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Principal Component Analysis of the start-up transient and Hidden Markov Modeling for broken rotor bar fault diagnosis in asynchronous machines

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ABSTRACT

This article presents a novel computational method for the diagnosis of broken rotor bars in three phase asynchronous machines. The proposed method is based on Principal Component Analysis (PCA) and is applied to the stator's three phase start-up current. The fault detection is easier in the start-up transient because of the increased current in the rotor circuit, which amplifies the effects of the fault in the stator's current independently of the motor's load. In the proposed fault detection methodology, PCA is initially utilized to extract a characteristic component, which reflects the rotor asymmetry caused by the broken bars. This component can be subsequently processed using Hidden Markov Models (HMMs). Two schemes, a multiclass and a one-class approach are proposed. The efficiency of the novel proposed schemes is evaluated by multiple experimental test cases. The results obtained indicate that the suggested approaches based on the combination of PCA and HMMs, can be successfully utilized not only for identifying the presence of a broken bar but also for estimating the severity (number of broken bars) of the fault.

1. Introduction

Asynchronous machines (AMs) are complex electromechanical devices that are being utilized in most industrial applications for the conversion of power from electrical to mechanical form Vas (1992) and Silva, Povinelli, and Demerdash (2008). These devices provide durability and robustness, which makes them excellent candidates for operating in harsh environments. On the other hand their operation in such demanding environments increases the need for preventing unscheduled downtimes. Different motor faults occurrences might result in different types of motor break downs and rather usual, small initial faults can propagate and grow bigger, even leading to a total breakdown of an industrial process (Acosta, Verucchi, & Gelso, 2004).

Among the most common faults in asynchronous motors are: (a) stator faults resulting from the opening or shorting of one or more of the stator phase winding (Acosta et al., 2004; Mustafa, Nikolakopoulos, & Guastafsson, 2012), (b) broken rotor bar or cracked rotor end-rings due to thermal, magnetic, residual, dynamic, and mechanical stresses (Santos & Lubiny, 2010), (c) bearing faults (Anel, Azenol, & Benbouzid, 2007), and (d) dynamic or static air gap irregularities (Nandi, Toliyat, & Xiaodong, 2005). For all these types of faults, it is of paramount importance to: (a) have an early fault detection scheme, and (b) categorize the fault in order to select the appropriate corrective action. For some fault types the corrective measures must be taken, within very short time after the fault occurrence.

Various input signals have been utilized quite successfully for monitoring of AC motors, such as induced voltage (Elkasabgy, Eastham, & Dawson, 1992), vibration signals (Khezzar, Oumaamar, Hadjami, Boucherma, & Razik, 2009), currents and vibration signals (Trana, Yanga, Oha, & Tanb, 2009; Widodo, Yang, & Han, 2007) instantaneous angular speed or power (Arif, Imdadullah, & Asghar, 2011; Kia, Mabwe, Henao, & Capolino, 2006). However, methods that rely only on the use of currents (Motor Current Signature Analysis (MCSA) methods (Benbouzid, 2000)) are usually preferred (Aydin, Karakose, & Akin, 2010; Garcfa-Escuderoa, Duque-Perezb, Morinigo-Sotelob, & Perez-Alonsob, 2011; Matica, Kulica, Snchezb, & Kamenkoa, 2012; Nandi et al., 2005), mainly due to their non-invasive nature.

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Among the various methods applied for the analysis of motor currents, one could mention the use of the Fast Fourier Transform (FFT) (Kliman, Koegl, Endicott, & Madden, 1988), Wavelets (Tsoumas, Georgoulas, Mitronikas, & Safacas, 2008) and Complex Park Vectors (Cruz & Cardoso, 2000) with a literature that has been growing rapidly over the last decade with a number of survey papers summarizing the latest findings and trends in the field (Awadallah & Morcos, 2003; Bellini, Filippetti, Tassoni, & Capolino, 2008; Benbouzid, 1999; Han & Song, 2003; Nandi et al., 2005; Zhang, Du, Habetler, & Lu, 2011; Mehrjou, Mariun, Marhaban, & Misron, 2011).

The analysis of the stator current for rotor fault detection during steady state operation has a subtle drawback as frequencies similar to those caused by a rotor fault can be generated by other sources too (Daviu, Guasp, Folch, & Palomares, 2006) and thus might lead to false alarms and reduce the overall reliability of systems based on steady state monitoring. Additionally, in the case of low load, the slip decreases and low current flows in the rotor circuit; this makes difficult the detection of the fault (Daviu et al., 2006). For this reason, recently, a second group of methods based on the examination of the stator current during start-up has become quite popular as a complementary/alternative means to steady state analysis (Elder, Watson, & Thomson, 1989; Sanchez et al., 2010). During the start-up process, asynchronous machines operate under more critical conditions (currents and thermal stresses), something which can help to amplify the "signatures" of incipient faults (Daviu et al., 2006). The main drawback of using the whole range of slip values during transient analysis (in contrast to steady state analysis) is that it complicates the automation of the detection process by explicitly inducing time dependencies. Multiple approaches in this field have appeared, like the Continuous Wavelet Transform (Zhang, Ren, & Huang, 2003), the Multi-Resolution Analysis (MRA) (Daviu et al., 2006), the Empirical Mode Decomposition (EMD) (Antonino-Daviu, Riera-Guasp, Pineda-Sanchez, & Perez, 2009), the Fractional Fourier Transform (Sanchez et al., 2010), the Gabor analysis (Pineda-Sanchez, Perez-Cruz, Puche-Panadero, Roger-Folch, & Antonino-Daviu, 2012), or a wavelet-SVM approach for multiple faults (Widodo & Yang, 2008) among others.

