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A PARTICLE FILTERING FRAMEWORK FOR FAILURE PROGNOSIS

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ABSTRACT

Bayesian estimation techniques are finding application domains in machinery fault diagnosis and prognosis of the remaining useful life of a failing component/subsystem. This paper introduces a methodology for accurate and precise prediction of a failing component based on particle filtering and learning strategies. This novel approach employs a state dynamic model and a measurement model to predict the posterior probability density function of the state, i.e., to predict the time evolution of a fault or fatigue damage. It avoids the linearity and Gaussian noise assumption of Kalman filtering and provides a robust framework for long-term prognosis while accounting effectively for uncertainties. Correction terms are estimated in a learning paradigm to improve the accuracy and precision of the algorithm for long-term prediction. The proposed approach is applied to a crack fault and the results support its robustness and superiority.

INTRODUCTION

Prediction of the evolution of a fault or fault indicator entails large-grain uncertainty. Accurate and precise prognosis of the time-to-failure of a failing component/subsystem must consider critical state variables, such as crack length, corrosion pitting, etc., as random variables with associated probability distribution vectors. Once the probability distribution of the failure is estimated, other important prognosis attributes -such as confidence intervals- can be computed. These facts suggest a possible solution to the prognosis problem based on recursive Bayesian estimation techniques that combine both the information from fault growth models and on-line data obtained from sensors monitoring key fault parameters (observations).

Prognosis or long-term prediction for the failure evolution is based on both an accurate estimation of the current state and a model describing the fault progression. If the incipient failure is detected and isolated at the early stages of the fault initiation, it is reasonable to assume that sensor data will be available for a certain time window allowing for corrective measures to be taken, i.e., improvements in model parameter estimates so that prognosis will provide accurate and precise prediction of the time-to-failure. At the end of the observation window, the prediction outcome is passed on to the user (operator, maintainer) and additional adjustments are not feasible since corrective action must be taken to avoid a catastrophic event.

Particle filtering is an emerging and powerful methodology for sequential signal processing with a wide range of applications in science and engineering [1]. It has captured the attention of many researchers in various communities including those of signal processing, statistics and econometrics. Founded on the concept of sequential importance sampling and the use of Bayesian theory, particle filtering is particularly useful in dealing with difficult nonlinear and/or non-Gaussian problems. The underlying principle of the methodology is the approximation of relevant distributions with particles (samples from the space of the unknowns) and their associated weights. Compared to classical Monte-Carlo method, sequential importance sampling enables Particle Filtering to reduce the number of samples required to approximate the distributions with necessary precision, and makes it a faster and more computationally efficient approach than Monte-Carlo simulation. This is of particular benefit in diagnosis and prognosis of complex dynamic systems, such as engines, gas turbines, gearboxes, etc., because of the nonlinear nature and ambiguity of the rotating machinery world when operating under fault conditions. Moreover, particle filtering allows information from multiple measurement sources to be fused in a principled manner.

A PARTICLE FILTERING FRAMEWORK FOR FAILURE PROGNOSIS

Figure 1 depicts a conceptual schematic of a particle filtering framework aimed at addressing the fault prognosis problem. Available and recommended PHM/CBM sensors and the feature extraction module provide the sequential observation (or measurement) data of the fault growth process z_k at time instant *k*. We assume that the fault progression can be explained through the state evolution model (1) and the measurement model (2)

$$x_k = f_k(x_{k-1}, \omega_k) \quad \leftrightarrow \quad p(x_k \mid x_{k-1}) \tag{1}$$

$$z_k = h_k(x_k, \upsilon_k) \quad \leftrightarrow \quad p(z_k \mid x_k) \tag{2}$$

where x_k is the state of the fault dimension (such as the crack size), the changing environment parameters that affect fault growth, ω_k and υ_k are the non-Gaussian noises, and f_k and g_k are nonlinear functions.

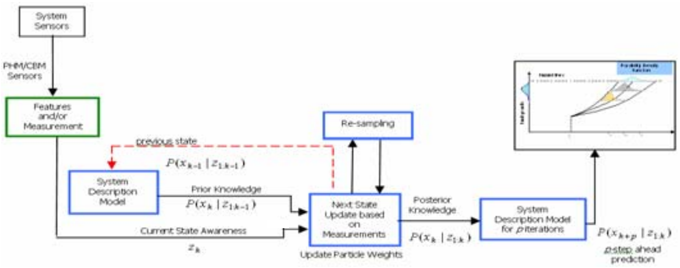

Figure 1. Fault Prognosis based on Particle Filtering

The first part of the approach is state estimation, i.e., estimating the current fault dimension as well as other important changing parameters in the environment. This task involves two basic steps. In the *Prediction Step*, the a priori state estimation is generated from the knowledge of the previous state estimation and the process model (Eq. (3)).

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1})\, p(x_{k-1} \mid z_{1:k-1})\, dx_{k-1} \tag{3}$$

The *Update Step* incorporates the new observation data z_k into the a priori state estimate $p\left(x_\kappa \middle| z_{1:\kappa-1}\right)$ in order to generate the posteriori state estimation $p\left(x_\kappa \middle| z_{1:\kappa}\right)$, as Eq. (4) shows.

