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An evolutionary lifting scheme Wavelet Packet Decomposition method for mechanical fault detection in elevator systems

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Abstract- The design procedure of a second-generation wavelet packet decomposition, based on an evolutionary approach, is introduced for industrial fault detection. The procedure has been validated by means of an experimental case study for an induction motor used as traction machine in an elevator system. Preliminary results on three mechanical faults related to ball-bearing show encouraging performance.

I. Introduction

Elevator system are most common transportation tools in modern buildings. However, long-time usage can increases fault-occurrence probability [1]. When occurred, a fault on an elevator system causes many problems to people living in the building, to workers and to each activity needing for a quick access to the building.

Generally, this problem is overcome by contracting service companies specialized in installation, ordinary maintenance and system repair. They consider correct inspection and fault detection a critical point to restore the system rapidly and, above all, preserve their business.

The most critical faults in elevator system regards the induction motor, used as traction machine [1],[3]. Therefore, on-line fault detection on elevator traction machine is a desirable task to ensure safe operation and timely maintenance.

Fault detection techniques for induction motors are classified generally according to electrical and mechanical faults. Electrical faults refer to problems occurred, as an example, in stator or rotor coils, while mechanical faults regards mechanical components deterioration. In technical and scientific literature, several diagnostic methods were proposed, such as temperature measurement, acoustic noise analysis, infrared measurements and so on [4].

Among these techniques, Motor Current Signature Analysis (MCSA) [5] is one of the most popular. MCSA is based on the following idea: a fault in the motor (mechanical or electrical), usually causes an abnormal change in the frequency spectrum of the stator currents, to be detected via Fast Fourier Transform (FFT). Hence, MCSA is an advantageous fault detection technique because is minimally invasive (stator currents can be detected from the terminals) and operates both on mechanical and electrical faults.

For these reasons, in lasts years, different faults detection techniques based on MCSA were proposed exploiting Discrete Wavelet Transform (DWT) [6] or Wavelet Packet Decomposition (WPD) [3], combined to FFT in order to obtain an effective features extraction, especially when the stator currents exhibit a complex spectrum due to power electronic drives of the induction motor.

However, these techniques are inappropriate for on-line fault detection embedded on low-cost microcontrollers due to the computational complexity, needing for excessive resources. One of the possible solutions is a WPD based on the lifting scheme [2]-[7], also called second-generation wavelet. This method has twofold advantages: (i) the WPD allows a time-frequency localization better than traditional DWT, fostering fault-features identification; and (ii) the second-generation wavelet are less computationally complex than traditional wavelet, because the lifting scheme technique not requires the FFT as design tool for wavelets. The lifting scheme consists of four main steps: split, prediction, compute and update. While the splitting is a trivial task, the last three steps (prediction, compute and update) needs for defining mathematical functions: thus, a detailed description of the analysed signal is not easy to be achieved.

On this basis, in a previous work [8], the authors showed the capability of evolutionary procedures (based on cultural algorithms (CA) [10]) of optimizing effectively the design of adaptive wavelet filters based on lifting scheme. However, from the fault detection point of view, the description of the analyzed signal should be as much accurate as possible in order to detect anomalies in frequency when the fault occurred.

In this paper, based on evolutionary procedure, an optimal lifting scheme Wavelet Packet Decomposition (LSWPD) of the signal, is proposed. In particular, the proposed procedure is applied experimentally on an induction motor to three typologies of mechanical faults related to ball-bearing: (i) Ball Bearing Defect (BBD), (ii) Inner-Race Defect (IRD) and (iii) Outer-Race Defect (ORD).Through an evolutionary algorithm-based procedure [8], for each kind of fault, an optimal LSWPD of signal capable of highlighting the corresponding features, is designed.

II. Proposed Method

In the following, (A) the *design problem,* and (B) the *proposed evolutionary approach* are detailed.

A. Design Problem

The optimum coefficients of the wavelet packet decomposition filter based on lifting scheme (LSWPD filter) capable of detecting a specified type of fault, have to be determined. The lifting scheme wavelet transformation consists of four recursive basic steps [2]: (1) split the signal $X_{0,1}$ into its odd and even components, (2) predict the odd from the even samples (function P), (3) compute the wavelet coefficients as difference between odd and predicted samples, and (4) update the even component with a combination of the detail (function U), in order to approximate the original signal. Wavelet coefficients are represented analytically by:

$$X_{i,j}(k) = X_{i-1,j-1}(2k+1) - \sum_m P(m)\cdot X_{i-1,j-1}(2m+2k) \tag{1}$$

where k = 0,…,2j ; the approximation Xi, j-1 is represented as:

$$X_{i,j}(k) = X_{i-1,j}(2k) + \sum_m U(m)\cdot X_{i,j-1}(2m+2k+1) \tag{2}$$

For the filter design, the wavelet packet decomposition is implemented by applying the lifting-scheme basic steps to wavelet and approximation coefficients, recursively (Fig. 1). Thus, level by level, the coefficients will be arranged in a binary tree, where each coefficient is also named *node,* pointed out as an integer value $X_{0,1} \equiv$ *node 0,* $X_{1,1} \equiv$ *node 1,* $X_{1,2} \equiv$ *node 2,* and so on. In Fig. 2, the inverse transform, LSWPR, is carried out simply by reversing the order of the operations and by changing the signs.

