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Quaternion Signal Analysis Algorithm for Induction Motor Fault Detection

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***Abstract*—Induction motor fault identification is essential to improve efficiency in industrial processes improving costs, production line and maintenance time. This paper presents a novel motor fault detection methodology based on Quaternion Signal Analysis (QSA). The proposed method establishes the quaternion coefficients as the value of motor current measurement and the variables *x*, *y* and *z* are the measurements from a triaxial-accelerometer mounted on the induction motor chassis. The method obtains the rotation of quaternions and applies quaternion rotation statistics such as mean, cluster shades and cluster prominence in order to get their features, and these are used to classify the motor state using the proposed tree classification algorithm. This methodology is validated experimentally and compared to other methods to determine the efficiency of this method for feature detection and motor fault identification and classification.**

***Index Terms*—Induction motors, fault detection, quaternion rotation statistics, tree classification.**

I. Introduction

INDUCTION motors are important in industrial processes. Motor fault detection improves costs, production line and maintenance time. The induction motor is affected by electrodynamic forces, winding insulation, large voltage stresses, thermal aging and mechanical vibrations from external or internal sources [?]. The typical mechanical faults that occur in induction motors are stator fault, bearing fault, broken bars fault and rotor fault.

The importance of the evaluation of induction motors has motivated the development of algorithms for early fault detection [?]. Bearing and rotor faults are the most common type of analysis performed on induction motor failures. For instance, in [?], a stator inter-turn fault is detected using an algorithm that analyzes impedance. The authors in this paper calculate the impedance using winding function theory, and then they compare their results with those in a database to detect a fault classification.

A statistical method such as the least-mean-square is used with this kind of algorithms to obtain bearing fault detection by analyzing the vibration signals that are taken throughout the endurance test [?]. Similarly, spectral kurtosis-based algorithms are used to find faults in the bearing elements by using the stator current or the vibration signal to analyze the characteristic frequencies [?]- [?].

Among the methods developed for the identification of motor faults are the space transformation methods and the estimation methods. The Fast Fourier Transform (FFT) and the wavelet transform are the most commonly used methods in space transformation analysis. For instance, the FFT is used to calculate the frequency spectrum of the stator currents which can be used to obtain the number of broken bars based on the relative magnitudes of the signals [?], [?]. Similarly, a method based on the discrete-wavelet-transform is proposed as a viable solution for the detection of outer-cage faults of double-cage motors by analyzing the stator current spectrum [?]. On the other hand, the authors of [?] proposed an estimation method that employs a frequency estimator, an amplitude estimator, and a fault decision module to detect a broken rotor bar using the stator current.

Quaternions have been increasing popularity in signal processing due to the reduction in the number of parameters and because they offer mathematically tractable solutions with few constraints [?]. This has motivated the development of algorithms with quaternions such as the vector correlation method that is based on hypercomplex Fourier transform to color image processing [?]. In the same sense, the concepts of existing algorithms have been expanded to the quaternion domain, such as the distributed quaternion Kalman filtering used in estimation applications such as target tracking [?] or in multiple model adaptive estimation for 3D and 4D signals [?]. Likewise, quaternions are applied in learning systems algorithms based on the novel GHR calculus [?], such as the quaternion least mean kurtosis (QLMK) [?], nonlinear adaptive filtering [?] and recurrent neural networks [?]. Quaternion Least Mean Square (QLMS) algorithm was proposed by Took and Mandic to design adaptive filtering of three and four-

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dimensional processes [?]. In turn, ANN (Artificial Neural Networks) and artificial intelligence methods are limited by the significant time required for training the network with the data, and their limited fault identification reliability when using untrained data [?]. Adaboost classification presents noise vulnerability [?].

The Quaternion Signal Analysis (QSA) method allows obtaining a model of signals behavior through three- or four- signal analysis simultaneously in the time domain. This method considers each sample as a point which shapes trajectories over time providing high levels of accuracy from a small number of samples. In the present paper, a novel algorithm is proposed to classify three states of an induction motor using at least two samples by means of the QSA method. Current and accelerometer signals are used to create the quaternion which is rotated and analyzed by means of second order statistical methods. Finally, a classification tree is applied to the vector of characteristics in order to obtain the induction motor conditions; these are labeled in this study as HLT (for healthy), BAL (for mechanical unbalance fault), and BRN (for bearing fault). In this study, different algorithm parameters are changed and the resulting performance is compared to find the best system.

