this regard, it would be desirable to have a signal processing algorithm with both the ability of identifying suitable and reliable features of signals for identifying BRB fault in different operating states and a low complexity for online analysis.

Similar to signal processing techniques, the classification algorithms play an important role in the automatic diagnosis of faults [19]. Different classification techniques such as neural networks [20, 21] and fuzzy logic [22, 23] have been successfully applied for monitoring the condition of induction motors. Unfortunately, the neural networks and other conventional artificial intelligent techniques require enough samples and have limitations on generalization of results in models that can overfit the samples [13]. Therefore, having in mind that online monitoring equipment may require low-complexity procedures, a classification algorithm with a suitable accuracy without the need of complicated processing, that requires a small number of samples, and, mainly, that allows developing a methodology capable of identifying several faults in different scenarios is a desirable tool. A promising classification technique is the K-means algorithm. It is a well-known signal classification technique that has been successfully utilized in many applications such as neuroscience [24], structural engineering [25], and mechanics [26]. This approach provides a high accuracy and good generalization for a small number of features; besides its computational cost during and after its design is relatively low.

In this work, a methodology to detect automatically the BRB fault in induction motors using vibration signals is presented. The proposal considers the analysis of both the startup transient and the steady state of operation, which is very important since the induction motor may be subject to both scenarios in real applications; besides, an implementation into a field programmable gate array (FPGA) is also presented as system-on-chip (SoC) solution. This allows offering a system for online and continuous monitoring. Regarding the BRB condition, half, one, and two bars are considered. For the analysis, the Shannon entropy is used as a measure of the information contained in the vibration signals. This information presents changes associated with the fault. Then, the obtained entropy values are classified for automatic diagnosis using the K-means algorithm. The results show that the proposal can be a low-complex and suitable tool for BRB detection in both the startup transient and the steady state of operation.

2. Theoretical Background

In this section, the two main topics of the proposed methodology are briefly described.

2.1. Entropy. In information theory, entropy describes how much information about the data randomness is provided by a signal or event [27]. It has been used in image processing [28], in gearbox fault detection [29], in structural health monitoring [30], for analysis of electroencephalogram signals to diagnose the patient's clinical condition [31], and in fault motor diagnosis [15, 19, 32] among others. In particular, Shannon entropy, named after Claude Shannon, of a random signal X with N possible outcomes $x_0, x_1, x_2, \ldots, x_{N-1}$ and with a probability of $p(x_i)$ can be computed as follows:

$$H(X) = -\sum_{i=0}^{N-1} p(x_i) \log_2 [p(x_i)], \tag{1}$$

where it is bounded by $0 \leq H(X) \leq \log_2(N)$.

Due to the number of applications and to the requirements of processing time, a hardware processing unit based on FPGA for entropy estimation is presented by [33], where a simplified mathematical expression is given as follows:

$$E(X) = \log_2(N) - \left(\frac{1}{N}\right) \sum_{i=0}^{N-1} r_i \log_2(r_i), \tag{2}$$

where r_i is the incidence rate or histogram of a signal X; therefore, $p(x_i)$ is r_i/N. In general, this expression follows the structure shown in Figure 1.

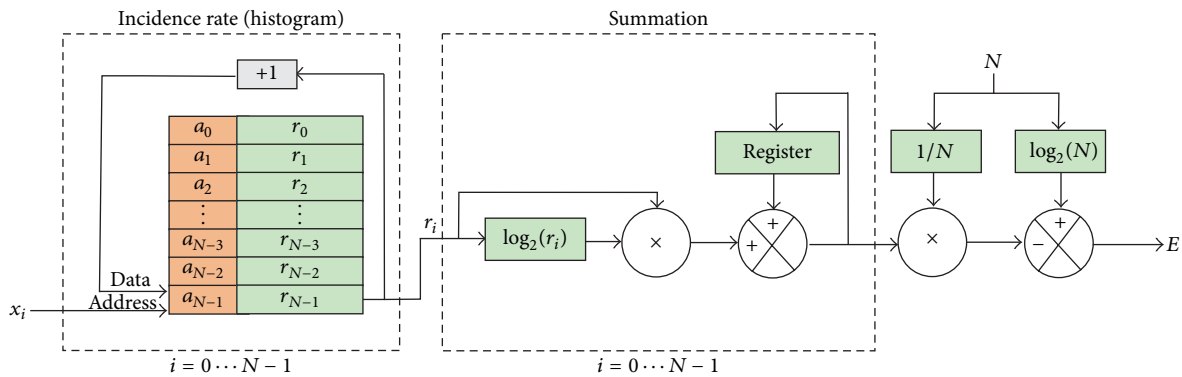

Figure 1: General structure for the entropy processor.

