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A Bayesian Damage Prognosis Approach Applied to Bearing Failure

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ABSTRACT

Bearings are one of the most important components in rotating machinery, and their failure can cause catastrophic consequences. Conventional damage detection technologies have been successfully applied to make early warning of defect occurrence, mostly via vibration-related quantities due to damage-induced rattling. However, when the operational environment is highly variable and the online data suffer large uncertainties, robust early detection becomes challenging. Beyond simple detection, however, in-situ prognosis is even of greater interest, since it seeks to determine the remaining useful life (RUL), given condition monitoring data. Under realistic conditions, the nominal operation life, usually in terms of L10, is not practical when the prognosis is subject to the aforementioned uncertainties. This paper aims at updating the most plausible model parameters to obtain an accurate failure curve. From this Bayesian model updating process, the prediction of RUL is therefore made, associated with posterior probability. Vibration data are collected from the SpectraQuest machinery fault simulator, with gradually deteriorating bearings subject to fine foreign particles in the lubrication.

Keywords: Bayesian decision-making, structural health monitoring, damage prognosis, remaining useful life, particle filter

1. INTRODUCTION

Structural health monitoring (SHM) and damage prognosis (DP) ideas have been widely employed in a variety of applications, and vibration-based features are often used for early detection of faults. For in-situ SHM/DP, the decision is inevitably subject to the influence of noise, thus the performance will be degraded. Nevertheless, sufficient data provide a decision-making capability in the statistically significant sense, in which numerous realizations of the inspection are required for a reliable and confident decision. However, under a lot of conditions, especially for prediction of system deterioration, repeatability is often hard or expensive to obtain. This demands an adaptive algorithm to keep updating the decision, as information is accumulating from very limited condition. The Bayesian framework generally connects prior belief with posterior confidence via the observed data; in other words, through evidence information. By adopting Bayesian decision-making, the most plausible feature estimation is given, and as the system is deteriorating, the decision is updated via the newly observed evidence.

Lifetime prediction is often concerned in the context of DP, which usually analyzes the state awareness index and seeks to determine the remaining useful life (RUL). In this paper, the RUL of rotary machine bearing is primarily concerned, and previous research shows that the average operation life, in terms of L10, can be 20 times different from each other even under the same nominal testing condition. As a result, the nominal operation life in prognosis is not meaningful under realistic circumstances with uncertainty, and the estimation of RUL should be updated in real time according to the actual state status.

In addition, most of the current RUL estimation algorithms with physical intuition involve frequent offline inspection, such as the measuring the crack dimension, spalling area, corrosion depth, etc. These offline inspections are difficult to embed into the in-situ system, and therefore real-time prognosis is unachievable. This paper aims at a data-driven approach, and adopts Bayes theory to forecast damage feature growing curve. In the meantime, uncertainty is quantified in terms order statistics.

The rest of this paper is organized as follows: Chapter 2 reviews the Bayesian prediction approach, and introduces a special case, namely the particle filter, which is the closed form of Bayesian framework if normality is held in the state transition; Chapter 3 implements the particle filtering of vibration data collected from a ball bearing, and an autoregressive moving average (ARMA) model is adopted to describe the state transition; then, Chapter 4 concludes the paper with future work suggested.

2. BAYESIAN PREDICTION AND PARTICLE FILTER ESTIMATION

Bayes theorem is the core of Bayesian decision-making, which is characterized in Equation (1):

$$p(x \mid z) = \frac{p(z \mid x)\, p(x)}{p(z)}, \tag{1}$$

in which x denotes the damage feature prediction given by the state transition model, and z is the data observation. The terms $p(x)$ and $p(x|z)$ are prior and posterior probability respectively, indicating the confidence of feature prediction given before and after the observed evidence is available. Likelihood $p(z|x)$ is interpreted as the probability of observing data z given the fact that the system state is predicted to be x, while the denominator is probability of occurrence of z, and is interpreted as up-to-date evidence monitored in the deteriorating process.

