Multiclass SVM Bearing Fault Diagnosis of Induction Motors using Hilbert Huang Transform

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***Abstract*—**Fault detection is a major challenge for asynchronous motor maintenance. Bearing defects are the most important defects that can occur in theseIn this context, we propose a new approach using Hilbert Huang transform-based stator current analysis (HHT) and multi-class support vector (MSVM) machines for the diagnosis of these failures.Experimental data, obtained from the stator current of the asynchronous motor subjected to various loads in the healthy and faulty cases of the bearings, are analyzed and classified. The applied MSVM classifier is able to identify the type of faulty bearing and our experimental results demonstrate the effectiveness of the proposed method.

***Keywords*—**Fault diagnosis, induction motors, bearing fault, Hilbert-Huang transform, multi-class support vector machine.

I. Introduction

THE induction motor machine is already being widely used in industry sector for various technical and economic reasons [1].This is due to its high reliability, low cost, its mechanical robustness and low maintenance needs. However, faults can always occur regardless of the strength of this type of motor. These machines, depending on their application are facing a variety of constraints resulting by their operating conditions. These constraints could lead to failures of stator or rotor. In fact, the occurrence of a fault often results irreversible shutdown of the induction machine also significant repair cost as well as production losses [2].There are different types of defects could be occurred in the induction motor such as: breaking of rotor bars, short-circuit of one or several stators, misalignment of the shaft, failure of bearings and gearboxes [3]. Classification of most occurred defects can be found in [4] and [5]. The bearing defects represent about 40% of the failures occurring on the machine [3].

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Therefore, the reliability of asynchronous machines is becoming increasingly important subject in terms of scientific research, industry as well. Traditionally, the monitoring of motor condition was based on measurement analysis of the quantities such as noise, vibrations and temperature. Vibration analysis is one of the most widely used methods for monitoring fault bearing defects of electrical machines. This approach involved using signal processing techniques such as FFT to monitor characteristic. Frequencies of these defects in the vibration spectrum as mentioned by [7]-[9]. However, the high cost of vibration sensors vibrations (such as piezoelectric accelerometers) makes these solutions often difficult to be implemented. In an effort to overcome this issue, the current analysis technique was used to get these defects monitored. Many scientific studies have demonstrated that he rolling defects signatures of electrical machines could be successfully extracted using the stator current measurements [10]- [13]. Generally, signal processing techniques are used by the methods based on current analysis.

Among these methods used, we can cite the motor current signature analysis (MCSA). [14]-[16]. MCSA technique has many advantages. It is non-invasive, where stator current is measured simply by using current sensor and no other special equipment is needed. By simply processing the motor current signals, fault diagnostic information is extracted. Numerous faults can be diagnosed using MCSA: damaged rotor bar, such as, broken rotor bars, static or dynamic eccentricities, for example, due to unbalanced rotor, bearing defects, stator winding shorted

Nevertheless, this method has limitations regarding detection of bearing defects. In fact, these defects have shown non-stationary behavior. Several researchers have looked to establish adapted methods to non-stationary signals for monitoring and detection of bearing defects in induction motor such as time-analysis frequency, spectrogram, wavelet decomposition, Wigner-Ville distribution and high-resolution frequency estimation [15]-[21].

Hilbert-Huang transform (HHT) [22] was recently used for the analysis of non-stationary and non-linear signals. HHT is a composition of empirical mode decomposition (EMD) [22] and Hilbert Transform (HT) [23].

HHT has been found to be powerful and successful in condition monitoring of electric machines using vibration data

[23] and in detection of rotor bar failures of induction machines using stator current data [24] and has recently been applied for rotating machinery diagnosis with notable success [25]-[26] and wind turbine [27] .

When applying the HHT, first, the EMD will decompose the acquired signal into a collection of intrinsic mode functions (IMF).The original signal could be expressed as the sum of these functions. However, in case EMD is applied to non-stationary signals, the original signal cannot be re-assembled due to mixing mode problem. In order to overcome this problem Wu and Huang suggested EEMD method (Ensemble Empirical Mode Decomposition) based on EMD algorithm de [28]-[29].The problem of mixing mode has been resolved through the addition of white Gaussian noise.

In this work, we apply the modified version of the Hi [28]-[29]. This method decomposes the original time series data in intrinsic mode function, using the EEMD. Subsequently, HT is applied to each intrinsic mode function.

