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RESIDUAL USEFUL LIFE ESTIMATION BASED ON STABLE DISTRIBUTION FEATURE EXTRACTION AND SVM CLASSIFIER

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ABSTRACT

The This paper deals with a data-driven diagnostic and prognostic method based on Stable distribution feature extraction and SVM Classier. The prognostic process of the proposed method is made in two steps. In the first step, which is performed online, the monitoring data provided by sensors are processed to extract features based on stable distribution, which are then used to learn SVM classifier that capture the time evolution of the degradation and therefore of the systems health state. In the second step, performed on-line, the learned models are exploited to do failure prognostic by estimating the assets current health state, its remaining useful life. The experiments on the recently published database taken from Pronostia of FEMTO, Prognostic data repository: Bearing data set, clearly show the superiority of the proposed approach compared to well establish method in literature.

Keywords: *Residual Useful Life, SVM, alpha stable, Bearing Prognostic.*

1. INTRODUCTION

Industrial systems are becoming more complex due, in part, to their growing size, and to the integration of new technologies. With ageing, these systems become more vulnerable to failures, and their maintenance activities are difficult and expensive. This situation, combined with requirements of productivity, operational availability, and safety, pushes practitioners under searchers to look for innovative tools and methods. One of the possible levers consists of maintenance activities. By maintaining the system, one can reduce its global life cycle costs, increase its availability, improve the safety of operators, and reduce the environmental incidents. For example, analysis of vibration and acoustic emissions data from rotorcraft drive trains have led to breakthroughs in predicting impending failures of these complex mechanical systems, resulting in the development of Health and Usage Monitoring Systems (HUMS) for rotorcraft [5]. Substantial advances were made in life estimation for components ranging from rotating machinery [1] to batteries [2], from printed circuit boards, to solid rocket motors [9]. In the U.S. military, two significant weapon platforms were designed with a prognostics capability as an integral element of the overall system architecture: the Joint Strike Fighter Program [10], and the Future Combat Systems Program [11]. Prognostic technology is also finding its way into future NASA launch vehicles and spacecraft [12]. As the technology matures further, prognostics will play an important role in the design and operation of commercial systems such as passenger aircraft, automobiles, ships, the energy infrastructure, and even consumer electronics. Despite substantial technical progress over the last decade, PHM does not yet have a universally accepted research methodology. More importantly, the scientific method that underlies all scientific disciplines has not made its way into PHM research. As a result, most component life estimation efforts are based on ad-hoc experimental methods that lack statistical rigor [3].

The choice of bearings can be explained by the fact that these components are considered as the most common mechanical elements in industry and are present in almost all industrial processes, especially in those using rotating elements and machines. Moreover bearing failure is one of the foremost causes of breakdowns in rotating machinery and such failure can be catastrophic [13], resulting in costly downtime. Many previously studies [14, 15] have developed theoretical

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foundation and tools to describe bearing failure modes.

In the state of the art, data driven approach is addressed in order to utilize the availability of condition monitoring data [6].

They can be divided into statistical methods (multivariate statistical methods, linear and quadratic regression ...) and Artificial Intelligent (AI) methods which have been largely applied to machinery remaining life prediction [7]. The most used models for prognostics are artificial neural networks (ANNs) [21], support vector machine (SVM) [21], Fuzzy theory [21]. SVMs shows outstanding performance in the classification process compared with the other classifiers [21], Also Markov chain model based on the transition probability matrix is appropriate to the analysis of a random dynamic system [22].

For accurate assessment of the residual life of bearings, Kim et al. [8] proposed a machine prognostics model based on health state estimation using Support Vector Machines (SVM). Kankar et al. [24] have also shown the effectiveness of SVM for bearing faults classification. Markov chain model based on the transition probability matrix is appropriate to the analysis of a random dynamic system [22]. Z. Lui et al. [23] have used hidden Markov models (HMM) to assess the degradations of bearings and to estimate the RUL. In their method the authors considered the degradation as a stochastic process with several states representing different health states of the physical component.

In this paper, we propose a Residual Useful Life Estimation based on α-stable stable distribution as features extraction and SVM Classifier. The use of this tool is motivated in the one hand by the fact that the α-stable described effectively the vibration data, and because is used for feature extraction in the literature [17]. In the second hand, SVM is chosen as classifier due to its promising empirical performance, moderate computation complexity and its strong mathematical foundation.