Currently, an increasing number of research works are concentrating on the use of data driven and computational intelligence techniques. The main reason of the popularity of these techniques is that they require "minimum configuration intelligence" since neither a detailed analysis of the fault mechanism, nor modeling of the system is necessary (Bacha, Henaob, Gossa, & Capolino, 2008). Moreover, they facilitate the implementation of the fault detection techniques in automatic diagnostic systems, as well as avoid the necessity of user intervention and interpretation of the results. Among the various methods in the field of fault diagnosis, Principle Component Analysis (PCA) and its variants, has received a significant attention in the last past years (Chiang, Russell, & Braatz, 2001; Cuia, Lic, & Wanga, 2008; Polat & Gnnes, 2008; Tharrault, Mourot, Ragot, & Maquin, 2008). PCA is a statistical technique that linearly transforms an original set of variables into a usually substantially smaller set of uncorrelated variables that represents most of the information in the original set of variables (Jolliffe, 1986). However, in this work PCA is utilized as a means to isolate the faulty component that arises in the phase currents during the start-up and not for its dimensionality reduction capabilities.

The output of PCA yields a time series with a distinctive pattern that can capture both the presence as well as the severity of broken bar faults. In order to automatically exploit the information contained in that component, Hidden Markov Models (HMMs) were employed since they are well suited for the analysis of temporal phenomena (Fink, 2008). HMMs are involved both in a multiclass classification scheme covering the case that data exists for both the normal and the faulty operation as well as in a one-class or an anomaly detection scheme in the case that data of only the normal operation are available. The obtained experimental results suggest that the multiclass approach can perfectly assess the severity of the fault by identifying the presence of one or two broken bars whereas the one-class approach is able to detect all deviations from normality without any false alarms.

The novelty of this article is quadruple. First, the PCA methodology is being utilized as a novel approach for isolating characteristic rotor fault components that appear during the start-up transient phase and not as in its conventional context for dimensionality reduction. Second, the detection procedure is based on the use of HMMs in the time domain and not in the time–frequency domain as most of the methods involved in the analysis of the start-up current do. Third, as far as we are concerned, it is the first time that an anomaly detection technique is applied in the field of broken rotor bar and last, but not least, it is the first time that these methods are experimentally evaluated with very promising results.

The rest of this article is structured as follows: In Section 2, the fundamental theory behind PCA and HMMs is summarized, and the proposed framework for the broken rotor bar fault detection is presented. In Section 3, multiple experimental results are presented, proving the efficiency of the proposed scheme and, finally, in Section 4, the conclusions are drawn and directions for future work are given.

2. PCA and HMMs fundamentals

2.1. Principal Component Analysis

PCA, also known as the Karhunen Loeve transform, is one of the most popular techniques for dimensionality reduction, lossy data compression, feature extraction and data visualization (Jolliffe (1986)). PCA falls under the general title of factor analysis (Diamantaras & Kung, 1996) and even though it is quite old, having its origins back in the beginning of the 20th century (Pearson, 1901), it still attracts the interest of the researchers, while forming the basis for a number of more advanced techniques (Theodoridis & Koutroumbas, 2009). The basic characteristic of PCA is the ability to perform a basis transformation of the original space in such a way that under the new representation the data are mutually uncorrelated.

It is interesting that the same algorithm for PCA can be derived following different paths, e.g. the maximum variance formulation or the minimum error formulation, while the interested reader can refer to any standard textbooks of machine learning and pattern recognition (Theodoridis & Koutroumbas, 2009; Bishop, 2006) or specialized texts on PCA (Jolliffe, 1986; Diamantaras & Kung, 1996) for a detailed description of the PCA methods. In this article, and without losing generality, only the outline of the process for generating the Principal Components (PCs) will be presented. In the general case, PCs are extracted from a set of multivariate data $\{x_i\}$ where $x_i \in R^d, i = 1, \ldots, N$, with $N \in Z^+$ (x_{ij} is therefore the value of the jth dimension of the ith example). The underlying procedure is described in Table 1.

In the standard utilization of the PCA technique after calculating the eigenvalue and the corresponding eigenvectors, only the eigenvectors corresponding to the l largest eigenvalues are retained, while the input vectors are being projected on them to get a reduced representation (Widodo et al., 2007). However, PCA can also be considered as a source separation method even though it does not retrieve independent sources (as in the case of Independent Component Analysis (ICA)) (Hyvarinen & Oja, 2000; Theodoridis & Koutroumbas, 2009), but only uncorrelates the input data. This specific utilization of the PCA methodology is exploited in this arti-

Table 1
Principal components extraction algorithm.

STEP 1 – Compute the mean value for each original variable:

$$\bar{x}_j = \frac{1}{N}\sum_{i=1}^{N} x_{ij}$$

STEP 2 – Subtract this mean from the original variable:

$$\acute{x}_{ij} = x_{ij} - \bar{x}_j, \quad i = 1,\ldots,N \text{ and } j = 1,\ldots,d$$

STEP 3 – Calculate the covariance matrix **S** of the zero-mean data matrix, whose elements are given by:

$$s_{nm} = \frac{1}{N-1}\sum_{i=1}^{N} x'_{in}x'_{im}, \quad n,m = 1,\ldots,d$$

STEP 4 – Calculate the eigenvalues and its corresponding eigenvectors of the covariance matrix **S**

cle, while the obtained evaluations under experimental results prove that the adopted technique is very effective for the examined fault occurrence case.

2.2. Hidden Markov models

HMMS are a powerful tool for modeling ordered sequence of data (Fink, 2008; Rabiner, 1989; Rabiner & Juang, 1986). Originally HMMs were almost exclusively utilized in the context of automatic speech recognition (Rabiner & Juang, 1986) but lately have found application in a variety of problems (Fink, 2008), such as biomedical signal classification (Georgoulas, Nokas, Stylios, & Groumpos, 2004), heat exchanger fault detection (Wong & Lee, 2010), lip reading (Puviarasan & Palanivel, 2011), bearing fault monitoring (Boutros & Liang, 2011; Marwala, Mahola, & Nelwamondo, 2006; Ocak, Loparo, & Discenzo, 2007; Peng & Dong, 2011) and fault detection in AC (Lebaroud & Clerc, 2008; Nakamura et al., 2010) and DC motors (Zaidi, Aviyente, Salman, Shin, & Strangas, 2011).