In the context of damage prognosis, the aforementioned condition-based damage features are evaluated from both the model-based prediction and the observation with contaminated uncertainty. Considering both of the unideal evaluations, Bayesian framework fuses the data with state transition model, with respect to maximized plausibility. Assuming the feature state vector $\mathbf{x}$ at time point k, denoted as $\mathbf{x}_k$, is defined in the state space f_k, with transition noise $\mathbf{m}_{k-1}$ shown in the flow in Figure 1, and similarly, denoted as h_k, the measurement $\mathbf{z}_k$ is a function of the state variable $\mathbf{x}_k$ and measurement noise $\mathbf{n}_k$. There are two major issues to be addressed: (i) consider both the system state transition model and data observation, to estimate the most plausible feature value; and (ii) based upon the most plausible state transition model, forecast the curve of feature value, therefore predict the RUL given any decision threshold.

state transition prediction

$$\mathbf{x}_k = \mathrm{f}_k\left(\mathbf{x}_{k-1}, \mathbf{m}_{k-1}\right)$$

$$p\left(\mathbf{x}_k \mid \mathbf{z}_{[0:k-1]}\right) = \int p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}\right) p\left(\mathbf{x}_k \mid \mathbf{z}_{[0:k-1]}\right) d\mathbf{x}_k \rightarrow$$

updating via measurement

$$\mathbf{z}_k = \mathrm{h}_k\left(\mathbf{x}_k, \mathbf{n}_k\right)$$

$$p\left(\mathbf{x}_k \mid \mathbf{z}_{[0:k]}\right) = \frac{p\left(\mathbf{z}_k \mid \mathbf{x}_k\right) p\left(\mathbf{x}_k \mid \mathbf{z}_{[0:k-1]}\right)}{p\left(\mathbf{z}_k \mid \mathbf{z}_{[0:k-1]}\right)}$$

Fig. 1 Bayesian prediction and adaptive updating of feature state

In Figure 1, the prior and posterior probability of $\mathbf{x}_k$ is given by Bayes theorem, in which probability of $\mathbf{x}_k$ given the measurement of $\mathbf{z}$ from time 0 to k is calculated. In this paper, f_k is determined to be an ARMA(1,1) model and h apparently is the transformation between physical value and measurement, which is an identity multiplier in this case. However, the flow characterized in Figure 1 is very computationally expensive, especially when the dimensionality is high. For certainty problems, such as Gaussian processes, an approximation of the posterior can be calculated via particles, as shown in Figure 2. The state space at time k-1 is sampled for N times and denoted as $\mathbf{x}_{k-1}^{P_{[i]}}$, in which the superscript P indicates the sampled "particles". After transforming the particles from time k-1 to k, the update weights can be calculated by evaluating the likelihood of data observation, given the particle value is true, and the weights are approximation of the probability of those sampled particles. Therefore the approximation of filtered $\mathbf{x}_k$ is calculated as the weighted sum.

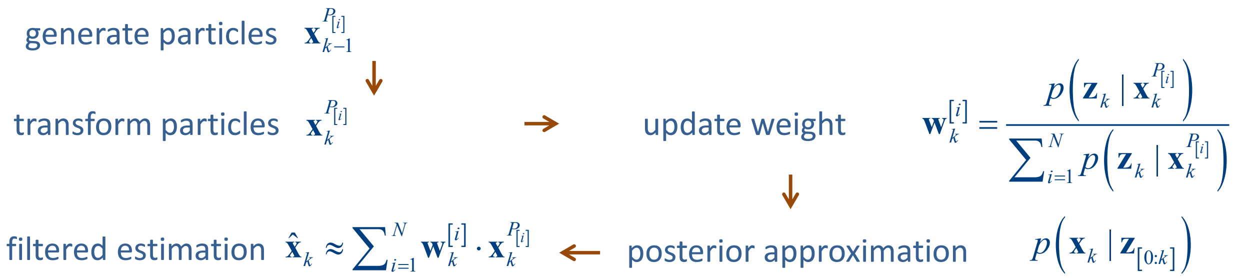

Fig. 2 Flow of particle filtering as an approximation of Bayesian recursive updating

By means of the particle filter, the measurement can be recursively filtered according to the confidence of model prediction, and if the filtered estimation is getting far apart from the measurement, lower weight will be assigned adaptively thus more confidence will be put on the measurements. On the other hand, if the measurements are known to be unreliable yet the model estimation characterize the state space in a more accurate way, the Bayesian estimation will rely on the model rather than the observation.

