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The influence of the wavelet filter in the parameters extraction for signal classification: An experimental study

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Abstract. This paper treats the influence of the wavelet filters on the parameter extraction for signal classification. Therefore, a database with vibration signal failures of an induction motor in stationary case was utilized. The classification is done by techniques based on the wavelet packet transform and dimension reduction, using the principal component analysis (PCA). Different wavelet filters with different supports are used for comparison. The use of signals from a validated experimental bench shows that the results of the classification model has a high precision.

Palavras-chave. Induction Machine, wavelet, Vibration, Principal Component Analysis, wavelet filter

1 Introduction

Electrical induction motors are essential components in most of industrial equipment. The several faults that occur with induction machines may have serious consequences for industrial projects. The main problems are related to the increasing products costs, worsening of the process and safety conditions, and above all lower quality of the final product. Many of these flaws are progressive. The vibration analysis has been one of the most used techniques for fault detection and diagnoses due to features such as easiness of use, relatively low cost, non-intrusive technique, among others. Through the analysis of the vibration signal spectrum, it is possible to detect both mechanical and electrical defects. In general, the detection of flaws in electrical motors are done by methods based on extraction of parameters and signal classification [1]. The application of classic techniques of signal processing and temporal series are done by parameter extraction methods, like the Fast Fourier Transform, Hlbert Transform, Power Spectrum Density, correlation methods and other techniques based on Integral Transform and statistical analysis. These techniques had been used for many decades in fault detection in machines and mechanical components.

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Over the last decade, many papers have employed methods based on the wavelet transform in the monitoring and detection of flaws on the area of mechanical systems , despite of the great amount of other engineering fields where signal processing techniques are applied. This technique had been applied with success on the analysis of the flaws on rotating machines [2]. On signal classification, the energy and entropy parameters associated with the wavelet packet transform (WPT) for disturbance identification in electric signal are used [3]. Other applications use the WPT with dimension reduction methods, as the principal components analysis (PCA), together with the WPT for parameter extraction. The technique that make use of the WPT and the PCA also showed to be effective when applied on electrical motors fault detection through the stationary vibration signal analysis [4].

2 Mathematical Background

2.1 Wavelet Packet Transform

The WPT can further decompose the detail information of the signal in the high frequency region. The wavelet packet transform (discrete form) of an arbitrary signal $x(t)$ is defined on Equation (1). To perform WPT of a signal at a certain level, where $u_0(t) = \phi(t)$, and $u_1(t) = \psi(t)$. Correspondingly, the signal is decomposed as [7].

$$u_{2n}(t) = \sqrt{2}\sum_k h(k)u_n(2t-k) \tag{1}$$
$$u_{2n+1}(t) = \sqrt{2}\sum_k g(k)u_n(2t-k)$$

The signal $x(t)$, decomposed by WPT, is expressed by Equation 2:

$$d_{j+1,2n} = \sum_m h(m-2k)d_{j,n} \tag{2}$$
$$d_{j+1,2n+1} = \sum_m g(m-2k)d_{j,n}$$

where $d_{j,n}$ denotes the wavelet coefficients at the j level, n subband, $d_{j+1,2n}$ and $d_{j+1,2n+1}$ denotes the wavelet coefficients at the $j+1$ level, $2n$ and $2n+1$ sub-bands, respectively, and mis the number of the wavelet coefficients.

The operators g and h are known as Quadrature Mirror Filters (QMF) and must satisfy the following orthogonality conditions [7]:

$$HG^* = GH^* \qquad | \qquad HH^* = GG^* \tag{3}$$

The calculation energy method of each packet from decomposition of the WPT is a more robust method of signal representation than using directly the decomposition coefficients [5]. The total signal energy is expressed by:

$$E_{tot} = \sum_{i=1}^{2^j} E_i \tag{4}$$

The energy of each sub-band is defined as E_i. The normalized energy value, which corresponds to the energy of each wavelet packed is given by:

$$P_l = \frac{E_i}{E_{tot}} \tag{5}$$

where P_l is the probability distribution of each sub-band, E_i is the energy atributed to each packet and E_{tot} is the total energy of the x(t) signal.

The concept of entropy has been widely used as a measure of systems disorder [8]. In this paper, the entropy is obtained by the WPT. The energy probability distribution for each sub-band(packet) is given by Equation (6). The entropy, in fact, measures the energy dissipation. Using the definition proposed by Shannon, the entropy is expressed by [5].

$$S = -\sum P_l \ln(P_l) nn \tag{6}$$

2.2 Wavelet Filters

On this paper four types of wavelet filters (Daubechies, Symlte, Coiflet, Fejer-Korovkin) are used with different supports. In the following a brief description of each type of filter used, is described.