We propose in our work the application of the EEMD and HT to design the feature vector of bearing fault. In order to identify these failures a multi-class classifier is needed. Several classification techniques have been developed in recent years for the classification of defects mechanical induction motor such as Artificial Neural Networks (ANN) [30]-[31] and SVM [32]- [33]. SVM has recently been successfully applied in several fields and more particularly in faults diagnosis of asynchronous motor.

In our work, we used multiclass SVM classifier for the classification of bearing defects in the induction motor.

II. HHT AND SVM

The Hilbert Huang transform, proposed in 1998 by Huang [22], is a technique for analysing data based on non-linear empirical data and non-stationary processes. HHT, considered as a time frequency analysis method, consists of adaptively decomposing a signal into a sum of oscillating components which has a single frequency for each sample. It then calculates the frequency and the instantaneous amplitude of each of these components using the Hilbert transform.HHT is the combination of EMD and HT.

A. EMD algorithm

EMD is an adaptive spectral decomposition algorithm method (it is entirely data-driven) [22]. It is defined by a process called sifting for decomposing a signal in basic functions. These functions called *IMF* (Intrinsic Mode Function) are zero mean signals. Two conditions must be met for obtaining these IMFs:

a) In a data set, the number of extreme values and zero crossings must be equal or different from one at most.

b) At any time, the average value of the envelope defined by the local maxima and the envelope defined by the local minima is equal to zero.

The IMFs of a signal x are obtained using the following steps:

(1) Put $d_1 = x$

(2) Identify the positions and the amplitudes of all the maxima and local minima in the d_1

(3) Create a line $u_{\max}$ of upper envelope and a lower envelope line $u_{\min}$ by cubic spline interpolation of maxima and local minima.

(4) Calculate the mean m of upper and lower envelopes

$$m = \frac{u_{\max} + u_{\min}}{2}, \tag{1}$$

(5) Get d_2 between the signal d_1 and average m the difference as follows:

$$d_2 = d_1 - m, \tag{2}$$

(6) Repeat operations (2) to (5) until the difference between d_{k+1} and d_k satisfies the following condition:

$$0.2 \le SD(k) = \frac{\left\|d_{k+1} - d_k\right\|}{\left\|d_k\right\|^2}, \tag{3}$$

(7) Put $c_1 = d_k$ as first IMF.

(8) Calculate the residue $r_1 = x - c_1$ .This residue is considered as the new signal c_2 and repeat steps (1) to (7) for the second IMF, rated c_2, and $r_2 = r_1 - c_1$ .Repeat steps (1) to (7) in order to finally get the *Nth* IMF. Thus, the input signal can be decomposed into N IMFs until the residue becomes a monotonic function so that no further extraction of an IMF is possible. The input x can be reconstructed from all IMFs so that:

$$x = \sum_{j=1}^{N} c_j + r_{N_j}. \tag{4}$$

B. EEMD algorithm

The EMD algorithm may have drawbacks to its output such as mode mixing and aliasing caused by overlapping spectra of IMFs [25]. To overcome these problems, Wu and Huang suggested the algorithm of EEMD [25]-[26].

The principle of the EEMD is based on the addition of the white noise in the signal with many trials. The noise in each trial is different. The EEMD method defines the IMF components as the mean of an ensemble of trials. The steps of this algorithm are as follows:

Calculate the signal x_j

$$x_j(t) = x(t) + \beta_0 n_j(t), \tag{5}$$

Where $n_j(t)(i=1,...,N)$ is the white noise of unit variance and β_0 its amplitude.

Decompose the signal obtained previously using the EMD algorithm to get the IMFs:

$$x_j(t) = \sum_{i=1}^{N_j} c_{ij} + r_{N_j}, \tag{6}$$

Where c_{ij} represents the *i*th IMF of the *j*th trial, r_{N_j} represents the residue of *j*th trial, and is the IMFs number of the *j*th trial.

To repeat steps (1) and (2) until the predefined ensemble trial number (M) (add different random noise signal each time).

To calculate the ensemble means of the corresponding IMFs of the decompositions as the final result $c(i)$:

$$c(i) = \frac{\left(\sum_1^M c_{ij}\right)}{M} i = 1, 2..., K. \tag{7}$$

Where K is the minimum number of IMFs among all the trials.