3. IMPLEMENTATION OF PARTICLE FILTER FOR DMAGE PROGNOSIS

In this paper, the Bayesian flow is demonstrated on a rotary machine, in which bearings will deteriorate as long duration of operation, as shown in Figure 3. Acceleration data are collected and the total energy of vibration, given by the variance of acceleration in the z-direction, is used as the condition-monitoring metric; and without developing sophisticated features, the variance of acceleration will be used in the rest of this paper to illustrate the data-driven prognosis process. To accelerate the deterioration, foreign particles are added into the lubrication. In order not to induce impact and jamming in the casing, the grain size of added sand is controlled to be less than 75 μm.

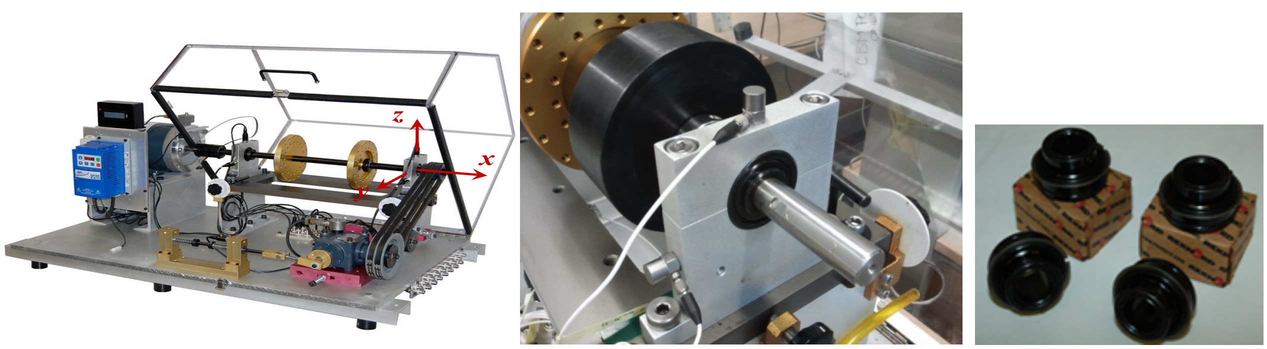

Fig. 3 SpectraQuest rotary machine test-bed

The test is implemented for 8 hours every day, and stopped during the rest of the day. Figure 4 shows the variance of vertical acceleration, as the condition assessment metric, for 10 consecutive days. Every hour, there are 60 samples and each sample is the variance of acceleration for the first 5 seconds of each minute. Superposed with the signal, is the uncertainty bounds of the sample variance measurements, given by Equation (2):

$$\operatorname{var}\left(S^2\right) = \frac{\mu_4}{n} - \frac{\sigma^4 (n-3)}{n(n-1)}. \tag{2}$$

where n is the total number of samples and μ_4 is the fourth-order statistical moment. The variance series is very clearly partitioned from day to day according to Figure 4, and the general trend is that, the vibration energy starts from a relatively low level at beginning of every day and increases rapidly then saturates. After a long period of "resting", the condition seems to be reset. A physical interpretation of the pattern in the curve is concerned with the lubrication and temperature of the structure. When the shaft is just started running, the bearing is not working under ideal condition and the vibration increases very fast. After about an hour, the lubrication arrives at a good viscosity and all parts are warmed up to a steady temperature, therefore the vibration becomes flat. Once the machine starts running after a full night of pause, all the conditions are reset, and a similar cycle begins. Despite of all these physics, there is a trend with slowly increasing vibration as the bearing is deteriorating. In view of this complicated pattern, it might be difficult to predict long term system behavior because of the heavily non-stationary data.

