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Development of a New Signal Processing Diagnostic Tool for Vibration Signals Acquired in Transient Conditions

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The diagnostics of mechanical components operating in transient conditions is still an open issue, in both research and industrial field. Indeed, the signal processing techniques developed to analyse stationary data are not applicable or are affected by a loss of effectiveness when applied to signal acquired in transient conditions. In this paper, a suitable and original signal processing tool (named EEMED), which can be used for mechanical component diagnostics in whatever operating condition and noise level, is developed exploiting some data-adaptive techniques such as Empirical Mode Decomposition (EMD), Minimum Entropy Deconvolution (MED) and the analytical approach of the Hilbert transform.
The proposed tool is able to supply diagnostic information on the basis of experimental vibrations measured in transient conditions. The tool has been originally developed in order to detect localized faults on bearings installed in high speed train traction equipments and it is more effective to detect a fault in non-stationary conditions than signal processing tools based on spectral kurtosis or envelope analysis, which represent until now the landmark for bearings diagnostics.

1. Introduction

Diagnostics in mechanical systems is aimed at the early detection of possible faults in mechanical components. In the case of small size components as rolling element bearings, signal processing of vibrating data is the most used approach to support diagnostics procedures. A lot of signal processing techniques have been proposed during time and added to the more traditional ones like the Fourier transform. Time synchronous average was introduced for example to analyze data acquired on gearboxes whose functioning are typically periodic (McFadden, 1987). Envelope analysis (Darlow at el., 1974), second order cyclostationary analysis (Capdessus et al., 2000) and spectral kurtosis (Antoni and Randall, 2009) are instead widely accepted and used for bearing monitoring and diagnostics. Others smart signal processing techniques, proposed in order to highlight the non-stationary behavior of a phenomenon, are, for example, wavelet transform (Ohue et al., 2004), which carries out a time-frequency analysis, and cepstrum analysis (Badaouiet al., 2001) able to detect echoes in the signal.
The effectiveness of the mentioned techniques for stationary signals acquired on laboratory facilities has been proven in various papers. Unfortunately, some difficulties arise when the considered signals are related to non-stationary phenomena or systems working in unsteady operating conditions. Moreover, a loss of effectiveness can be observed also in the case of complex systems, in which the measured signals can be a mixture of different sources, and in real applications in which the signals are affected by high level of noise. For these reasons, adaptive techniques became very attractive in the last years. These techniques, also called data driven techniques, are able to overcome the hypothesis of periodicity and stationarity of the signals. Empirical Mode Decomposition (EMD) has been probably the first technique belonging to this category. Proposed for the first time by Huang in 1998, EMD is used either as an independent tool (Loutridis, 2004) or as preliminary method for the Hilbert-Huang Spectrum (HHS) calculation with good results (Ricci, 2011) to signals measured on mechanical systems. The Minimum Entropy Deconvolution (MED) (Gonzàlez et al., 1995) is another example of adaptive signal processing technique. Conversely to the EMD, which is based on the decomposition of the experimental signal in

different functions corresponding to different signal modes, the MED algorithm improves, by means of a filter, the peakedness of the signal highlighting the transient components. MED is particularly effective in the separation of subsequent bursts in experimental signals caused by shocks generated by localized defects (Pennacchi et al. 2011).

Notwithstanding the EMD and MED algorithms have been proven in some laboratory applications, the diagnostics effectiveness of both techniques for non-stationary real applications, characterized by high level of noise and in the presence of external sources, must be still tested.

In this paper, a new tool, the Empirical Envelope MED (EEMED) is proposed. The procedure has been developed and tuned for the detection of localized faults on bearings installed in high speed train traction equipments. The developed tool allows the fault in transient conditions to be detected with better results than those proposed by spectral kurtosis or envelope analysis which nowadays represent the landmark for bearings diagnostics.

2. EEMED algorithm

2.1 Empirical Mode Decomposition (EMD) algorithm

Considering a generic signal x(t), the EMD is based on the research of its stationary points. Indicating with $s_{max}(t)$ and $s_{min}(t)$ respectively the splines interpolating the maxima and minima points of the signal $x(t)$, their mean function $m(t)$ can be removed from the original signal:

$$x_1(t) = x(t) - m(t) \tag{1}$$

The signal $x_1(t)$ is an intrinsic mode function (IMF) if the two particular conditions are respected. If the resulting signal $x_1(t)$ is not an IMF, $s_{max}(t)$, $s_{min}(t)$ and $m(t)$ must be recomputed starting from $x_1(t)$ with an iterative procedure called sifting process. The sifting process stops when the first intrinsic mode function $C_1(t)$ is extracted. Therefore, $C_1(t)$ can be subtracted from the original signal:

$$r_1(t) = x(t) - C_1(t) \tag{2}$$

The residual signal $r_1(t)$ represents the input for the second IMF calculation by means of the sifting process. The EMD algorithm for the original signal $x(t)$, stops when the residual signal $r_N(t)$ is a constant or monotonic function, after the extraction of the N-th intrinsic mode function. This stop condition can be expressed in terms of standard deviation threshold and number of extremes.