The remainder of the paper is organized as follows. In Section 2, the proposed approach is presented, are explained. In Section 3 we give more information about the used data in this work. Also in this section an experimental results are presented and discussed. Finally, in Section 4, conclusions and future recommendations are given.

2. THE STABLE DISTRIBUTION AND SVM BASED PROGNOSTICS METHOD

The proposed methods rely on two main phases: a learning phase and an exploitation phase [16]. During the first phase, the raw data are used to extract reliable features based on α-stable distribution, which is then used to learn behavioral models representing the dynamic of the degradation in the bearing. In the second phase, the learned models are exploited on line to assess the current health state of the bearing and to estimate the value of the RUL. The modeling of the degradation is done by using Support Vector Machine (SVM). The method is based on a non-destructive control, and uses the data provided by the sensors installed to monitor the components condition. The acquired signals are first processed to extract features in the form of stable distribution coefficients (μ, c, α and β), which are then used to learn the SVM classifier) of the degradation. In addition, multiple observations, instead of the traditional mono observation approach, are considered for both learning and exploitation phases. The principle of the proposed method relies on two main phases, as shown in Figure 1: a learning phase, and test phase. In the first phase, conducted o_-line, the raw data recorded by the sensors are processed to extract the alpha stable distribution. These features are then used to learn several SVM classifier (one versus all) corresponding to different initial states and operating conditions of the component.
Indeed, each raw data history corresponding to a given components condition is transformed to a feature matrix F, by using stable distribution coefficients. In the matrix F, each line vector (of c features at time t) corresponds to a snapshot on the raw signal. The advantage of using several features instead of only one is that a single feature may not capture all the information related to the behavior of the component. The parameters μ, c, α and β of each state are learned by using SVM classifier. The estimation of the RUL is done according to the following steps.

- The first step consists in detecting the appropriate alpha stable coefficient that best fits and represents the on-line observed sequence of vibration data. Indeed, the features are continuously fed to the SVM learned models to compute the RUL.
- The second step of this procedure concerns the identification of the current state of the component.

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2.1 Features Calculation and Selection

For machinery fault diagnosis and prognosis, signals such as vibration, temperature and pressure are commonly used. In this research, we only use vibration data because the other data had no relationship with bearing failure directly and they were simply process information, for feature extraction we calculated 8 statistical parameters from the time domain data. These feature parameters were rms, shape factor, skewness, Kurtosis, crest factor,Entropy estimation, histogram lower and upper. In addition to these parameters, two parameters (rms frequency and root variance frequency) in the frequency domain were calculated. A total of 20 features (10 parameters, 2 positions) were calculated as shown in Table 2.1. In general, features selection is required to avoid the problem of dimensionality and high training error value for the estimation of health states. In this paper we divided the bearing failure process into six stages that could minimize the classification training error of each bearing degradation stage. For better training and testing of bearing failure degradation steps, four features that represent the degradation of bearing failure among the 10 features were selected. The selected features were RMS, Kurtosis, Entropy estimation and Crest factor because the feature mapping of selected features gives the best separation between classes at the end we compared the obtained result with the four parameters obtained from stable distribution that will detailled in the next.

2.2 Stable Distribution

Although the probability density function for a general stable distribution cannot be written analytically, the general characteristic function for any probability distribution is determined by its characteristic function φ(t) by :

$$F(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \varphi(t) e^{-ixt}\, dt \qquad (1)$$

A random variable X is called stable if its characteristic function can be written as :

$$\varphi(t; \mu, c, \alpha, \beta) = \exp[it\mu - |ct|^{\alpha}(-i\beta sgn(t)\Phi)] \qquad (2)$$

Where sign(t) is just the sign of t and Φ is given by $\Phi = \tan(\pi\alpha/2)$ for all α except α = 1 in which case: $\Phi = -\frac{2}{\pi}\log|t|$. Such distributions form a four-parameter family of continuous probability distributions parameterized by location and scale μ and c, and two shape parameters α and β, roughly corresponding to measures of asymmetry and concentration. The alpha-stable are rich classes of probability distributions that include the Gaussian (α = 2), Cauchy (α = 1) and Levy (α = :5); all have the above property: it follows that they are special cases of stable distributions. For more information about the distribution for various values of distribution's parameters, see the figure 2. In our approach, we are fitting the data with stable distribution based on McCulloch method. With this method we obtained four consistent estimators in terms of five sample quintiles and tabulated the values of the four estimators [21]. To justify our choice of α-stable for extracting the features, the figure 3 shows that experimental data are good fitted by an α-stable distribution. The table 2 gives the values of α- stable's parameters.