HMMs are dynamic models that describe a two stage stochastic process (Fink, 2008; Rabiner, 1989; Rabiner & Juang, 1986). The first stage consists of a discrete stochastic process that probabilistically describes the state transitions within a finite state space. The behavior of the process at any given time instance t solely depends on the immediate predecessor state. In the second stage, at every point in time t, an emission (the observable output) is generated, which can be either discrete or continuous. The sequence of the states of the first stage is never observed or measured directly, it is therefore “hidden”, and the behavior of the model is only reflected through the sequence of emissions, most commonly referred as the observation sequences.

An HMM, which is usually denoted as λ, is fully characterized by: (a) a finite set of states, $\{s|1 \leqslant s \leqslant M\}$, (b) the state specific observation probability densities for the case of continuous output space $\{b_j(\mathbf{x})b_j(\mathbf{x}) = p(x|S_t = j)\}$ with $j = 1,2,\ldots M$, describing the distribution of the observations x emitted for state j, (c) the state transition probability matrix $\mathbf{A}_{M\times M}$ denoted as: $\mathbf{A} = \{a_{ij}|a_{ij} = P(S_t = j| S_{t-1} = i)\}$, and (d) the vector $\boldsymbol{\pi}$ with the initial state probabilities $\boldsymbol{\pi} = \{\pi_i|\pi_i = P(S_1 = i)\}$.

HMMs with continuous outputs (continuous HMMs) have an increased expressive power, when compared to their discrete counterparts, however, this comes with a corresponding cost of increasing complexity and with the need to represent continuous distributions in a suitable way. The most common, and computationally tractable way, to represent arbitrary continuous distributions, within the HMM framework, relies on the use of a finite mixture of Gaussians (Fink, 2008). In this context the output probability density function is given by

$$b_j(\mathbf{x}) = \sum_{k=1}^{M_j} c_{jk} N(\mathbf{x}|\mu_{jk}, \mathbf{C}_{jk}) \tag{1}$$

where, M_j is the number of the mixtures components for state j,c_{jk} is the mixing coefficient of the kth mixture in state j, N is a multivariate Gaussian density function with mean μ_{jk} and covariance matrix $\mathbf{C}_{jk}$ for the kth mixture in state j.

In practice HMMs are utilized to solve the following three problems: (a) the evaluation problem, (b) the decoding problem, and (c) the learning problem, which is the most difficult among the three (Fink, 2008). For application of HMMs to condition monitoring, problems (a) and (c) need to be tackled (Cartella, Liu, Meganck, Lemeire, & Sahli, 2012). More specifically one or more models must be trained with data of a certain class (i.e. estimation of the aforementioned parameters – the learning problem) and then once a new observation sequence is produced it is assigned to the class whose model best fits the observation sequence.

While for this stage (evaluation problem) efficient solutions exist (the forward or the backward algorithms Fink, 2008), for the learning problem (the estimation of the model parameters) until now, no method has been proposed that is able for a given sample set to create a model, which is optimal in some respect (Fink, 2008). The most widely utilized optimization method of HMMs is provided by the Baum–Welch algorithm (also known as the forward–backward algorithm) (Bishop, 2006; Fink, 2008), which is an instance of a generalized expectation-maximization algorithm and can nearly always provide a good solution. The interested reader is referred to relevant literature for a detailed derivation of the updating formulas (Fink, 2008; Rabiner & Juang, 1986) as well as for other optimization alternatives (Aupetit, Monmarche, & Slimane, 2007; Levinson, Rabiner, & Sondhi, 1983).

2.3. Broken bar fault detection framework

As pointed out in the introductory part, the methods that employ the analysis of the start-up currents for the detection of broken rotor bars usually require advanced signal processing techniques, such as the Continuous Wavelet Transform (Zhang et al., 2003), the MRA (Daviu et al., 2006), the EMD (Antonino-Daviu et al., 2009), and the Gabor analysis (Pineda-Sanchez et al., 2012) in order to extract specific components that appear after the event of one or more broken bar fault occurrences. The evolution of this characteristic fault component (the left sideband harmonic (LSH)) has been analyzed by Riera-Gasp, Antonino-Daviu, Roger-Folch, and Palomares (2008) and it is depicted in Fig. 1. Ideally, the frequency of the LSH frequency varies from the stator supply frequency to zero and back again to near the supply frequency (Fig. 2) as it is described by:

$$f_{LSH} = |1 - 2s| \cdot f_s \tag{2}$$

where f_s is the power supply frequency and s is the slip. In all the aforementioned approaches (Daviu et al., 2006; Zhang et al., 2003) the extracted component was analyzed in the time–frequency domain, mainly in an attempt to discover the characteristic V pattern (or part of it Zhang et al., 2003) of the instantaneous frequency of the faulty component (LSH).

In this research effort the focus will be only on the analysis in time domain of the “faulty” component, without resorting to frequency or time–frequency analysis. For the extraction or the isolation of the faulty component the PCA technique is adopted for this specific problem.

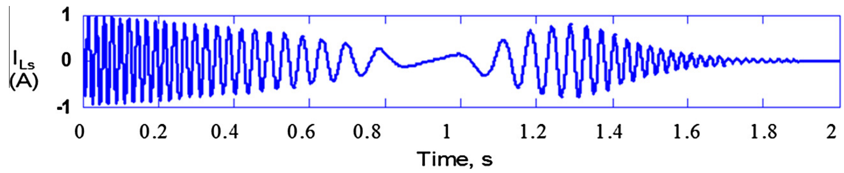

Fig. 1. Evolution of left side band harmonics during the start-up.