Many methods have been used in the identification of faults in induction motors. Some of them are known as spectral methods, and those are based on the FFT, which has some drawbacks including poor resolution, spectral leakage, inefficiency to provide a good time-frequency relation, etc. [?]. It is never an easy task to find if a fault has occurred, and less so if the magnitude of the fault is low when compared to the noise produced in the induction motor. Thus, to overcome these drawbacks of the FFT, many advanced signal processing techniques have been implemented such as zoom FFT, ESPRIT and MUSIC algorithms as high-resolution techniques; however, spectral leakage is still a challenging task for researchers, the computation costs are high, and the techniques are very sensitive to the parameters used, which sometimes results in the misidentification of faults (spurious fault frequencies) [?]. Other so-called statistical methods have the characteristic that the physical sense is lost, they require large amounts of data, and involve high computation costs.

To address these problems, Quaternion Signal Analysis (QSA) is used because it provides high speed and accuracy with a small number of samples. A simple classification tree is needed to obtain the induction motor conditions. Thus, the advantage of QSA is that it does not require a complex or advanced classifier to obtain the induction motor conditions. In this paper, QSA classifies three states of an induction motor using at least two samples with a time of processing of 0.0412 sec.

II. QUATERNION

The Quaternion domain is considered a non-commutative extension of complex numbers with four components (*1*, *i*, *j* and *k*) that allows for a unified treatment of four-dimension processes. The Quaternion structure is defined by [?] as

$$q = q_0 + q_1 i + q_2 j + q_3 k \tag{1}$$

q_0, q_1, q_2 and q_3 correspond to the magnitude of each component. Quaternions have three imaginary operators

$$i^2 = j^2 = k^2 = i \cdot j \cdot k = -1. \tag{2}$$

The quaternion components abide by the following product rules

$$i \cdot j = -j \cdot i = k \tag{3}$$
$$j \cdot k = -k \cdot j = i \tag{4}$$
$$k \cdot i = -i \cdot k = j. \tag{5}$$

These properties allow operations such as multiplications as described in [?]

$$\begin{aligned} q \otimes p = &(q_0p_0 - q_1p_1 - q_2p_2 - q_3p_3) \\ &+(q_0p_1 + q_1p_0 + q_2p_3 - q_3p_2)i \\ &+(q_0p_2 - q_1p_3 + q_2p_0 - q_3p_1)j \\ &+(q_0p_3 + q_1p_2 - q_2p_1 + q_3p_0)k. \end{aligned} \tag{6}$$

The coefficients of a quaternion can be represented as a vector, as follows

$$q = [q_0, q_1, q_2, q_3]. \tag{7}$$

Rotation quaternions are elements used to represent rotations in three dimensions, and they are related to the axis-angle representation of rotation. They follow Euler's rotation theorem, whereby any rotation can be specified using a unit vector and an angle θ. The axis-angle components $(\theta, \hat{x}, \hat{y}, \hat{z})$ can be converted to a rotation quaternion q as

$$q_0 = \cos\left(\tfrac{\theta}{2}\right) \tag{8}$$
$$q_1 = \hat{x}\sin\left(\tfrac{\theta}{2}\right) \tag{9}$$
$$q_2 = \hat{y}\sin\left(\tfrac{\theta}{2}\right) \tag{10}$$
$$q_3 = \hat{z}\sin\left(\tfrac{\theta}{2}\right) \tag{11}$$

where θ is the rotation angle $\hat{x}, \hat{y}$ and $\hat{z}$ are the unit vectors that represent the rotation axis [?]. The vector v is a 3D vector, $v = v_1 i + v_2 j + v_3 k$, and can be expressed as

$$v = [v_1, v_2, v_3]^T. \tag{12}$$

Then, the rotation of a 3D vector v is

$$v' = q \otimes v \otimes q^{-1} \tag{13}$$

where v' is the rotated vector, q is a quaternion and q^{-1} is the inverse of this quaternion [?].

The last equation can be expressed as in [?], and it is adapted to the variable $q(t)$ that is present quaternion. Thus, $q(t + \Delta t)$ is a shifted quaternion while $q_{rot}(t)$ is the rotation vector, and it is defined as

$$q(t + \Delta t) = q_{rot}(t) \otimes q(t) \otimes q_{rot}^{-1}(t). \tag{14}$$

In the same way, the rotation can be expressed as

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$$q(t+\Delta t) = R(t) \cdot q(t). \tag{15}$$

[**?**] shows the rotation matrix R resulting from $q_{rot}(t)$. If that substitution is represented as $R(t)$, the structure is given by

$$R(t) = \begin{bmatrix} 1-2r_2^2-2r_3^2 & 2(r_1r_2+r_0r_3) & 2(r_1r_3-r_0r_2) \\ 2(r_1r_2-r_0r_3) & 1-2r_1^2-2r_3^2 & 2(r_2r_3+r_0r_1) \\ 2(r_1r_3+r_0r_2) & 2(r_2r_3-r_0r_1) & 1-2r_1^2-2r_2^2 \end{bmatrix} \tag{16}$$

in which, $r = [r_0, r_1, r_2, r_3]$ and

$$\begin{aligned} r_0 &= q_{0\_rot}(t) \\ r_1 &= q_{1\_rot}(t) \\ r_2 &= q_{2\_rot}(t) \\ r_3 &= q_{3\_rot}(t). \end{aligned} \tag{17}$$