2.3 Classification by SVM

The support vector machine (SVM) is based on a simple idea which originated in statistical learning theory by Vapnik [25]. This simplicity comes from the fact that this technique uses a simple linear method, but applied in high-dimensional feature space non-linearly related to the input space. It represents one of the most broadly used classification techniques because of its robustness, its performance and its rigorous underpinning compared to other technique likes neural network [18]. For the identification, support vector machines separate the different classes of data by a hyper plane [19].

$$(W,\varphi(x)) + b = 0 \qquad (3)$$

Corresponding to the function:

$$F(x) = sign\,((w,\varphi(x)) + b) = 0 \qquad (4)$$

Where φ(x) is a predetermined function, and wand b are unknown parameters of the classifier. These parameters are determined based on the training set$\{X_k l_k\}_{k=1}^{N}$, where $X_k \in R^n$and $l_k \in$ {-1, +1} are the inputs and labels, respectively. In some cases, the two classes can be separated and the SVM determines the separating hyper plane that maximizes the margin between the two classes. Generally, most practical problems involve classes which are not separable. In this case, the SVM is obtained by solving the following optimization problem:

$$argmin_{w,b,\varepsilon} \frac{1}{2}//w//^2 + \gamma\sum_{k=1}^{N} \varepsilon_k \text{ with } l_{ky}(X_k) \geq 1\text{-}\varepsilon_k, \forall k \qquad (5)$$

Where, ε_k are slack variables that allow the SVM to tolerate misclassifications and γ controls the trade-off between minimizing training errors and complexity [2].

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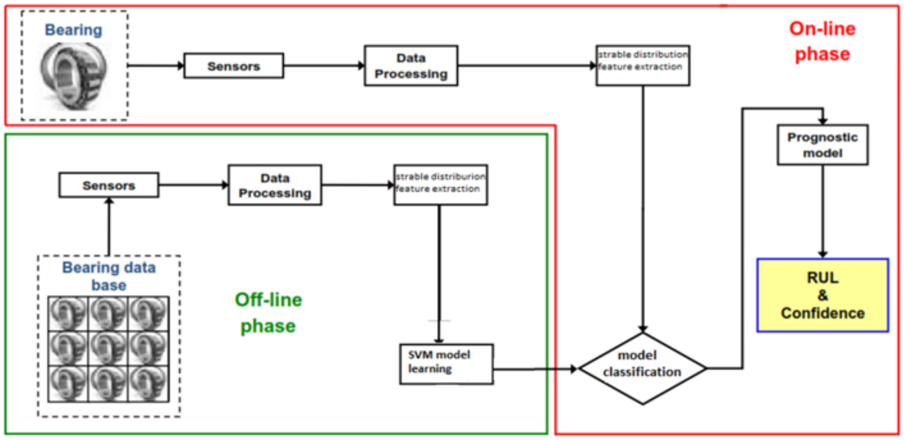

Figure 1 The Principle Of The Proposed Method: A Learning Phase, And Test Phase

Table 1 : Feature Parameters Based In Our Study

Position	Time domain parameters	Frequency domain parameters
Horizontal vibration vertical vibration	RMS, Shape factor , Skewness, kurtosis, Crest factor, Entropy estimation, Histogram lower and histograme upper	Root mean square frequency, Root variance frequency

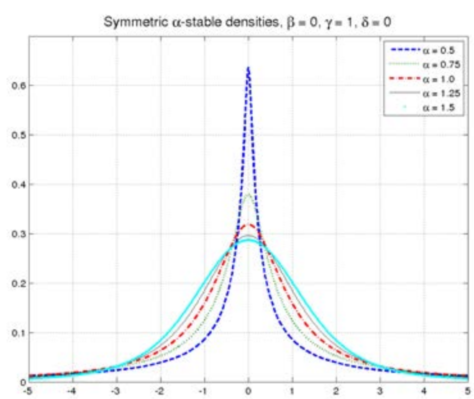

Figure 2 : Symmetric Α-Stable Densities For Parameters : Β=0, Γ=1 And Δ=0.