The EMD is a deterministic decomposition; therefore the original data can be re-obtained by adding the extracted IMFs to the last residual signal.

2.2 Analytic signal

The IMFs extracted by means of the EMD process can be considered a sort of sub-signals of the original one since they enclose only some components. Therefore, the IMFs represent favorable starting points for further analysis. With reference to roller bearing diagnostics, it is widely accepted that the analytic signal is particularly sensitive to the slippage occurring among the rolling elements and the rings of the bearings as effects of the presence of localized faults. The analytic signal $z(t)$ is defined as:

$$z(t) = x(t) + \mathrm{i}\, y(t) \tag{3}$$

where $x(t)$ is the experimental signal and $y(t)$ its Hilbert transform defined as:

$$y(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{4}$$

The polar notation of the analytic signal $z(t)$ is:

$$z(t) = a(t) \mathrm{e}^{\mathrm{i}\vartheta(t)} \tag{5}$$

where $a(t)$ and $\theta(t)$ represent respectively the envelope and the instantaneous phase of the analytic signal. Usually, the procedures using the Hilbert transform are devoted to the calculation of the instantaneous frequency (e. g. the Hilbert-Huang spectrum). The attention is here focused on the treatment of the analytic signal envelope $a(t)$ which can be obtained by root squaring the sum of the squares of the real and the imaginary components. The envelope of the analytic signal considers simultaneously the variation in the time domain of the original signal and the variations of the two components of $z(t)$ along the real and imaginary axis. In other words, the envelope lies the original signal with its phase-shifted signal, preserving the energy of the measured signal. In the proposed signal processing tool, the analytic signal is calculated on the IMFs. Since the bearings functioning is characterized by high frequency phenomena, the first IMF extracted by the EMD will be considered.

2.3 Minimum Entropy Deconvolution (MED) algorithm

The aim of MED, is to separate the components of a signal. The MED is based on the concept of signal entropy, namely the randomness degree of the signal. The MED algorithm reduces the randomness of a signal by minimizing its entropy. The generic signal *v(t)* could be considered as composed of two terms:

$$v(t) = h(t) * w(t) + \eta(t) \tag{6}$$

The first term is the convolution between the component related to the system behavior *h(t)* and its excitation *w(t)*. The second term *η(t)* considers the signal noise randomly distributed. If the signal *v(t)* is processed with a filter *f(t)*, it is possible to obtain:

$$u(t) = v(t) * f(t) = h(t) * w(t) * f(t) + \eta(t) * f(t) \tag{7}$$

Expressing the previous equation as a function of sampled points, it follows:

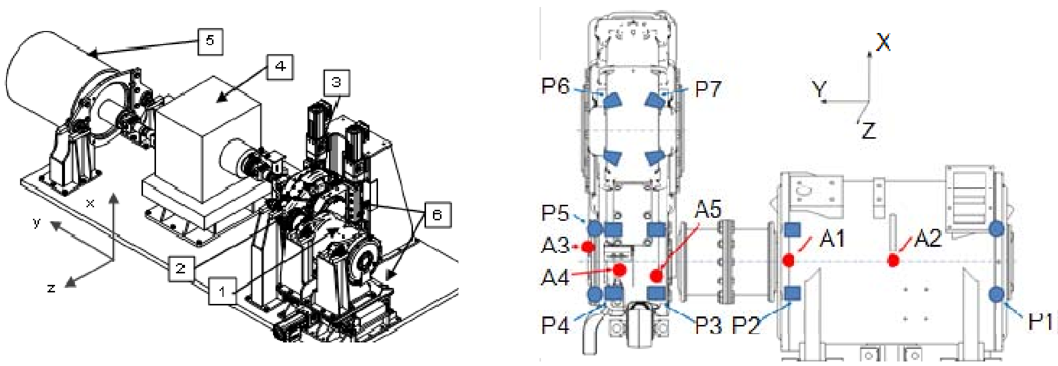
$$u(n) = v(n) * f(n) = \sum_{i=1}^{M-1} f(i) v(n-1) \qquad \text{with } n = 0,1,\dots,T+M-2 \tag{8}$$

