



Condition Monitoring Techniques of Ball Bearings in Non-stationary Conditions

Matteo Strozzi^(✉), Riccardo Rubini, and Marco Cocconcelli

Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Giovanni Amendola 2, 42122 Reggio Emilia, Italy
matteo.strozzi@unimore.it

Abstract. Frequently, the Industry suggests non-trivial problems and new fields of research for the Academy. This is the case of the ball bearing diagnostics in direct-drive motors. Direct-drive motors are brushless motors fully controlled by the drive system. Thanks to an encoder or a resolver mounted on the shaft, they can perform complex motion profiles, such as polynomials or splines, including reverse rotation of the shaft. The main advantage of direct-drive motors is the removal of cams or gearboxes afterwards motor with a consequent strong reduction of economic and maintaining costs. Indeed, their main drawback is the difficulty to make diagnostics on the bearings. Regarding bearing diagnostics, most of the techniques present in literature are based on the search of fault-characteristic frequencies in the vibration spectrum of the motor. These fault frequencies are linearly dependent on the rotational frequency of the shaft if it is supposed constant. However, in direct-drive motors the rotational speed changes continuously and consequently the fault frequencies are meaningless. The paper reports a brief overview of some techniques for the condition monitoring of ball bearings in non-stationary conditions used by the Authors in the case of a packaging machine working under variable speed. The techniques adopted include an improved version of the computed order tracking, the cross-correlation function and three supervised learning approaches: artificial neural networks, artificial immune systems and support vector machines.

Keywords: Condition monitoring · Non-stationary conditions · Ball bearings

1 Introduction

The issue of the condition monitoring of bearings for fault detection and diagnostics purposes results of great industrial interest and has been successfully dealt for decades with different methods based on the analysis of the vibration signals [1–13].

In particular, the vibrations induced by defective bearings have characteristics that make them recognizable by analysing the statistical distribution in the time domain and the periodicities in the frequency domain. The reliability of the current techniques of bearing monitoring has lifted up the objectives of the maintenance personnel who are engaged in the identification of sophisticated analytical procedures able to anticipate the location of defects in the service of predictive maintenance of machines.

The widespread use, in the field of automatic packaging machines, of servomotors that replace some organs of powertrains to perform tasks requiring complex motion laws, invalidates the effectiveness of classical approaches, making non-Gaussian the distribution of the vibratory signal, even in healthy cases, and eliminating, within the spectra, the characteristic frequencies that distinguish the signals of damaged machines operating at constant speed.

Diagnostics of rotating machines in non-stationary conditions, e.g. bearings and gears, is a very attractive and promising research field. Recently, several works have been published in literature [14, 15] or presented in thematic Conferences [16–18], covering a wide range of applications, from manufacturing [19] to mining industry [20].

This paper reports the state of the art of the research carried out by the Authors in the areas of condition monitoring and diagnostics of ball bearings operating at variable speed. The Authors have proposed a series of solutions to the problem described, which are based on two different approaches of vibration signal analysis: (i) the modelling of the vibration characteristic signal of a rolling bearing, (ii) the application of expert systems. Considering the two previous approaches, five different diagnostics methodologies are proposed: computed order tracking [21], cross-correlation function [22–24], artificial neural networks [25], artificial immune systems [26] and support vector machines [27].

2 Methods Based on the Mechanical Model of the Defect

The knowledge of the physical phenomena that control the dynamics of the bearing allows to predict the expected vibration signal in both healthy and faulty condition of the bearing. The classical approach used to model the ball bearings is based on the similarity between ball bearings and epicycloid gears: the inner ring acts like the sun gear, the outer ring like the annulus gear, the spheres like the planet gears and the cage like the planet carrier. The kinematics relations that stand for the epicycloid gear allow to calculate the speed ratio between each bearing component as a function of the bearing geometry. Moreover, the modelling of the bearing allows to compute the well-known fault frequencies that are the basis of the diagnostic methods proposed in the literature in the last decades.