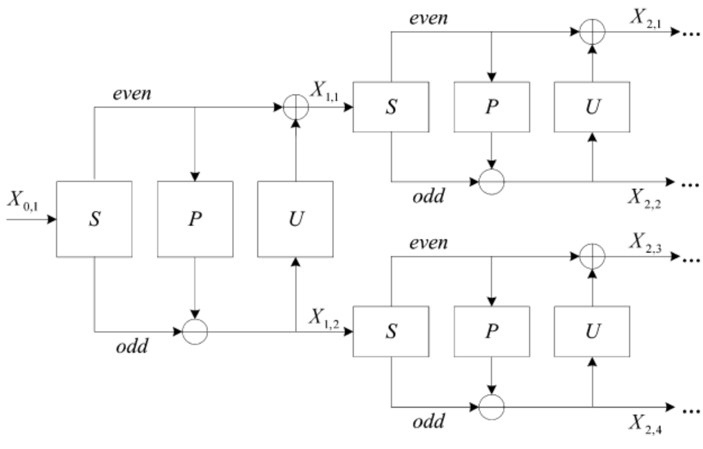

Figure 1 Lifting Scheme Wavelet Packet Decomposition

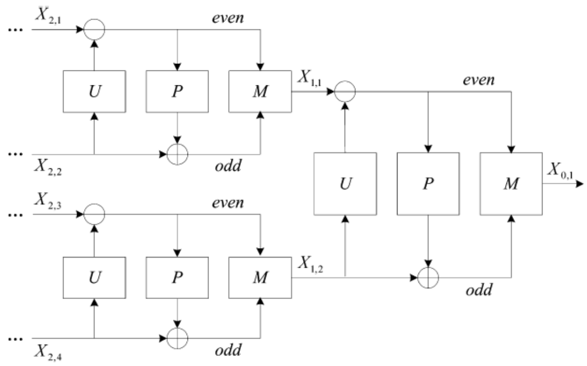

Figure 2 Lifting Scheme Wavelet Packet Reconstruction

The optimal configuration, expressed by the filter's coefficients *U* and *P*, capable of detecting faults and highlighting their features , has to satisfy the following constraints [2]:

$$\sum_{m} P(m) = 1 \ , \ \sum_{m} U(m) = 1/2 \tag{3}$$

B. The Proposed Evolutionary Approach

The optimization problem of LSWPD filter's coefficients was faced by two complementary algorithms: genetic and cultural evolution.

Genetic Algorithm (GA) for solution search uses three basic steps [9]: (1) mutation, (2) combination, and (3) natural selection. In mutation, filter configurations are modified randomly in order to generate new potential solutions. In combination, the genetic patrimony of two or more filter configurations are shared (crossover), in order to obtain new solutions to be evaluated. In natural selection, a suitable function (fitness) selects the best filter configurations, in order to transmit their genetic patrimony on best search paths to new potential solutions (elite count), to be generated by a further mutation.

Cultural Evolution adds further functions in order to identify best search paths [10]-[12]. After a first complete genetic evolution, the best filter configurations are selected by an accept function. By means of the function update, the characteristics of accepted solutions create and upgrade a suitable archive (the Belief Space) where the best research paths are stored. This archive contains also information about the last best candidate solutions and a map of the search. This knowledge is transferred to new population's individuals by means of the influence function, so by giving rise to a Cultural Evolution.

In this approach, "culture" is designated for storing and updating information on the solution search to the above problem of filter design optimization. The information is made available to the population as a whole during evolution. Thus, new generations of filter configurations can access also to information not experimented directly by their ancestors (such as it happens in genetic strategy, conversely). In this way, the intrinsic resource waste of GA, due to (1) only direct inheritance via genetic mechanism, and (2) purely random generation at each evolution step, is avoided.

The development of a CA imposes a overhead of work with respect to standard GA developments aided by suitable tools. However, CA proved to enhance efficiency and accuracy significantly for problems to be optimized in a continuous domain [11] [12].

