Real-time multi-features dynamic classification for bearing monitoring by vibrations analysis

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Résumé :

La naissance d'un défaut dans un système mécanique se traduit le plus souvent par un changement de comportement vibratoire dans le domaine temporel et spectral. La détection de défaut par l'analyse vibratoire se base sur la surveillance continue du comportement d'un composant en examinant l'évolution des indicateurs de défaut.

Cependant, le diagnostic du roulement en fonction des indicateurs de défaut traditionnels seulement n'est pas suffisant pour assurer une évaluation fiable de l'état du composant. C'est pourquoi, nous proposons dans cet article une méthode de diagnostic et de suivi des roulements basée sur une combinaison de plusieurs indicateurs temporels et fréquentiels couplée avec une méthode de classification dynamique.
Ce papier a pour objectif d'introduire la classification dynamique comme outil de détection et de suivi d'état d'endommagement. Cette méthode de classification regroupe plusieurs indicateurs, en temps réel, en des classes dynamiques représentant chacune un état d'endommagement du roulement.

Mots clés : Suivi de roulements, classification dynamique, CEEMDAN, KPCA, les ondelettes.

Abstract:

The emergence of a bearing fault is always associated with a change in vibration behavior in the spectral and temporal domains. Traditional techniques based on vibration analysis extract features of the raw signal and examine their temporal evolution to detect any changes. However, mere traditional bearing diagnosis is not sufficient to ensure effective and reliable assessment of the component's health condition.

This paper proposes a multi-features dynamic classification as a new method for fault detection and health condition monitoring for bearings. This technique uses multiple features, namely traditional features extracted from the raw signal, in addition to singular values of the decomposed signal by Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), two new features extracted by wavelets analysis, nonlinear principal component, and a dynamic classification to capitalize on the hidden information in the temporal evolution of the features.

Index Terms: Bearing monitoring, dynamic classification, CEEMDAN, KPCA, wavelets.

1. Introduction

Rolling element bearings are essential components in rolling machines. Bearings, however, are generally seen as critical mechanical components, and the responsible for the majority of machines failure. Therefore, a correct and continuous monitoring of bearing health condition is vital for maintaining a smooth functioning of the machine.
Traditional diagnostic techniques based on vibration analysis extract statistical features from the raw signal in its temporal and spectral forms [1,2]. However, due to all the nonlinear factors that affect the rotating machine and add to the complexity of the system [3], effective diagnostic or monitoring techniques cannot depend only on traditional fault indicators [4,5]. Hence, there is great interest in finding alternative and

complementary tools, the majority of which are originated from two domains: new signal processing techniques, and data mining methods.

Among all the time–frequency analysis methods, wavelets have been established as the most widespread tool in many areas of signal processing, due to their flexibility, and efficiency of detecting transients [6]. Aside from the original purpose of the wavelets as a non-stationary analysis method, recently it became a fault feature extraction technique.

Empirical Mode Decomposition (EMD) was first used for bearing fault detection by Peng et al [7], and has received increasing attention ever since, *EMD* can allow a good visibility of the fault, however *EMD* suffers from the mode mixing problem. Wang [4] and Zhang [5] suggested replacing the *EMD* by Ensemble Empirical Mode Decomposition (*EEMD),* which is an alternative decomposition method that solves the mode mixing problem, but it initiates other issues. We suggest using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise *CEEMDAN,* an *EEMD* variation that provides an exact reconstruction of the original signal and a better spectral separation of the modes, with a lower computational cost [8]. The singular values of the vector matrix composed of intrinsic mode functions *IMF*s obtained by applying the Singular Value Decomposition (*SVD)* can be used as special fault indicators employed to describe signal characteristics in each frequency band [3,5]. Once the final fault indicators' vectors matrix is formed, Kernel Principal Component Analysis *KPCA* will be performed to eliminate any correlation or redundancy, which will increase the accuracy of the diagnosis.