2.2. K-Means. In general, cluster analysis consists of creating groups of objects with similar features [34]. It implies that an object has to comply or has certain features for belonging to a specific group. In this regard, a classification task for unseen data can be carried out by looking for a group that fits better.

K-means is a simple and popular algorithm to solve clustering problems. The goal of the algorithm is to divide a data set $Y = \{y_1, y_2, \ldots, y_N\}$ with N data into k clusters. The number of clusters is fixed *a priori*. The objective function based on squared Euclidian distances is calculated as follows [35]:

$$F(m_1, \ldots, m_k) = \sum_{i=1}^{k} \sum_{j=1}^{M_i} \left\| y_{ij} - m_i \right\|^2, \quad (3)$$

where M_i is the number of objects of each ith cluster, y_{ij} is the jth object of the ith cluster, and m_i is the center of the ith cluster, which is defined as

$$m_i = \frac{1}{M_i} \sum_{j=1}^{M_i} y_{ij}, \quad i = 1, \ldots, k. \quad (4)$$

The overall procedure is summarized as follows [34]: (1) select randomly the initial positions of the K-centroids; (2) assign the data set Y to the closest centroid; (3) relocate iteratively the K-centroids in order to minimize the objective function. It is worth noting that K-means algorithm is sensitive to the initial k clusters; however, it can be applied a number of times in order to find either the global objective function minimum or an acceptable error.

3. Proposed Methodology

The overall work is carried out in two stages, design and implementation, as shown in Figure 2.

3.1. Design Stage. In this stage, the extraction of the K-centroids for automatic diagnosis of BRBs in induction motors is carried out and shown in Figure 2(a). First, a set of vibration signals for each induction motor condition, healthy (HLT), half broken rotor bar (HBRB), one broken rotor bar (1BRB), and two broken rotor bars (2BRB), are acquired during the startup transient and the steady state. The vibration signals are measured through a triaxial accelerometer (Ax, Ay, and Az). Second, the Shannon entropy of each signal is computed using (2). Third, the K-means clustering algorithm is applied several times in order to look for the best clusters for each induction motor condition. The overall analysis is carried out using Matlab software. It is found, as will be discussed in the next sections, that the entropy values, Ex and Ez, present the best classification results; therefore, the Kx and Kz centroids for each cluster are selected as baseline for each condition.

3.2. Implementation Stage. In order to offer an online diagnosis tool, the proposed methodology is implemented into an FPGA as shown in Figure 2(b). First, the K-centroids for startup transient and steady state of each induction motor condition are stored into read-only memories, which are chosen by the user according to the actual motor operation. Second, the entropy values are estimated using the entropy processor, which follows the digital structure presented in Figure 1. Third, the Euclidian distances from entropy values to each cluster are computed using the coordinate rotation digital computer (CORDIC) algorithm [36]. Finally, a decision-making unit looking for the nearest cluster determines the induction motor condition.

4. Experimentation and Results

4.1. Design Stage. The vibration signals acquired for each induction motor condition during startup transient and steady state are presented in Figures 3 and 4, respectively. The total number of tests for each condition is 20, giving a total of 160 tests; their entropy values are shown in Figure 5. These values are bounded by the mean (μ) and ± 3 standard deviation (σ) in order to ensure an occurrence of 99.7% [33]; Table 1 presents the numerical values. The best K-means clusters are obtained using Ex and Ez since they offer more nonoverlapped patterns. The clusters are shown in Figure 6, where the Voronoi cells are used. The estimated values for the Kx and Kz centroids are summarized in Table 2.