The convolution between the signal, with a length of *T*, and the filter with length *M*, can be expressed as a sum of products. The crucial point of the approach is the selection of a proper filter length *M*.
Considering the output of eq. (8), the final signal is a simple solution, characterized by the maximum possible order. A measure of the signal order is the Varimax norm:

$$V(u(t)) = \sum_{j=0}^{N} u^4(j) \Big/ \left(\sum_{j=0}^{N} u^2(j) \right)^2 \tag{9}$$

with $N = T + M - 2$.
By exploiting the Varimax norm definition, the signal entropy can be minimized, by means of an iterative procedure, as function of the filter *f(t).* The norm maximization allows to find the output *u(n)* which best fits the components of *h(t)*.
MED algorithm is applied to the envelope of the first IMF analytic signal. In this is way, MED is applied to simplified (i.e. due to EMD decomposition) and enhanced signals (i.e. due to the Hilbert envelope of the IMF), thus improving the effectiveness of MED itself.

3. Description of the test-rig

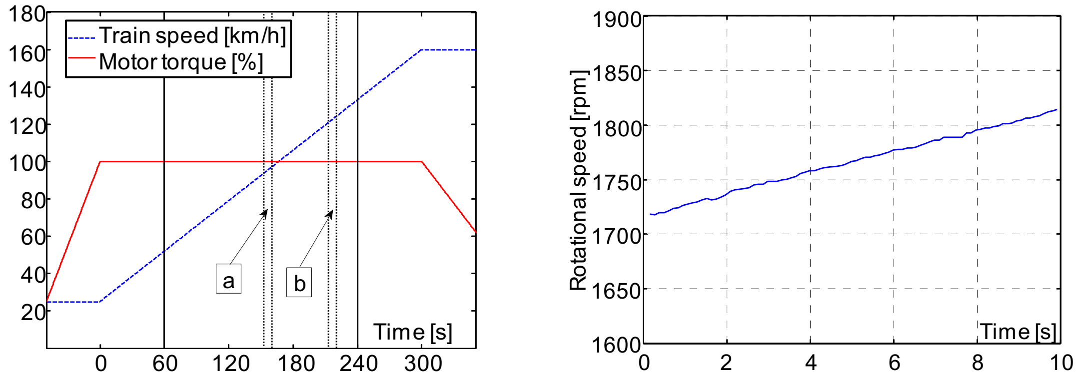


(a) (b)

Figure 1: (a) Test-rig layout: ① HST motor, ② HST toothed coupling, ③ HST gearbox, ④ Additional gearbox, ⑤ Braking motor; (b) Traction system arrangement with bearing position (from P1 to P7) and accelerometer position (from A1 to A5)

The EEMED procedure described in the previous section is applied to vibration signals measured on the test-rig shown in Figure 1(a). The test rig is equipped with a complete HST traction system: a 265 kW 4-

poles asynchronous HST motor is connected to the input shaft of the HST gearbox by means of a toothed coupling. The braking torque is providede by a braking system composed of a braking motor and an industrial gearbox connected to the HST traction system through a double cardan shaft.
Different operating conditions in terms of train speeds and motor supplied torques were tested. Stationary conditions, i.e. constant speed and torque due to cruise trip of the train travelling on a flat track, and non-stationary conditions with train speed and motor torque variations, i.e. train approaching or leaving the railway station, were considered. In the paper, only the signals measured during the tests performed in non-stationary conditions will be considered. Vibration signals were measured by means of several accelerometers placed on the traction motor and the gearbox acquired with a sampling frequency of 20 kHz. The operating conditions are shown in Figure 2(a) and only the vibration data acquired during an interval of 10 s of the test and indicated with [a] in Figure 2(b) will be considered.



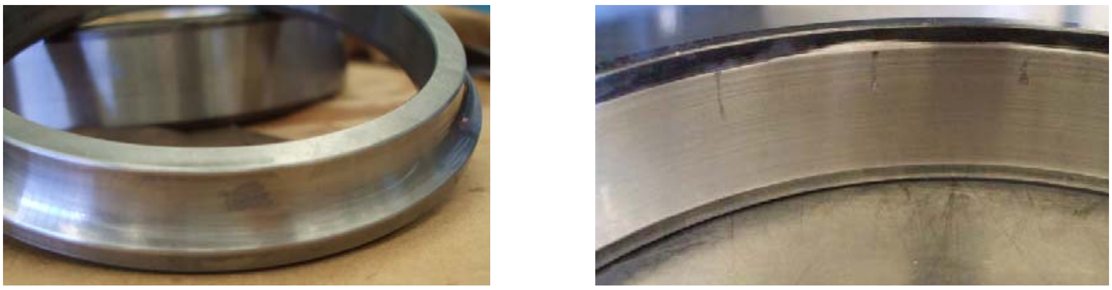
(a) (b)

