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Machine component health prognostics with only truncated histories using geometrical metric approach

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A B S T R A C T

Prognostics plays a vital part in modern decision making for maintenance. Many related valuable approaches have been reported by scientists with both truncated and failure histories. However, for cases where the actual asserts have no failure histories, one important topic of prognostics is to focus on modeling with only truncated histories. Here we first describe an algorithm called time-continuous relevant isometric mapping (TRIM) to establish a manifold space where the health state evolutionary laws within truncated histories can be cognized. Unlike classical methods, such as isometric feature mapping, TRIM involves the vital element of state evolution (time), establishes a state evolutionary manifold space by utilizing both local geometrical structures and global isometric features of a given truncated data set. Meantime, two geometrical metrics, neighborhood geodesic distance (NGD) and cumulative geodesic distance, were defined and used in this study to indicate the health state of a given component. Then the feed-forward neural network (FFNN) was trained with inputs from the NGD series. The corresponding target vectors (survival probabilities) of FFNN were estimated by intelligent product limit estimator using truncation times and generated failure times. After validation, the FFNN was applied to predict the machine component health of individual component. To validate the proposed method, case study was conducted by using the degradation data generated by a bearing test rig. Results demonstrate that the proposed method can highlight the intrinsic health state evolutionary laws by TRIM even with only truncated histories. The more accuracy prognostics results can be consequently achieved based on the cognition of the evolutionary laws.

1. Introduction

Prognostics is regarded as a kernel and promising tool for realizing condition-based maintenance, condition-based monitoring, or prognostics and health management [1]. Data-driven methods as one important branch of prognostics models have been comprehensively researched. This kind of prognostic models require abundant historical event data, such as continuous observations and failure times.

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In real applications, however, it cannot be acceptable if unexpected failures occur, especially in the cases where the failures will result in huge costs and significantly raising safety hazards. To stop these unexpected failures, any unit or component will be replaced or overhauled before it fails once a defect is detected, which makes sense for critical unit or component when no other options are available. Thereby, no further information (e.g. the signals to fail as well as the failure time) related the replaced unit or component will be available for prognostics. The related publications engaging in predicting with these kind of suspended condition monitoring (CM) data sets are limited [2]. Conventional reliability analysis use only failure and suspension times to estimate the lifetime distribution of the probability density function and the cumulative distribution function [1,3,4]. In these cases, suspension times are actually treated as failure times and some classical distributions (e.g. Weibull distribution) are widely applied to analyze reliability [5] and to predict residual useful lifetime (RUL).

With the purpose of maximizing the usage of all data available, some models based on degradation data from both failure and suspension histories (including failure and suspension times) were developed. The proportional hazard model estimated the model parameters by incorporating both failure and suspension history data [6]. Moreover, Heng et al. [7] used both the suspended CM and event data in training an intelligent prognostics model, where the survival probability at future time horizons were achieved [2]. In [8], a two-stage statistical method for estimating the fix-effect and random-effect parameters was developed by using the remaining life distribution model with both failure and suspension histories. In [9], the authors trained a special artificial neural network for predicting the RUL of equipment by utilizing the failure histories and suspension histories. In addition, survival analysis and support vector machine were utilized in [10] to establish an intelligent machine prognostics system by utilizing the truncated and un-truncated data collected from the CM routine. A residual life prediction model was presented by Gebraeel et al. [11], where the degradation model and prediction process depended both on a degradation database and failure times.

All these preceding methods rely on failure histories. However, as aforementioned, in real world, there are many cases with only truncated histories available (without failure histories), for which these current approaches would not be able to obtain accurate prognostics models. At the same time these cases are also different from those prognostics methods which focus on incomplete data (e.g. sparse, fragmented [12], and partial signals [13,14]).

Recently, a couple of publications attempted to focus on this topic. Zhang et al. [15] developed a method based on neural network with dynamic windows to extrapolate RUL when no failure was available, which showed good performance in case of the stationary indicator rather than non-stationary variation degradation indicators. In [16], a functional time warping approach was designed with the assumption that the engineering components degrade according to a common shape function with a similar trend. The requirement of either stationary indicator or common shape function widely limits these methods to be applied to the real world.

On the basis of our published paper on the similar topic, we carried out some further researches and developed an algorithm called time-continuous relevant isometric mapping (TRIM) to solve these issues. In this study, TRIM, the combination of time and geometry, was employed to establish the intrinsic health state manifold where two geometrical metrics, the neighborhood geodesic distance (NGD) and the cumulative geodesic distance (CGD), were defined and were utilized as indicators of machine health. All these preceding developed method and metrics aim to highlight the intrinsic health evolutionary laws under truncated histories. These truncated histories, generated from machine components, generally do not own a stationary indicator or a common shape. In addition, the feed-forward neural network (FFNN) was trained by data inputs from the NGD series that correspond to the target vectors of the survival probability, which were estimated by using the intelligent product limit estimator (iPLE) method using the existing truncation times and the generated failure times. After validation, the FFNN was applied to predict the component health of individual units. Case study was conducted by using the degradation data generated by a bearing test rig to validate the proposed method. Results demonstrate that the proposed method can highlight the intrinsic health state evolutionary laws by TRIM. The more accuracy prognostics results can be consequently achieved based on the cognition of the evolutionary laws.

The following sections of this paper are organized to describe clearly the modeling and validation process.

2. Related theories and modified models

2.1. The TRIM algorithm

The isometric feature mapping (ISOMAP) [17] is a global method that maps a dataset from a high-dimensional space to a low-dimensional space and maintains the global geodesic distances of the corresponding pairwise in the high-dimensional space. In this study, the framework of ISOMAP is incorporated into the TRIM algorithm to cognize the health state evolution laws underlying truncated histories.

Originally, the points in the ISOMAP are equally viewed with no differences. Graph G over all data points is constructed by connecting nearby points i and j (closer than a preset e or j is one of the K nearest neighbours of i). The local relationship can be achieved and represented as $d(x_i,x_j)$ with no directivity. K in TRIM is also preset, which denotes the number of the 'nearest time-related neighbors' of i. Accordingly, K is no longer obtained by distances but by time-related relationships (i.e., each point i has K 'nearest time-related neighbors', which are the latest K points ahead of the ith point). The relationship of the ith point and any point j of the latest K ones is denoted as $d_{t\text{-}G}(i, j)$. All the relationships determined within the high-dimensional space will be mapped to the low-dimensional manifold space (i.e., health state evolutionary manifold space