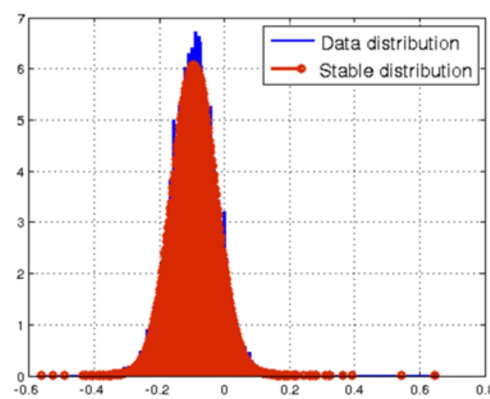

Figure 3 : Fitting Of Mesured Data Based On Alpha-Stable Distribution.

Table 2 : The Values Of Α-Stable Parameters.

Iteration	α	β	γ	c
0	1.917	-0.3537	0.04641	-0.09426
1	1.922	0.01798	0.04648	-0.09409

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3. EXPERIMENT PHM DATABASE AND RESULTS

3.1 Data Presentation

PRONOSTIA platform enables to perform run-to failure experiments. In order to avoid propagation of damages to the whole test bed (and for security reasons), tests were stopped when the amplitude of the vibration signal over passed 20g. Figures 4 depicts a global overview of experimental platform Pronostia. Pronostia is composed of two main parts: a first part related to the speed variation, and a second part dedicated to load profile 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. The load profiles part is composed of a hydraulic jack connected to a lever arm used to create different loads to degrade the bearing mounted on the platform. The figure 5 shows the experimental platform Pronostia speciely the type of the tested bearing and vibration raw signal from an experiment.

For the Experimental data, a total of 12 accelerated life tests (separated in two groups of 6 tests) under two constant operating conditions are realized on the Pronostia platform. In this paper, only the first six tests (first group) are used. The six experiments are realized under specific operating conditions: the constant speed of the shaft is controlled at 1800 rpm, and the radial load at 4000N. For the estimation of the RUL and the associated confidence, the historical data related to tests 1, 3, 4, 5, and 6 are used in the learning phase to estimate the parameters of the DBNs, representing the degradation, while the historical data related to test 2 is used in the exploitation phase to calculate the RUL, and the confidence.

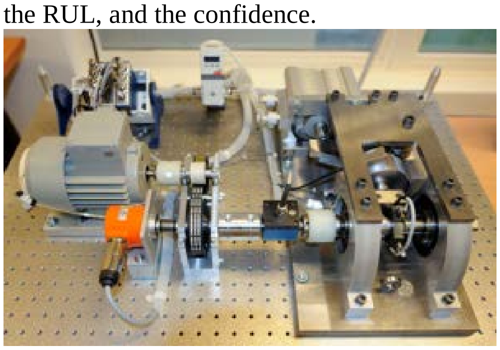

Figure 4 : Experimental Platform Pronostia : Global Overview.

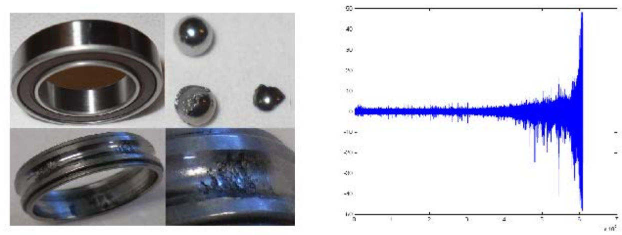

Figure 5 : Experimental platform Pronostia :type of the tested bearing and vibration raw signal from an experiment.

The learning set was quite small while the spread of the life duration of all bearings was very wide (from 1h to 7h). Performing good estimates was thereby difficult and this made the challenge more exciting. The table 3 shows the organisation of the database with the respect of the expirments conditions.