III. Fault Designs and Experimental Results

The proposed procedure has been tested on three kinds of mechanical defects related to the ball bearing. In the following: (A) an overview on theoretical aspects for the considered faults is reported and (B), the experimental results are detailed.

A. Fault Designs

Local defects or wear defects cause periodic impulses in vibration signals. Amplitude and period of these impulses are determined by shaft rotational speed, fault location, and bearing dimensions. The frequency of these impulses, considering different fault locations as in Fig.3, are obtained by (4)–(7) [13].

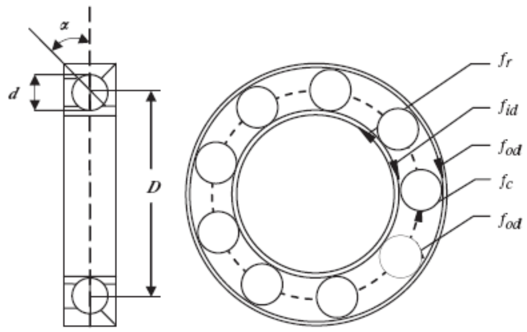

Figure 3 Bearing dimension and characteristic defect frequencies

Fundamental cage frequency is given by:

$$f_c = \frac{f_r}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{4}$$

where f_r is the shaft rotation frequency, d is the roller diameter, and D is the pitch diameter of the bearing. Local Defects, owing to wear, bring frequency vibrations to the system. These depend on the cage frequency, therefore amplitudes and periods of these components will depend on shaft rotation speed, position defect, and bearing sizes. The bearing faults can be classified according to the defect position. Three kinds of defects can be distinguished: (i) Ball Bearing, (ii) Inner Race, and (iii) Outer Race Defect.
(i) Ball Bearing Defect (BBD) frequency is two times the ball spin frequency and can be calculated as:

$$f_{bd} = \frac{D}{d} f_r \left(1 - \frac{d^2}{D^2} cos^2(\alpha)\right) \tag{5}$$

(ii) Inner Race Defect (IRD) frequency is given by:

$$f_{id} = n(f_r - f_c) = \frac{n f_r}{2}\left(1 + \frac{d}{D}\cos(\alpha)\right) \tag{6}$$

(iii) Outer Race Defect (ORD) frequency is given by:

$$f_{od} = n f_c = \frac{n f_r}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{7}$$

where n is the number of rollers.
Since these mechanical vibrations produce anomalies in the air gap flux density, they result in the modulation of stator current. These frequency components can be calculated by [14]:

$$f_{FD} = |f_A \pm m \cdot f_V| \tag{8}$$

where $m = 1,2,3 \ldots$, f_A is the electrical power supply frequency, and f_V is one of the characteristic vibration computed by (4)–(7).

B. Experimental Results

The proposed method was validated preliminarily by some experimental case studies. The case studies are carried out on a 5 kW induction motor, 50 Hz, powered at 380 V (without power electronic equipment), with number of poles 4. The stator currents are detected from the terminals by three LEM – LA 55-P current transducers. The signals from transducers are acquired by a National Instruments data acquisition board NI-USB 6211 and processed on a laptop PC by NI Labview 8.1 software.

