Bearings Prognostics based on Blind Sources Separation and Robust Correlation Analysis

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Keywords: Blind Sources Separation, Empirical Modes Decomposition, Robust Correlation, Prognostics, bearings, RUL.

Abstract: Prognostics and Health Management (PHM) for condition monitoring systems have been proposed for predicting faults and estimating the remaining useful life (RUL) of components or subsystem. For gaining importance in industry and decrease possible loss of production due to machine stopping, a new intelligent method for bearing health assessment based on Empirical mode decomposition (EMD) and Blind Source Separation (BSS). EMD is one of the most powerful time-frequency analysis decompose the signal into a set of orthogonal components called intrinsic mode functions (IMFs). BSS method used to separate IMFs of one-dimensional time series into independent time series. The health indicator based on the robust correlation coefcient is proposed based on a weighted average correlation calculated from different combinations of the original data. The correlation coefficients between separated IMFs used to estimate the health of bearing; The correlation coefficient used for comparison between the estimated sources with differents degradation levels. The correlation coefficient values are then fitted to a regression to obtain the model for Remaining Useful Life (RUL) estimation. The method is applied on accelerated degradations bearings called PRONOSTIA. Experimental results show that the proposed method can reflect effectively the performance degradation of bearing.

1 INTRODUCTION

Bearings performance degradation assessment plays an important role in various rotating machines fault prognostics to avoid catastrophic accidents (Yan, 2015). Several researches have been made to develop methods for machine condition monitoring. Qiu et al (Qiu et al., 2003) used using Self Organizing Map and neural network for developing a robust technique for performance degradation assessment of *REB*. Liao et al (Liao and Lee, 2009) used Support vector machine based on wavelet packet analysis and Gaussian mixture model for assessment of machine performance degradation. Xiaoran et al (Zhu et al., 2013) propose a method based on support vector data description; The proposed solution can effectively reflect the health of bearing's, some limitation of this technique for generalized performance the problem for different operating condition.

For improving prognostics it is necessary that the collected raw signals from different sensors be 'clean' enough that small changes in in the raw signal can reflect the severity defect; But this problem is complicated in complex machines because the combination between different sources measurement such as vibrations or acoustics effect the signal energy produced by different components in the machine in addition to the noise. In this area Blind Source Separation (BSS) proposed in the literature for recovering the various independent sources exciting the system given only the outputs of the system (Sánchez A, 2002). BSS has become a mature field of research with many technological applications in areas such as medical, image processing, communications, ...etc (Naik and Wang, 2014). Several researches for machines condition monitoring proposed in this area; Roan et al (Roan et al., 2002) Proposed an application for information maximisation based on BSS algorithm for tooth failure detection and analysis. Serviere et al (Serviere and Fabry, 2004) proposed a new estimator of the whitening matrix and the signal subspace for the separation of rotating machine signals.

Recently, Haile et al (Haile and Dykas, 2015) applied the blind source separation for demixing vibration signals from defective bearings, by comparing five well-known algorithms using experimental

Benkedjouh, T., Zerhouni, N. and Rechak, S.
Bearings Prognostics based on Blind Sources Separation and Robust Correlation Analysis.
DOI: 10.5220/0006472006580663
In *Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2017) - Volume 1*, pages 658-663
ISBN: 978-989-758-263-9

data collection from degraded and healthy bearings. Theodore et al (Popescu, 2010) purpose a new approach for machine vibration analysis and health monitoring combining blind source separation (BSS) and change detection in source signals.

The purpose of this research is to propose a method combining EMD and BSS is applied in bearing degradation performance assessment. The method consists of three processing stages. In stage one; EMD is used to decompose the collected signal in to intrinsic mode functions (IMFs) ; In stage two ,the BSS used to separate the IMFs signals into independent components sources signal, and hence to complete the BSS process. In addition, .Finally, the health state of bearing identified by the calculation of the correlation between separated signals.

