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Remaining useful life estimation for mechanical systems based on similarity of phase space trajectory

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ABSTRACT

When evolving from a normal state to failure, mechanical systems undergo a gradual degradation process. Due to the nonlinearity of damage accumulation, degradation data always exhibit a distinctive trend and random fluctuations. It makes the prediction of remaining useful life (RUL) very difficult and inaccurate. The phase space trajectory reconstructed from the time series of degradation data is capable of reliably elucidating the nonlinear degradation behavior. In this paper, a novel method based on the similarity of the phase space trajectory is proposed for estimating the RUL of mechanical systems. First, the reference degradation trajectories are built with historical degradation data using the phase space reconstruction. Second, the similarities between the current degradation trajectory and the reference degradation trajectories are measured with a normalized cross correlation indicator, which is determined solely by the trajectory shape and is not interfered with the scaling and shifting of the trajectory. Trajectory shape and degradation stage matching algorithms are combined to find the optimal segments in the reference degradation trajectories compared with the current degradation trajectory. Finally, the RULs corresponding to the optimal matching segments are subjected to weighted averaging to obtain the RUL of the current degradation process. The proposed method is evaluated utilizing both simulated data in stochastic degradation processes and experimental data measured on an actual pump. The results show that the predicted RULs are very close to the actual RUL.

1. Introduction

Following increasing demands in the field of operational safety, asset availability and resource conservation, the area of prognostics has emerged as one of the key foundations for the maintenance scheme of modern industry. The main task of prognostics is to estimate the remaining useful life (RUL) of a mechanical system, which is defined as the period from the current service time until the component or system fails. It is important to predict the RUL of an asset as the incipient damage or performance degradation occurs because it provides valuable information toward decreasing future risk and loss due to failures or accidents. Over the past decade, RUL prediction has become a research topic of high interest, investigated in application fields (Heng, Zhang, Tan, & Mathew, 2009; Si, Wang, Hu, & Zhou, 2011; Sun, Zeng, Kang, & Pecht, 2012).

Most failures in mechanical systems result from gradual degradation processes rather than sudden occurrences. Incipient damage is formed under the effects of repeated load and adverse conditions, such as wear and erosion, and then evolves into a distinct failure. Numerous prognostic approaches have been developed to model the degradation processes of mechanical systems and estimate the RUL. The physics-based and data-driven models are representative prognostic approaches, which have a wide range of applications.

Generally, physics-based models implement the mathematic formulas deduced from the physics of failures to predict the theoretical damage evolution, such as crack propagation and spall growth. Due to its convenience and accuracy, physics-based models are used as the basis of some expert systems for RUL prediction, which can be found in references (Jin, Matthews, Fan, & Liu, 2013; Kim, Song, & Park, 2009; Liu, Xuan, Si, & Tu, 2008; Zhao, Tian, & Zeng, 2013). However, the damage that modeled by physics-based models is specific and cannot be used for reference to other types of mechanical components. Moreover, it is hard to construct an

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adequate physics-based model when the real-life system is complex.

Data-driven models are the more available solutions in many practical cases where degradation data are collected either continuously or periodically from operating systems. This type of models can be further classified as random coefficient models, artificial intelligence approaches and trend-based approaches. In random coefficient models, the degradation process is usually represented as a linear, polynomial, exponential, or any other functional form (Gebraeel, 2006). To characterize the complicated relationship between the hidden degradation behavior and the observed fluctuating data, stochastic processes, such as the Wiener process (Si, Wang, Hu, & Zhou, 2013; Son, Fouladirad, Barros, Levrat, & Iung, 2013) and Gamma process (Guida & Pulcini, 2013), are used to fit the distribution of the degradation path. For the random coefficient models, it is necessary to acquire prior degradation knowledge and abundant historical data to determine the model form and stochastic parameters. Therefore, some improved strategies, such as expectation maximization (Si et al., 2013) and Bayesian updating (Gebraeel, Lawley, Li, & Ryan, 2005), have been utilized to reduce the prediction errors caused by inappropriate parameters and to enhance the generalization ability of the models. Artificial intelligence is currently the most common foundational technique in the prognostics literature due to its flexibility in generating appropriate model. Huang et al. (2007) developed a set of feed-forward back propagation networks to model the exponential degradation process and estimate the bearing life. Other types of neural networks, such as the cerebellar model articulation controller neural networks (Lee & Kramer, 1993), recurrent neural networks (Tse & Atherton, 1999) and self-organizing map neural networks (Niu & Yang, 2010), have also been used to quantify the degradation level and predict failure. In addition, some prognostics approaches are developed based on artificial intelligence algorithms, such as support vector machine (Kim, Tan, Mathew, & Choi, 2012; Widodo & Yang, 2011), relevance vector machine (Hu & Tse, 2013) and hidden Markov model (Peng & Dong, 2011). Because the degradation characteristics are learned by hidden neural units or are mapped into a high dimensionality space, artificial intelligence approaches usually provide non-transparent solutions to failure prognosis, or rather it cannot be observed that how predict results are inferred. Trend-based approaches built degradation model utilizing the time series of experience data acquired from long-term degradation processes. The main difference with random coefficient models is that the degradation path is not predefined but completely determined by historical data. These approaches utilize advanced statistical techniques, such as sequential Monte Carlo method (Caesarendra, Niu, & Yang, 2010), state-space model (Sun, Zuo, Wang, & Pecht, 2014) and Bayesian hierarchical model (Zaidan, Harrison, Mills, & Fleming, 2015), to deal with the various degradation trends of mechanical systems, which work on variable operating conditions. For the above data-driven models, the bottleneck problem is that their accuracy is highly dependent on the quantity and quality of available degradation data.