Once the right fault indicators are extracted and processed, the fault detection and performance assessment of the machine becomes a pattern recognition problem. For this purpose, various classification methods have been used, namely artificial neural network [3], decision tree [9], Support Vector Machine (*SVM)* [4-5], among others. These methods showed more or less satisfactory results, but they all neglected one aspect of the fault indicators extracted from vibratory signals, i.e. the fact that these features are just like any data issued from any evolving system; they are constantly changing over time. Therefore, using a static classification method deprives us of the information conveyed in the temporal evolution of the indicators.

The combination of multi-fault indicators and dynamic classification has two direct results: first, the use of multi features enhance the accuracy of the diagnostic process resulting in early and accurate detection of the fault, and second, the dynamic classification add more visibility of the bearing behavior once defected; resulting in a close monitoring of the behavior of the defected bearing.

2. Feature extraction

2.1. Traditional Features

There are two types of fault indicators used traditionally to diagnose rotating machines: temporal and spectral features. The traditional time domain analysis computes characteristics' features from time waveform signals as descriptive statistics - such as mean, peak, standard deviation, and crest factor, etc. and high order statistics, such as Root Mean Square (*RMS*), skewness, and kurtosis among others. As for frequency domain, the analysis is based on the transformed signal in frequency domain. Its main advantage over time domain analysis is its ability to isolate certain frequency components of interest that enable the localization of bearing faults. The same descriptive statistics can be extracted from the transformed signal [1-2].

2.2. Wavelets analysis

Wavelets are well known signal processing technique used to examine the frequency composition of the signal [6]; therefore technical descriptions will be omitted. Instead the two new features extracted will be introduced: W_{RMS} is the Root Mean Square frequency of the signal's wavelets spectrum and *PCWT* represents the sum of all the spectrum lines.

$$W_{RMS} = \sqrt{\frac{\sum_{j=1}^{K} f_j^2(WS(j))}{\sum_{j=1}^{K} WS(j)}} \qquad (1) \qquad\qquad PCWT = \frac{\sum_{j=1}^{K}(WS(j))}{K-1} \qquad (2)$$

Where $WS(j)$ corresponds to the spectral density of the coefficients maximum of the continuous wavelet transform for j=1,2,…,K, K is the number of spectrum lines, f_j is the frequency value of the j^{th} spectrum line. W_{RMS}' unit is Hz.

2.3. *EMD, EEMD* and *CEEMDAN*

EMD is a modern time-frequency analysis method developed by Huang et al [10], and it originated from the simple assumption that any signal consists of different simple intrinsic modes of oscillations. Therefore, the main principle of *EMD* is decomposing any signal into a number of Intrinsic Mode Functions (*IMF*),

However, the major inconvenient of *EMD* is the mode mixing problem, which is defined as either a single *IMF* containing widely disparate frequency scales, or a component of a similar frequency scale residing in different *IMF*s. The existence of the mode mixing can not only cause serious aliasing in the time–frequency distribution, but also make physical meaning of individual IMF unclear. When the mode mixing problem occurs, an IMF can cease to have physical meaning by itself, suggesting falsely that there may be different physical processes represented in a mode [4,6,11]. *EEMD* is an improved algorithm of *EMD*. It was developed to reduce the mode mixing problem by introducing an independent white noise into the signal in many trials, then applying the *EMD* decomposition, and finally averaging all the *IMF*s computed in each trial. The noise chosen in *EEMD* is not adaptive though, which makes the *EEMD* lose some of the *EMD* advantages [8]. *CEEMDAN* is another variation of the *EMD*, and has the advantage of needing a smaller ensemble size compared to the *EEMD,* resulting in a substantial computational cost saving. In that sense, *CEEMDAN* recovers some of the *EMD* properties lost by *EEMD*, such as completeness, and the fully data-driven number of modes.

The algorithm of *CEEMDAN* is similar to that of *EEMD,* with one difference, i.e. the noise added to the signal is different for every trial and for every *IMF*.

2.3. Singular Value Decomposition

Singular Value Decomposition extracts dominant shapes from a series of raw input vectors by using orthogonal components. It allows better visibility of the dispersion around the origin through its decomposition of the signal into principal components, and it is also known for its good stability [5].