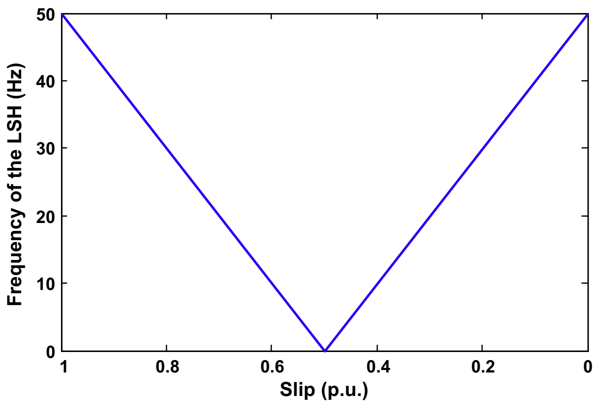

Fig. 2. Theoretical evolution of the LSH as a function of the rotor slip.

Since, in this article the transient phenomena during start-up are being considered, the proposed analysis scheme involves a pre-processing (segmentation) step where a steady state detector should be utilized for detecting the end of the transient phase. After that the PCA technique is involved and the projection of the three space currents on the least principal component, i.e. the eigenvector which corresponds to the minimum eigenvalue of the covariance matrix, is retrieved. A number of conducted experiments suggest that the retrieved component can be used both for setting an alarm once an anomaly occurs – in an anomaly detection scheme – as well as to assess the severity of the fault in a multi-class classification scheme, with both schemes utilizing HMMs. In the rest of this section the proposed procedure and the involved methods are presented.

2.4. Segmentation

For the isolation of the startup current, instead of using a "transient detector" we are seeking for the point when a steady state has been reached. In case that no measuring of the speed of the asynchronous machine is available, the start-up currents can be analyzed over a predefined sliding window (Kim, Yoon, Domanski, & Payneb, 2008). Over that window, the mean of the sum of the energies of the three current signals are sampled as:

$$ME(i) = \frac{1}{N}\sum_{j=1}^{j=i+N-1}\left(i_a^2(j) + i_b^2(j) + i_c^2(j)\right) \quad (3)$$

while the standard deviation of this ME is utilized for detecting the steady state operation. Once its value falls below a user selected threshold, the rest of the recording is discharged from subsequent processing.

2.5. Application of PCA

In the examined case of an asynchronous motor we have a three dimensional input space and we are only interested in the projection to the eigenvector that corresponds to the minimum eigenvalue. This can be more easily explained by visualizing the result of this process as Fig. 3 depicts the healthy/normal case of the three dimensional input space along with the three eigenvectors of the covariance matrix. Moreover, Fig. 4 depicts the original phase currents for a healthy machine, while in Fig. 5 the projection of the original signals onto the first, the second and the third -which is of interest in our case- PC are being presented. The same results can be depicted in Figs. 6 and 7, this time for the case of a faulty machine with one broken bar.

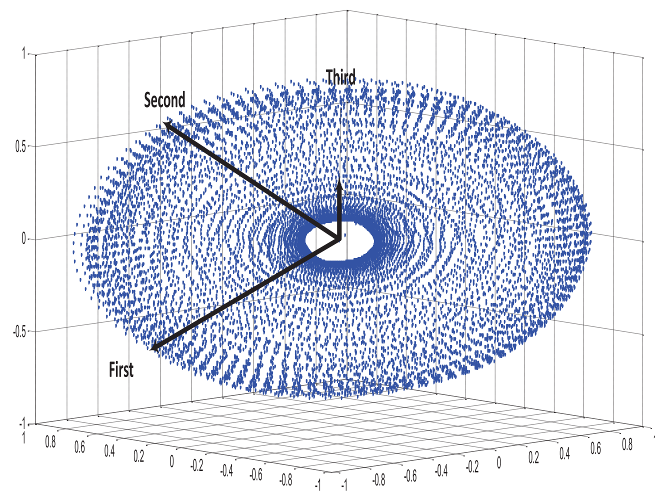

Fig. 3. Scatter plot of the three phase currents for the case of a healthy machine during start-up along with the estimated eigenvectors of the covariance matrix. As it can be seen most of the variance is contained on the subspace spanned by the first two PCs.

As it can be observed, from the obtained experimental results, the first 2 PCs (that correspond to the two major eigenvalues) capture the fundamental sinusoidal component, whereas the third one seems to capture noise. However, in case that some of the noise is being filtered through the utilization of a Butterworth filter (with a cut-off frequency of 40 Hz), the results that are presented in Fig. 8 are obtained, where the faulty case of two broken bars has also been included. As it can be seen the filtered signal has a striking resemblance with the faulty component depicted in Fig. 1. It should be noted that the cut-off frequency was selected based on our previous experience in the analysis of the transient in the frequency domain where the edge effects were obscuring both the starting and the ending (Georgoulas, Tsoumas, Mitronikas, Stylios, & Safacas, 2012). As a result the frequency content of the component was always restricted to ~35 Hz.

For the extraction of the PCs in the case of start-up currents there are two possibilities. The first one is to put together all the data coming from the same category and utilize them to estimate the covariance matrix and then estimate the eigenvalues and the eigenvectors.