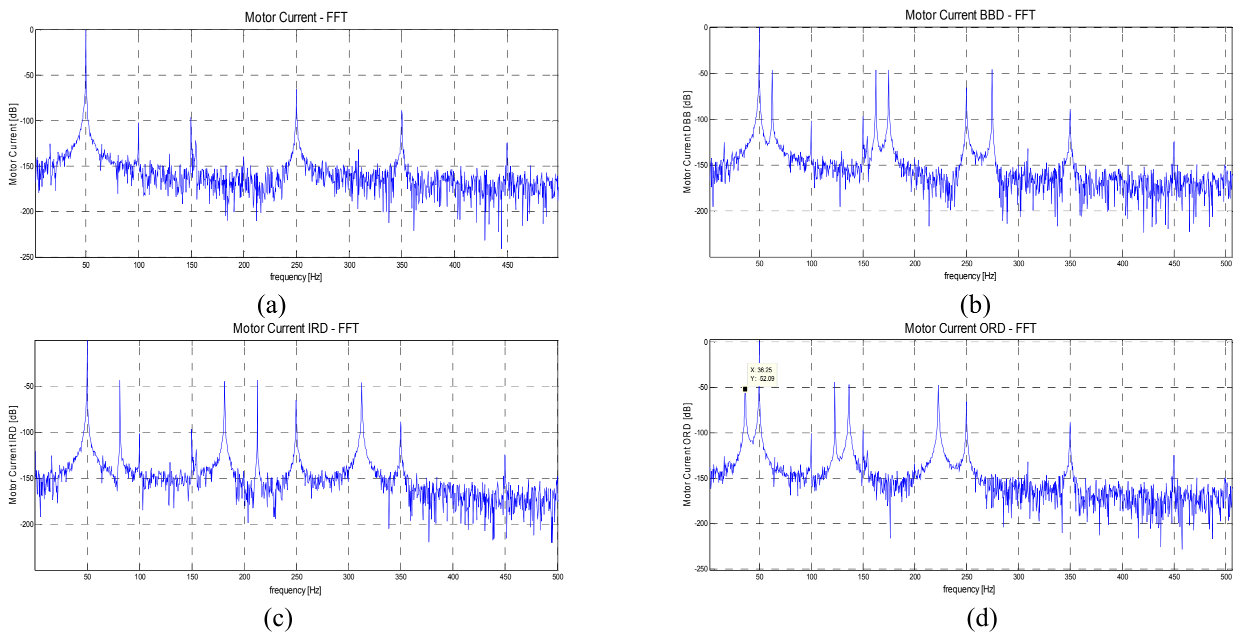

Figure 2 FFT of Motor Current Signal: (a) without fault, (b) BBD, (c) IRD, and (d) ORD Faults.

Table 1 - Characteristic vibration frequency and modulation effect on the stator current

Fault	f_V (Hz)	f_{BB} (Hz)
IRD	131	81, 181, 212, 312
ORD	86	36, 122, 136, 222
BBD	112	62, 162, 174, 274

From the 6205-2Z bearing data sheet, the outside diameter is 52 mm and the inside diameter is 25 mm. Assuming equal thickness for the inner and outer races leads to a pitch diameter equal to 38.5 mm (D = 38.5 mm). The bearing has nine balls (n = 9) with an approximated diameter *d* of 7.938 mm. Assuming a contact angle, α, of 0°, and motor operation at the measured shaft speed of 1452 rpm (f_r = 24.2 Hz), the characteristic vibration frequencies are calculated from (4)-(7), and the modulated frequency on stator current is derived by (8), such as shown in Table 1. Three tests were conducted to evaluate the detection performance of the proposed method.

Table 2 - Experimental Results Test 1: IRD

Test	Dec. Level	Nodes (Freq. Range)	Thresholds ΔE^2	ΔE^2
(I) IRD	4	2 (103.125; 206.250)Hz	3.50e-04	7.00e-04
		3 (206.250; 309.375)Hz	1.00e-03	4.40e-03
		4 (309.375; 412.500)Hz	1.00e-03	1.90e-03

In the first test, a hole was drilled on the inner race, while in the second experiment a similar hole was drilled on the outer race. At last, in order to study a ball bearing defect, two holes were drilled on the outer race. In all tests stator current was sampled at $f_s = 3.3$ *KHz,* before and after defects were made. In Fig. 2, FFT results are shown for motor current signal without fault (a), and with the three aforementioned faults (b) BBD, (c) IRD and (d) ORD. All the tests plan a fourth decomposition level, where every decomposition node represents a frequency range, $f_{range} = 103.125\ Hz$. In the tables the number of node indexes and the associated frequency ranges are showed for every considered fault. Only the nodes interesting fault modulation frequency components are shown, each one with a particular threshold, fixed experimentally. In Tab. 2, the comparison between the measured ΔE^2 (i.e. the square of the energy wavelet coefficients) and threshold'one in case of a Inner Race Defect, like a millimetric hole in the inner race of bearing, is reported.
As shown in Tab.2 the measured ΔE^2 overcomes the threshold level in all three nodes.
In Tabs. 3 and 4 , similar results for the cases of Outer Race and Ball Bearing Defects, respectively, are reported.

Table 3 - Experimental Results Test 2 ORD

Test	Dec. Level	Nodes	Thresholds ΔE^2	ΔE^2
(II) ORD	4	2 (103.125; 206.250)*Hz*	1.50e-03	1.60e-03
		3 (206.250; 309.375)*Hz*	3.00e-04	5.00e-04

Table 4 - Experimental Results Test 3 BBD

Test	Dec. Level	Nodes	Thresholds ΔE^2	ΔE^2
(III) BBD	4	2 (103.125; 206.250)*Hz*	1.50e-03	1.90e-02
		3 (206.250; 309.375)*Hz*	3.00e-04	1.20e-03

In particular, for ORD defect (Tab. 3) the measured ΔE^2 slightly exceeds the threshold level, while for BBD defect (Tab. 4) the difference between ΔE^2 and the threshold level is evident.

IV. Conclusions

In this paper, an evolutionary design for a lifting scheme wavelet package decomposition method for fault diagnosis is proposed. The method is experimentally validated on induction motor used as traction machine for elevator system. The experimental tests are currently ongoing, but preliminary tests show encouraging performance.

Acknowledgments

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