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Remaining lifetime of degrading systems continuously monitored by degrading sensors

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We consider degrading engineering systems that operate in varying environments. The external environment along with internal ageing processes in items cause deterioration not only of the systems but also of the monitoring sensors. Since accurate data is crucial for predicting systems' health conditions and the subsequent decision-making, considering the effect of sensor degradation is important to obtain the justified reliability characteristics of systems such as the remaining useful life (RUL). Although the concept of sensor degradation has been introduced previously in the literature, parameter estimation in the presence of sensor degradation has not been studied in detail. To fill this gap, our study aims to develop the parameter estimation procedure, followed by state and RUL estimation when sensor degradation is present.

Keywords: Calibration sensor, Kalman filter, Remaining useful life, Sensor degradation

1. Introduction

Prognostics and Health Management (PHM) models are highly reliant on sensors for collecting accurate information about the systems' health. Even though sensor data is crucial for anomaly detection, fault isolation, RULE and planning maintenance actions, very few studies have focused on the influence of non-ideal sensors on the monitoring of system health. Sensor degradation is often observed when sensors operate for a long time in a severe environment, which is quite common in areas such as the nuclear industry. The existence of sensor degradation makes it difficult to obtain accurate information about the health of monitored systems (Cheng et al., 2010; Guan et al., 2020; Liu et al., 2019). To fill the above-mentioned research gap, in this paper, we develop a model to investigate the impact of a deteriorating sensor on monitoring the health condition of a degrading system.

2. Methodology

We consider the case that both the system and sensor suffer degradation processes, which are modelled by Wiener processes with linear drift

At a time t the resultant degradation measurement $Y(t)$ obtained from the degrading (monitoring) sensor can be written as:

$$Y(t) = (\alpha + \beta)t + \sqrt{(\sigma^2 + \eta^2)}B(t) + \epsilon \quad (1)$$

where α, β are system and sensor drift parameters, σ, η are the diffusion parameters, $B(t)$ is the standard Brownian motion representing the stochastic dynamics of the degradation process, $B(t) \sim N(0, t)$.

Since both the system and the sensor are degrading and have their own sets of unknown parameters, readings from one sensor alone are not sufficient for the estimation process. To estimate the unknown parameters and attack the issue of "identifiability", the concept of a calibration sensor is used which can accurately inspect system states at certain periods. The unknown parameters are estimated using Maxium a posteriori estimation (MAP) from calibration data and Maximum Likelihood estimation (MLE) from monitoring data. Kalman filter (KF) is then used to estimate the system and sensor states, followed by RUL estimation.

3. Numerical example and results

In this section we discuss some parts of our numerical example (not all) with a few selected observations from the main work.

3.1. *Data Simulation*

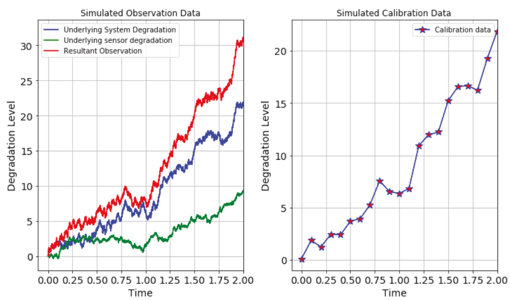

Fig. 1.: System and sensor degradation and resultant observation including measurement error

Figure 1, plots the underlying system (blue line) and sensor (green line) degradation processes, and also the resultant observations (red line). The calibration data (sampled at every 1000 measurement points), is shown as the blue line plot with the red starred marking in subplot 2 of Figure 1.

3.2. *Parameter estimation of the degradation processes*

For the estimation the system degradation parameters, the calibration data is used as inputs for the MAP method. From Figure 2 it can be observed that with 21 calibration data points, the estimated value of α ranges from 9.95 to 9.98, with the value at the last calibration point being 9.98. This value is close to $\alpha = 10$, which has been used for simulating the degradation data. The accuracy of estimated value of α highlights that MAP estimation technique works well even with less frequent calibration data.

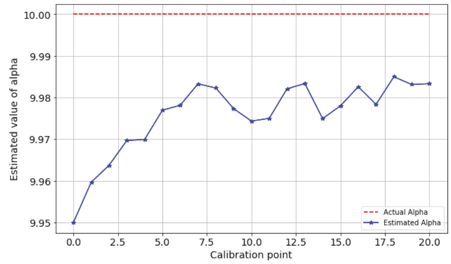

Fig. 2.: Estimated α vs actual α

3.3. *State estimation*

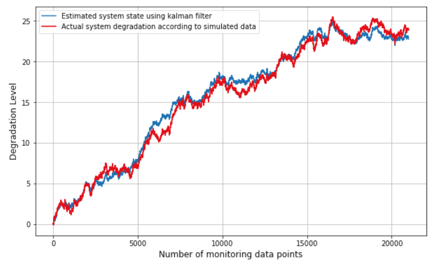

Fig. 3.: Comparison of state estimation using Kalman filter and actual degradation

Figure 3 compares the degradation obtained from simulated data and the state estimation using the Kalman filter and shows that the curves are very close, indicating the effectiveness of the developed approach.

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