In our work, we opted for the choice of EEMD instead of EMD. This choice is motivated by the benefits of EEMD relative to the latter. Indeed, EMD is a completely data-driven approach, but it includes a mixing mode problem, causing oscillations in the same mode or similar oscillations in different modes. Wu and Huang proposed the EEMD to overcome this disadvantage.

C. Hilbert transform (HT)

The transformation of Hilbert is one of the most important operators used in the field of signal theory. Generally, the HT transform is used to determine the instantaneous amplitude, phase, and frequency.

The Hilbert transformation is carried out at each IMF $c(t)$ obtained after the application of EEMD method at the signal $x(t)$. The analytic signal $h(t)$ of $c(t)$ is follows:

$$h(t) = c(t) + j\hat{c}(t) = a(t)e^{j\theta(t)} \tag{8}$$

Where $\hat{c}($is the amplitude function and the envelope signal of the IMF component $c($ is:

$$\hat{c}(t) = H[c(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c(s)}{t-s} ds \tag{9}$$

The instantaneous amplitude of signal $c(t)$ can be determined as:

$$a(t) = \sqrt{c(t) + \hat{c}(t)^2} \tag{10}$$

D. SVM

SVM is a modern method of computer learning based on the theory of statistical learning presented by Vapnik [34]. The foundation of this method is to find a linear classifier between two classes of data, and arrange it so that the margin is maximal. This margin represents the distance between the border and the nearest data point in each class. These points, used to define the margins, are called support vectors (SV). The concept of this method that is presented in this article was conceived on the basis of the theory of statistical learning. The basic idea deals with two-class problems separating two classes by a hyperplane. This one is determined by a number of support vectors. In the separable linear case, there exists a separation hyperplane whose function is:

$$wx + b = 0, \tag{11}$$

Where the vector defines the boundary, is the input vector of dimension *d*, and *b* is a scalar threshold. The optimal hyperplane can be obtained as follows:

$$minJ(w) = \frac{1}{2}\|w\|^2, \text{subject to } y_i(wx+b) = 0 \geq 1, \tag{12}$$

Where $\|w\|$ is the Euclidean norm of w , $i = 1,...,l$ is the number of training sets, and labels $y_i = 1$ and $y_i = -1$ are for positive and negative classes, respectively. The solution can be obtained by:

$$w = \sum_{i=1}^{l} \alpha_i y_i x_i, \tag{13}$$

Where $\alpha_i \geq 0$ are Lagrange multipliers and x_i are support vectors obtained from training. After training, the decision function for the linear SVM is obtained as follows:

$$f(x) = sign\left(\sum_{i=1}^{l} \alpha_i y_i x_i (x.x_i) + b\right). \tag{14}$$

In a linear non-separable case, SVMs can create a hyperplane, which allows linear separation in the higher dimension, to perform a nonlinear mapping. The nonlinear mapping by the kernel function converts the input vector x from a $d-$dimensional space into a higher dimensional feature space. In nonlinear SVMs, kernel functions such as linear, polynomial, and Gaussian RBF may be selected to obtain the optimal classification results. The most widely used kernel functions are represented in Table I.

Table I. Formulation of kernel functions

Kernel functions	Representation
Kernel	$K(x, x_j)$
Linear	$x^T . x_j$
Polynomial	$(\gamma x^T x_j r)^d, \gamma \geq 0$
Gaussian RBF	$exp(-\left\| x - x_j \right\|^2 / 2\gamma^2)$

Support vector machines are in their binary origin. However, real-world problems are in most cases multiclass such as rotating machines that are subject to more than two defects. In such cases, one does not attempt to assign a new example to one of two classes but to one of several, ie the decision is no longer binary and a single hyperplane is no longer sufficient. The methods of multi-class support vector machines reduce the multi-class problem to a composition of several two-cell hyperplanes for drawing the decision boundaries between the different classes. These methods decompose the set of examples into several subsets, each representing a problem of binary classification. For each problem a separation hyperplane is determined by the binary SVM method. These methods include strategies one against all (OAA) and one against one (OAO).

The rest of the article is organized as follows. HHT and SVM algorithms are presented in Section II. The proposed method is described in section III. Section IV describes the experimental setup of the induction motor. Section V presents the detection process. The results and discussion are highlighted in Section VI.

III. PROPOSED METHOD

The proposed method can be summarized as follow:

(1) Decompose current signal by applying the EEMD and generate a set of IMF according to the process described above.

(2) Select the first four IMFs.