The second option is to use the data from each recording "as its own control" meaning that for each start-up only its phase current time series is used to estimate the covariance matrix that is needed for the calculation of PCs and not any data from other start-ups of the same category/class. It turned out that the two approaches yield almost identical results as it can be seen in Fig. 9. Therefore

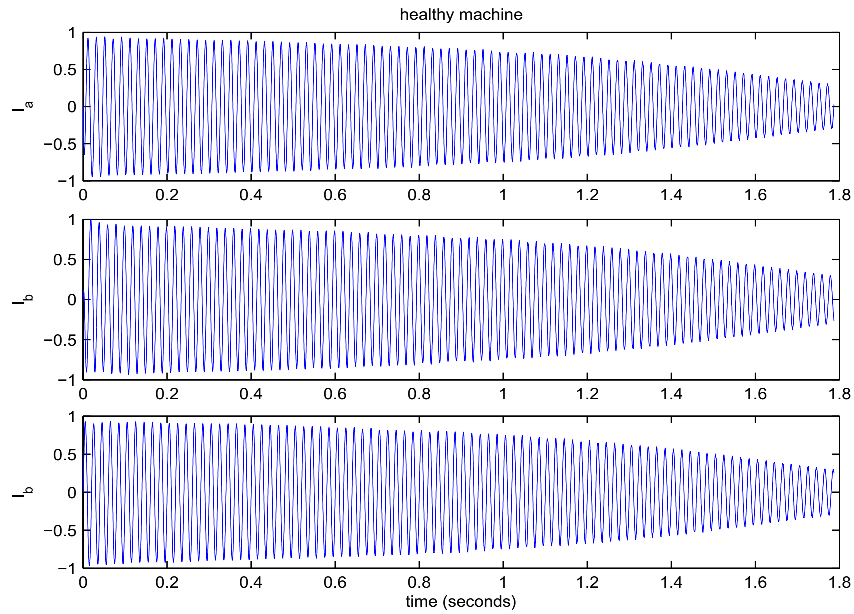

Fig. 4. The original phase currents for healthy machine during start-up.

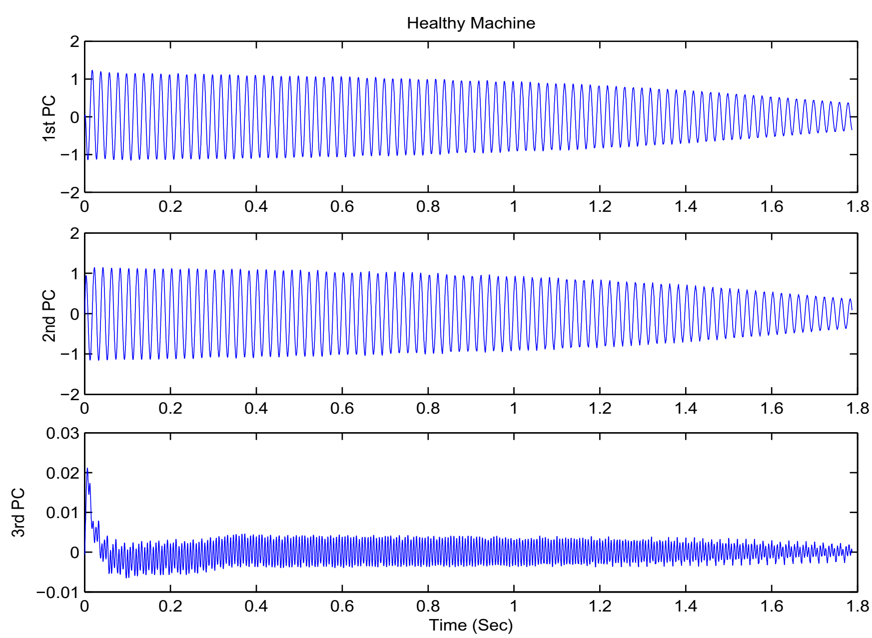

Fig. 5. The projection of the original phase currents of the healthy machine depicted in Fig. 6, onto the 1st, 2nd and 3rd principal components.

the selection is not crucial for the subsequent analysis. In the presented test case it has been selected to estimate the covariance matrix based on individual recordings, for speeding up the estimation process and minimizing the required storage, even though for the specific application these parameters are not crucial. It must be noted that in order to make our approach invariant to the particular characteristics of the machine, the current vectors are normalized to have maximum magnitude equal to unity before any further processing takes place.

3. Experimental results

For evaluating the performance of the proposed fault detection scheme, several experimental studies have been performed with an 1.1 kW squirrel cage induction motor having the following characteristics: Star connection, rated voltage (U_n): 400 V, rated power (P_n): 1.1 kW, 2 pair of poles, primary rated current (I_{1_n}): 2.7 A, rated speed (n_n): 1410 rpm and rated slip (s_n): 0.06, and 28 rotor bars, while the overall experimental setup is presented in Fig. 10.

The motor has been directly coupled to a DC machine acting as a load. Different load levels could be achieved by changing the excitation current of the DC machine. Stator currents were sampled with a frequency of 5 kHz. Ten recordings for each one of the three classes (healthy, one broken bar, two broken bars) with different duration of the transient phenomenon were acquired.

During this initial design phase, it was noticed that similar high values (both negative and positive) were present at the beginning of the recordings, both for the faulty and the normal cases (the edge effect phenomenon was stronger than the imposed faulty