2 Description of the Proposed Method

Various prognostic researches have been conducted for improving the RUL prediction. In figure 1 three steps procedure can be achieved in Bearing prognostics process :

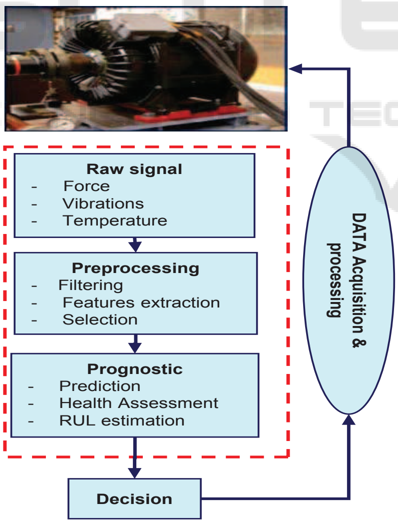

Figure 1: Steps of the proposed method.

Data acquisition step is to collect the data related to system health; Data preprocessing is to analyze the acquired signals Including centering, filtering to remove the offset in the measured signals. In preprocessing step, a EMD used to IMFs that contains information about sources as the input signal for BSS; the correlation coefficients value of independent sources based regression used for the health assessment; in maintenance decision-making step, effective maintenance policies will be obtained based on information analysis.

2.1 Empirical Mode Decomposition

The EMD method was first developed by (Huang et al., 1998). It decomposes the time signal into a set of intrinsic mode functions (IMFs). In EMD, two conditions should be satisfied:

1. the number of extrema and zero crossings may differ by no more than one;
2. the local mean is zero.

Figure 2 show the sensors measurements of the normal condition and degradation bearing . The decomposed results of vibration signal with degraded cutter by using EMD are given in Figure. 4 that has 9 IMFs .

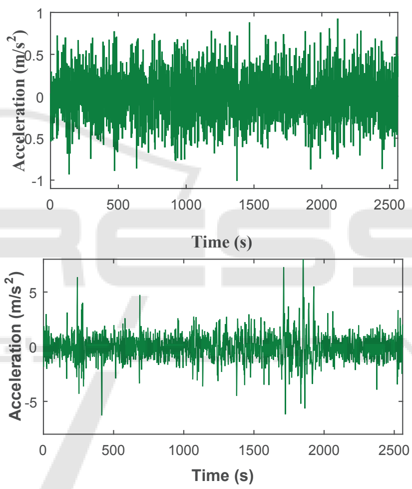

Figure 2: Sensors measurement for normal condition (top) and degradation bearing (bottom).

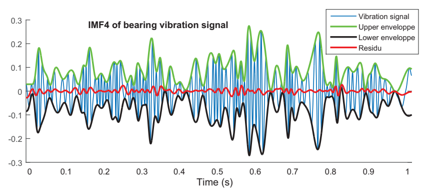

Figure 3: The EMD results of vibration signal.

2.2 Description of the BSS Techniques

Blind Source Separation (BSS) is a method for recovering the signal produced by individual sources from their mixtures. In the simplest case, m mixed signals from$m$ different sensors $x_i(k)$ are assumed to be linear combinations of unknown mutually statistically independent signals from n vibrating components $s_j(k)$

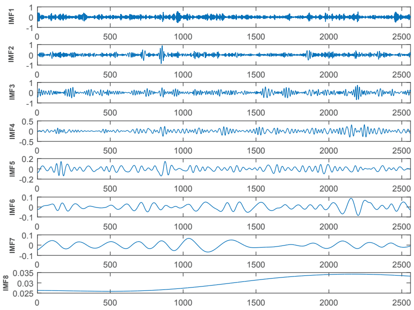

Figure 4: The EMD decomposed results of vibration signal.

with noise. This can be stated as:

$$X(t) = A.S(t) + N \tag{1}$$

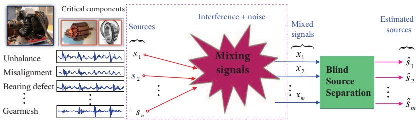

Figure 5: Blind source separation model.