Figure 2: (a) Operating conditions (train speed and supplied motor torque) for the considered test; (b) Rotational speed of the traction motor measured during the interval [a]

4. Experimental results

Two damaged configurations will be compared with respect to a reference configuration with all brand new bearings. In each configuration all the bearings are new except the artificially damaged one:

- Configuration ①: damage on the inner ring of the ball bearing (Figure 3(a)) in the high speed shaft of the gearbox (P5 in Figure 1(b));
- Configuration ②: damage on the outer ring of the roller bearing (Figure 3(b)) in the traction motor (P5 in Figure 1(b)).



(a) (b)

Figure 3: Bearing damages for (a) configuration ① and (b) configuration ②.

4.1 Configuration ①: damaged bearing on gearbox NDE side

The vibration signals are measured by the accelerometer A3 placed on the gearbox close to the bearing and measuring the vibration along the y-direction that is the direction of the motor shaft axis.
By applying a widely accepted technique in bearing diagnostics as the envelope analysis to the signals, the results shown in Figure 4 can be obtained. In Figure 4(a), for the healthy bearing, no particular component is detectable in the plot apart that corresponding to the rotational speed of the motor (29.9 Hz). Components with high amplitude can be detected on the contrary in Figure 4(b). All these components are harmonics of the motor rotational speed and again, no indication about the presence of the fault on the bearing inner ring can be obtained. It is worth noting that the same analysis performed in stationary

operating conditions offers better results since the characteristic frequencies of the bearing fault can be traced in the envelope domain. This confirm that the envelope analysis, as well as the spectral kurtosis, is ineffective when applied to data acquired in transient conditions and this remarks the necessity to develop a tool able to provide good results in this kind of conditions.

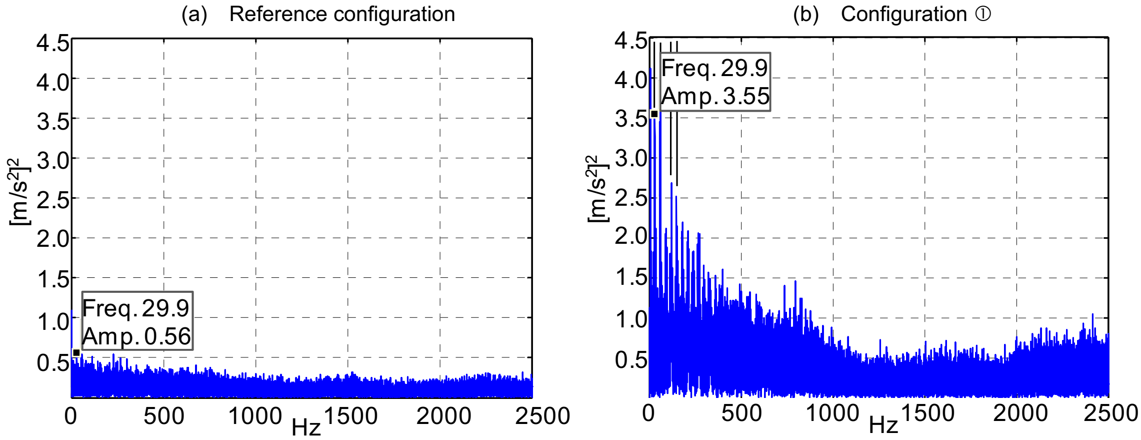


Figure 4: Envelope analysis of the signal for the reference configuration and the configuration ①

The final results provided by the EEMED in time domain are then treated with Fourier Transform for the reference condition and the one with damaged bearing as shown in Figure 5, where the * symbol in the vertical labels indicates that the amplitude is modified by the MED filter.
In Figure 5(a) the frequencies with higher energy are those related to the motor shaft rotation, whereas for the damaged bearing of configuration ①, the highest frequency component is represented by the frequency of the passage of balls on the inner ring (with reference to the actual rotational speed, the nominal BPFI is equal to 273 Hz).