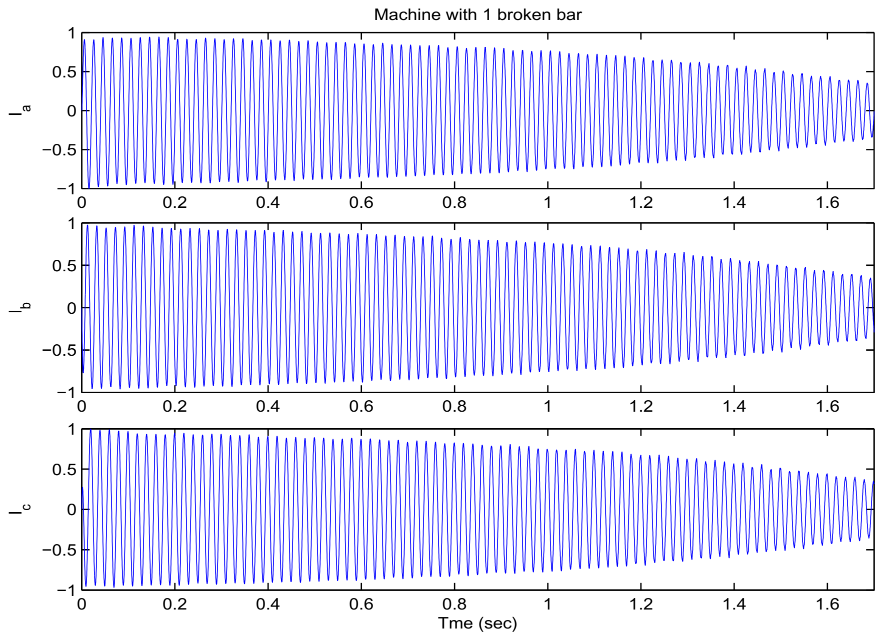

Fig. 6. The original phase currents for a machine with one broken bar during start-up.

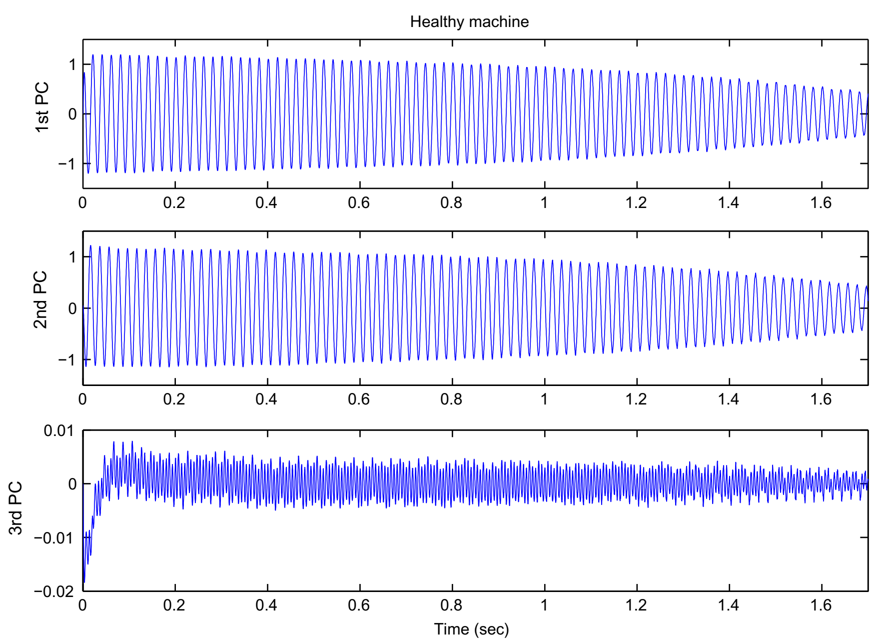

Fig. 7. The projection of the original phase currents of a machine with one broken bar, onto the 1st, 2nd and 3rd principal components.

component). Therefore, we decided to exclude the initial 20% samples of the recordings. In the following experimental results, both the multiclass classification approach and also the one class classification (or anomaly detection) approach have been applied and evaluated.

3.1. Multiclass classification approach

In the case that data from all the classes under investigation are available, a multiclass classification approach can be employed. Especially, for the severity assessment, each severity level constitutes a separate category/class and the overall goal is to assign each recording to the corresponding severity level/class.

In the multiclass approach, based on the component that corresponds to the minimum eigenvalue, the goal is to train three "left to right" HMMs (Fink, 2008), one for each of the three categories (healthy/normal, 1 broken bar, 2 broken bars) and utilize them in the sequel to assign each observation sequence to the model that was more probable to have generated it. The selection of the "left to right" architecture was based on the natural temporal progression of the phenomenon as well as on our previous successful application of the same architecture for the case of discriminating simulated rotor asymmetries using discrete HMMs (Georgoulas et al., 2012). In order to evaluate the proposed approach with a minimum bias (Salzberg, 1997), an "inner" and an "outer" loop validation scheme has been applied. The outer loop was included to

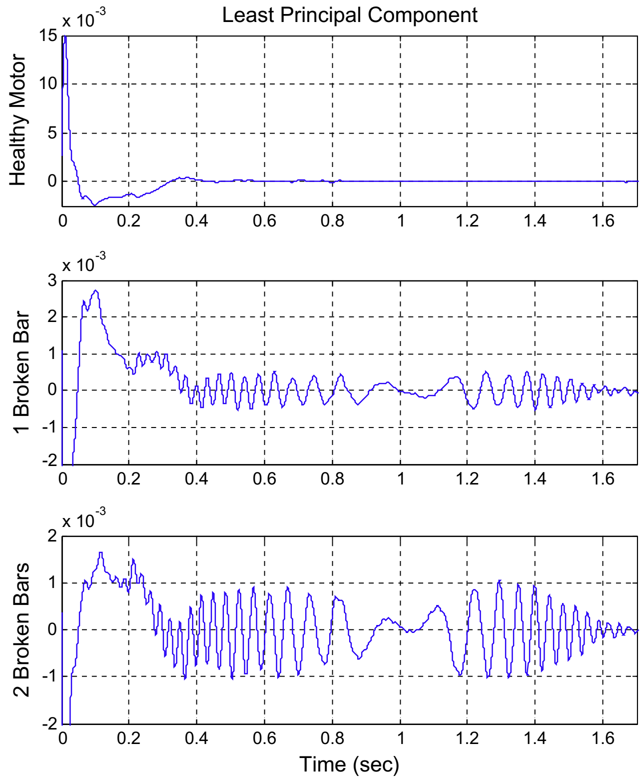

Fig. 8. The third (least) principal component after low pass filtering for the case of a healthy machine (top), a machine with one broken bar (middle) and a machine with two broken bars (bottom).

assess the performance of the proposed approach, while the inner scheme was applied to tune the HMM parameters (number of hidden states, number of mixtures).