A quaternion can be used to model 3D signal vibrations of the behavior of a machine. Assuming we have a set of discrete signals $I(t)$, $x(t)$, $y(t)$ and $z(t)$ with m samples where $I(t)$ is the current, and $x(t)$, $y(t)$ and $z(t)$ are the accelerometer coordinates, then, these four signals can be represented as the quaternion

$$q(t) = I(t) + x(t)i + y(t)j + z(t)k \tag{18}$$

or in a vector form

$$q(t) = [I(t), x(t), y(t), z(t)]^T. \tag{19}$$

Analyzing the signal of the last equation in time and taking into consideration m samples with a Δt time shift in each sample, the rotation equation (**??**) is applied recurrently until obtaining the estimation of the $R(t)$ model, which describes the time signal behavior as

$$\begin{bmatrix} q(t+\Delta t) \\ q(t+2\Delta t) \\ q(t+3\Delta t) \\ \vdots \\ q(t+m\Delta t) \end{bmatrix} = \begin{bmatrix} R(t) \\ R(t+\Delta t) \\ R(t+2\Delta t) \\ \vdots \\ R(t+(m-1)\Delta t) \end{bmatrix} \bullet \begin{bmatrix} q(t) \\ q(t+\Delta t) \\ q(t+2\Delta t) \\ \vdots \\ q(t+(m-1)\Delta t) \end{bmatrix} \tag{20}$$

This model is expressed as a quaternion through equations (**??**) and (**??**) obtaining $m - \Delta t$ models, which can be expressed as

$$Q_R = \begin{bmatrix} q_{rot}(t) \\ q_{rot}(t+\Delta t) \\ q_{rot}(t+2\Delta t) \\ \vdots \\ q_{rot}(t+(m-1)\Delta t) \end{bmatrix} = \begin{bmatrix} R(t) \\ R(t+\Delta t) \\ R(t+2\Delta t) \\ \vdots \\ R(t+(m-1)\Delta t) \end{bmatrix} \tag{21}$$

III. Statistics

The features that describe the model behavior can be obtained by performing a statistical analysis of Q_R. For instance, the mathematical expectation can be calculated through the modulus of the N models of Q_R as is described in [**?**]

$$\mu(t+k\Delta t) = \frac{1}{N}\sum_l |q_{rot}(t+(k+l)\Delta t)|. \tag{22}$$

Using this value we can obtain second order characteristics such as the cluster shades (CS) and the cluster prominence (CP). The cluster shades are the measure of skewness of a matrix, i.e, the lack of symmetry. According to [**?**], the cluster shades can be rewritten in vector form as

$$CS(t+k\Delta t) = \frac{1}{N}\sum_l (|q_{rot}(t+(k+l)\Delta t)| - \mu(t+k\Delta t))^3. \tag{23}$$

Similarly, the cluster prominence indicates the lack of symmetry, and it can be written as

$$CP(t+k\Delta t) = \frac{1}{N}\sum_l (|q_{rot}(t+(k+l)\Delta t)| - \mu(t+k\Delta t))^4. \tag{24}$$

Through these statistic values, a characteristic vector can be created as

$$w(t+k\Delta t) = [\mu(t+k\Delta t), CS(t+k\Delta t), CP(t+k\Delta t)]^T. \tag{25}$$

IV. Classification Tree

A classification tree is a tool in machine learning that divides the feature space into two parts, with each resulting part divided into two again, and so on for $w(t+k\Delta t)$ values as shown in Fig. **??**.

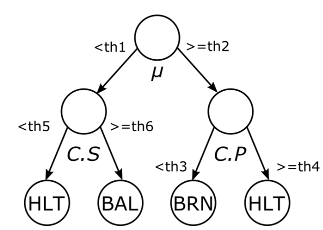

Fig. 1. Structure of classification tree.

The top node, known as 'the root node', is the most effective classification node. The last nodes are called 'leaves', and can be eliminated in order to secure the best classification results according to the number of samples that present errors. This kind of classification tree is known as the 'pruning decision tree' [**?**]. The classification tree was trained with 6.66% of the test bench data (as described later) to associate each motor property to a label $L(t+k\Delta t)$ as

$$L(t+k\Delta t) = \{HLT, BAL, BRN\}. \tag{26}$$

Once training is completed, the decision tree can classify a set of characteristic vectors with a response $c(t+k\Delta t)$ to each one of the induction motor conditions as

$$\begin{aligned} \mathbf{W} = \{&(w(t+\Delta t), c(t+\Delta t)), (w(t+2\Delta t), c(t+2\Delta t)) \ldots \\ &(w(t+k\Delta t), c(t+k\Delta t))\}. \end{aligned} \tag{27}$$

The response $c(t+k\Delta t)$ has a label that classify the motor condition.