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)\, p(x_k \mid z_{1:k-1})}{p(z_k \mid z_{1:k-1})} \tag{4}$$

Particle Filtering approximates the state pdf by using samples or "particles" having associated discrete probability masses. The actual distributions would be then approximated by a set of samples [1] drawn from an importance distribution $q(x_{0:k} \mid z_{1:k})$ and the corresponding normalized importance weights $\tilde{w}_k^i = \tilde{w}_k(x_{0:k}^i)$ for the i-th sample,

$$p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{N} \tilde{w}_k(x_{0:k}^i) \cdot \delta(x_{0:k} - x_{0:k}^i) \tag{5}$$

where the update for the importance weights is given by [1]:

$$w_k = w_{k-1} \frac{p(z_k \mid x_k)\, p(x_k \mid x_{k-1})}{q(x_k \mid x_{0:k-1}, z_{1:k})} \tag{6}$$

The second part of the approach is the long-term prediction based on the current estimate of the fault dimension and the fault growth model with parameters refined in the posteriori state estimation according to Eq. (7). A novel recursive integration process based on both Importance Sampling and *pdf* approximation through Kernel functions is then applied to generate state predictions from (k+1) to (k+p).

$$\begin{aligned} p(x_{k+p} \mid z_{1:k}) &= \int p(x_k \mid z_{0:k}) \prod_{j=k+1}^{k+p} p(x_j \mid x_{j-1}) dx_{k:k+p-1} = \\ &\sum_{i=1}^{N} \tilde{w}_k^{(i)} \int \cdots \int p(x_{k+1} \mid x_k^{(i)}) \prod_{j=k+2}^{k+p} p(x_j \mid x_{j-1}) dx_{k+1:k+p-1} \end{aligned} \tag{7}$$

Long-term predictions can be used to estimate the probability of failure in a process, given a hazard zone that is defined by its lower and upper bounds (H_{lb} and H_{up}, respectively). The prognosis confidence interval as well as the expected time-to-failure (TTF) can be deduced from the TTF pdf:

$$p_{TTF}(ttf) = \sum_{i=1}^{N} \Pr\left\{H_{lb} \le x_{ttf}^{(i)} \le H_{up}\right\} \cdot \tilde{w}_{ttf}^{(i)} \tag{8}$$

The uncertainty usually increases as the prediction farther into the time future is made. To reduce the uncertainty in the failure prognosis based on the particle filtering approach, we use an additional learning paradigm for prediction correction on the time-to-failure.

IMPLEMENTATION FOR CRACK GROWTH ANALYSIS

The results obtained for the analysis of a crack in blades of a turbine engine are shown next. The fault growth model is assumed to be:

$$N = P \cdot L^6 + f(L^5) + \omega(N) \tag{9}$$

where L is the length of the crack (in inches), N is the number of stress cycles applied to the material, P is a random variable with known expectation, f is a fifth order polynomial function known from a FRANC-3D model, and $\omega(N)$ is I.I.D. white noise. The measurement model is considered to be corrupted with Gaussian noise $v(N)$, $y(N) = L(N) + v(N)$. Figure 2 shows the simulation results of the prognosis. In the first plot, the blue curve is the actual evolution of the crack length, the light green curve is the observation of the fault dimension, and the curves in dark blue/green are the prediction bounds generated by the particle filtering approach. The TTF estimate corrected by the learning paradigm is shown in the second plot, in light green. The prognosis result closes to the true values as time goes on.

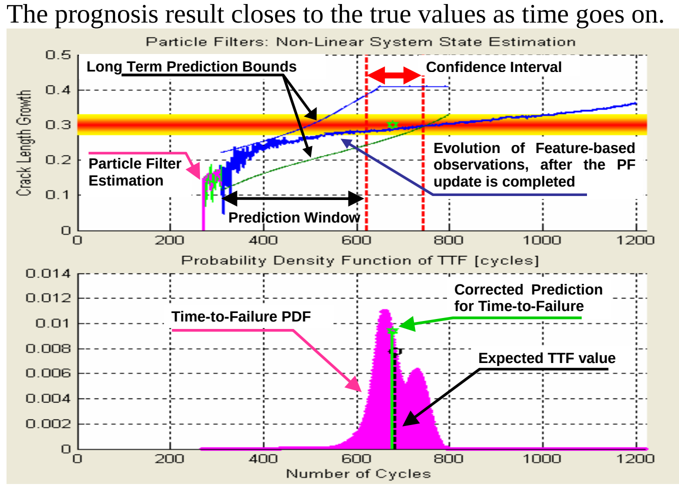

Figure 2. Prognosis Results for Crack Growth Analysis

REFERENCES

[1] Arulampalam, M.S., Maskell, S., Gordon, N., Clapp, T., 2002, "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking", IEEE Transactions on Signal Processing, Vol. 50, No. 3, pp. 174-188.