More specifically, in the "outer" loop, the "leave one out" method has been applied (Japkowicz & Shah, 2011): each time we excluded one out of the 30 available time series from the training process and we used it only for testing the performance of the constructed HMM based classifier. The "inner" loop consisted of a random resampling stage (Japkowicz & Shah, 2011); each time three time series were randomly selected and excluded from the training process and only employed for testing. During this procedure which was repeated five times, six different configurations of the HMMs were tested (one and three Gaussian mixtures and two, three and four hidden states) – the selection of the range of the parameters was based on our previous experience with a similar configuration and by observing the segregation of the time series values. Therefore, through this simple grid search the "optimal" set of parameters was selected (in terms of average classification performance) for each one of the thirty folds of the "leave one out" method. After the selection of the parameters (the same for all three HMMs, even though HMMs with different parameters could have been selected) the 29 cases (divided into three sets, each one for each class) were used to train three HMMs and the one case left out was assigned to the class that corresponded to the model that yielded the maximum log-likelihood. Since the training of the HMMs is a stochastic process the whole procedure was repeated five times and the results were averaged.

Our results indicate that the method is quite promising, yielding 100% classification accuracy as it can be seen in Table 2. In terms of the parameters setting, more than one configurations were proved "optimal" as it can be observed in Fig. 11. In all 150 (5×30) repetitions, an HMM with 2 hidden states and 3 mixtures was selected. The number of mixtures seems to play the most important role since models with three mixtures were consistently selected, whereas the number of hidden states could also be in-

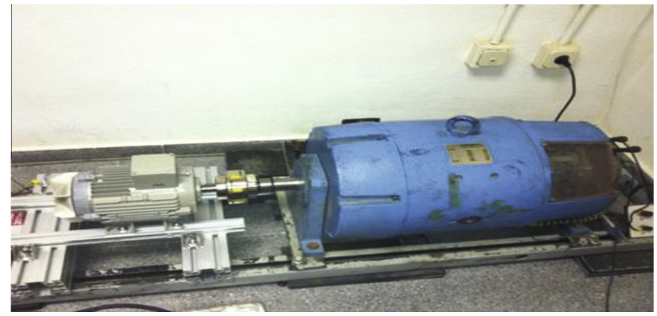

Fig. 10. Experimental setup.

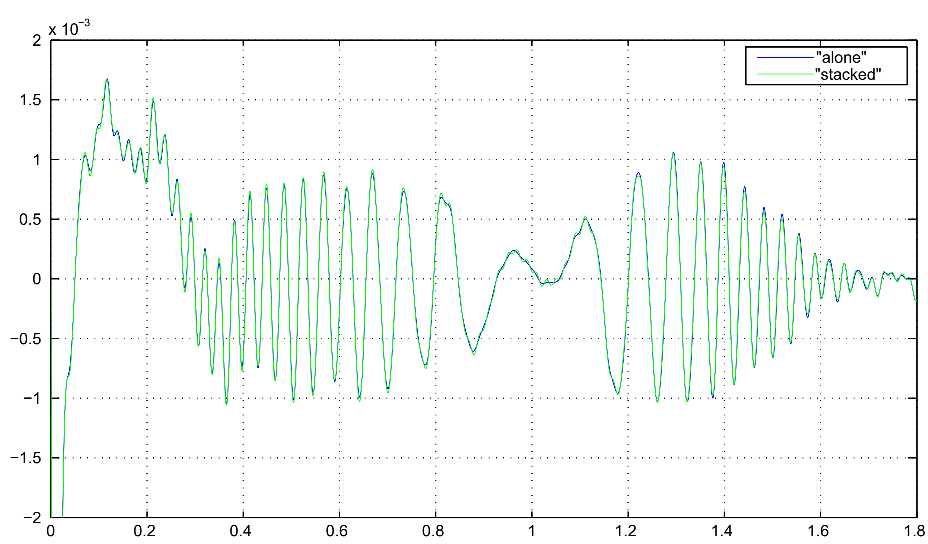

Fig. 9. The "faulty" component for a machine with two broken bars. The differences between the components extracted using all recordings corresponding to the machine with two broken bars and the one estimated using a single recording are practically indistinguishable.

Table 2
Average confusion matrix.

		Predicted		
		Healthy (%)	1 BB (%)	2 BB (%)
Actual	Healthy	100	0	0
	1 BB	0	100	0
	2 BB	0	0	100

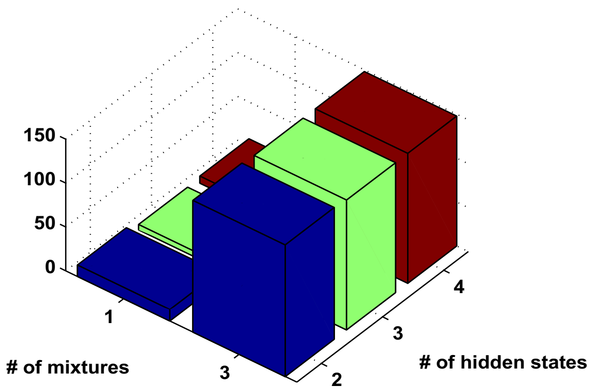

Fig. 11. The two-dimensional histogram for the selection of each model configuration over the 150 repetitions. The number of Gaussian mixtures plays the most important role.

creased to 3 or 4. However, since in data driven modeling the major trend is to select simpler models, in the case that the number of data is restricted (Cherkassky & Mulier, 2007) the use of HMMs with three mixtures and two hidden states seems to be an efficient choice.