2.2.1 Haar Filters

The Haar Filter is a FIR (Finite Impulse Response) type with a linear phase and a frequency response which is very distant from the ideal (due to the support 2) [9]. The Haar filter is a special case of the Daubechies' filter which is described below.

2.2.2 Daubechies Filters

The construction of Daubechies wavelet is done based on the scale or dilatation function and a set of coefficients h_k, $k \in z$. The equation that generates the scale function is shown on (7):

$$\varphi(t) = \sum_{k=0}^{N-1} h_k \varphi(2x - k) \tag{7}$$

And the wavelet function:

$$\psi(t) = \sum_{k=0}^{n-1} g_k \varphi(2x - k) \tag{8}$$

where $g_k = (-1)^k h_{N-1-k}$ and $\int_{-\infty}^{\infty} \varphi(x)dx = 1$.

2.2.3 Symlet Filters

On the literature, the Symlet Filters are named Sym-N, where 2N represents the filter's support (or number of filter coefficient). The Symlet Filters represent the FIR type with an almost linear phase and a frequency response tending to an ideal response as the support increases [5]. The symlet filters are also deducted from the Daubechies' filters.

2.2.4 Coiflet filters

The Coiflet wavelet are named Coif-N, where 6N represents the number coefficient of the filter built with the Daubechies, limit the decay moments in the wavelet function and the scale function. Advantageously, the approximation coefficients can be represented by the samples of the signal. However, the filter's order becomes higher.

2.2.5 Fejer-Korovkin

It's a wavelet filter more symmetric than the Daubechies filters, but less soft [8]. This filter has a wide application on the approximation theory, and a frequency response adequate as the support increases.

3 Proposed Methodology

3.1 Test Bench

On this paper a set of experimental vibrations signals that were measured at the Faculty of Mechanical Engineering of the Campinas University [4], in the Laboratory of Vibrations and Control are used. The test bench used on this paper is composed by a three-phase induction motor 1. A generator is connected to the electric motor through flexible couplings 2 a torque wrench 3 model MCRT 9-02T (1-3), 0-7500 rpm, bidirectional and maximum torque of 1000 lb-in from S. Himmelstein and Co . A direct continuous current machine 4. Figure 1 shows a general vision of the test bench.

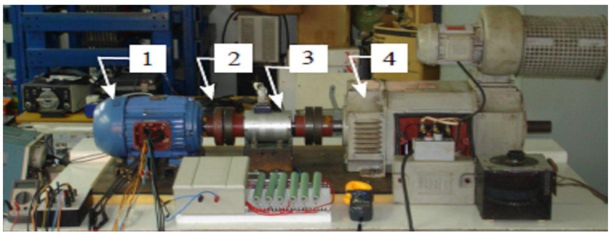

Figure 1: Test bench.

The project of the test bench allows fault introduction of the motor. On this paper, four types of faults: unbalancing, mechanical clearance, short circuit and phase unbalance [4]. The method by which the faults are induced to the engine are described on [5].

3.2 Vibration Signals

On the signal acquisition, the NI-6251 plate from *National Instruments* was used. The vibration signals were passed through an *anti-aliasing* filter, with a cutting frequency of 2 kHz. Prior to the tests, the bench was balanced and aligned in order to eliminate any undesirable source of vibration. By this, it was possible to determine the normal working conditions of the motor-generator compound (the bench signature), which was stipulated

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as a max of 0.5 mm/s of vibration amplitude in the stationary operation according to the VDI 2056. The signals were collected with a sample frequency of 5 kHz and 20480 points on order to analyze the complete frequency range in which the faults are identified.

For the Normal condition (faultless) 960 signals were obtained in stationary operations resulting from 360 measurements carried out with 3 accelerometers placed on the induction motor. For the fault signals, 360 signals were obtained in stationary operations for each fault condition (phase imbalance, short circuit, unbalance and mechanical clearance) resulting from 120 measurements (for each fault condition) taken randomly with 3 accelerometers placed on the induction motor.

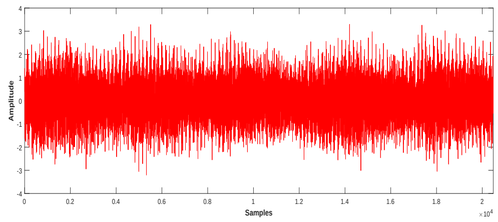

Figure 2: Typical vibration signal of the eletric motor.