2.4. Kernel Principal Component Analysis

In view of the high correlation and redundancy exhibited by the matrix formed of all the signal extracted features, methods need to be applied to correct this problem and increase the accuracy of the diagnosis. Principal Component Analysis (PCA) is a well-known linear method for feature extraction and dimensionality reduction. However, if the data has more complicated structures that cannot be simplified in a linear sub-space, traditional *PCA* will become invalid. To overcome the linearity of the *PCA,* several variations have been introduced. One such method that is directly related to *PCA* is called Kernel *PCA (KPCA)* [12]. The basic idea of *KPCA* is to first map input data into some new feature space *F,* typically via a non-linear function Φ (polynomial of degree p), and then perform a linear *PCA* in the mapped space whose dimension is assumed to be larger than the number of training samples.

3. The pattern recognition

The main objective of pattern recognition is the study of how machines can observe the environment, learn to distinguish the interesting patterns of their background, ignore the non-informing ones, and make sound and reasonable decisions about the categories of patterns [13-14].

The performance of statistical pattern recognition methods depend on prior knowledge about the process operating' states. This knowledge is often imperfect and incomplete. Knowledge imperfection is due to the use of sensors, the existence of noise, and expert evaluations. Prior knowledge is incomplete because it cannot contain information about all process operating states. The problem of imperfect knowledge can be solved by using the fuzzy sets theory. The problem of incomplete knowledge can be solved by a continuous learning in order to add the information carried by each new classified pattern to the database or prior knowledge. Hence the necessity of choosing a fuzzy pattern recognition method with a continuous and adaptive classifier [15].

Furthermore the classes of an evolving system are dynamic; their characteristics change over time, in a slow, progressive way or in abrupt way. The change in classes' behavior is directly linked to the state of the functioning system. In the bearing monitoring case, abrupt change is always associated with the existence of a fault.

The right classifier has to be capable of detecting all changes in the classes' behavior, such as fusion, drift, creation and splitting, among others. The classifier has to be able to adjust its parameters over time.

There are three types of classifiers, i.e. supervised, unsupervised and semi-supervised; and the adequate one depends on prior knowledge of the system and on the classes [16]. Semi-supervised classifiers are well-suited for evolving systems and then for bearing monitoring.

For all these reasons, the semi-supervised version of Dynamic Fuzzy K-Nearest Neighbors (*DFKNN*) is more suitable for monitoring the health condition of the bearings.

3.1 Semi-supervised Dynamic Fuzzy K-Nearest Neighbors

The semi-supervised *DFKNN* is a dynamic pattern recognition method specially developed for evolving systems. It can detect any classes' evolution and adapt them according to the dynamic of their evolutions. The particularity of this method is its ability to create new classes if needed, and taking into account the pattern usefulness [16]. *DFKNN* is a four stages method: learning and classification by Fuzzy K-Nearest Neighbors (*FKNN*), evolution detection, adaption of the classifier, and finally validation to keep useful classes and delete useless ones.

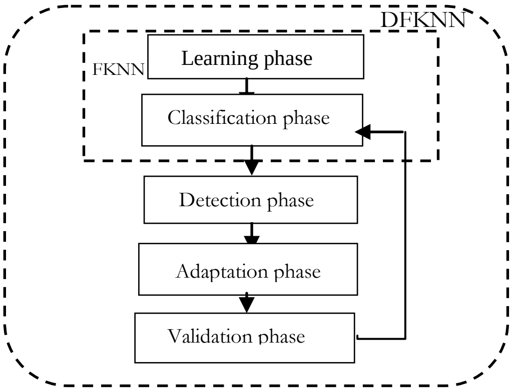

Figure 1: The general algorithm of *DFKKN*

The learning and classification phase in the *DFKNN* are very similar to *FKNN*. The only difference is the initialization of two parameters CG_{Acurr} - the center of gravity of each class *C* to each attribute-, and Std_{Ainit} - initial standard deviation of each class *C* to each attribute.