4.2. Experimental Setup. The experimental setup used to test the proposal is shown in Figure 7(a). The induction

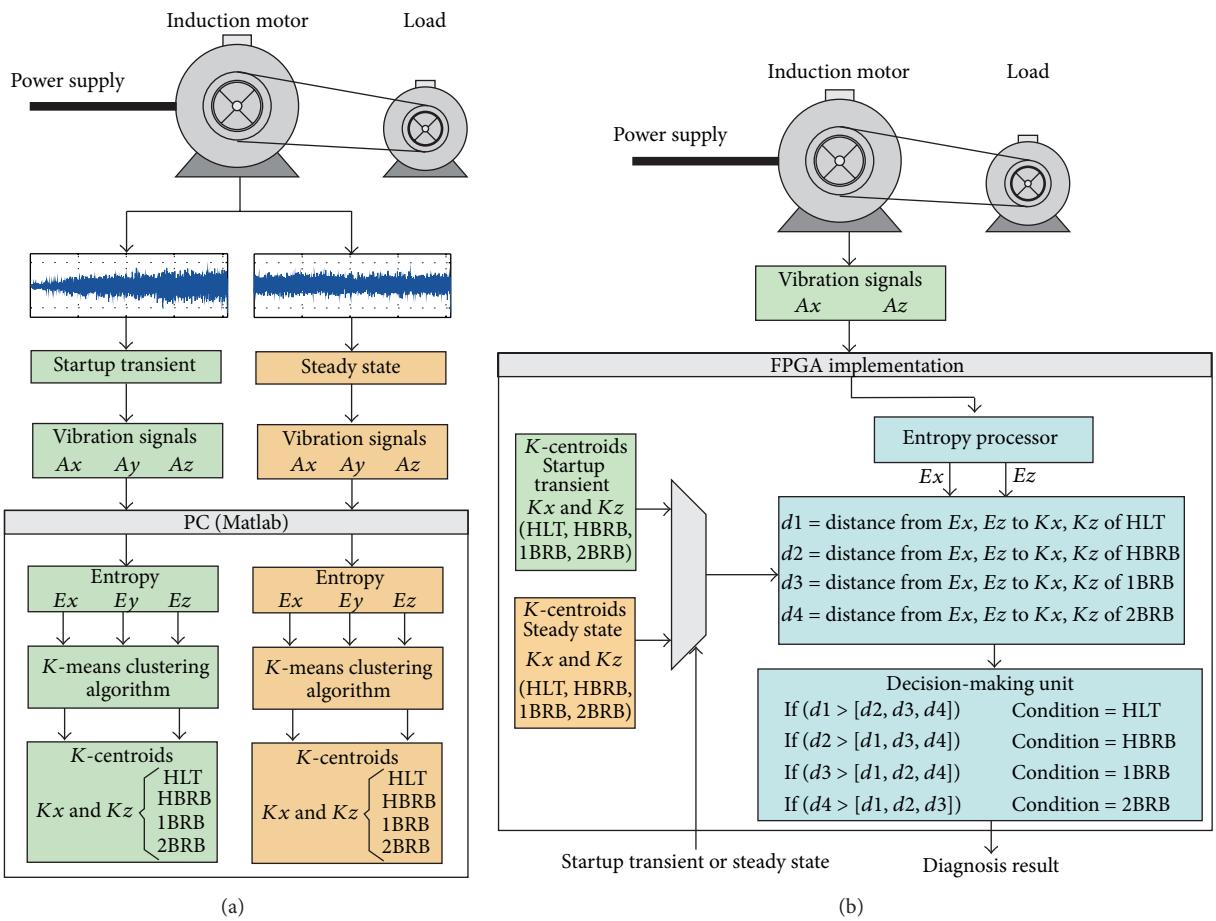

Figure 2: Proposed methodology: (a) design stage and (b) implementation stage.

Table 1: Entropy values.

Condition	Entropy (μ, σ)					
	Startup transient			Steady state		
	Ex	Ey	Ez	Ex	Ey	Ez
HLT	8.7530, 0.0416	9.1929, 0.0484	9.0489, 0.0644	8.6236, 0.715	9.4280, 0.0526	9.0940, 0.0941
HBRB	8.1024, 0.0445	8.9868, 0.0487	8.7272, 0.0566	7.8979, 0.0528	9.0849, 0.0544	8.6348, 0.0596
1BRB	9.0152, 0.0716	9.3918, 0.0345	9.7105, 0.0345	8.4532, 0.1763	8.9832, 0.0927	9.8297, 0.0927
2BRB	9.1787, 0.0511	9.4535, 0.0430	9.2498, 0.0589	8.8621, 0.0629	9.6350, 0.0647	9.2908, 0.0484

Table 2: Values of the K-centroids.