3.3 Model for Classification

The classification method consists in applying the WPT to all signals up to the fourth level of decomposition, with different filters (Daubechies, Symlet , Coiflet e Fejer-Korovkin) and supports, resulting in 16 frequency sub bands (Packet). The decomposition to the fourth level proved to be sufficient for detecting alterations in the frequency spectrum [4].

The energy, relative energy and entropy of each sub-band of the fourth order level of decomposition frequency are calculated. Another point to justify the WPT decomposition only up to the fourth level is that the energy of the signals under analysis is concentrated up to the eighth frequency sub-band.

The Energy/Entropy vector is obtained for each signal by using the values obtained on the calculation of the relative energy and entropy. A 32-characteristic vector is obtained with 16 relative energy parameters and 16 entropy parameters. The dimension of the characteristic vector of each signal is reduced by separately using the Principal Components Analysis (PCA) method [4, 10]. The dimension reduction is necessary, because in these types of application the use of only Energy and Entropy parameters showed ineffective for the classification [4]. The first three main components are used because they preserve 98% of the variance of the system. Finally, the classification is carried out by using the parameters of the reduced vector and the k-Nearest Neighbor (kNN) algorithm, which was calculated with the use of the Euclidian distance. 30% of the classes are used for training, and 70% for classification. The filters used are:

- Haar
- Daubechies-Daub-5, Daub-10, Daub-20, Daub-40;

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- Symlet-Sym2, Sym4, Sym6, Sym8, Sym10;
- Coiflet-Coif1, Coif2, Coif3, Coif4, Coif5;
- Fejer-Korovkin-FK4, FK8, FK10, FK16, FK22;

4 Results

Five classes for classification of the engine's faults will be used for the following motor conditions: faultless, short circuit, unbalancing and mechanical clearance. The energy and entropy parameters will be extracted with the use of the filters Daubechies (Daub-2, Daub-5, Daub-10, Daub-20, Daub-40), Symlet (sym2, sym4, sym6, sym8 e sym10), Coiflet (Coif1 , Coif2 , Coif3, Coif4, Coif5) and Fejer-Korovkin (FK4, FK8, FK10, FK16, FK22). The dimension reduction of the characteristics vector is provided by the principal components method (PCA) and delivered to kNN classifier.In relation to this classification the values of k=1,k=3,k=5,k=7 are used and meaningful disagreements are found. Table 1 shows the success rate results in the classification for each filter used. One can note that, generally, the filters with higher support have the highest success rate. The Coiflet filter presented a higher success rates than the results obtained with the filters Daubechies and Symlet. However, the best success rate, in all cases, is gotten by the use of the Fejer-Korovkin filter.

Table 1: Hits index in the classification of the faults on stationary operations using the proposed filters.

Results Classification - Faults - Overall Hit Rate							
Haar	91.00%	Sym-2	96.00%	Coif-1	94.00%	FK4	96.00%
Daub-5	98.72%	Sym-4	96.62%	Coif-2	97.30%	FK8	98.70%
Daub-10	98.81%	Sym-6	97.81%	Coif-3	98.61%	FK10	98.70%
Daub-20	98.80%	Sym-8	99.82%	Coif-4	99.00%	FK18	100%
Daub-40	99.20%	Sym-10	99.82%	Coif-5	100%	FK22	100%

In general, on Table 1 is observed that the hit rate increases as the support and filter size increases. This fact occurs because the high support gives as an output a frequency response close to ideal cases. This is justified because engineering faults are characterized by alterations on the frequency spectrum. Being this, this paper´s main contribution in relation to [4].

5 Conclusions and discussions

The objective of this work was the development of a model for automatically classifying anomalies in three-phase electric induction engines [4] with the use of techniques based on the wavelet transform. The classification of the anomalies was achieved by extracting and analyzing the characteristics of waveforms with the energy and entropy parameters associated to the wavelet transform packet, using different wavelet filters.

The high success rates and experimental results pointed to a potential implementation of this technique in a monitoring and fault detection system through the vibration signal classification. It is a relevant result concerning the monitoring and faults detection and the signal classification, besides, is in conformity with the literature. The increase on the support of the used filters improves the effectiveness of the classification.

The Daubechies, Symlet, Coiflet e Fejer-Korovkin filters showed high success rates by the fact that they are FIR filters with a nonlinear phase and a frequency response tending to be ideal as the support increases. Because of that, one can observe that the higher success rates occurred when a higher support was used (Daub-40, Sym10, Coif5, FK14 and FK22). With the use of the Fejer-Korovin filters, one have the best results in all cases, because the frequency response gets closer to ideal as the support increases, disposing more accurate results even when compared to the other filters utilized.

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