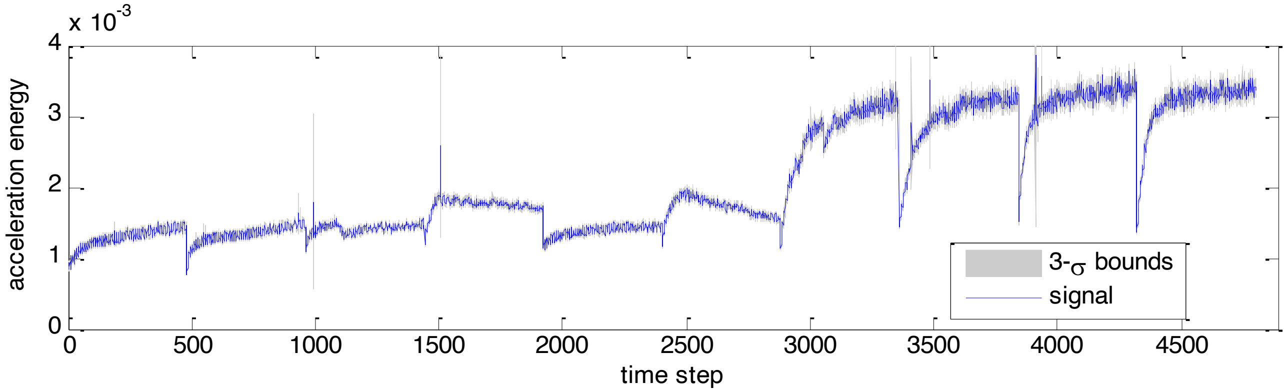

Fig. 4 Variance of acceleration for 10 consecutive days, with uncertainty boundaries

Figure 5 shows the spectrogram of data illustrated in Figure 4, and from day to day, the vibration energy spectrum is moving and magnified at high frequency range. The spectrogram shows a slow transforming from baseline to a degraded status, mostly because of the spall-induced rattling, but does not quantify the deterioration and predict the RUL given current status.