The ball-bearing fault frequencies are proportional to the rotational frequencies of the shaft (in the rest of the paper it's supposed that the inner ring of the bearing is integral with the rotating shaft, while the outer ring is fixed to the motor frame), then a constant value of the rotational speed of the shaft is an essential condition to perform the diagnostics of the bearing and it has been fulfilled for a long time by the working condition of asynchronous motors used in the Industry. As mentioned in the Introduction, the new concept of motors - the brushless servomotors - that have been started to be used in packaging machines no longer satisfies the constant-speed condition. It must be pointed out that the working condition of the motor is changed, but the physics of the bearing has remained the same, that is the mechanical model of the bearing and its defect can still be used with some tricks that are presented in this section.

In variable speed applications two ideal reference systems may be supposed in figurative sense: one is fixed in the variable speed domain and one in the constant speed

domain. The vibration data are acquired in the variable speed domain while the algorithms developed in the literature belong to the constant speed domain. As a consequence, two different methodologies are possible: transform the vibration data in the constant speed domain or try to adapt the literature algorithms for the variable speed domain. In this section the Authors describe the Computed Order Tracking to tackle the first task and the Cross-Correlation Function to tackle the second task.

2.1 Computed Order Tracking

The choice of a technique based on the computed order tracking (COT) [28, 29] is justified because the scientific research in the field of monitoring of rolling bearings has always been focused, historically, to address the problems of machines operating at constant speed, by improving the signal analysis methodologies operating in the frequency domain.

The application of COT to a signal produced by the operation of a machine that must follow a complex law of motion - extrapolating the relationship between the magnitude of the parameter under observation (acceleration) and the angle of rotation of the shaft, by means of a re-sampling of the signal for constant angles of rotation - allows to get a signal in which, if you neglect the slippage between the surfaces in contact, the transient events induced by the presence of defects involving the elements of the bearings, appear periodically with a periodicity dependent on the geometry of the bearing. This processing procedure justifies the application, downstream from the COT, of the classical techniques of monitoring of the bearings.

The methodology proposed by the Authors [21] is covered by international patent [30] and can be summarized as follows:

- acquisition of the vibration signal of the support in the radial direction (radial ball bearings);
- identification of a resonance frequency of the system;
- extraction of the modulation signal of the resonant frequency selected in the previous step;
- application of the COT by referring to the signal of the crankshaft rotation speed acquired by an encoder;
- slip of the signal corresponding to rotations of the crankshaft in the opposite direction to that chosen as positive (inversion of the time axis);
- determination of the characteristic period of the defect based on the geometry of the bearing;
- selection, for each rotation period of the machine, of a signal section corresponding to an integer number of characteristic periods of the defect;
- application of the synchronous average of the signal sections selected, from the entire acquired time history, by following the criteria of the previous step;
- spectral analysis of the averaged signal.

In order to carry out a complete monitoring of the health conditions of the bearing, it is necessary to repeat this procedure for all possible types of defect. A flowchart of the procedure is reported in Fig. 1.

