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Fault prognostic of electronics based on optimal multi-order particle filter

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ABSTRACT

The accurate fault prediction is of great importance in electronics high reliability applications for condition based maintenance. Traditional Particle filter (TPF) used for fault prognostic mainly uses the first-order state equation which represents the relationship between the current state and one-step-before state without considering the relation with multi-step-before states. This paper presents an optimal multi-order particle filter method to improve the prediction accuracy. The multiple τth-order state equation is established by training Least Squares Support Vector Regression (LSSVR) via electronics historical failure data, the τ value and LSSVR parameters are optimized through Genetic Algorithm (GA). The optimal τth-order state equation which can really reflect electronics degradation process is used in particle filter to predict the electronics status, remaining useful life (RUL) or other performances. An online update scheme is developed to adapt the optimal τth-order state transformation model to dynamic electronics. The performance of the proposed method is evaluated by using the testing data from CG36A transistor degradation and lithium-ion battery data. Results show that it surpasses classical prediction methods, such as LSSVR, TPF.

1. Introduction

Prognostic and Health management (PHM) in electronics high reliability applications have attracted increasing concern in the critical field of space, avionics and military owing to the fact that it has ability to mitigate the risks of catastrophic failures and reduce the life cycle costs [1]. Electronics prognostics which mean prognostics for electronics determine the current system health status, their progression, accumulated damage and provide assessments of remaining useful life (RUL) of the product [2]. The accuracy of the future status prediction guarantees the effectiveness of fault prognostic. Accordingly, the raise of prediction accuracy is a key issue in fault prognostic of PHM techniques, especially for such highly reliable electronic product.

In the last few years, numerous research efforts have been reported in the field of electronics prognosis [3,4]. Electronics prognostic methods can be classified into two main classes: physics-based (or model-based) and data-based methods [5]. Physics-based methods use knowledge of an electronic product's life cycle loading conditions, geometry, material properties, and failure mechanisms to estimate its fault evolution trend or RUL [6,7]. Given an appropriate physical model, e.g., mathematical representation based on the specific knowledge for a specific system, physics-based methods can obtain accurate prediction assessment. However, it is usually hard to acquire the specific knowledge in most practical applications, especially when the process of fault evolution is complicated and/or is not fully known [8]. In comparison, data-based methods apply the measured condition data to establish the fault evolution models by using statistical method, e.g., Gamma process [9], Bayesian method [10],and machine learning techniques, e.g., neural networks (NN) [11], support vector machines (SVM) [12], which avoids developing high-level physical models of the system, so that they are less complex than physics-based approaches [6]. However, data-based methods have requirements on training data while physics-based methods do not. Sometimes it is costly to obtain the data for some complex systems, e.g., history data, fault injection data, and simulation data. These data are used for construct or train prediction model, then the uncertainty and imperfection of data can cause difficulties for data-based methods. While for the systems whose data measured easily and reflected the health status correctly, data-based methods are suitable. Since most data-based methods, such as NN, SVM, particle filter (PF), can be employed in various systems, they have become prevalent prediction tools in electronics prognosis [13].

In data-based methods, support vector machines (SVM) has been employed successfully in various machine learning domains of prediction and regression analysis, such as power system [14],battery state of charge (SOC) [15]. For small sample data, SVMs outperform the neural network models particularly [16]. However, SVM predictor used for data with noise is unfavorable. Since the health states of electronics in actual applications vary with time, e.g., the changes of components' parameters caused by degeneration, and the measured data usually include noises, the trained SVM may not have the ability to implement

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accurate predictions if various states including noises are considered during the prediction process.

Considering that recursive Bayesian algorithm, PF is a sequential Monte Carlo (MC) method that approximates the state probability density function (PDF) by using particles with associated weights. PF are able to solve problems of real-time state estimation, and has been successfully applied in many fields such as visual tracking [17], navigation [18], speech recognition [19], fault detection [20,21], prediction [22, 23], and so on. The outstanding advantage of PF is that it can handle effectively non-Gaussian noises and nonlinear state estimation problem because of the capability of represent arbitrary probability densities [24]. Recently, PF has been applied in prognosis since the fault degradation is a complex nonlinear problem while PF is particularly useful in solving those difficulties. In most applications, mathematical models have been established to describe the fault evolution process. Some mathematical models are established by using the specific knowledge related to the physical mechanism, e.g. life cycle loading conditions, geometry, material properties, and failure mechanisms, which are considered as physics-based models. Some mathematical models are established by using statistical and machine learning techniques based on measured condition data, which are considered as data-based model. However, these mathematical models are complex and need expert knowledge of the degradation process to estimate the parameters' values of the fault evolution model. Furthermore, note that most of fault evolution model adopted in these studies based on PF method is a first-order state equation $\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1})$ which represents the relationship between the current state $\mathbf{x}_k$ and one-step-before state $\mathbf{x}_{k-1}$, while multi-order state equation can be defined by $\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{x}_{k-2}, \cdots, \mathbf{x}_{k-\tau}, \mathbf{u}_{k-1})$, e.g. $\tau = 2,3,4,\cdots$. However, in many practical applications the first-order model cannot represent the actual evolution, and a multi-order model may be more suitable to describe the fault degradation trend. This means that the current system state depends not only on the previous state but also on τ-step-before states, e.g. $\tau = 2,3,4,\cdots$. Chen et al. [13] proposed the multi-order model by using Neuro–Fuzzy and set τ to a fixed value and then the optimum τ value is needed to be found so that τth-order model can reflect the actual system as well as gives high prediction accuracy. PF approach can update system states via new data in real time; the SVM is integrated with a PF so that online data can be employed to improve the prediction accuracy. In this paper, an optimal multi-order PF method is presented for electronics prognosis, where a combination of the Least Squares Support Vector Regression (LSSVR) and the process noise, as a multi-order state equation, is used to describe the fault growth process.