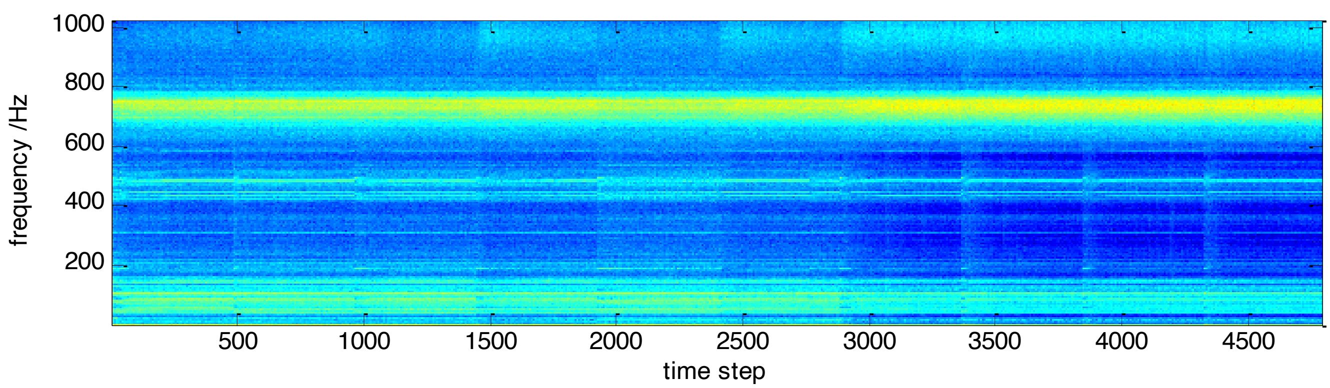

Fig. 5 Spectrogram of vibration for 10 consecutive days

Deploying the Bayesian framework on an arbitrary single-day data and using the particle filter process described in Figure 2, the measurement is filtered ending up with smaller variation, as shown in Figure 6. The first 60 data points, mapping to the first hour, are used to build up a training process to establish the ARMA model; thus the particles and expectation of the state space at 61st time step are thereby available. Running this process in a recursive fashion at every time point, ARMA model is reevaluated based upon the adjacent former 60 points. In the process of forecasting, where the training data are not fully available from the observations, the predictions of ARMA model trained by the last available 60 points of observations are used instead. In the forecasting process, shown in Figure 6, predicted values from time step 480 to 540, the ARMA models have their training data partially from real observation. After time point 540, the forecasts are only dependent on the ARMA model itself. Therefore, the forecasting in this region is very smooth, without the influence from the uncertainty in real data.

When the condition metric reaches certain threshold, failure can be decided, or operation is interrupted for maintenance. In this paper, the time interval between the time of prediction and time of reaching the ceiling is denoted as RUL. Because of the existence of uncertainty, from both the model framework and the data observation, the RUL is inevitably a random variable. At each time point, the sample variance of acceleration can be accurately modeled as a Gaussian variable under central limit theorem, i.e. the one-standard-deviation interval given by Equation (2) corresponds to 68 percentile, but the associated uncertainty bounds in RUL estimation generally does not deliver distribution information, therefore no normally can be claimed to RUL. In this work, the standard deviation is used to quantify the uncertainty, and in Figure 7, the lower and upper bounds of data measurements are also plotted. Using the same ARMA model, the two boundaries can be propagated through time, thus the boundaries of RUL are also obtained.