The sources must satisfy two conditions: statistical independence and the Non-Gaussianity (Haile and Dykas, 2015). The problem of BSS is reduced to a mathematical optimization problem, for which a multitude of techniques are reported in the literature. Five algorithms implemented in this paper selected from the most used in the fault diagnosis (Peter et al., 2006) such as : FastICA , Second Order Blind Identification, COMBI, Algorithm for Multiple Unknown Signals Extraction and EWASOBI.

In order to obtain an accurate and quantitative measure of the performance of the algorithms, several techniques used in the literature for the performance measurement of distortion are given in (Chen et al., 2013). The performance measuring criteria used are crosstalk, performance index (PI) and signal to interference ratio (SIR).

2.3 Robust Correlation Analysis

Correlation is a signal matching method. It is a key component of many systems such as: sonar, radar and digital communications. In this study, the application of digital correlation to blind sources separation was addressed.

The least median of square (LMS) estimation (Simpson, 1997). is one of the most robust methods for estimating correlation; The LMS regression coefficients minimize the median of the squared residuals. The advantages of the LMS estimator can give reliable results (Niven and Deutsch, 2012).

The some well known correlation coefficients, namely, Pearson's, Spearman's and Kendall's, are examined (Niven and Deutsch, 2012). The results shows that these correlation coefficients are sufficiently robust against a substantial number of outliers, The correlation coefficient based on the LMS is proposed. II is given a higher breakdown point than the well known correlation coefficients.

In this section we present the correlation between the estimated sources obtained by BSS technique using vibrations signals, more advanced prognostics interested on performance degradation assessment, so that failures can be predicted and prevented. As soon as, the concept of correlation coefficients for accurately assessing the bearing performance degradation is a critical step toward realizing an online tool condition monitoring platform.

$$Correlation = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

In this study; The correlation coefficients of each level used in regression for performances degradation assessment. In this combination strategy, the raw signal is first decomposed in different scales by EMD. Accordingly, it is expected that the proposed EMD-BSS model can more accurately model and compensate the performance degradation of the raw signal characteristic.

The correlation coefficients values has been used for follow-up the level or the system severity. In experimental setup, this value is used to monitor the overall signal force level. The RMS value of the signal force is a very good temporal descriptor of the overall condition for the other monitor signal figure 10 .

2.4 Experimental System and Signals Acquisition

An accelerated bearing life test platform called *PRONOSTIA* (Figure.6) used in this paper to verify the prognostics of proposed technique. *PRONOSTIA* is an experimental platform dedicated to test, verify and validate developed methods related to bearing life acceleration, diagnostic and prognostic. The four data shown in Table 1 for the different operating conditions.

Table 1: Bearings dataset from PRONOSTIA experimental setup.

Tests duration	Loading (N)	Speed (RPM)
6h50 (410 minutes)	4000	1800
3h25 (205 minutes)	6000	1500
1h30 (90 minutes)	8000	1500

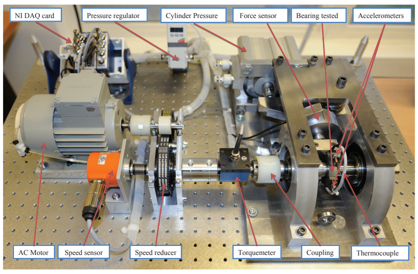

Figure 6: Platfrom pronostia.

The platform PRONOSTIA composed of two main parts: The first part related to the speed variation and a second part dedicated to load profiles generation. The speed variation part is composed of a synchronous motor, a shaft, a set of bearings and a speed controller. The synchronous motor develops a power equal to 1.2 kW and its operational speed varies between 0 and 6000 rpm.
A pair of ball bearings is mounted on one end of the shaft to serve as the guide bearings and a $NSK6307DU$ roller ball bearing is mounted on the other end to serve as the test bearing. The transmission of the movement between the motor and the shaft drive is done by a rub belt.

Two accelerometers $(DYTRAN3035B)$ mounted horizontally and vertically on the housing of the tested bearing to pick up the horizontal and the vertical accelerations (Table. 2). In addition, the monitoring system includes one temperature probe and a torque sensor (Figure 6). The sensors are connected to a data acquisition card .

