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# A multi-time scale approach to remaining useful life prediction in rolling bearing

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ABSTRACT

This paper presents a novel multi-time scale approach to bearing defect tracking and remaining useful life (RUL) prediction, which integrates enhanced phase space warping (PSW) with a modified Paris crack growth model. As a data-driven method, PSW describes the dynamical behavior of the bearing being tested on a fast-time scale, whereas the Paris crack growth model, as a physics-based model, characterizes the bearing's defect propagation on a slow-time scale. Theoretically, PSW constructs a tracking metric by evaluating the phase space trajectory warping of the bearing vibration data, and establishes a correlation between measurement on a fast-time scale and defect growth variables on a slow-time scale. Furthermore, PSW is enhanced by a multi-dimensional auto-regression (AR) model for improved accuracy in defect tracking. Also, the Paris crack growth model is modified by a time-piecewise algorithm for real-time RUL prediction. Case studies performed on two run-to-failure experiments indicate that the developed technique is effective in tracking the evolution of bearing defects and accurately predict the bearing RUL, thus contributing to the literature of bearing prognosis .



## 1. Introduction

Over the past decades, machine maintenance strategies have progressed from a condition-based maintenance (CBM) strategy towards a futuristic view of intelligent, predictive maintenance [1]. This requires real-time failure tracking and reliable remaining useful life (RUL) prediction before failure occurrence. Particularly, since bearings are critical element to almost all forms of rotating machines, bearing health monitoring has a significant effect on the working status of the machine system. Accordingly, bearing failure tracking and RUL prediction have received considerable attention in recent years.

The majority of prior research reported in the literature on bearing failure tracking and RUL prediction took a data-driven approach, with models derived from data collected by sensors on running machines to monitor bearing degradation and predict its RUL. Several time-frequency methods, such as wavelet transform [2,3] and empirical mode decomposition (EMD) [4], have been reported to extract features from vibration signals for bearing degradation tracking. In addition, support vector data description [3], local and nonlocal preserving projection [5], Gaussian mixture model [6], hidden Markov model [7] and Kolmogorov–Smirnov test [8] have been investigated to construct health indicators for describing the bearing

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degradation progress. Based on the obtained degradation features, various data-driven prediction models were applied to estimating the RUL of bearings. For example, neural networks [2,9], Kalman filter [10,11], Bayesian algorithms [12], particle filter [13–16], support vector regression [17] and hidden Markov model [18] were all investigated for bearing RUL estimation and other prediction-related applications. The main advantage of these data-driven techniques is that they reflect realistically the dynamical behavior of the system being monitored, and lend themselves readily to adjustment of model parameters to capture the trend of the sensor signals. A common limitation associated with these techniques is that they do not establish a theoretical or functional link between the physical damage state and the feature vectors obtained from the models, due to the "data only" nature. In comparison, physics-based prediction models, such as Paris crack growth model [19,20], Forman crack growth model [21,22] and spall progression model [23], describe variations in the physical states and evolution of structural damage according to the mechanistic law that governs the material response of a bearing to loading conditions that it is subject to. The constraint in developing physics-based prediction models is that they require explicit analytical understanding of the damage evolution, which is obtained from historical data gathered by sensors beforehand. Once a physics-based model is established, relevant model parameters cannot be adjusted in real time. This means that the actual change in states as reflected in the measured signals will not be utilized in real time. From a "time-scale" perspective, data-driven methods extract features from real-time sensor data, thus is considered as reflecting the characteristics of a dynamical system on a *fast* time-scale. In comparison, physics-based methods describe the physical state evolution on a *slow* time-scale. A dynamical system is modeled as a hierarchical system consisting of both a fast and a slow time subsystem [24]. Using either data-driven approach or physics-based approach alone can only address partial or a specific aspect of the entire system. This observation motivates the study of an integrated method for bearing RUL prediction, which combines the strength of both data-driven and physics-based techniques [25,26]. In this paper, phase space warping (PSW) [24,27,28], which has shown to be effective in damage identification [29], damage evolution tracking [27,28,30,31] and failure prediction [32] in a nonlinear dynamic system, is investigated. PSW constructs a tracking metric by evaluating the phase space trajectory warping of vibration data measured by sensors, and builds a linear relationship between the tracking metric on the fast time-scale and the actual physical damage on the slow time-scale [32]. As a result, the tracking metric obtained by the PSW cannot only monitor the damage evolution in real time, but also serve as input to physics-based models, such as the Paris crack growth model, for bearing failure tracking and RUL prediction. Furthermore, the performance of PSW is enhanced by a multidimensional auto-regression model to improve its damage tracking accuracy, and the Paris crack growth model is modified by a time-piecewise algorithm to meet the real-time computational requirement for RUL prediction.

The rest of the paper is organized as follows. Section 2 provides the theoretical background and improvement made to enhance the PSW technique. In Section 3, a platform for bearing RUL prediction based on a modified Paris crack growth model is introduced. Experimental results, together with related discussions, are presented in Section 4. Finally, conclusions are drawn in Section 5.

## 2. Enhanced phase space warping

### 2.1. Damage tracking based on multi-time scale modeling

From the perspective of systems theory, a machine or machine component with an embedded structural defect that evolves over time is viewed as a hierarchical system consisting of a "fast time" subsystem coupled with a "slow time" subsystem, defined as [24–26]:

$$\text{Fast time: } \dot{\boldsymbol{x}} = f(\boldsymbol{x}, \mu(\boldsymbol{\phi}), t) \tag{1}$$

$$\text{Slow time: } \dot{\boldsymbol{\phi}} = \varepsilon g(\boldsymbol{\phi}, \boldsymbol{x}, t) \tag{2}$$

where $\boldsymbol{x} \in R^n$ is a fast-time variable which is observed directly and $\boldsymbol{\phi} \in R^m$ is a slow-time variable representing the hidden damage state which is not accessible directly; $f(\bullet)$ and $g(\bullet)$ are the fast-time system function and the slow-time system function, respectively; $t$ is the time and $\mu(\bullet)$is the function of $\boldsymbol{\phi}$; $\varepsilon(0 < \varepsilon \ll 1)$ is constant, which defines the drift rate of the hidden damage state.

Considering a dynamical system as described by Eqs. (1) and (2), the fast-time state with initial damage state $\boldsymbol{\phi}_0$ at the initial time $t_0$ is purely a function of $\mu(\boldsymbol{\phi}_0)$ and is represented as

$$\boldsymbol{x}_0 = F(x_0, \mu(\boldsymbol{\phi}_0), t_0) = F(\mu(\boldsymbol{\phi}_0)) \tag{3}$$

where $F(\bullet)$ is a function relating $\boldsymbol{x}$ to $\mu(\boldsymbol{\phi})$. Then, at time $t$ ($t > t_0$) the state of the fast subsystem is represented as:

$$\boldsymbol{x}_t = F(\mu(\boldsymbol{\phi}_t)) \tag{4}$$

At $\boldsymbol{\phi}_t = \boldsymbol{\phi}_0$, Taylor expansion of Eq. (4) is expressed as:

$$\boldsymbol{x}_t = F(\mu(\boldsymbol{\phi}_t)) = F(\mu(\boldsymbol{\phi}_0)) + \frac{\partial F}{\partial \mu}\frac{\partial \mu}{\partial \boldsymbol{\phi}_t}(\boldsymbol{\phi}_t - \boldsymbol{\phi}_0) + O\left(\|\boldsymbol{\phi}_t - \boldsymbol{\phi}_0\|^2\right) \tag{5}$$

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