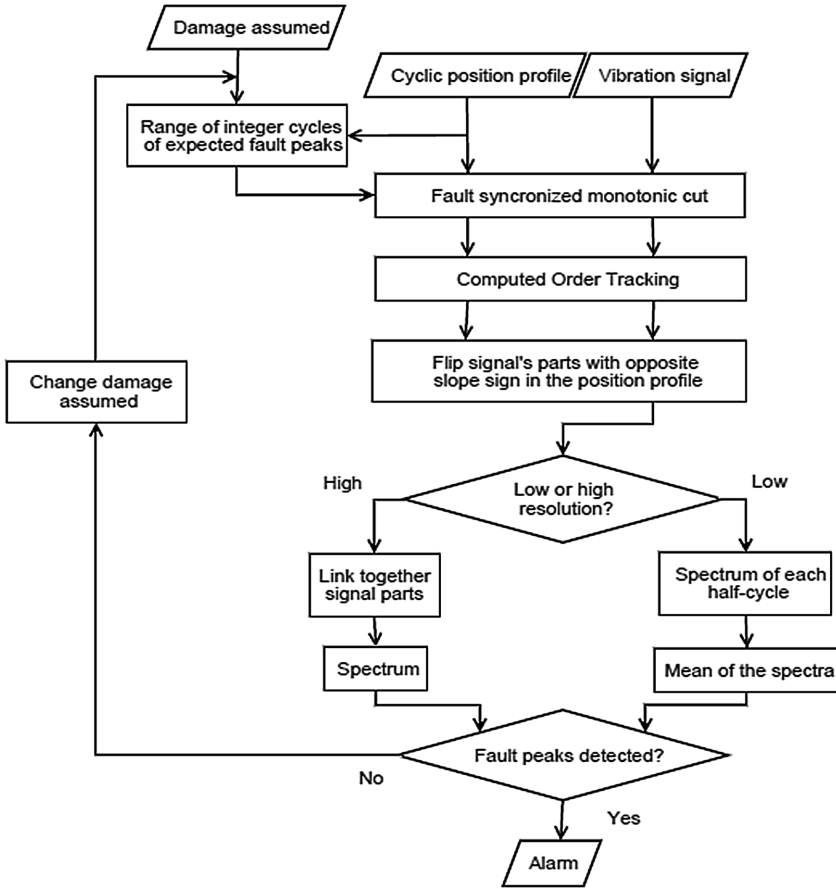


Fig. 1. Flowchart of the proposed procedure of computed order tracking.

2.2 Cross-Correlation Function

The use of servomotors, devices which transmit complex laws of motion to the rotating parts of the supports, invalidates the application of the more effective classical technique for the monitoring of rolling bearings, based on the detection of periodic events induced by the presence of surface defects on the components: the impulses, that arise in the vibration signal due to interaction with the damaged zones in operating conditions, occur with a complex time distribution dependent on the operating conditions, as well as the geometry of the supports.

The Authors have proposed a monitoring methodology [22–24] based on the construction of a simplified model of vibration signal, which looks like a train of Dirac impulses, which occupy on the time axis, unless the phase, the location of the events that would appear, if it was the defect to be monitored, under the expected operating conditions. This simplified model of signal must be compared with the one actually acquired from the supports, which is also affected by mechanical and electrical noise

and the dynamic effects induced by complex laws of motion: accelerations and motion inversions.

In order to highlight, in the vibration signal, any fast transients that arise in the presence of localized defects, an analysis is performed in the time-frequency domain using the wavelet transform with impulse wavelet [31] as a mother function, particularly suitable for the detection of shocks.

With reference to Fig. 2, the proposed procedure can be summarized as follows:

- acquisition of the vibration signal of the support in the radial direction (radial ball bearings);
- application of Wavelet Transform with impulse wavelet;
- extraction of the filtered signal at a suitable frequency for the localization of possible pulses in the signal;
- construction of a model of the signal corresponding to a possible damage of the bearing located on a component, based on the law of motion imposed by the actuator: it consists of a Dirac pulse train;
- calculation of the cross-correlation function between the signals obtained in the previous steps (the actual signal and processed model);
- assessment of the degree of correlation by appropriate statistical parameters (kurtosis, maximum value, crest factor)

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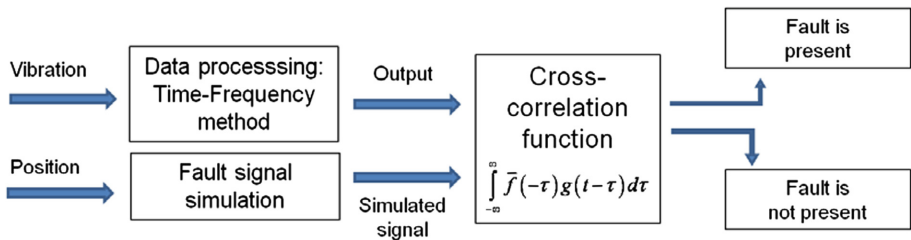


Fig. 2. Flowchart of the proposed procedure based on the cross-correlation function.

The suggested technique can be extended in order to use the electric current absorbed by the motor instead of the vibration signal. Although vibration data have demonstrated their effectiveness in diagnostics, there is a line of research in the literature that tries to use the current fluctuation absorbed by the motor as sensor of an incipient fault.

In fact, the presence of a defect induces fluctuations of the airgap between the stator and the rotor - that is a sort of vibration of the rotor - with a consequent presence of ripples in the current signal.

