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Switching Kalman filter for failure prognostic

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ABSTRACT

The use of condition monitoring (CM) data to predict remaining useful life have been growing with increasing use of health and usage monitoring systems on aircraft. There are many data-driven methodologies available for the prediction and popular ones include artificial intelligence and statistical based approach. The drawback of such approaches is that they require a lot of failure data for training which can be scarce in practice. In lieu of this, methods using state-space and regression-based models that extract information from the data history itself have been explored. However, such methods have their own limitations as they utilize a single time-invariant model which does not represent changing degradation path well. This causes most degradation modeling studies to focus only on segments of their CM data that behaves close to the assumed model. In this paper, a state-space based method; the Switching Kalman Filter (SKF), is adopted for model estimation and life prediction. The SKF approach however, uses multiple models from which the most probable model is inferred from the CM data using Bayesian estimation before it is applied for prediction. At the same time, the inference of the degradation model itself can provide maintainers with more information for their planning. This SKF approach is demonstrated with a case study on gearbox bearings that were found defective from the Republic of Singapore Air Force AH64D helicopter. The use of in-service CM data allows the approach to be applied in a practical scenario and results showed that the developed SKF approach is a promising tool to support maintenance decision-making.

1. Introduction

The prevalence of health and usage monitoring systems (HUMS) on aircrafts in the past decades has fueled the growth of prognostics for maintenance decision support. From Ref. [1], diagnostics is defined as the examination of symptoms (usually in the form of condition monitoring (CM) data) while prognostic is the analysis of the symptoms to predict future condition and remaining useful life (RUL). The use of CM data for prognostics has significant advantages over traditional reliability methods as they allow individual component to be monitored and for maintenance to be prescribed based on their condition or usage severity. In comparison, reliability methods such as Weibull analysis can describe different failure types in the classical bathtub curve but it does not distinguish between individual components. A wide variety of approaches in the use of CM data for prognostics were comprehensively reviewed by different authors in [2–4]. Their works showed that the methods can be grouped into three main categories, namely, machine learning, statistical, and model-based methods.

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Both machine learning and statistical methods such as neural networks and hidden Markov models (HMMs) can model highly nonlinear problems and different failure modes, respectively. In Ref. [5] accelerated bearing run-to-failure test data was used by Shao to train the neural network before it is applied for RUL prediction while Zhang et al. [6] applied HMM for bearing prognostics. The key drawback of these methods is that they require a large number of datasets for training which are often not available in practice. In lieu of this drawback, most of the applications in these literature used experimental or simulated data for model training and little work was done with fielded applications as mentioned in Ref. [4]. Model-based method uses mathematical representation of system's physical or degradation behavior. In [7], a comprehensive bearing spall propagation model that is adaptive to usage loads was developed by Marble for RUL prediction. Such models however, can be very difficult and expensive to develop. Besides physical models, known degradation behavior can be modeled as well using regression based or state space methods. Gebraeel et al. [8] proposed a Bayesian approach for updating the stochastic parameters of an exponential degradation model for RUL prediction. The Kalman filter (KF) is a state space-based method that has also been researched for prognostics application [9–12]. Such methods require less training data, but knowledge of the system's degradation process is required. Besides the RUL prediction, the RUL's probability density function (pdf) and its confidence bounds are important in aiding decision support. For a linear degradation process, such as in steady degradation, the RUL pdf can be obtained with closed form solution using a special case of Bernstein distribution as described by Lu and Meeker in [13] after which the confidence bounds can be obtained. For non-linear unsteady degradation however, a closed-form solution is generally not available. For measuring the overall effectiveness of prognostics tools, several performance metrics has been proposed by Saxena et al. in [14,15]. In this paper, the performance of the switching Kalman filter (SKF) as a prognostics tool is investigated through model inference and RUL prediction of rolling element bearing degradation. Actual CM data gathered from AH64D helicopters' belonging to the Republic of Singapore Air Force (RSAF) is used in the study.

2. The Kalman filter and its limitations for prognostics

From [4], the basic Kalman filter is a stochastic filtering process which recursively estimates the state of a dynamic system in the presence of measurement noise and process noise by minimizing the mean squared error. The Kalman filter consists of a discrete state-space model describing a linear process is given by:

$$\begin{aligned} x_t &= A_{t-1}x_{t-1}+q_{t-1} \\ y_t &= H_t x_t + r_t \end{aligned} \tag{1}$$

where x_k is the true but hidden state of the system and y_k is the observable measurement of the state. A is the fundamental matrix describing the system dynamics and H is the measurement matrix. $q_{t-1} \sim N(0, Q_t)$ is the process noise and $r_{t-1} \sim N(0, R_t)$ is the measurement noise. The Kalman filter estimates the value of x_t, given the measurement, y_t by filtering out the noise. This is carried out using the 'Prediction' and 'Update' steps also known as the Ricatti Equations [16] as follows.

Prediction step:

$$\begin{aligned} &\text{Predicted state estimate:}\ \hat{x}_t = A_t x_{t-1} \\ &\text{Predicted estimate covariance}\quad \hat{P}_t = A_t P_{t-1} {A_t}^T + Q_t \end{aligned} \tag{2}$$

Update step:

$$\begin{aligned} &\text{Measurementresidual:}\quad v_t = y_t - H_t \hat{x}_{t|t-1} \\ &\text{Residualcovariance}\quad C_t = H_t \hat{P}_t H_t^T + R_t \\ &\text{Kalman Gain}\quad K_t = \hat{P}_t H_t^T {C_t}^{-1} \\ &\text{Updated state estimate}\quad x_t = \hat{x}_t + K_t v_t \\ &\text{Updated estimate covariance}\quad P_t = (I - K_t H_t)\hat{P}_t \end{aligned} \tag{3}$$

The Kalman filter can also perform prediction repeating the prediction step in Eq. (1) using the last known state and covariance estimate without updating the state and covariance estimate. However, the accuracy of the estimates will fall with increasing steps with the prediction confidence bounds widening accordingly. The KF has been used in a wide range of applications from navigation and tracking to economic forecasting. In maintenance application, it has been applied to engine health diagnostic [17] and in recent years to electronics prognostic for estimating remaining useful life of ball grid array connections [9,11] and electrolytic capacitors [10]. The key advantage of using KF for diagnostic is that it accounts for measurement and system noise in the CM data and the system state and parameters of the degradation model can be adaptively estimated as they evolve through time [18]. It can also be used for prognostics by forecasting the system state into the future using the degradation model and the latest available measurement. As it does not need to store and re-process all past measurements at each time step, the Kalman filter is well suited for online application. For nonlinear system dynamics or non-Gaussian noise, particle filtering can be applied instead of the KF [19]. The use of particle filtering, however, can be very computationally intensive as Monte Carlo simulation is employed heavily in the procedure to estimate the non-Gaussian distributions.