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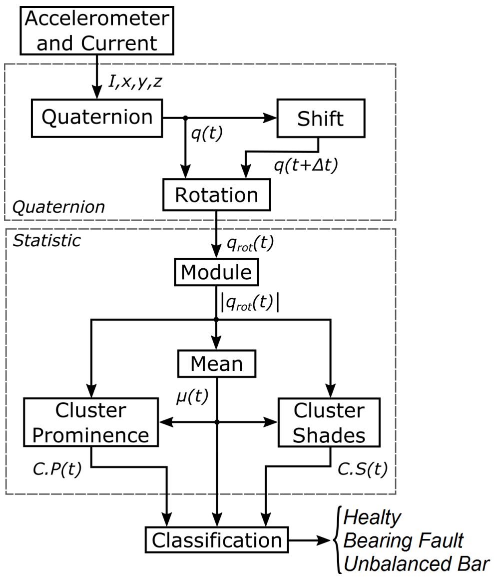

Fig. 2. Algorithm of Quaternion Signal Analysis.

V. Algorithm

The algorithm presented in this paper is shown in Fig. **??**. It is divided into the formulation of quaternion, statistical operations and classification. The quaternion $q(t)$ is created using measurements from accelerometer axes (x, y and z) and current measure (I), which comes from an induction motor. The quaternion is structured as was shown in (**??**).

After that, quaternion $q(t)$ is shifted Δt samples in the original signal to obtain $q(t+\Delta t)$, which has the same length as $q(t)$. Both quaternions are used to get the rotational quaternion $q_{rot}(t)$ by $R(t)$. The module is applied to $q_{rot}(t)$ for statistical computation. The cluster prominence and cluster shades are calculated using the mean and module of $q_{rot}(t)$. Next, cluster prominence and cluster shades results are applied to the classification tree to assign a label that corresponds to one of the following conditions: healthy induction motor, bearing fault or mechanical unbalance conditions.

VI. Experimental Setup

The experimental setup for this paper consists of the analysis of four signals, three axis signals from a MEMS-based accelerometer (LIS3L02AS4) mounted on a three- phase induction motor chassis model (WEG 00136APE48T) with 0.75 hp, 2 poles, 28 bars a weight of 9 kg, a length of 239 mm and width of 150 mm. One signal from the measure of induction motor current acquired using a current clamp model i200s from Fluke. The experimental setup is shown in Fig. **??**.

The four signals have a sampling frequency of $1.5\ KHz$, which provides 4096 samples per test during the steady state operation of the motor. The bearing fault bench is obtained when the motor is running at $3,402$ RPM with the fault being generated by drilling one hole of $7.938\ mm$ diameter. Similarly, the mechanical unbalance bar bench is acquired by adding some mass to the pulley, which produces a mass center out of the motor shaft. The test bench consists of five tests of bearing fault, twenty tests of mechanical unbalance bar and twenty tests of a healthy induction motor. A sample of the total bench is illustrated in Fig **??**.

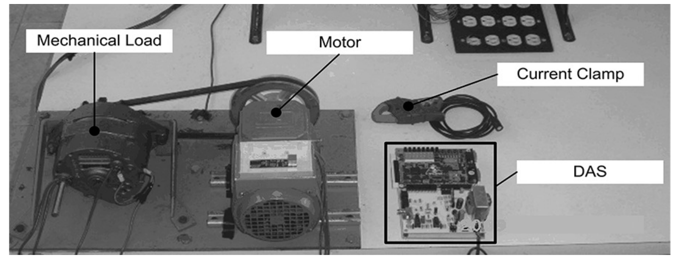

Fig. 3. Elements of the experimental setup.