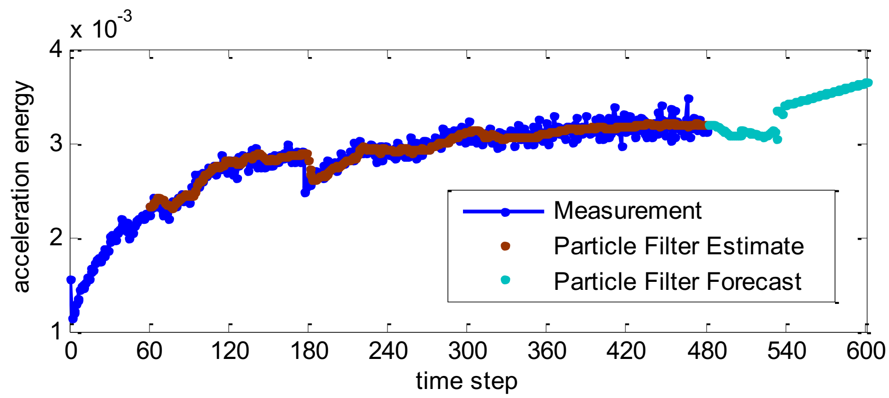

Fig. 6 Particle filter estimate and forecast

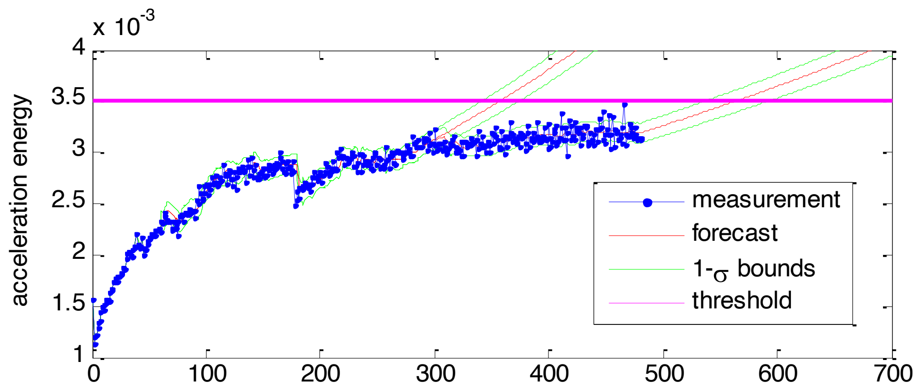

Fig. 7 RUL prediction and uncertainty boundary

Apparently, the ARMA model and its particle-filtered evaluations are highly dependent on the data, and at different time point, different training data sets lead to different forecasts. Figure 8 plots all the forecast curves starting from each of the data points after the first 60-minutes. The slope of acceleration is getting flat, so that the point of hitting the ceiling is moving to the farther side. Consider the physics-based interpretation, when the machine just starts to run, the accelerations increase rapidly. As a result, the RUL estimation is pessimistic, while when the vibration reaches a relatively stable level, the RUL estimation is getting more and more optimistic.

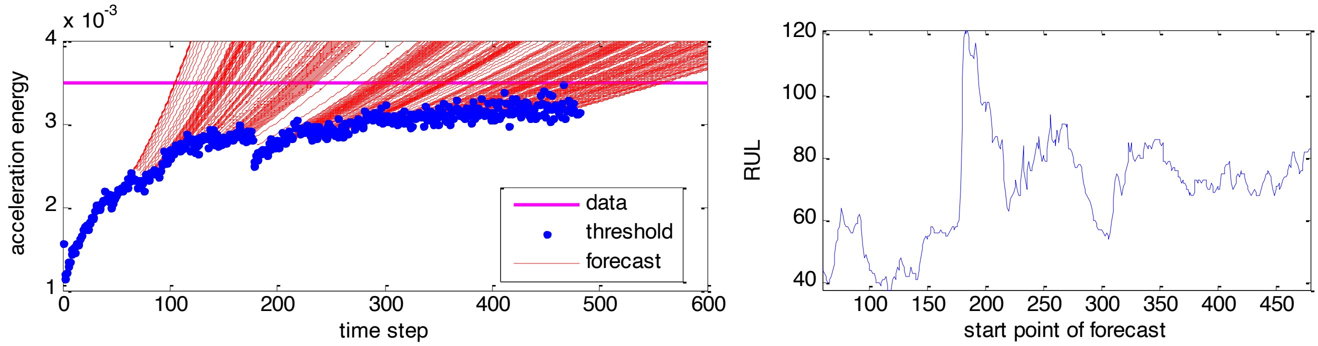

Fig. 8 RUL prediction at different time

The plot on right hand side of Figure 8 shows clearly the RUL as the testing moving forward. Instead of dropping off linearly to zero, the RUL in this case maintains a moderate level. In this study, first order ARMA model and one-hour training data are used, so that the global trend, especially in the daily time scale, is not captured in the estimation.

4. SUMMARY AND CONCLUSION

This paper adopts Bayesian decision theory, particle filter in particular, to hybridize the data measurements with system state model. For a condition-based monitoring purpose, the state assessment metric is decided to be the variance of acceleration, which is fully compatible with online-monitoring and prognosis. In this paper, a first-order ARMA model is used to characterize the vibration level of bearings, when there is deterioration going on. Foreign particles with very small grain size (<75mm) are added in the bearing to accelerate the failure process. Testing data show a consistent pattern which is associated with the physical behavior of the lubrication and temperature increase during the long-duration fatigue test.

Particle filtering is employed to fuse the data observation with the ARMA model, and a smooth time series with less uncertainty is obtained. Moreover, the framework forecasts the acceleration level, which can be used to determine the lifetime of the bearing, given an arbitrary decision threshold. Uncertainty bounds of the acceleration variance can be also propagated in the time axis, therefore the RUL uncertainty is characterized via standard deviation.

For the data-driven flow adopted in this work, prediction of RUL is made considering the current state. Because of the uncertainties in data, and the incompleteness of model in characterizing the entire fatigue mechanism, the RUL prediction fluctuates with different stage of operation and training data. Future work will be focused on the model selection process, employing statistical machine learning algorithm, to have a better global characterization of the vibration energy curve. Also, more sensitive assessment indices will be investigated.

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