Recently, condition monitoring is widely applied to detect the degradation process of critical mechanical system. It provides a favorable situation for data-driven models. However, due to the nonlinearity of mechanical damage accumulation, unstable operating conditions and accidental disturbances can significantly alter the associated degradation behavior. Therefore, the practical degradation data, which represent the time series indicating system performance, always exhibit a distinctive trend and random fluctuations. In most data-driven models, the time series of degradation data are directly engaged as the learning samples to model degradation evolution. When the available samples are insufficient, the distinctive trend and random fluctuations within the degradation data may produce unacceptable errors.

Nonlinear degradation behavior is the major challenge confronting the effective prediction of the RUL of mechanical systems. From the viewpoint of dynamical systems, the time series of degradation data are products of systems, which are undergoing degradation progresses. Although the degradation data present nonlinear behavior and possible chaos, the underlying data generating mechanisms can still be identified by phase space reconstruction technique. By virtue of the ability of revealing the nature of system state, phase space reconstruction has become a powerful tool for pattern recognition (Sharma & Pachori, 2015) and been wildly applied to differentiate the failed state from the normal state for mechanical systems (Aydin, Karakose, & Akin, 2014; Wang, Li, & Luo, 2007). In phase space reconstruction, the time series is rearranged into a phase space based on time delay embedding. The evolving state of a system over time traces a path, which is called the phase space trajectory, through the reconstructed phase space. The shape of the trajectory represents the system behavior that is compatible with a particular operating state. Because degradation leads to changes in the dynamics that are characteristic of the system state, the phase space trajectory is capable of elucidating the latent degradation behavior from the observed time series. In our research, the phase space trajectory, rather than the original degradation data, is used to analyze the degradation process.

In this article, we present a method for remaining useful life estimation based on the similarity of the phase space trajectory. The phase space reconstruction is adopted to build reference degradation trajectories from the time series of historical degradation data. The similarities between the current trajectory and the reference trajectories are robustly measured and used to estimate the RUL. The reminder of the paper is organized as follows. Section 2 describes the main principle of our method, which includes the phase space reconstruction (PSR) and normalized cross correlation (NCC). The methodologies of RUL estimation are also given in this section. Section 3 shows the results from the simulation verification. Next, a case study demonstrating the application on an actual pump is presented in Section 4. Finally, the conclusions are given in Section 5.

2. Methods and principles

2.1. Phase space reconstruction

According to Takens' theorem (Takens, 1981), the underlying dynamics characteristic of a system can be obtained by reconstructing the phase space, preserving the topological properties of the original unknown attractor. To characterize the nonlinear feature of a scalar time series, time delay embedding is commonly used, allowing for the construction of a high-dimensional phase space in which the time series are unfolded. Suppose a time series is $x = (x_1, x_2, \ldots, x_N)$; then, a point in the phase space is represented as a row vector:

$$X_i = [x_{i-(d-1)\tau}, x_{i-(d-2)\tau}, \ldots, x_{i-\tau}, x_i], \tag{1}$$

where N is the number of points in the time series, i is the index of the row vector, ranging from $1 + (d-1)\tau$ to N, d is the embedding dimension, and τ is the time delay. The sufficient condition for the topological equivalent of the reconstructed phase space is that d is greater than twice the box counting dimension of the original system.

Because d is the most critical parameter for PSR, many have discussed how to determine the minimum embedding dimension from a scalar time series. In this paper, we adopt Cao's algorithm (Cao, 1997), which is a practical and non-subjective method. Suppose the embedding dimension is chosen as d; then, the ith point in