In the detection phase, the characteristics of the class *C* (CG_{Acurr}, Std_{Acurr}) are computed to detect the class' evolution; they are updated as follows (Eq.3 and Eq.4):

$$\mathrm{StdAcurr} = \sqrt{\frac{\mathrm{Nc}-1}{\mathrm{Nc}} \times \mathrm{Std}^2{}_{\mathrm{Acurr}-1} + \frac{(\mathrm{x_A} - \mathrm{CG_{Acurr-1}})^2}{\mathrm{Nc}+1}} \quad (3)$$

$$CG_{Acurr} = \frac{CG_{Acurr-1}}{Nc+1} + \frac{x_A}{Nc+1} \quad (4)$$

Based on the computed values of CG_{Acurr} and Std_{Acurr}, two new parameters are introduced (i_{A2} and i_{A1}) to monitor the temporal changes of the class; i_{A1} represents the compactness of the class, and i_{A2} represents the distance between x_A the attribute A of the signal x and CG_{Acurr}.

$$i_{A1} = \frac{\mathrm{Std_{Acurr}} \times 100}{\mathrm{Std_{Init}}} - 100 \quad (5)$$

$$i_{A2} = \frac{|x_A - \mathrm{CG_{Acurr}}| \times 100}{\mathrm{Std_{Acurr}}} - 100 \quad (6)$$

A third parameter called *NbMin* is defined by the user to regulate the minimum number of patterns for class creation so a class with a single pattern will not be created. *DFKNN* integrates a mechanism to adjust the evolved class parameters in the adaptation phase. When a class evolution is confirmed, a new class is created based only on useful patterns.

The adaption phase permits online follow up of the classes' evolution. It takes into account splitting and drifting and deletion of useless classes as well.

DFKNN uses extra parameters to consider the case of the fusion of two similar classes into one; Th_{fusion} a threshold user specified to be respect in case of merging two classes, and δ_{iZ} another parameter used to measure the overlapping or the closeness of two classes.

4. APPLICATION

The multi-features dynamic classification has been implemented on an experimental bench, and vibration signals were extracted by piezoelectric accelerometers fixed on the bearing referenced 6206. The defect was artificially made. 15 signals were chosen to test the multi-features diagnosis process. Each signal characterizes a bearing condition; the first signal is of a healthy bearing, the second is of the same bearing but with a fault surface of 2mm² located on the outer race, and the last signal is of a the same faulty bearing in an advanced stage (20 mm²).

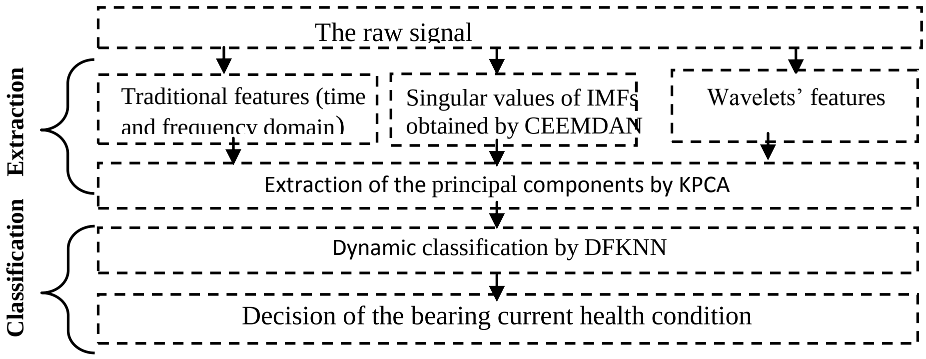

Figure 2: A flowchart of the bearing diagnosis by a multi-features dynamic classification for an incoming signal.

The first step of the diagnosis procedure was the feature extraction. Firstly, 11 traditional features in both time and frequency domains were calculated (*RMS*, kurtosis, crest factor, standard deviation, peak, skewness, impulse factor, frequency *RMS*, frequency standard deviation, and central frequency). Concurrently, the first six *IMF*s of every signal by *CEEMDAN* were computed, the two wavelets features (W_{RMS}, PCWT) were extracted as well, and then the singular values of each *IMF* and of each signal were conserved as features as well. All the features' vectors were normalized.