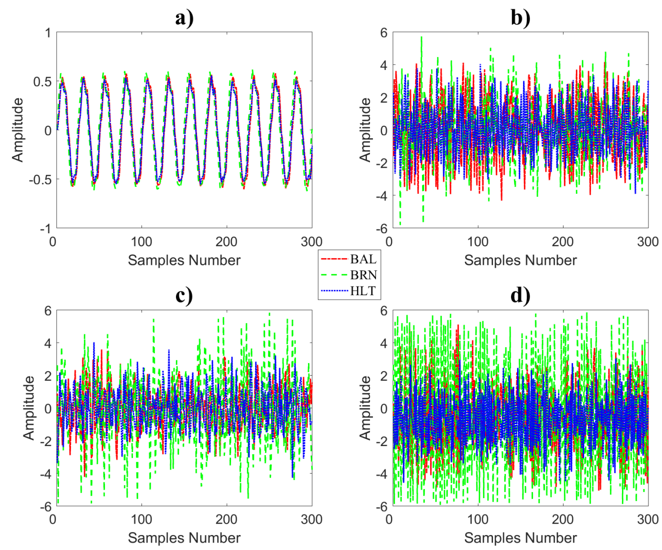

Fig. 4. Signals samples. a) Current signals. b) X axis vibration signals. c) Y axis vibration signals. d) Z axis vibration signals.

A test for each condition is randomly chosen to extract the cluster prominence and cluster shades of the rotated quaternion module using a window length ranging from two samples to two hundred samples. The statistical results of each condition are used to train the classifier. The algorithm is tested with the remaining bench data applying the same variable window lengths to check for assertiveness.

VII. Results

The methodology proposed in this paper has been applied to the test bench from two to two hundred samples. The distribution of attributes using the classification tree is shown in Figs. **??**-**??**. The distribution is reduced as the number of samples increases as shown in Figs. **??**-**??**.

The classification distribution is more noticeable when the number of samples is above one hundred as shown in Figs. **??** and **??**. In these cases, the classification is determined only by the mean and this generates a plane as the limiting among classes.

The generated classification trees use the statistical values in their branches and this provides the best classification for the test bench and the number of samples applied. Figs. **??** and **??** show the branches and the evaluation results using fifty

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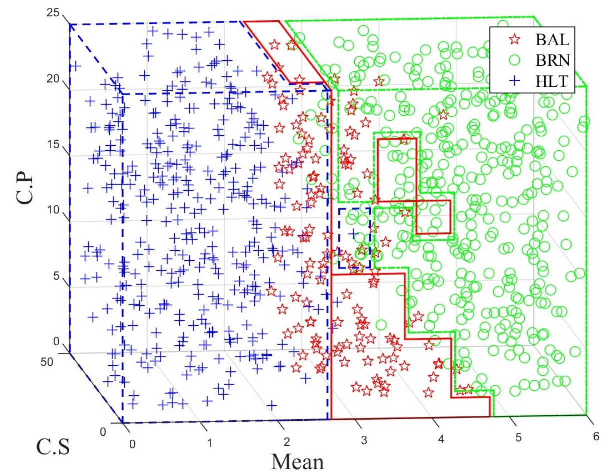

Fig. 5. Classification distribution using ten samples test.

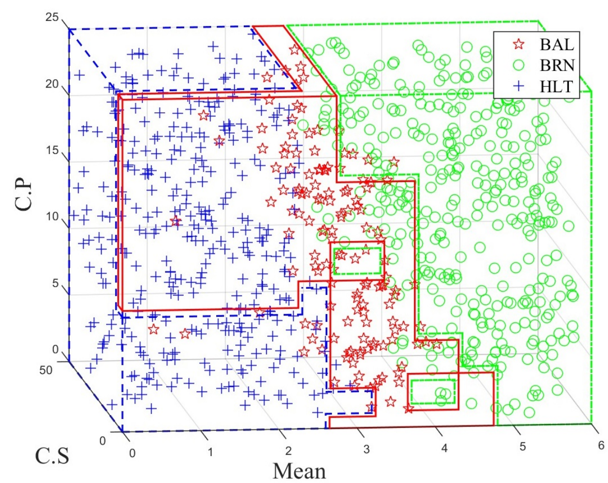

Fig. 6. Classification distribution using fifteen samples test.

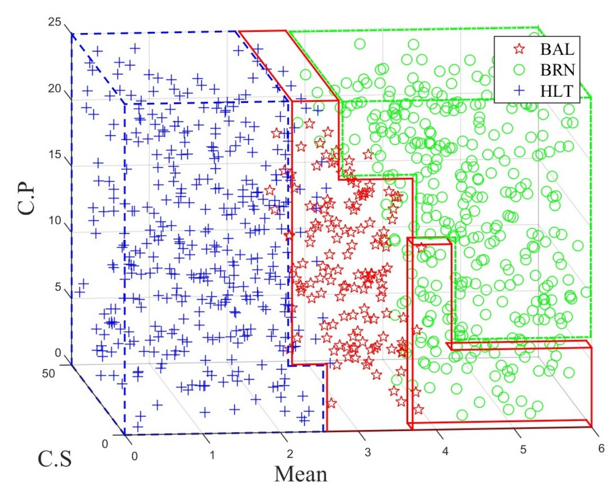

Fig. 7. Classification distribution using thirty samples test.