Although the view of an intrinsic sensor is quite attractive for the industries (external sensors are no more needed), the sensibility of the currents is very low compared to the one of the vibration signal. Starting from the idea that the current ripples are consequences of mechanical phenomena, like the impact of a sphere with a damage on

the outer ring of the bearing, the Authors suggest to correlate the current data with the simplified model of vibration signal as shown in Fig. 3.

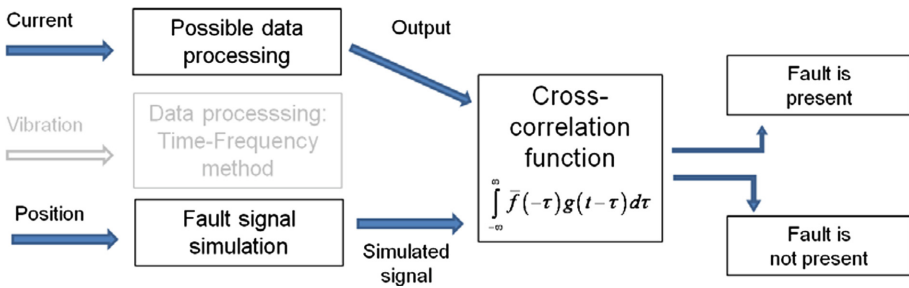


Fig. 3. Extension of the algorithm to the current measurement.

The simulated vibration signal acts like a map that highlights the similarity between the expected impulses in the vibration signal and the ripples in the current data through the cross-correlation function. The signal-to-noise ratio of the correlation can be improved with a pre-processing of the current data. For example, the presence of ripples in the current data can be highlighted calculating the gradient of the current data themselves.

3 Expert Systems

The adoption of expert systems for the recognition of signal patterns of damaged bearings [32–40] does not require the determination of a mechanical model. As is well known, in order to use the expert systems as efficient instruments of pattern recognition, it is necessary to educate them with information derived from actual operating conditions, by including all the possible manifestations of the phenomenon to be studied.

So, if one has the advantage of avoiding the simulation of the failure of the rolling bearings by proposing a signal model - which, to be efficient, should also consider the slippage of the rolling elements and the vibrations transmitted by other parts of the system - however, the application of expert systems requires a wide experimental phase and the identification of signal parameters that are sensitive to the different states of classification required.

For the identification of the presence of a particular defect in all the different operating conditions of a machine driven by servomotors, it is opportune to provide an indication of the hourly capacity of the machine (number of machine cycles per unit time, that in the paper will be addressed as *working speed* of the machine): this parameter can alter significantly the dynamics of the machine, acting on the shape of the vibration signal and the separation time between impulsive events induced by the surface damages.

3.1 Artificial Neural Networks

The Authors have obtained the maximum efficiency for bearing state recognition (100%) using an artificial neural network (ANN) feed-forward with single hidden layer consisting of 70 neurons, with hyperbolic tangent sigmoid transfer function and a training function based on the resilient back-propagation algorithm [25].

The network was provided, as inputs, by the root mean square value (RMS) and the kurtosis of the vibration of a large number of bearings, healthy or damaged on a particular component (natural or artificial damage), at different speeds. In order to obtain an adequate number of data for training and test phases, long acquisitions were made, then separated into parts corresponding to one machine cycle.

The combination of RMS-kurtosis, with the value of speed, allows to recognize the condition of the bearing, even in health cases with 0 h of operation: in this early stage of adjustment, the machine can vibrate with higher RMS value, but the signal remains stochastic, with a low value of kurtosis.

3.2 Artificial Immune Systems

The Authors developed a simple method inspired and derived from the mechanisms of the immune system to recognise bearing faults [26]. The proposed algorithm was a simplification of the original process, adapted to a particular case of a much bigger class of algorithms and methods named Artificial Immune Systems (AIS). These systems have proven to be useful and promising in many application fields [41, 42]. The AIS mimic the human body immune system that is able to recognize and react against never seen before virus. Figure 4 depicts the main idea of AIS: in (a), training dataset for healthy and faulted bearings is given in the space of the features (antigens). In (b), random antibodies are generated with a proper area of interest. Based on the major number of specific antigens, in (c) the antibodies are associated to a healthy or faulty status. Finally, once a new dataset is given in (d), its classification is given as the result of collisions with the antibodies. In particular, the proposed algorithm is based on the Euclidean distance minimization (EDM) method in the evaluation of binding between antigens. Applied to bearing diagnostics, the generic antigen used is created collecting together four features computed from the vibration signal: Kurtosis, Jerk-peak, RMS and the hourly capacity of the packaging machine the motor is mounted on.