(3) Apply the Hilbert transform to selected IMFs.

(4) Calculate the entropies of the envelopes of selected IMFs. The value of the entropy is calculated as follows:

We define the energy of selected signals as total energy Ei and the total energy as E. They are expressed in equations (13) and (14) as shown below:

$$E_i = \sum_{n=1}^{T} \left| c_i(n) \right|^2 , \tag{14}$$

$$E = \sum\nolimits_{i=1}^{N} E_i , \tag{15}$$

Where T is the number of samples of the signals and N is the total number of selected signals. Whereas the energy values are often large and to facilitate the calculation and analysis, we take the ratio of the energy as defined in equation (15).

$$P_{Ei} = \frac{E_i}{E}, \tag{16}$$

Let us form the energy vector ratio:

$$P_E = \left[P_{E_1}, P_{E_2}, P_{E_3}, \ldots, P_{E_N} \right], \tag{17}$$

The entropy of the energy vector ratio of the selected N IMFS is defined by the following equations:

$$E_{Entropy} = -\sum_{i=1}^{N} P_{E_i} \log P_{E_i} , \tag{18}$$

The value of the entropy calculated in equation (18) is considered as a bearing fault feature.

(5) Create the feature vector with the entropies of the IMFs selected for M fault signals:

$$FV = [\, E_{entropy1,} E_{entropy2,\ldots,} E_{entropyM} \,], \tag{19}$$

(6) Calculate the Euclidean distance defined below:

$$D = \sum_{i=1}^{M} \left| E_{entropy_i} - E_{entropy-Healthy-noload_i} \right|. \tag{20}$$

The value of the entropy calculated in equation (20) is considered as a bearing fault feature.

By applying the steps described above, the two-dimensional fault feature is constituted. The application of the SVM multiclass classification algorithm having as input two-dimensional fault feature has demonstrated the effectiveness of the proposed method.

IV. EXPERIMENTAL SYSTEM

The scheme of the experimental system is illustrated in Figure (1). Figure (2) shows the experimental setup which consists of two parts. The mechanical part consists of a tachometer generator, a three-phase asynchronous motor and an alternator. The tachometer generator is a DC machine that generates 90 V at 3000 rpm. It generates a linear voltage between 2500 and 3000 rpm. The alternator is a three-phase synchronous machine with a regulator and a rectifier circuit that stabilizes the DC output voltage of 12 V. The electrical part of the experimental system consists of: three current transformers, lamps used as loads and a data acquisition card for PC.

The induction motor bearings are single-row ball bearings, type 6204 • 2ZR. Each bearing has 8 balls. Experiments were carried out on 5 bearings: one of them is intact, while the other four have been drilled with holes of diameters between 3 and 6 mm, as illustrated in Figure 3.

The parameters of the asynchronous machine and the rolling data are given respectively in the appendix and in Table II.

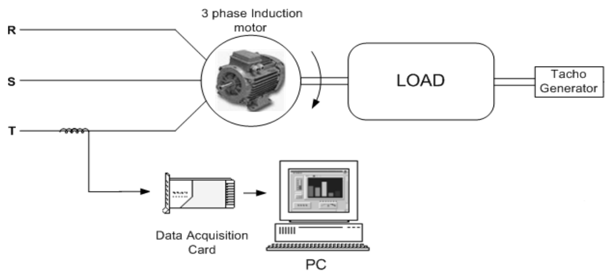

Fig. 1. Experimental system scheme

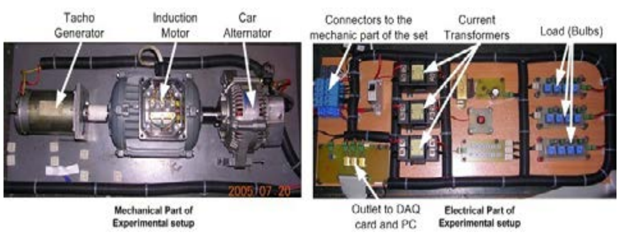

Fig. 2. Experimental setup

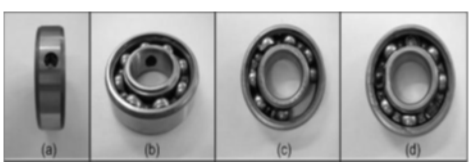

Fig. 3. Artificially deteriorated bearings: (a) outer race deterioration, (b) inner race deterioration, (c) cage deterioration, (d) ball deterioration.