Induction motor condition	K-centroids			
	Startup transient		Steady state	
	Kx	Kz	Kx	Kz
HLT	8.7530	9.0489	8.6118	9.0811
HBRB	8.1024	8.7272	7.8979	8.6348
1BRB	9.0152	9.7105	8.4532	9.8297
2BRB	9.1787	9.2498	8.8614	9.2930

motor (model WEG 00136APE48T) has two poles and 28 bars. It is fed with 220 Vac at 60 Hz. The mechanical load is provided by an ordinary alternator. The 3-axis vibration signal is measured by an accelerometer model LIS3L0AS4 placed on the top of the induction motor as shown in Figure 7(b). A 12-bit 4-channel analog to digital converter model ADS7841 is used for analog to digital conversion. The data acquisition system has a sampling frequency of 1500 Hz and captures 4096 samples (2.73 s), which is enough to capture the startup transient; the same time is used for the steady state. Figure 7(c) shows the four rotor conditions; the BRB condition is artificially created by drilling half, one, and two bars in the rotor without damaging the rotor shaft. The instrument in based on a proprietary Spartan 3E XC3S1600E FPGA with a frequency operation of 48 MHz; the FPGA resource utilization for the proposed methodology appears in Table 3. It is observed that it has a low consumption since a

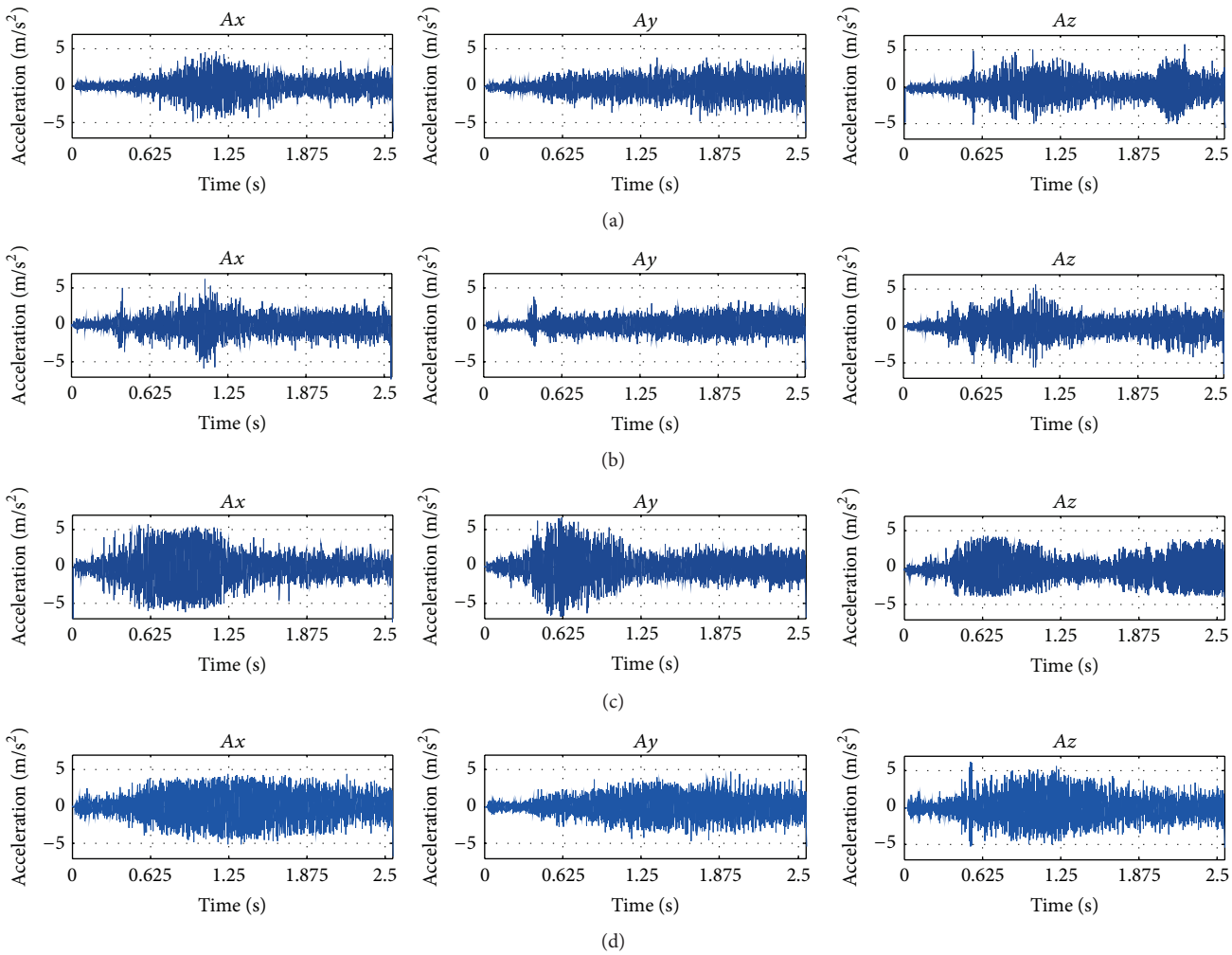

Figure 3: Vibration signals for startup transient: (a) HLT, (b) HBRB, (c) 1BRB, and (d) 2BRB.

Table 3: FPGA resources.

	Available	Used	Percentage (%)
Programmable logic	29504	1870	6.33
LUTs	29504	3445	11.67
Multipliers	36	2	5.55
Clock cycles		57632	

maximum of 11.67% is obtained; besides, the computational cost is also low since 57632 clock cycles (1.2 ms) are required to compute the final result. The overall system is tested 20 times for each motor condition. Tables 4 and 5 present the obtained classification results for startup transient and steady state, respectively. The correct results are located in the diagonals (highlighted in bold). Regarding the startup transient results, most the cases present an effectiveness of 100%, which means that, of the 20 actual HLT conditions, the system classifies 20 HLT conditions. A mistake for HBRB is obtained; yet, it is a positive false since it is classified as 1BRB. On the other hand, the classification results for steady state regimen have 100% of effectiveness in all cases.

Table 4: Classification results for startup transient tests (confusion matrix).

Induction motor condition	HLT	HBRB	1BRB	2BRB	Percentage of effectiveness (%)
HLT	**20**	0	0	0	100
HBRB	0	**19**	1	0	95
1BRB	0	0	**20**	0	100
2BRB	0	0	0	**20**	100

Finally, it is worth noting that different vibration levels generated by other faults, neighboring equipment, and uncontrolled conditions can be induced in the motor frame, which will modify the vibration patterns shown in Figure 5 and, as a consequence, the performance of the classification algorithm; in this regard, new calibrations in known conditions will be required.