A normalization with respect to the maximum computed value of the features is required in order to compare the antigens developed in training phase with the antigens under classification: experimental activity performed by the Authors considering this AIS based algorithm for bearing state recognition proved the maximum efficiency (100%) of the developed methodology.

3.3 Support Vector Machines

The Support Vector Machines (SVM) is a learning methodology based on the statistical learning theory [36–40]: it classifies a set of input into two categories.

During the training phase of the SVM the classification rule is generated by the specific kernel function selected, in order to obtain and optimize - on a plane or space

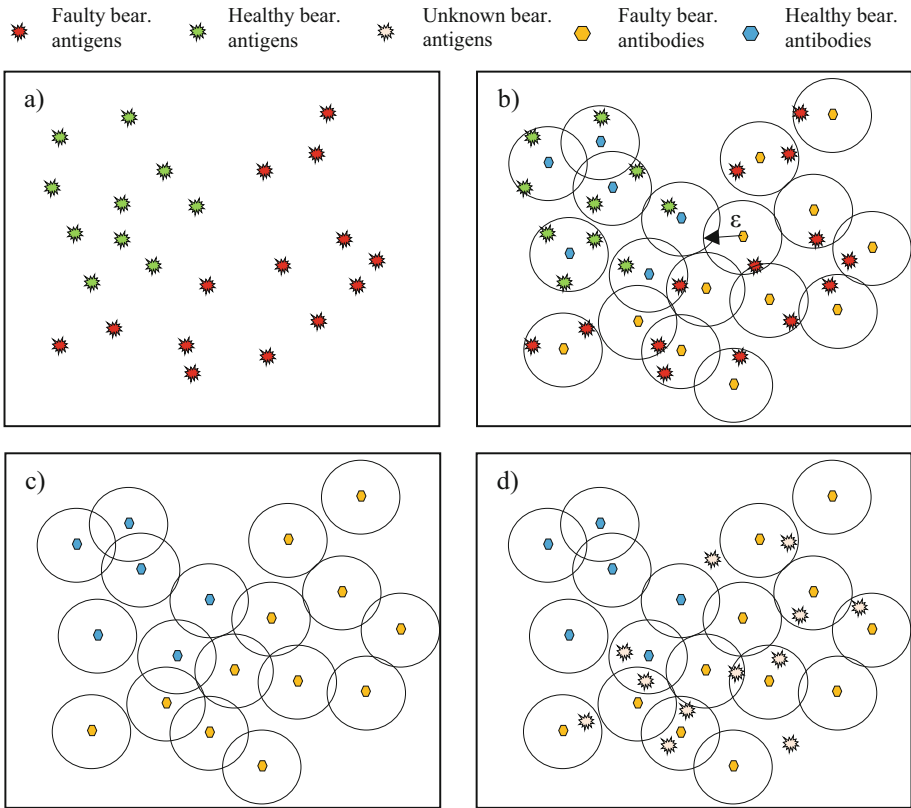


Fig. 4. Faulty and healthy bearing antigens (a). Generation (b) and separation (c) of the antibodies. The generated antibodies are used to classify the unknown antigens (d).

whose axes are represented by the input parameters - a curve or a surface boundary able to divide the two categories of outputs, maximizing its distance from the border cases.

The Authors used the algorithm of Professor Gunn [43] and the same input vector previously used for the ANN in order to make a comparison between the two expert systems. The results return the maximum efficiency for bearing state recognition (100% like in the ANN case) adopting an exponential radial-basis-function with sigma equal to five as kernel.

A second test has been done removing the speed information from the input vector, which is now made by the combination of RMS-kurtosis only. The results are 100% of success and it proves the capability of SVM as classifier. This second test has been applied also to ANN but with several errors in the recognition of the health of the bearing.

