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A novel method using adaptive hidden semi-Markov model for multi-sensor monitoring equipment health prognosis

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ABSTRACT

Health prognosis for equipment is considered as a key process of the condition-based maintenance strategy. This paper presents an integrated framework for multi-sensor equipment diagnosis and prognosis based on adaptive hidden semi-Markov model (AHSMM). Unlike hidden semi-Markov model (HSMM), the basic algorithms in an AHSMM are first modified in order for decreasing computation and space complexity. Then, the maximum likelihood linear regression transformations method is used to train the output and duration distributions to re-estimate all unknown parameters. The AHSMM is used to identify the hidden degradation state and obtain the transition probabilities among health states and durations. Finally, through the proposed hazard rate equations, one can predict the useful remaining life of equipment with multi-sensor information. Our main results are verified in real world applications: monitoring hydraulic pumps from Caterpillar Inc. The results show that the proposed methods are more effective for multi-sensor monitoring equipment health prognosis.

1. Introduction

Modern machinery equipment needs to operate at high reliability, low environmental risks and human safety. The maintenance plays a critical role in their efficient usage in terms of cost, available and safety. Being able to perform reliable prognosis is the key to condition-based maintenance (CBM) since prognosis is critical for improving safety, planning missions, scheduling maintenance, and reducing maintenance costs and down time [1]. As an important part of CBM, proper production and logistic activities can be scheduled to minimize the loss if equipment health can be estimated and predicted by condition monitoring information. Hence, how to achieve useful health prognosis and diagnosis has attracted much attention, as seen from [2–4]. Health prognosis is a process of assessment of equipment health. Health prognosis involves in evaluating the current condition, observing the future condition and predicting the residual useful lifetime (RUL) of equipment before the failures. Health prognosis is a relatively new area of research.

The advanced prognosis focuses on performance degradation and evaluation so that failures can be predicted and prevented [5]. Most of methods in the reliability arena involve in intensive computations and the processing of large amounts of historical

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data [6–8]. The health prognostic activity is gaining during this last decade more and more interest among the engineers as well as the industrial communities. Some prognostic models have been introduced and developed with various degrees of success.

Currently, three kinds of approaches have been proposed with monitoring information for equipment health prognosis. The first applies physical modeling and advanced parametric identification techniques, along with failure detection and prognosis algorithm for estimating the time-to-failure of equipment [9–11]. Banjevic et al. [11] applied the proportional hazard model to illustrate the estimation of the residual life distribution. The limitations of these models are their higher costs and lower accuracy. Furthermore, it is very difficult to build a good type of model. The second uses the monitored data to predict the health of equipment [12–14]. Tran and Yang [12] applied the adaptive neural fuzzy inference system to predict the condition trend of equipment. Leu et al. [14] proposed a model for probability prediction of tunnel geology based on a hidden Markov model (HMM) and a neural network. However, the slow convergence and local minimum value are main drawbacks of these models and the computational explosion problems will occur when the number of observation increases dramatically. The third relies on the use of a mathematical model to represent the degradation behavior of equipment [15–17]. Gobbato et al. [15] applied a new method for real-time failure prognosis by combining the capabilities of the HMM and the belief rule base. Peng and Dong [17] presented an age-dependent HSMM based prognosis method to predict equipment health. These models have very rich mathematical structures and can form the solid theoretical foundation for use. However, the major drawback is that computation and training processes are often time consuming which is disadvantageous. All three kinds of approaches predict the health of equipment with single-source information.

However, in order to obtain a better prognostic accuracy, there usually are multiple sensors to collect monitoring information. By comparing with the single-source information, the multi-sensor measurements may result in more accurate health prognosis, while bringing more complex modeling analysis [18]. Thus, in this paper, by using multi-sensor information, a new health prognosis method will be proposed. In the literature, two categories of multi-sensor prognostic models can be classified: data-driven models and model-driven models.

First, data-driven models use all multi-channel data as the measurement matrix without any treatment in the state space model of equipment. Sun et al. [19] used the sensor signals to characterize the hidden health state in a state space model, and predicted the system-level RUL. Lu et al. [20] described the data as multivariate time series with a state space approach, and predicted the mean and covariance of performance measures recursively. Meanwhile, some data-driven models focus on the multi-dimensional data reduction for subsequent prediction. Niu and Yang [21] provided the data-level fusion for RUL prediction with the tools of neural networks and wavelets. Caesarendra et al. [22] proposed an application of relevance vector machine, logistic regression, and autoregressive moving average/generalized autoregressive conditional heteroscedasticity models to assess failure degradation based on run-to-failure bearing simulating data.

Then, model-driven models stress the prediction-level fusion from independent sensor information. Dong et al. [23] firstly studied the diagnostics from each sensor with a hidden semi-Markov model, and then adjusted the fusion weights of sensors using an *F*-test to combine the measurements linearly for RUL prediction. Wei et al. [24] applied the stochastic filtering for RUL prediction of each sensor, and fused the results under the linear weighted policy. Wei et al. [25] considered the remaining useful life prediction with anticipated performance for a class of multi-sensor dynamic systems subject to latent degradation, and analyzed the uncertainty index to quantitatively evaluate the benefits of increasing multi-sensor information for predicted remaining useful life.

In this paper, maximum likelihood linear regression (MLLR) is used to represent the differences among the multiple sensors and modify probability density function of duration and observation. Thus, an AHSMM can be proposed to conduct normalization of sensor differences in both state duration and observation distributions of a canonical model by using HSMM-based MLLR transformation, and it can be used to get the health prognosis of equipment with multi-sensor information. As an inherent physical process, the degradation state is indirectly measured by multiple sensors. First, the basic algorithms of AHSMM can be proposed, and the AHSMM with multi-sensor information is applied, in which the hidden degradation process can be seen as equipment state. The AHSMM method with multi-sensor information can decrease the computational and space complexity. Then, the maximum likelihood linear regression transformations method is used to train the output and duration distributions to re-estimate all unknown parameters. Thus, the new Baum–Welch algorithm of AHSMM is proposed. The AHSMM can be used to obtain the transition probabilities among health states and health state durations of equipment. Finally, a health prognosis model is developed based on AHSMM with multi-sensor information for equipment, and it is used to estimate the RUL values of equipment.

Compared with some previous researches [9–17,19–25], our work is different in several major aspects. First, the expression of duration probability and observation probability are improved, and AHSMM are presented in order for multi-sensor health prognosis of equipment. AHSMM can decrease the computational and space complexity. Then, MLLR is used to represent the differences among the multiple sensors and modify probability density function of duration and observation. Thus, AHSMM can be used to recognize the hidden degradation state monitored by multiple sensors, and the health prognosis can be realized without information loss or much computational complexity. Finally, RUL prediction model is developed, and the degradation process and the state estimation can be obtained to predict the RUL, while quantifying the effect of multi-sensor information on the performance of health prognosis. To illustrate the application of the proposed method, a practical study is finally presented. The ability of health prognosis with multi-sensor information is analyzed, comparing with the prediction results by the traditional HSMM with fewer sensors and single-source information.

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