Note that the errors between the actual condition and the prediction estimates from the LSSVR model do exist even with a well-trained LSSVR model. Besides, system dynamics may change in the future. Therefore, an online multi-τth-order model adaptation which can really reflect electronics degradation process is desirable. In this paper, the order value is optimized by Genetic Algorithm (GA). The optimal τth-order state equation can be updated online by training LSSVR when the latest data is acquired. The online model update scheme can adapt the fault evolution model to various dynamic electronics.

In this paper, the combination of the LSSVR and multi-order PF presents a novel method for electronics fault prognosis that possesses the advantages involving nonlinear mapping and real-time state estimation. Experimental data from CG36A transistor degradation and lithium-ion battery are employed to verify the proposed method. Results show that it surpasses the two classical prediction methods: LSSVR and traditional particle filter (TPF).

The remainder of this paper is organized as follows: Section 2 introduces the TPF to perform condition prediction and the multi-order particle filter (MPF) based on multi-τth-order model. Section 3 presents the proposed prediction method. Multi-order state model is introduced first, and then, the integration of the LSSVR in a multi-order PF is demonstrated. Next, the order value of state model and LSSVR parameters is optimized by GA. An online state model update is presented. Finally, the concrete step of the prediction algorithm is illustrated. Section 4 presents the experimental results of the proposed approach on two electronic products, and the performance comparison with TPF and LSSVR predictors is given. Section 5 provides some concluding remarks.

2. Particle filter

2.1. Traditional Particle filter

Particle filter (PF) is an effective state estimation algorithm for implementing a recursive Bayesian filter using Monte Carlo (MC) simulations and, as such, is known as a sequential MC (SMC) method [16]. Traditional PF (TPF) methods assume that the system state dynamics can be represented as a first-order model with the outputs being conditionally independent [25]. This is expressed as follows:

$$\boldsymbol{x}_k = f_k(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}) \tag{1}$$

$$\boldsymbol{z}_k = h_k(\boldsymbol{x}_k, \boldsymbol{v}_k) \tag{2}$$

where $\{\boldsymbol{x}_k, k \in \mathrm{N}\}$ is state sequence, k is the time index and N is the natural number set, and $\{\boldsymbol{z}_k, k \in \mathrm{N}\}$ is the corresponding measurement sequence $\{\boldsymbol{z}_k, k \in \mathrm{N}\}$.$f_k$ is state evolution function, h_k is measurement function that denotes the nonlinear mapping relationship between the model states and the noisy measurements, $\{\boldsymbol{u}_k, k \in \mathrm{N}\}$ is an independent and identically distributed (i.i.d.) process noise sequence and $\{\boldsymbol{v}_k, k \in \mathrm{N}\}$ is an i.i.d. measurement noise sequence.

Within a Bayesian framework, the estimation problem is the recursive process of constructing the PDF of the state $\boldsymbol{x}_k$ at time k given the measurements up to time k, i.e. calculating $p(\boldsymbol{x}_k | \boldsymbol{z}_{1:k})$. The core idea of the PF is to approximate the posterior PDF, $\{\boldsymbol{x}^i_{0:k}, i = 1, 2, \cdots, N_s\}$ with associated weights $\{\omega^i_{0:k}, i = 1, 2, \cdots, N_s\}$,

$$p(\boldsymbol{x}_k | \boldsymbol{z}_{1:k}) \approx \sum_{i=1}^{N_s} \omega^i_k \delta\left(\boldsymbol{x}_k - \boldsymbol{x}^i_k\right) \tag{3}$$

where $p(x_k | z_{1:k})$ is the PDF available at previous time k, $\delta(\cdot)$ is the Dirac function, N_s is the number of particle.

For the discrete weighted approximation to the true posterior $p(\boldsymbol{x})$, the weights need to be defined and this can be done via importance sampling. Thus, the weight of each ith particle is calculated as:

$$\omega^i_k \propto \frac{p(\boldsymbol{x}^i_{0:k} | \boldsymbol{z}_{1:k})}{q(\boldsymbol{x}^i_{0:k} | \boldsymbol{z}_{1:k})} \tag{4}$$

where the set of samples $\boldsymbol{x}^i \sim q(\boldsymbol{x}), i = 1, 2, \cdots, N_s$, which we easily generate from a proposal distribution $q(\boldsymbol{x})$, called importance density.

Factorizing the importance density as:

$$q(\boldsymbol{x}_{0:k} | \boldsymbol{z}_{1:k}) = q(\boldsymbol{x}_k | x_{0:k-1}, \boldsymbol{z}_{1:k}) q(\boldsymbol{x}_{0:k-1} | \boldsymbol{z}_{1:k-1}). \tag{5}$$

The weight update is given as follows:

$$\omega^i_k \propto \omega^i_{k-1} \frac{p(\boldsymbol{z}_k | \boldsymbol{x}^i_k) p(\boldsymbol{x}^i_k | \boldsymbol{x}^i_{k-1})}{q(\boldsymbol{x}^i_k | \boldsymbol{x}^i_{k-1}, \boldsymbol{z}_k)} \tag{6}$$

where $p(\boldsymbol{z}_k | \boldsymbol{x}_k)$ is the likelihood function.