Table 3 :Pronostic Database

datasets	Conds1	Conds 2	Conds 3
Learning set	Bearing1-1 Bearing1-2	Bearing2-1 Bearing2-2	Bearing3-1 Bearing3-2
Test set	Bearing1-3 Bearing1-4 Bearing1-5 Bearing1-6 Bearing1-7	Bearing2-3 Bearing2-4 Bearing2-5 Bearing2-6 Bearing2-7	Bearing3-3

3.2 Training And Classification Of Degradation Stages

In this work, a second order polynomial with C= 8, $\gamma = 2$ was used as the basic kernel function of SVM. Multi-class classification using one-against-one was applied to perform the classification of degradation. For training and testing of the six stages of failure degradation, 6 data sets of FEMTO Dadataset were employed to perform the classification of health stages. The percentage of training error was 18:75% for classification of the six classes. Table 4 shows the classification accuracy. From the table we remarque clairly that the α-stable presents the good percent error on experiment for the different expirements. The percent error on experiment i is defined by :

$$\%Er=100*\frac{RealRUL-\widehat{RUL_i}}{RealRUL_i} \quad (6)$$

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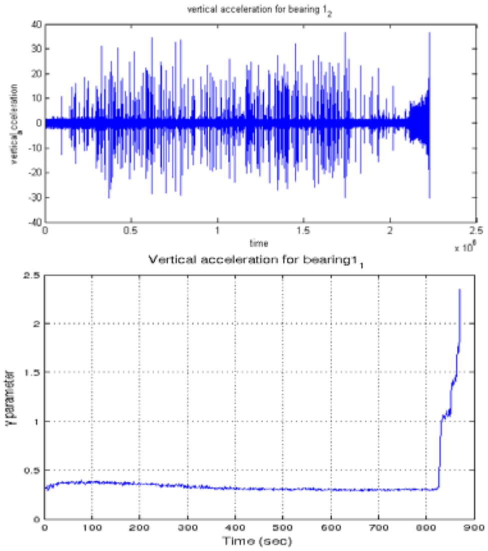

Figure 6 : The Measurement Of Vertical Acceleration Of Bearing1, And Its Equivalent Γ Parameter Of Α-Stable Distribution.

Underestimates and overestimates will not be judged in the similar means: most excellent performance of estimates relates to early predictions of RUL (i.e. cases where %Eri > 0), with deduction to early removal, and more strict deductions for RUL estimates that go beyond real component RUL (i.e. cases where %Eri < 0). From our results we have observed that the precision of the estimated RUL increases as the prediction time is approaching the real failure time. Similarly, after 256 min the mean estimation error drops below 24:5% and continues to decrease as the real failure time approaches. After 310 min the mean error stabilizes arround the value of 1:9%.

4. CONCLUSIONS

An estimation of the current health condition of physical components, particularly bearings, and an estimation of their remaining useful life before their complete failure has been proposed in this work. The method is based on the use of α-stable distribution for the features extraction from the data provided by the sensors installed to monitor the component into relevant models. These latter are classified by SVM, which take as input extracted parameters and permit to classify the state of the component at each time. This type of processing allowed getting deeper into the signal features by adjusting the time scales. These features are then used to model the degradation behavior of the component by learning the parameters of the corresponding SVM models. The obtained models are finally exploited to assess the current condition and to estimate the RUL and the confidence value. Finaly, based on the analysis of the estimation RUL error we have concluded that the α-stable gives a good RUL estimation.

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Table 4 : Training Data Sets For Classification Of Degradation Stages

Bearing 1-3	features	Estimated RUL	RUL estimation error % Eri	Features	Estimated RUL	RUL estimation error % Eri	Real RUL
	RMS, Kurtosis, Entropy and Crest factor	5h50	5,40%	μ,c,α and β (location, scale, skewness and index)	6h03	1,89%	6h10
Bearing 1-4	RMS Kurtosis, Entropy and crest factor	3h37	-16,66%	μ,c,α and β (location, scale, skewness and index)	2h47	10,21%	3h06
Bearing 1-5	RMS Kurtosis, Entropy and crest factor	6h59	-2,19%	μ,c,α and β (location, scale, skewness and index)	6h47	0,73%	6h50
Bearing 1-6	RMS Kurtosis, Entropy and Crest factor	6h33	3,43%	μ,c,α and β (location, scale, skewness and index)	6h45	0,49%	6h47