The data acquisition software is programmed by using a LabView interface. Each record is stored in a matrix format where the following parameters are defined: the time, the horizontal acceleration, the vertical acceleration, the temperature, the speed and the torque.

Table 2: Experimental data acquisition.

Measurement	Type
Acceleration	$DYTRAN3035B$
Temperature	$PT100$
Torque	$DR2269$
Force	$AEPC2S$
Acquisition card	$NIDAQCard-9174$
Sampling frequency	$25600Hz$
Motor speed	$6000rpm$,1.2 kW

With this experimental platform, several types of profile can be created by varying the operating conditions (speed and load). The bearing's behavior is captured during its whole degradation process by using the dedicated sensors shown in (Table. 2) . The tested bearing have the characteristics shown in Table3.

Table 3: Tested Bearing.

Bearing type	NSK6804DD
⊘ Outside	32 mm
⊘ Inside	20 mm
Number of Balls	8
⊘ Ball	3.5 mm

3 RESULTS AND DISCUSSION

In order to confirm the validity of the proposed method EMD-BSS. The correlation values between different sources obtained by IMFs separation are shown in Table. 4 for the vibrations signal.

Table 4: The Correlation Values Between Sources.

Source	$\hat{s}_1$	$\hat{s}_2$	$\hat{s}_3$	$\hat{s}_4$	$\hat{s}_5$	$\hat{s}_6$
IMF1	0.95	0.23	0.00	0.00	0.00	0.00
IMF2	0.28	0.97	0.00	0.00	0.00	0.00
IMF3	0.06	0.01	0.99	0.02	0.00	0.00
IMF4	0.05	0.02	0.04	0.99	0.01	0.00
IMF5	0.04	0.01	0.01	0.04	0.99	0.02
IMF6	0.04	0.00	-0.01	0.03	0.01	0.99

Separated signals based on EWASOBI are shown in Figure 7 have high dependent, the other BSS technique have not a good separation of the original source signals, but the proposed approach based IMFs can separate the desired signals properly and given a good correlation.

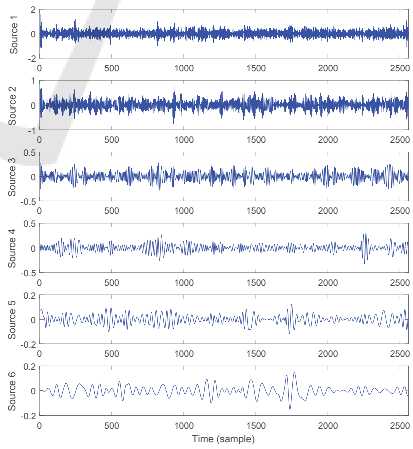

Figure 7: Sources estimation.

The proposed EMD-BSS algorithm can separate the signals properly. Next, for comparison between different BSS algorithms along the criteria statistical whose performance, the results shown in Table 1.

In order to confirm the validity of the proposed method EMD-BSS . The independence between estimated sources can be measured by using some performances criteria shown in Table 5 of various algorithms .

Table 5: Performance criteria for various BSS algorithms.

Algorithms	Performance Index (PI)	Signal to Interference Ratio (SIR)
SOBI	0.28	18.45
JADE	0.25	33.15
FastICA	0.27	29.54
COMBI	0.23	9.46
FPICA	0.98	12.60
EWASOBI	0.02	35.31

Table 5 shown the performance evaluation of sources separation, the value of PI is less than 5% and the technique Efficient Weights Adjusted SOBI (EWASOBI) (Tichavskỳ and Yeredor, 2009) given a good separation with a small time computing , whereas JADE, FastICA and SOBIRO and COMBI has the lowest performance.

3.1 RUL Estimation

The experimental data sets are generated from PRONOSTIA run-to-failure tests under constant load conditions . In order to prove the effective prediction of the EMD-BSS method 4 data sets was used with the same operating condition. The failure threshold limited by using the international standards (ISO 13381-1, ISO 10816 and ISO 7919). The ISO standards limited in vibration signals energy (the root mean square RMS of vibration signal), and for different indicators are used (AFNOR, 2005). An illustration of RUL progression is shown in Figure 8.