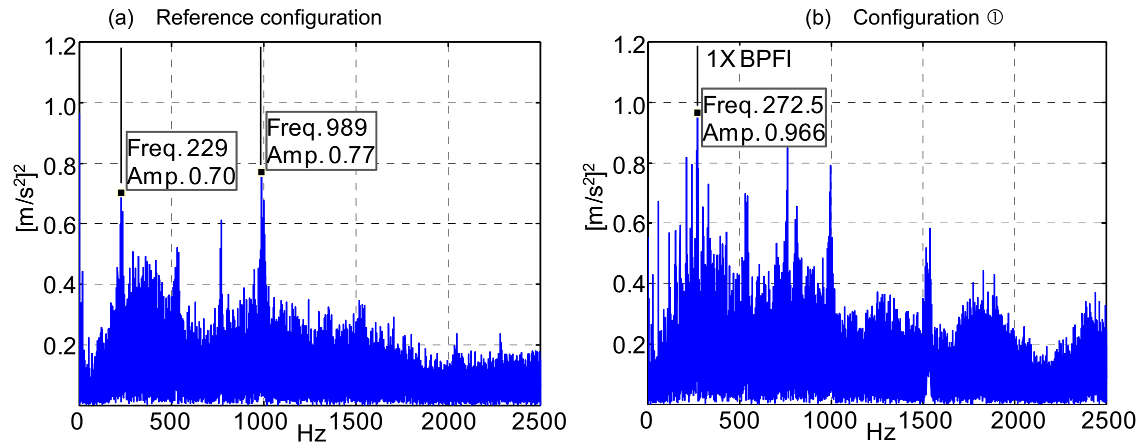


Figure 5. Fourier Transform of the EEMED signals for the reference configuration and the configuration ①

4.2 Configuration ②: damaged bearing on motor DE side
In this case, a defect on the outer ring of the roller bearing of the traction motor is considered. The damages are the indentations shown in Figure 3(b). The vibration signals are acquired by the accelerometer A1 placed very close to the bearing and measuring the vibration along the z-direction
For the sake of brevity, the results provided by the EEMED for the measured signals are shown in Figure 6. While for the reference configuration (Figure 6(a)) the components with high amplitude are those related to the motor rotational speed (e.g. 1x component at 120.1 Hz and 3x component at 359.7 Hz), for the configuration ② with the damaged bearing (Figure 6(b)), the frequency component with maximum energy is that due to the passage of the rolling element on the bearing outer ring (BPFO). For the considered speed profile indeed, the nominal BPFO for that damaged bearing, evaluated with the average value of the speed, is equal to 213 Hz: the identified component located at 212.8 Hz in Figure 6(b) is very

close to the nominal BPFO. Therefore, also in this case, the EEMED procedure is able to detect the bearing damage in non-stationary condition.

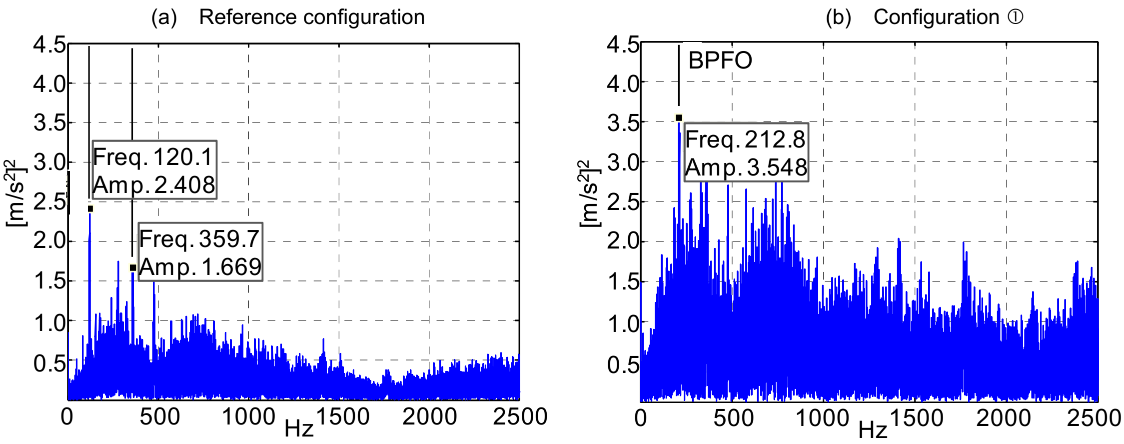


Figure 6: Fourier Transform of the EEMED signal for the reference configuration and the configuration ②

5. Conclusions

The application of a newly proposed tool, the EEMED, for bearing diagnostics in non-stationary operating conditions has been discussed. The effectiveness of EEMED has been tested on vibration signals measured on a test-rig reproducing the functioning of speed train traction equipments.
The application of EEMED to the vibration signals measured for different bearing damages and for non-stationary operating conditions has provided encouraging results. The comparison with both traditional and widely applied techniques as the envelope analysis and more complexes algorithms as the Hilbert-Huang Spectrum shows the suitability of the EEMED for the detection of bearing damages in non-stationary conditions, when other approaches are affected by a loss of effectiveness.

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