4.3. Discussion. Table 6 summarizes a performance comparison of the proposed method against recently reported

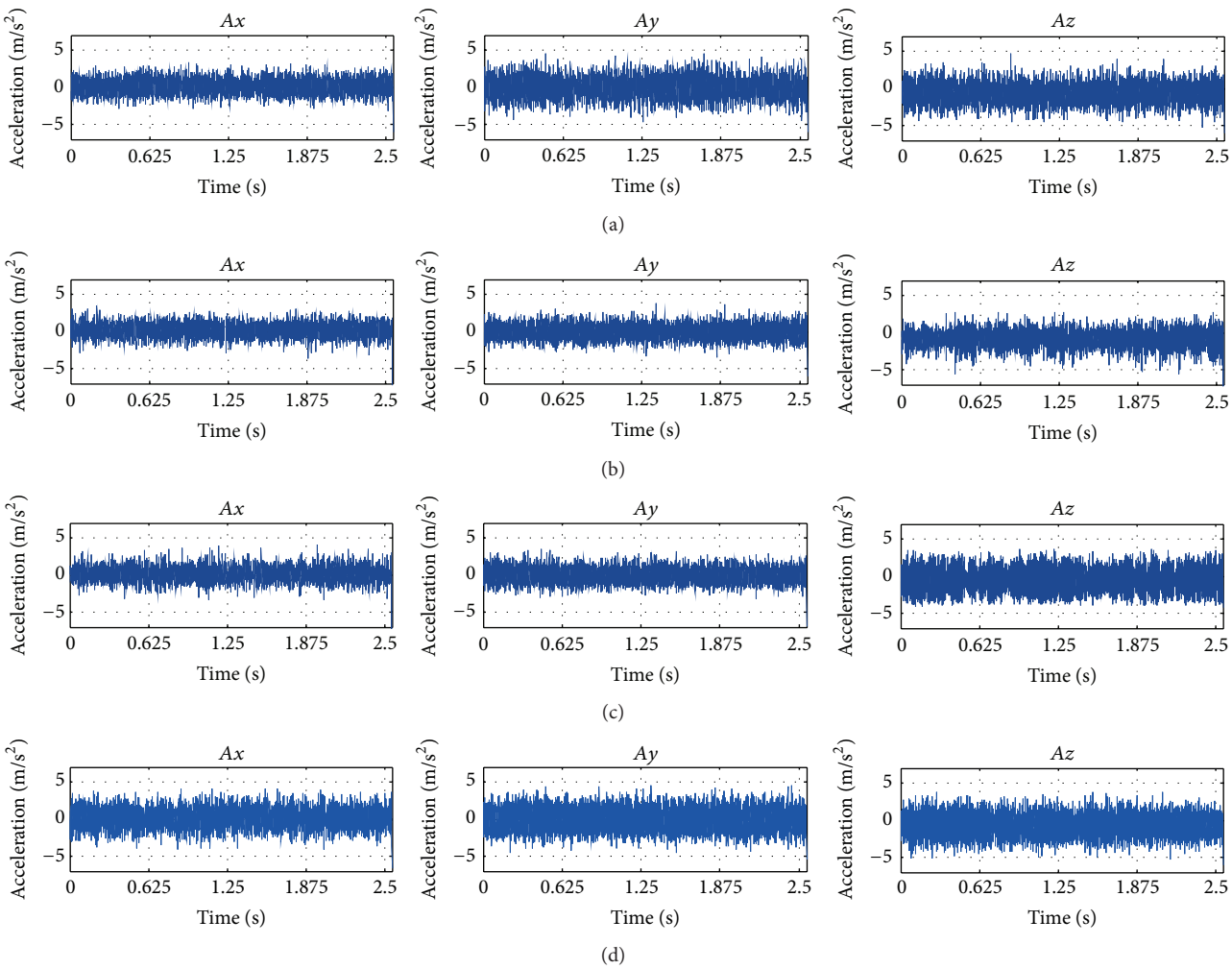

Figure 4: Vibration signals for