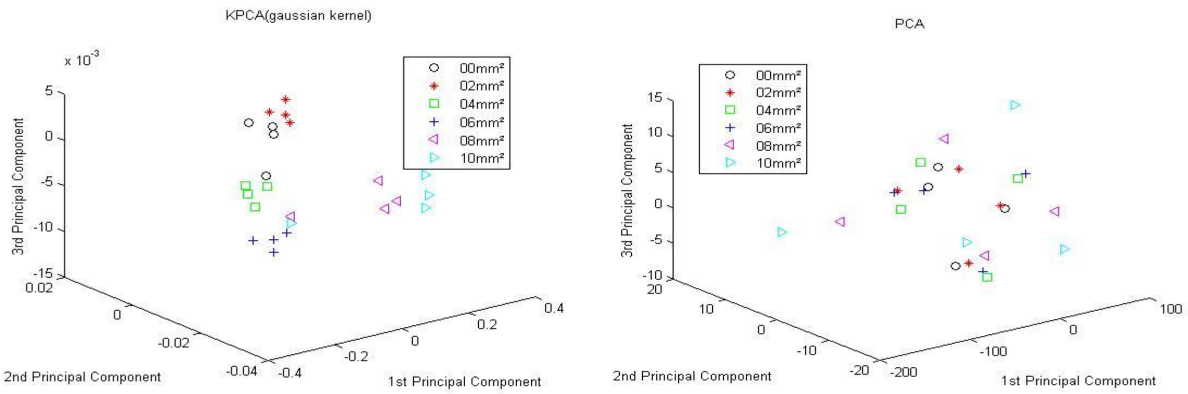

Figure 3: The first three principal components of six signals (00mm² to 10mm²), with the PCA on the right and the KPCA on the left.

The second step was extraction by principal components; the *KPCA* was applied on the features' vectors, and the first three principal components were enough to represent the data (the first three components account for 98% of the variance).The chosen kernel for the *KPCA* is the Gaussian kernel. A comparison between the performance of *FKNN* by feeding it data extracted by *PCA* and *KPCA* showed that *FKNN* was able to recognize the classes formed by the different signals with 83,33% rate of success, compared to a success rate of 66,00% in case of *PCA*. The figure 3 shows clearly the superiority of KPCA's performances applied to the first six signals extracted from the bearing compared to *PCA*'s.

The vectors' features formed by *KPCA* are fed to the dynamic classification *DFKNN*. The parameters of the DFKNN were set according to DFKNN recommendations and test; th_1= 5, NbMin =8, k=4, th_{fusion}=0.5, n_1=6, n_2=20.

5. RESULTS AND DISCUSSION

During the process of bearing monitoring, 15 signals were extracted from a bearing exhibiting an artificial outer race defect; each signal corresponds to a different fault surface (0mm², 02mm², 04mm², 06mm², 08mm², 10mm², 12mm², 13mm², 14mm², 15mm,² 16mm² ,17 mm², 18mm², 19mm², and finally 20mm²). Each signal went through the feature extraction process, and then fed to the dynamic classification method *DFKNN*. The parameter responsible for classes' deletion (n_2) was initialized in a way that it will never be reached, since the information that a class holds (even a non- active one) can be used for prognostic or in calculating the speed with which the damage is spreading in the bearing.

The results of the classification showed that DFKNN creates a new class whenever the surface of the fault increases, this new class gathered all the features describing the same state of the bearing health. The rate of recognition of classes can reach the 98,6 % with the right initialization of *DFKNN'* parameters.

In the light of *DFKNN* tests, conclusion arise; DFKNN provides tools that can be integrated in a system expert to automate bearing monitoring, since a class creation is directly linked to a change in health condition. However, like many dynamic classification methods, *DFKNN* is very sensible to its parameters' definition, which depends on the prior knowledge of the system.

6. CONCLUSION

A new diagnostic and monitoring method is proposed in this paper, a method that ensures diagnosis accuracy by using both traditional and original features combined with a dynamic semi-supervised fuzzy pattern recognition method; the fuzzy aspect of the method covers the imperfection of the prior knowledge, and the continuous learning of the method covers the incompleteness of the prior knowledge. Therefore, the semi-supervised *DFKNN* was chosen for bearing monitoring. The new monitoring process showed effectiveness in detecting changes in bearing behavior. However, the usefulness of *DFKNN* is limited by a few drawbacks, such as the learning of the classifier which is not dynamic, and the great dependence of classification performances on the initial values of many parameters of *DFKNN*.