The differences between SVM and ANN are probably due to the capability of the SVM to pass the data to a multi-dimensional space through the use of the kernel function, where the single data can be divided in two categories by an hyperplane (see [43]). The ANN elaborate data in the input space and therefore they need an input

vector with an increased dimension (RMS-kurtosis-speed instead of RMS-kurtosis only) from the beginning. Figure 5 shows a graphical representation of the features' space and the separation of the healthy (yellow) and faulty (blue) classification area.

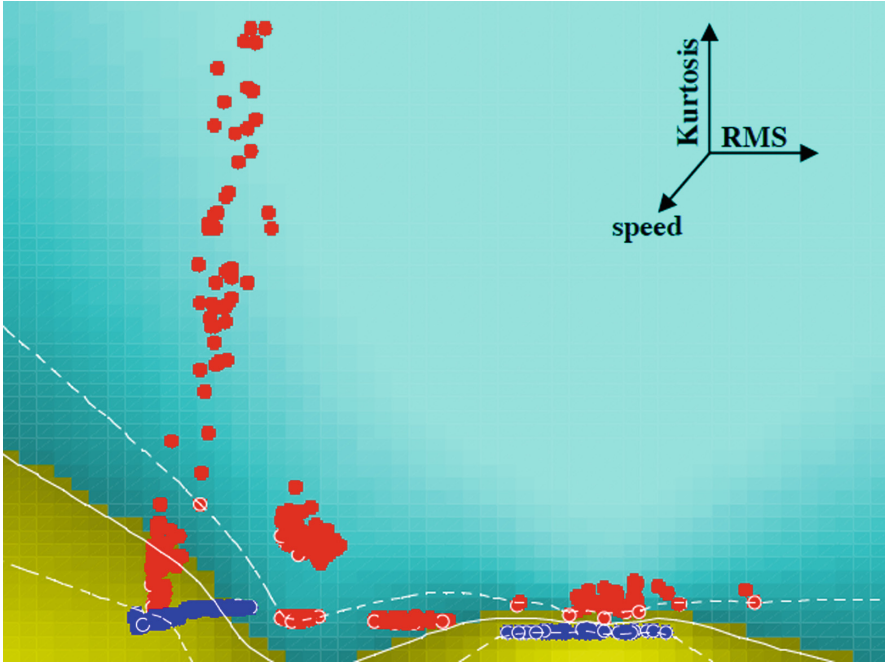


Fig. 5. Projection on the plane RMS-Kurtosis of the best Radial Basis SVM classification; the blue and red points represent the healthy and faulty patterns. White lines are the support vector machines (dotted) and the projection of separation hyperplane (solid).

The experimental activity made by the Authors proves that different expert systems give excellent results if the input parameters are suitably chosen. Often the expert systems seem to be an easy solution for pattern-recognition and classification tasks since they automatically build the weight matrix to classify new inputs, but it is just an appearance since the researcher still has the responsibility to define the right input vector that describes the physics of the process under consideration.

4 Conclusions

In this paper, the Authors run through their experience in the diagnostics of ball bearings in variable speed applications and outline the adopted solutions from a methodological point of view. All the methods are based on a specific test case, which is the condition monitoring of ball bearings for a brushless servo-motor in a packaging machine. Many mechanical devices, and in particular the automatic machines for

packaging, continually increase the use of servo-motors which normally work at variable speed. Unfortunately, most of the literature on diagnostics assumes constant although arbitrary rotational frequencies of the motor. In fact, a continuous change of speed makes difficult to recognise the presence of fault characteristic frequencies within the spectrum of vibration. The condition monitoring techniques of ball bearings proposed by the Authors in the last ten years proved to be effective in non-stationary conditions and the present paper is focused on the followed methodology. Future developments of the present work will concern the study and verification of the applicability of the previously described condition monitoring methods for ball bearings: (i) also for other types of bearings (tapered roller bearings, angular contact ball bearings with preload), (ii) in case of improper mounting of bearings (angular contact without proper preload leading to sphere slipping), and (iii) accelerometer acquisition replacement with acoustical signal acquisition.

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