Table II. Bearings parameters

Type	6204.2ZR
Outer diameter	47 mm
Inside diameter	20 mm
Pitch diameter D_p	31.85mm
Number of balls N	8
Diameter of balls D_B	12 mm

V. Detection Process

The results of the proposed method are presented in this section. The algorithm of EEMD is applied to the stator current for healthy and faulty bearing with different loads. Figure (4) shows the results of the decomposition of the stator current by the EEEMD (ratio at rated load 40%). The signals from the first four IMFS, considered relevant for them. It can be concluded that these IMFs will be considered signals that contain more information on the bearing.

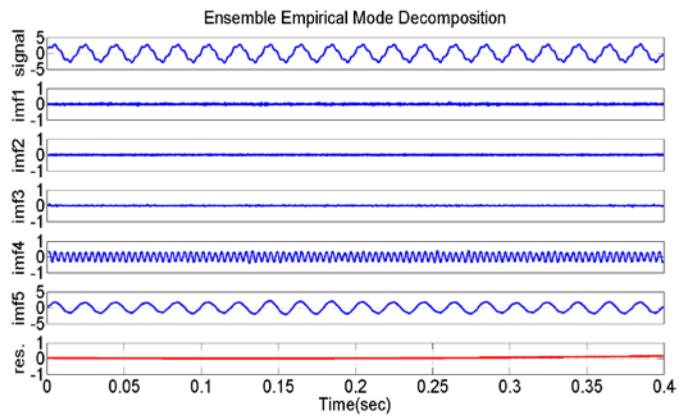

Fig. 4. Stator current EEMD (cage damage).

By applying the steps in the proposed method, we calculate the entropy of the envelope signal of IMFS selected for different loads and bearing defects.

The results obtained after calculation of the entropies for selected IMFS envelopes are illustrated in the bar graph shown in Figure (5). The analysis of these results shows that the criterion based on the entropy of the signals provides a good discrimination of bearing defects. Note the entropy in the case of healthy bearings is higher than those for faulty bearings. The entropy will be used as a component of the vector features.

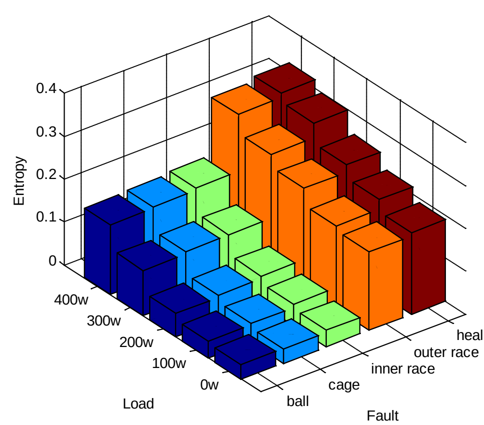

Fig. 5. Entropy values of healthy and faulty bearings.

VI. RESULTS AND DISCUSSION

In order to classify the different defects in classes with the SVM classifier, we use the vector features having as components the entropy and the Euclidean distance between the healthy signal without load and the signals with the different loads. In figure (6), we have represented the distribution of fault data of the five classes (healthy, ball, cage, inner race and outer race) for a ratio to nominal load of 53.33%. We notice in this figure, that the data of the class 'healthy' and those of the class 'outer race' are almost confused.

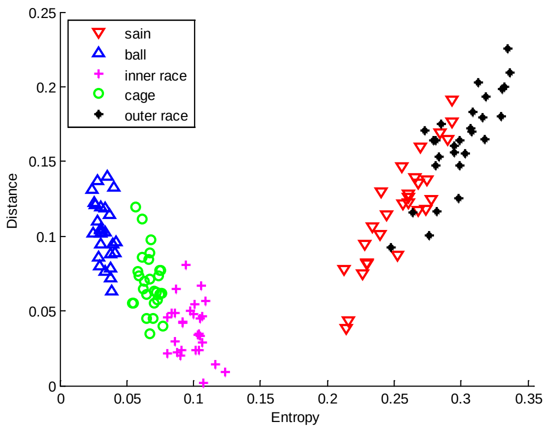

Fig.6. Data distribution of 5 fault classes of rolling element bearings for ratio to nominal load 53.33%.