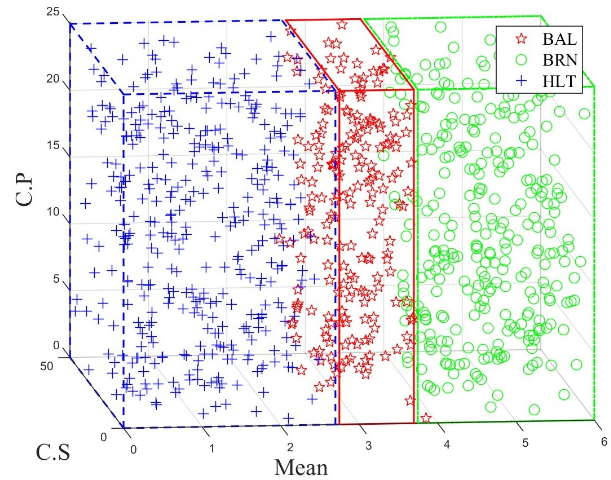

Fig. 8. Classification distribution using one hundred samples test.

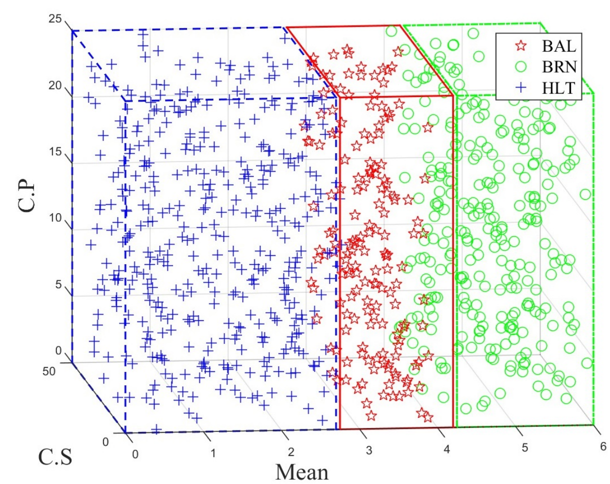

Fig. 9. Classification distribution using two hundred samples test.

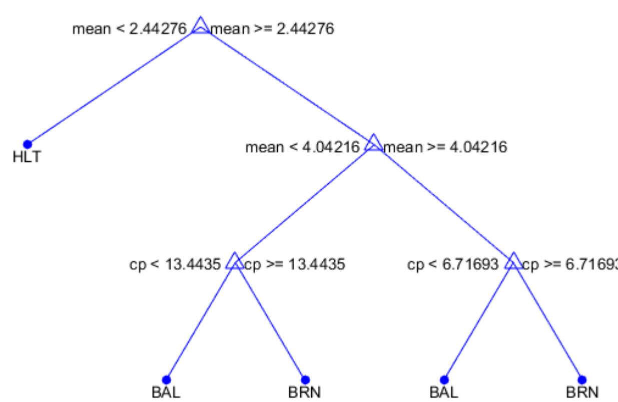

Fig. 10. Classification tree generated using fifty samples.

and two hundred samples respectively. The classification tree uses the mean, the cluster prominence or the cluster shades to obtain an evaluation and produce a large number of nodes if the signal samples are low and vice versa.

It is important to evaluate the general classification accuracy to demonstrate the method's efficiency. The evaluation compares the accuracy of the three classes presented for different numbers of samples. Fig. **??**, illustrates the maximum and

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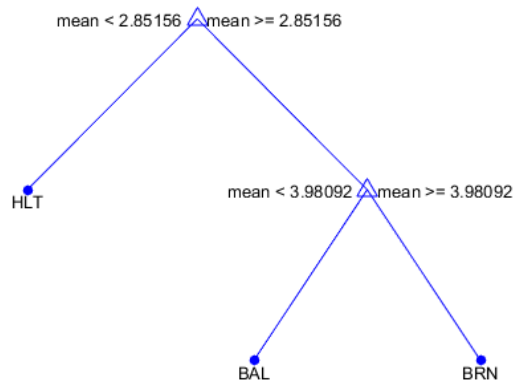

Fig. 11. Classification tree generated using two hundred samples.