steady state: (a) HLT, (b) HBRB, (c) 1BRB, and (d) 2BRB.

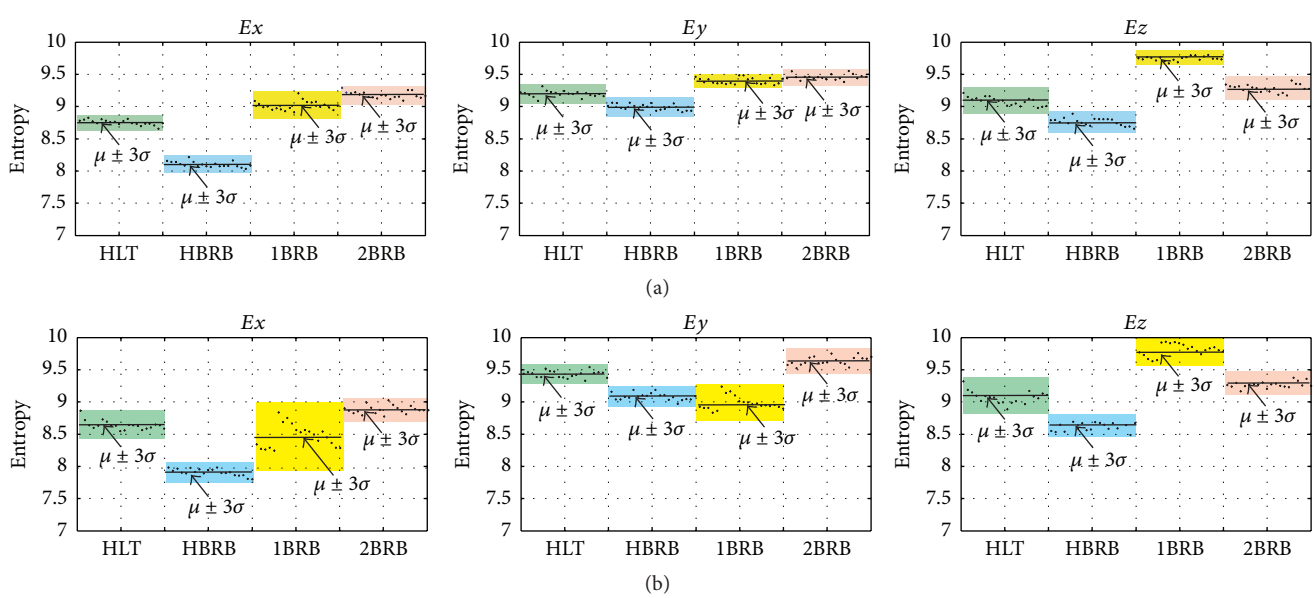

Figure 5: Entropy values for (a) startup transient tests and (b) steady state tests.