For a best distribution of defects in classes, we reduce the classification of these into four classes (healthy, ball, cage, inner ring). As shown in Figure (7), we note that the four classes of defect data are well discriminated. This demonstrates that the feature vector with entropy and distance components gives better class discrimination for fault diagnosis of rolling element bearing based on current analysis.

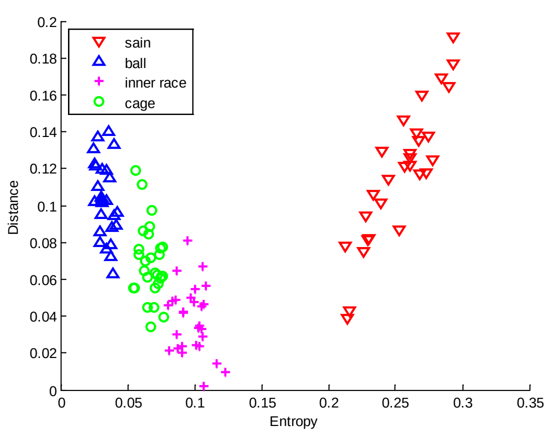

Fig.7. Data distribution of 4 fault classes of rolling element bearings for ratio to nominal load 53.33%.

When applying the SVM toolbox [35] in our study, two kernel functions, polynomial and Gaussian, were used in fault classification. Figures (8) and (9) illustrate the results of the SVM multi-class classification of signals for a healthy state and faulty states of bearings for ratio to nominal load 53.33%.

Table III shows the accuracy of the classification for the two SVM multiclass strategies; OAO and OAA. Each value in the table indicates the classification accuracy obtained with two different kernel; Gaussian and polynomial. It is shown in this table that the best accuracy for both strategies is obtained using the polynomial kernel. Further analysis of these results shows that the OAA strategy has higher classification accuracies than OAO. As shown in Table III, the accuracy rate of 100% is obtained when using the polynomial kernel and the OAA strategy.

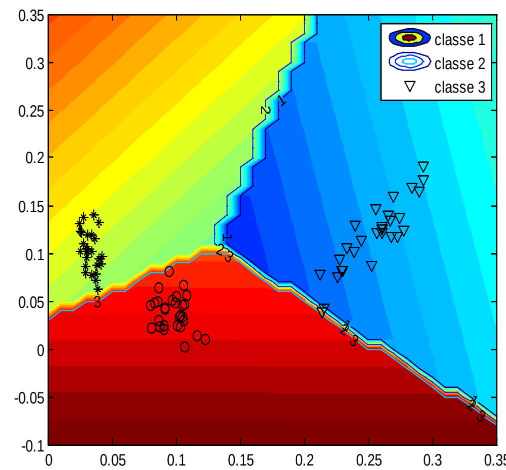

Fig.8. Multiclass SVM (OVA, kernel=gaussian)
Rate of correct class in training data: 98.81%

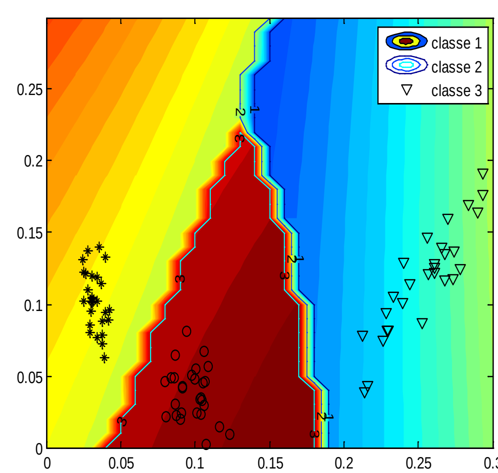

Fig.9. Multiclass SVM (OVA, kernel=polynomial)
Rate of correct class in training data: 100%

Table III. Classification accuracy

Kernel functions	SVM test accuracy (%)	
	OAA	OAO
Gaussian	98.81	94.75
Polynomia	100	97.87

VII. CONCLUSIONS

In this paper, a stator current analysis method using the Hilbert Huang transform and the SVM is presented for the diagnosis of induction motor bearing defects. The proposed method uses the entropy of the first four IMFS of the stator current decomposition based on the EEMD as an indicator of defects. The analysis of the experimental results demonstrated the effectiveness of the proposed method.

APPENDIX:

The parameters of the asynchronous motor used in this article are as follows:

0.7 kw, 220/3380V, 1.95/3.4A, 2780 rpm, 50Hz.

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