3.2. One class classification approach

Sometimes it is difficult to have access to data regarding all the possible classes or the damage modes that a complex engineering system is likely to encounter. In such cases it is more practical to require a detector instead of a classifier. These kinds of detectors are usually trained using data coming from only one known class (usually the healthy one) and actually detect any object that deviates from what it has been learnt before. In the machine learning literature these detectors are called novelty detectors (Markou & Singh, 2003) or anomaly detectors (Chandola, Banerjee, & Kumar, 2009). Since information from a single/one class is exploited, this kind of novelty detectors is closely related with the one-class classification approach (Tax, 2001).

Therefore in the one class classification approach (Tax, 2001) the objective is to develop a methodology, which will be able to characterize anomalous situations using information coming solely from the healthy class. A number of detectors for fault detection have been developed and new applications appear every day especially for complex engineering systems (Chandola et al., 2009). In our case, due to the temporal nature of the phenomenon and also for consistency reasons regarding the multiclass-severity diagnosis approach, an HMM was selected as the basic element for modeling the normal/healthy class.

In other words, an HMM was trained using only data coming from the normal/healthy case and the detection of an anomaly was based on the value of the log-likelihood resulting from that model (the evaluation problem that was mentioned in Section 2.2). A similar approach with only one HMM was applied for tracking bearing degradation with the HMM being trained with data coming from a healthy bearing and thereafter evaluating the condition

Table 3
Average confusion matrix.

		Predicted	
		Healthy (%)	Faulty (%)
Actual	Healthy	100	0
	Faulty	0	100

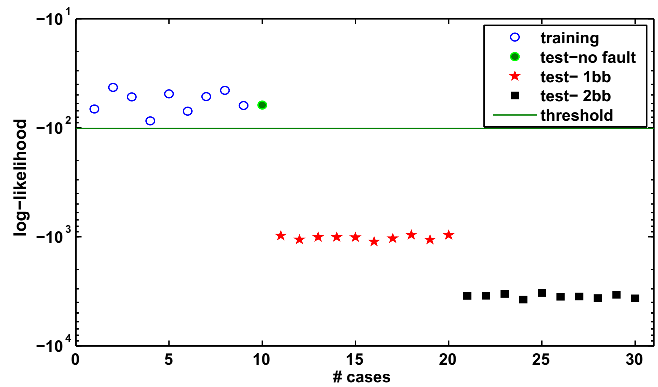

Fig. 12. The calculated log-likelihood using an HMM trained with nine normal recordings.

of the bearing based on log-likelihood estimated using that model (Ocak et al., 2007).

Since the investigation in Section 3.1 during the multiclass approach revealed that a "compact" HHM with two hidden states and three Gaussian mixtures was sufficient for the discrimination between three classes, the same configuration was also adopted for the one class classification scheme. In order to experimentally evaluate the proposed approach, again the "leave-one-out" method was applied by utilizing each time nine of the healthy recordings for training and the one left out for testing along with the 20 faulty cases (10 with one broken bar and 10 with 2 broken bars). As in the previous case, the overall procedure was repeated five times and the results were averaged. For the examined case, it should be noted that since the length of the time series can affect the value of the log-likelihood, a stage for fixing the length to 200 samples was involved (using linear interpolation). For setting the detection threshold, a simple approach based on the three-sigma rule (Ruan, Chen, Kerre, & Wets, 2005) was used. In other words, if the log-likelihood was three standard deviations away from the mean log-likelihood of the training data, the unknown recording was declared as an anomaly/fault. As the experimental results indicate, the anomaly detector has 100% detection rate and without any false alarms as it is summarized in Table 3.

Moreover, as it can be observed graphically in Fig. 12, where the calculated log-likelihoods for one of the folds of the aforementioned procedure is depicted, the anomaly detector could be also utilized as a method for severity evaluation even, though it was not explicitly designed to do so; the more severe the fault is the less the log-likelihood value becomes. This is inline with the fault degradation perspective described in Ocak et al. (2007).

4. Conclusions

In this article, two automatic methods, one for the detection of broken rotor bars and the second for the exact estimation of the number of broken bars, were presented. The core of the proposed approach is based on the use of PCA applied on the stator's three phase start-up current. PCA was utilized to extract a characteristic component, which reflects the rotor asymmetry caused by the broken bars. This component was subsequently processed using Hidden Markov Modeling following two paths: a multiclass and a one-class approach.

During the multiclass approach each severity level was treated as a separate class and the goal was to assign each recording to one of the severity levels/classes. Three HMMs (normal, 1 broken bar, 2 broken bars) were built. Each one corresponds to one severity class level and the new recordings were classified to the class whose model best described them. Using experimental data and a quite compact HMM configuration, perfect classification performance was achieved indicating that the method was able to "assess" the severity of the fault.

In the one-class – anomaly detection – approach the condition of the machine was assessed based on the log-likelihood calculated using only one HMM which was built using data coming only from the normal class. Using the calculated log-likelihood and a simple threshold derived by the three-sigma rule the proposed method was able to detect all anomalous/faulty situations without any false alarm. Moreover this scheme although it was not explicitly developed for severity assessment, it could potentially be applied as such (without however being able to explicitly estimate the number of broken bars – this would require the use of labeled data which were assumed absent).

One of the drawbacks of the method is the high computational time for building and testing the HMMs. However since this method is not meant for continuous monitoring this time demanding process does not pose any serious implementation issues. It should be mentioned that the key, as in most machine learning applications, is the PCA stage, i.e. the feature engineering phase (Domigos, 2012). The distinctive extracted pattern is what makes the whole diagnosis process successful.

In future research we will test our method using data coming from other machines in order to further validate its applicability in an industrial setting. Moreover we will try to test scenarios involving several faults in a fault isolation scheme.

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