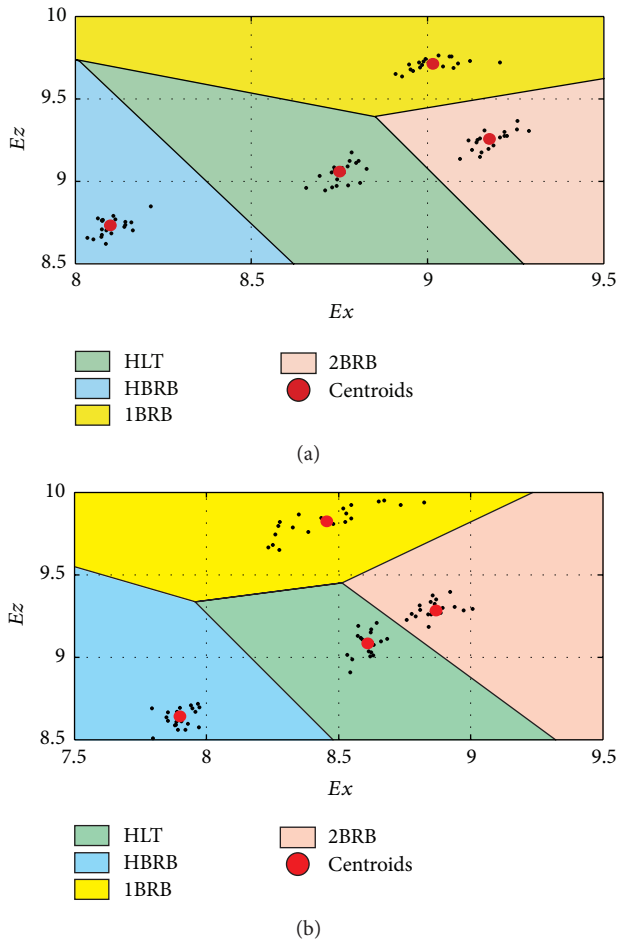

Figure 6: K-means clusters: (a) startup transient and (b) steady state.

Table 5: Classification results for steady state tests (confusion matrix).

Induction motor condition	HLT	HBRB	1BRB	2BRB	Percentage of effectiveness (%)
HLT	**20**	0	0	0	100
HBRB	0	**20**	0	0	100
1BRB	0	0	**20**	0	100
2BRB	0	0	0	**20**	100

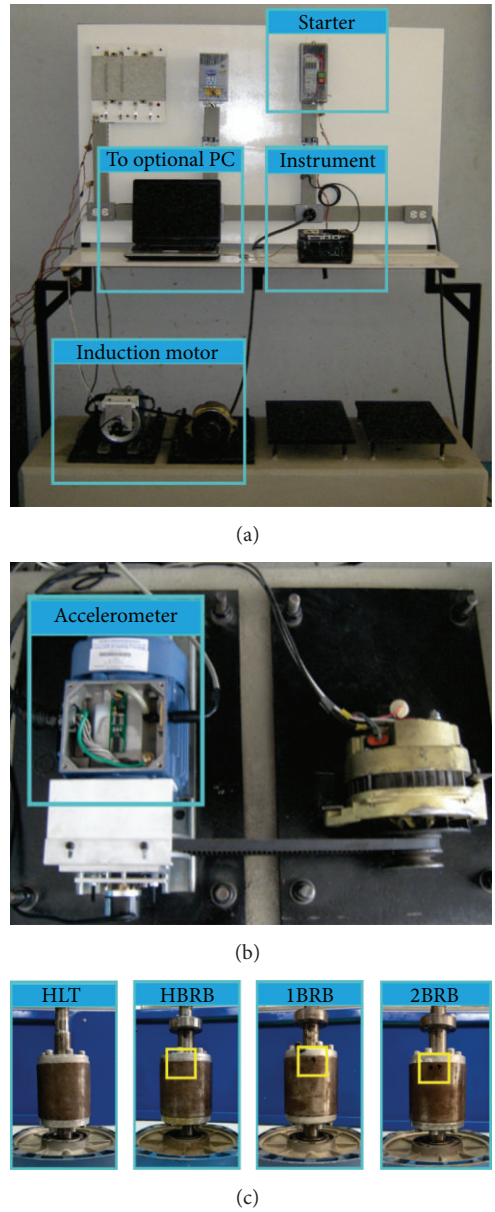

Figure 7: Experimentation: (a) experimental setup, (b) top view accelerometer, and (c) rotors.