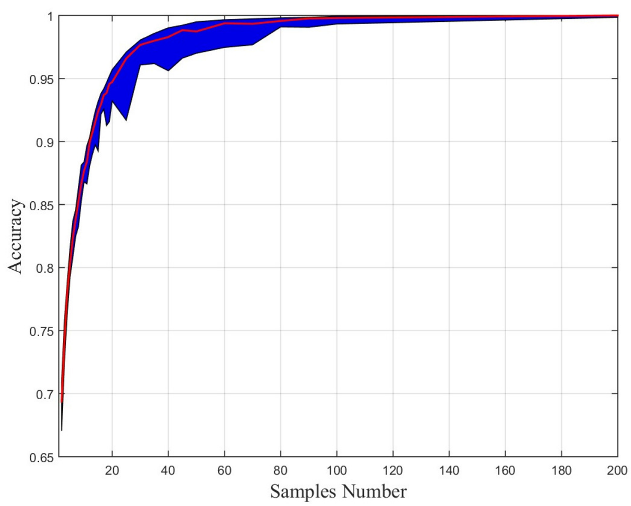

Fig. 12. General classification accuracy.

minimum accuracy obtained for the test bench. Note that the accuracy increases rapidly as the number of samples increases. About one hundred sample tests are enough to obtain an acceptable classification accuracy.

Fig. **??** shows classification accuracies for different numbers of samples.

In addition, the resulting accuracies for the proposed method are shown in Table **??**, where the mean, minimum and maximum percents are presented including error percentages for each class. The HLT condition classification has more accuracy than the BRN and BAL conditions classification with fewer samples. As the number of samples increases, the BRN condition reaches the best detection.

The proposed method is applied to a set of test signals with a sampling frequency of 750 Hz, and window samples from two to two hundred. The accuracy averages are shown in Fig. **??**, where they are compared against the results obtained from the signals obtained using a 1.5 kHz sampling frequency. The QSA method accuracy is not affected when the sampling frequency in the input signals is changed, and 1.5 kHz is an adequate sampling frequency because most of the fault spectral harmonics in the signal are kept.

In Table **??**, the proposed method is compared to other

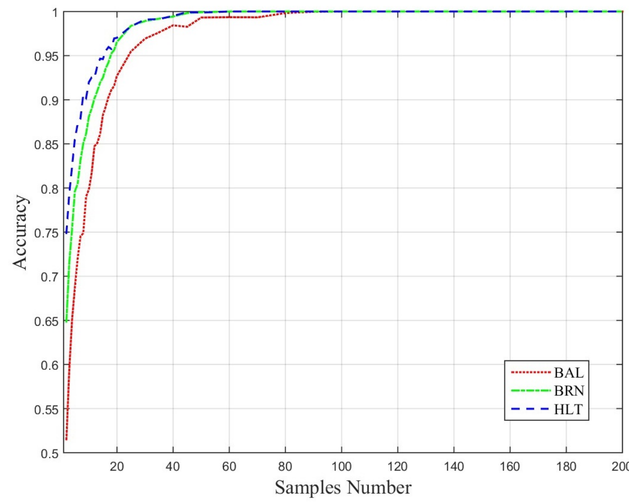

Fig. 13. Classification accuracy.

TABLE I
MEAN, MAXIMUM AND MINIMUM CLASS CLASSIFICATION ACCURACY.

Samples	True Class	Assigned Class BAL	BRN	HLT
		Mean(min,max)	*Mean(min,max)*	*Mean(min,max)*
2	BAL	0.53 (0.43,0.70)	0.22 (0.07,0.32)	0.25 (0.15,0.39)
	BRN	0.27 (0.17,0.37)	0.65 (0.56,0.75)	0.08 (0.06,0.11)
	HLT	0.22 (0.07,0.42)	0.04 (0.00,0.13)	0.74 (0.50,0.93)
5	BAL	0.69 (0.56,0.81)	0.15 (0.05,0.27)	0.16 (0.08,0.28)
	BRN	0.19 (0.12,0.27)	0.79 (0.70,0.86)	0.02 (0.01,0.03)
	HLT	0.15 (0.02,0.38)	0.00 (0.00,0.06)	0.85 (0.58,0.98)
10	BAL	0.80 (0.66,0.91)	0.10 (0.03,0.19)	0.10 (0.03,0.25)
	BRN	0.12 (0.07,0.18)	0.88 (0.81,0.93)	0.00 (0.00,0.01)
	HLT	0.09 (0.00,0.40)	0.00 (0.00,0.02)	0.91 (0.60,1.00)
15	BAL	0.88 (0.76,0.97)	0.06 (0.01,0.14)	0.06 (0.01,0.16)
	BRN	0.08 (0.04,0.13)	0.92 (0.87,0.96)	0.00 (0.00,0.00)
	HLT	0.07 (0.00,0.51)	0.00 (0.00,0.01)	0.93 (0.49,1.00)
30	BAL	0.96 (0.86,1.00)	0.02 (0.00,0.08)	0.02 (0.00,0.11)
	BRN	0.01 (0.00,0.07)	0.99 (0.93,1.00)	0.00 (0.00,0.00)
	HLT	0.02 (0.00,0.43)	0.00 (0.00,0.01)	0.98 (0.57,1.00)
100	BAL	0.99 (0.95,1.00)	0.01 (0.00,0.05)	0.00 (0.00,0.00)
	BRN	0.00 (0.00,0.00)	1.00 (1.00,1.00)	0.00 (0.00,0.00)
	HLT	0.01 (0.00,0.11)	0.00 (0.00,0.00)	0.99 (0.89,1.00)
200	BAL	1.00 (1.00,1.00)	0.00 (0.00,0.00)	0.00 (0.00,0.00)
	BRN	0.00 (0.00,0.00)	1.00 (1.00,1.00)	0.00 (0.00,0.00)
	HLT	0.01 (0.00,0.07)	0.00 (0.00,0.00)	0.99 (0.93,1.00)