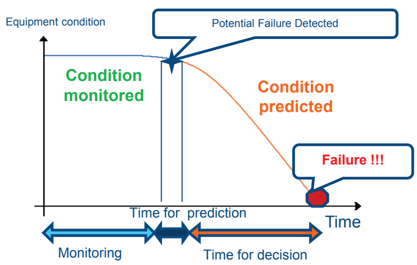

Figure 8: Illustration of remaining useful life.

The regression results are presented in Table 6 in terms of the factors of determination R^2 for the different training models. The R values, indicating the fraction of the total variance that could be explained by the model, are very high. From the results, it is seen that all the predictors perform very well. The objective is to apply the best power fit on the degradation model obtained by equation 4.

$$f(t) = a.t^b + c \tag{3}$$

$$RUL(t) = t_{final} - HI^{-1}(t) \tag{4}$$

Where t_final is the time when the fault occurs and HI^1 the inverse of the health indicator $HI(t)$ used to get the current cycle or time (t). The validation of these results shown in table 6 by computing of the sum square error (SSE), R square and root mean square error (RMSE).

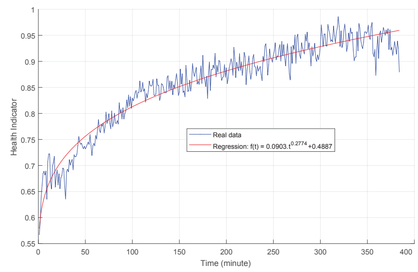

Figure 9: Health indicator for the bearing (6H50).

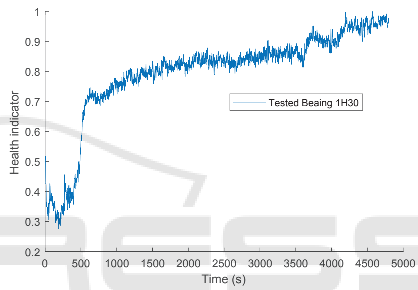

Figure 10: Health indicator for the bearing (90 minutes).

Table 6: Prediction performance.

Bearings	SSE	RMSE	R^2
1H30	0.3959	0.03562	0.9453
3H25	0.0750	0.01550	0.9974
6H50	0.1933	0.0225	0.9570

The goal of this technique is to analyze prediction capabilities by using EMD-BSS. A comparative study between different algorithms used in BSS on reliability performance analysis was summarized in Table 1. The RUL estimation is the distance between the current time and the time for which the regression model given in equation (3). The threshold or the acceptable limit of the vibration magnitude (AFNOR, 2005) of each degradation in bearings, corresponds to the end of each experiment. The power fitting of the smoothed health indicator is shown in Figure 9.

4 CONCLUSION

This paper presented a new approach of using the EMD-BSS based correlation. The study of bearing degradation assessment is done by using vibrations

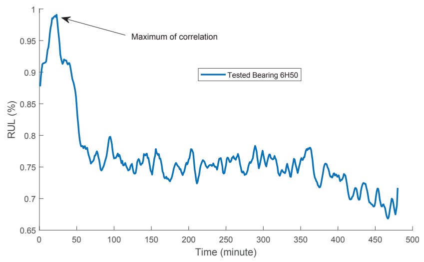

Figure 11: RUL estimation for the tested bearing (6H50).

signals. The proposed models were developed based on the acceleration signal. The potential of EMD-BSS based correlation shown in this paper for performance degradation assessment. The health indicator calculated in this contribution by using a correlation between the nominal and degraded bearing signal of estimated sources. The method is applied on vibrations signals acquired from the experimental platform PRONOSTIA. The proposed technique based on robust correlation coefficient is shown to have a higher accuracy than either Pearsons and Spearmans correlation. It is expected that with additional development, EMD-BSS can drastically improve the accuracy of RUL estimation based bearing condition monitoring across the full range of working. The accuracy of the estimated results was tested using validation experiments,showing a good results.

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