works in literature, where parameters such as methodology applied, analyzed state, and the percentage of effectiveness are considered. From Table 6, it is clear that the proposed methodology can detect the presence of BRB with high accuracy in both states of induction motor. Unlike other reported works [37–42], the proposal considers HBRB in both states. Although HBRB detection, in both states, has been considered in [5], the proposal outperforms in several cases the effectiveness for diagnosing the induction motor condition, which makes it more attractive for industrial applications. Further, it is important to mention that the proposal presents two essential characteristics: (1) the automatic identification of different grades of severity of broken bar faults and (2) the use of a single-parameter, which reduces the complexity and computational load. In addition, the designed FPGA implementation offers a low-cost and a real-time solution for online monitoring of induction motor condition.

5. Conclusions

In this work, a methodology based on Shannon entropy and K-means clustering algorithm for automatic diagnosis of BRBs during the startup transient and steady state is proposed. It allows diagnosing three severities of damage, HBRB, 1BRB, and 2BRB, as well as the HLT condition. Although a triaxial accelerometer to measure Ax, Ay, and

Table 6: Results and characteristics of previous works and of the proposed work.

Work	Applied methodology	Analyzed state	Effectiveness (%)			
			HLT	HBRB	1BRB	MBRB
Matić et al. [37]	(1) Feature selection through Hilbert transform. (2) Fault diagnosis classification through support vector machine.	Steady	100	—	100	—
Da Silva et al. [38]	(1) Feature selection through time-stepping finite-element simulations. (2) Fault diagnosis classification through a Bayesian classifier.	Steady	100	—	100	100[3,5]
Georgoulas et al. [39]	(1) Extraction features by means of complex empirical mode decomposition. (2) Fault diagnosis classification through hidden Markov models.	Transient	100	—	100	100[2]
Keskes et al. [40]	(1) Stationary Wavelet Packet transform for statistical feature extraction. (2) Fault diagnosis classification through improved support vector machine.	Steady	100	—	99	99[2]
Rangel-Magdaleno et al. [41]	(1) Mathematical morphology. (2) Spectral analysis for identification of frequency components related to the fault using FFT. (3) Amplitude analysis from estimated spectrum for statistical feature extraction. (4) Fault diagnosis classification through a decision tree.	Steady	95	—	95	95[2]
Menacer et al. [42]	(1) Spectral analysis using discrete wavelet transform and Hilbert transform to obtain the envelope of the signal. (2) Fault diagnosis classification through measured features (Eigenvector changes).	Transient	100	—	100	100[2]
Valles-Novo et al. [5]	(1) Signal decomposition by means of empirical mode decomposition method. (2) Standard deviation of zero crossings and the time between successive zero crossings of the decompositions for fault diagnosis classification.	Transient	98.2	99.7	98.2	—
		Steady	98.2	98.2	98.5	—
Proposal	(1) Shannon entropy for statistical feature extraction. (2) Fault diagnosis classification through K-means method.	Transient	100	95	100	100[2]
		Steady	100	100	100	100[2]

HLT: healthy condition; HBRB: half broken rotor bar; 1BRB: one broken rotor bar; MBRB: multiple broken rotor bars, where 2 means two broken bars, 3 means three broken bars, and 5 means five broken bars.

Az vibration signals is used, it is found that Ax and Az provide enough information to diagnose the treated fault, which simplifies even more the computational cost of the proposal.

The FPGA implementation as SoC solution for online and continuous monitoring is also developed. In general, a low consumption of FPGA resources with a maximum of 11.67% is obtained. This is possible since the K-centroids are computed offline and in the implementation stage only a search for the nearest cluster through the Euclidian distance is required. It is worth noting that the same methodology can diagnose the faults during both transient and steady regimens with a high accuracy; therefore, the processor cores can be reused with an only change in the selected K-centroids.

In a future work, different load conditions in both states will be explored in order to improve the usefulness and applicability of the proposed methodology. Besides that, other mechanical and electrical faults will be analyzed using the proposed methodology; in fact, other signals such as current or temperature will be also explored in order to obtain unique and reliable patterns for each condition.

Competing Interests

The authors declare that they have no competing interests.

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