We are currently developing a new classification method that corrects all the limitations of the existing methods in bearing monitoring and diagnosis, and associates the classes' dynamic with physical changes in the bearing condition.

7. References

[1] Andrew K.S. Jardine, D. Lin, and D. Banjevic, A Review On Machinery Diagnostics And Prognostics Implanting Condition-Based Maintenance, Mechanical systems and signal processing, 1483-1510, 2005.
[2] R.B. Randall, J. Antoni, Rolling Element Bearing Diagnostics—A Tutorial, Mechanical systems and signal processing, Elsevier, 485-520, 2011.
[3] Y. Yu, YuDejie, C. Junsheng, A Roller Bearing Fault Diagnosis Method Based on EMD Energy Entropy and ANN, Journal of Sound and Vibration, Elsevier,. 269–277, 2006.
[4] Y. Wang, S. Kang, Y. Jiang, and G. Yang, Classification Of Fault Location And The Degree Of Performance Degradation of a Rolling Bearing Based on an Improved Hyper-Sphere-Structured Multi-Class Support Vector Machine, Mechanical System and signal Processing, Elsevier, 404-414, 2012.
[5] Y. Zhang, H. Zuo, and F. Bai, Classification of Fault Location and Performance Degradation or a Roller Bearing, Measurement Elsevier, 1178-1189, 2013.
[6] Z.K. Peng, F.L. Chu, Application Of The Wavelet Transform In Machine Condition Monitoring And Fault Diagnostics: A Review With Bibliography, MSSP Elsevier, 199–221, 2004.
[7] Z.K. Peng, P.W. Tse, and F.L. Chu, A Comparison Study of Improved Hilbert–Huang Transform And Wavelet Transform: Application To Fault Diagnosis For Rolling Bearing, MSSP Elsevier, pp974–988, 2005.
[8] M.E. Torres, M.A. Colominas., G.Schlotthauer, and P. Flandrin, A Complete Ensemble Empirical Mode Decomposition With Adaptive Noise, IEEE Ann. ICASSP'11, 4144-4147, 2011.
[9] M. Boumahdi, J.Dron, S. Rechak, and O. Cousinard, On The Extraction Of Rules In The Identification Of Bearing Defects In Rotating Machinery Using Decision Tree, Elsevier, 5887–5894, 2010.
[10] N.E. Huang, The Empirical Mode Decomposition And The Hilbert Spectrum For Nonlinear And Non-Stationary Time Series Analysis, Mathematical Physical and Engineering Sciences, 903-995, 1998.
[11] Y. Lei, Z. He, and Y. Zi, Application of the EEMD Method to Rotor Fault Diagnosis of Rotating Machinery, MSSP Elsevier, 1327–1338, 2009.
[12] B. Schölkopf, A. Smola, and K.R Müller, Nonlinear Component Analysis as a Kernel Eigenvalue Problem, Neural computation, 1299-1319, 1998.
[13] M. Sayed-Mouchaweh A.Devillez ,G.V.Lecolier, and P. Billaudel, Incremental Learning In Fuzzy Pattern Matching, Fuzzy Sets And Systems Elsevier, 49 - 62, 2002.
[14] M. Sayed-Mouchaweh, E.Lughofer, Learning in Non-Stationary Environments, Springer, 2012.
[15] A.K Jain, Robert P.W Duin, and Jianchang Mao Statistical Pattern Recognition: A Review, Pattern Analysis And Machine Intelligence, IEEE, vol.22, No.1, 2000.
[16] L. Hartert, M. Sayed Mouchaweh and P. Billaudel, A Semi-Supervised Dynamic Version Of Fuzzy K-Nearest Neighbors To Monitor Evolving Systems, Evolving Systems Springer Verlag, 1:3-15, 2010.