methods used to detect induction motor failures. It is noticeable that very few samples are required compared to the proposed methods to obtain a high accuracy classification, recall and specificity without space transformations; this effectively reduces the sampling time.

The method proposed in this paper involve low processing times for each sample as shown in Fig. **??**. The average time was captured from the implementation of the method using MATLAB R2017a to activate the parallel pool. MATLAB simulations were executed on a personal computer DELL optiplex 7040 with an IntelTM Core i7 processor, 4 cores, 3.4 GHZ, 8 MB cache, and 8 GB RAM. During the computer

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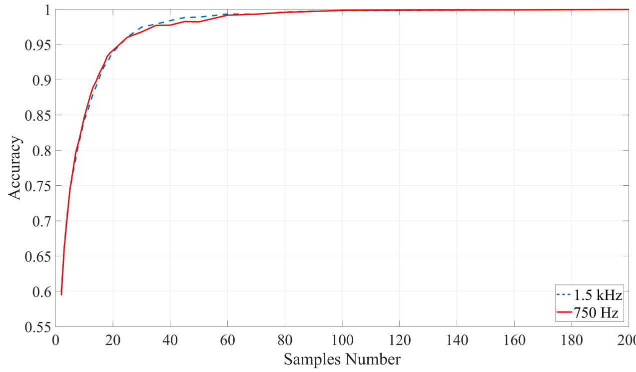

Fig. 14. General classification accuracy comparison of the QSA with low frequency

TABLE II
METHODS COMPARISON TABLE.

Method	Classification	Classes	Samples	Sampling Time	Accuracy	Recall	Specificity
CCA [?]	Hierarchical Neural Network	6	10 000	1 s	0.8-1.0	0.97	0.99
AAC [?]	Artificial Intelligence	3	100 000	5 s	0.71-1.0		
PCA & LDA [?]	Neural Network	5	270 000	1 s	0.90-0.92	0.92	0.98
SMOTE [?]	ADABOOST	5	800 000	10 s	0.8-1.0	0.93	
QSA (Our approach)	Classification Tree	3	2	1.3 ms	0.53-0.74	0.64	0.78
			30	20 ms	0.96-0.99	0.97	0.98
			200	130 ms	0.99-1.0	0.99	0.99

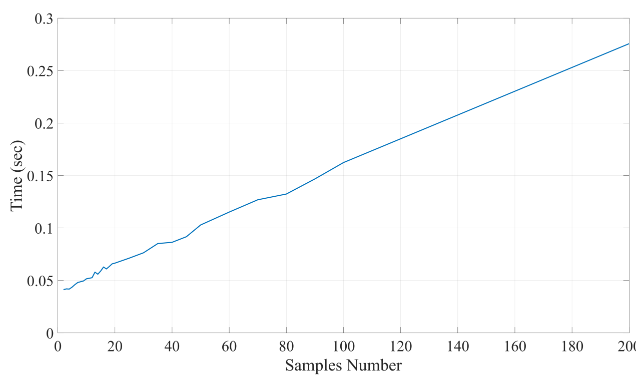

Fig. 15. Computation time

simulations, the processing time went from 0.0412 seconds (when using two samples) to 0.2756 seconds (when using two hundred samples in each test).

VIII. CONCLUSIONS

In this paper, the number of conditions analyzed was set to 3 in order to show the efficacy of the proposed method. However, the proposed methodology can be used to analyze more than three conditions. This method extracts features for the detection of faults in induction motors through statistical quaternion analysis. This method uses basic operations without requiring space transformations. Experimental results show that the proposed method obtains clear features, which can be used to detect three different states of induction motors even when only a few samples are available. As the number of samples increases, the accuracy of the method improves, and consequently, the feature-separation performance levels increase. Additionally, the proposed method requires less data than other traditional methods used for fault identification in induction motors. This results in low data processing times, and it could be used for online monitoring in other industrial machinery to identify other faults.

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