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A virtual sensing based augmented particle filter for tool condition prognosis☆

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ABSTRACT

Timely evaluation and prediction of tool condition is critical to establish optimized maintenance plans in order to enhance production, minimize costly downtime. This paper presents an augmented particle filter based on virtual sensing technique with support vector regression (SVR) model to account for uncertainties in the tool condition degradation process. Tool condition is predicted by recursively updating a physics-based tool condition degradation model with virtual measurement approximately estimating tool degradation condition through virtual sensing technique, following a Bayesian inference scheme. Additionally, in order to improve estimation accuracy of virtual sensing model, different state-of-the-art dimension reduction techniques including principal component analysis (PCA) and its kernel version (KPCA), locality preserving projection (LPP) method have been investigated for feature fusion in a virtual sensing model, and the KPCA method performs best in terms of sensing accuracy. Afterwards, virtual measurement is then incorporated into particle filter. The effectiveness of the developed method is experimentally validated in a set of machining tool run-to-failure tests on a computer numerical control (CNC) milling machine.

1. Introduction

Tool condition prognosis refers to the estimation of time to failure of the machine, as well as the risk associated with existing or future failure modes [1]. It is critical for establishing optimized maintenance plans to enhance production, minimize material waste, and avoid catastrophic damage. As for tool degradation process, it can be divided into the gradual process (e.g. tool wear) and the abrupt process (e.g. tool failure). In this paper, we focus on the prediction of gradual degradation process with trendability. Regarding to the tool failure prediction, the presented method is not suitable to this case. And it is still a challenging issue to predict the abrupt change from one state to another state which needs more research efforts. Additionally, in order to improve the prediction accuracy in the gradual degradation process, numerous efforts have been made to develop a variety of methods for tool condition prognosis over the past years. According to the utilization of sensing information, these methodologies can be categorized into: (1) physics based approach, (2) data driven approach, and (3) model based approach (also known as physics-data integrative approach) [2]. Physics based approach typically describes system physics using empirical models which are usually expressed by a series of ordinary or partial differential equations [2]. For tool condition/life prediction, tool life model (e.g., Taylor's tool life equation, Taylor's extended tool life equation, and Hastings tool life equation, etc.) and tool wear rate model (e.g., Takeyama & Murata's wear rate model, and Usui's wear rate model, etc.) have been widely investigated in literature [3–6]. However, such equations are usually described in a deterministic fashion and involve parameter identification using offline measurements through extensive experiments. In practical application, physics based approach may not be the most practical solution since it does not incorporate the uncertainty in manufacturing operation and component variation, as well as difficulty to obtain extensive offline measurement in real application.

Data driven approach derives a model representing the relationship between online and offline historical measurements based on artificial intelligence model which does not need physical knowledge [1]. Different artificial intelligence techniques have been investigated for machinery condition prognosis, including artificial neural network [7] and fuzzy logic [8], etc. However, data-driven approaches have their own disad-

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vantages for component condition prognostics. Firstly, a large amount of historical data is required to train the model and its performance highly relies on the quality of training data. On the other hand, it is usually a costly and time consuming process to obtain the required run-to-failure experimental data.

In comparison, model based approach takes advantage of the merits in physics based approach and data driven approach, and addresses their limitations. Given that the physical knowledge governing tool wear growth has been well established in physics based approach, model based approach adopts the physical knowledge as a state space model of tool wear and represents the tool wear evolving with time in this paper. Since the machinery defect condition is usually not directly accessible, tool degradation condition needs to be estimated or predicted from in-process measurements, in which Bayesian inference provides a rigorous mathematic solution. Based on Bayesian inference, the present tool wear state is estimated based on previous wear condition. The estimated tool wear state is then updated using in-process measurements based on Bayes rule. For multi-step-ahead prediction, recursive process is applied to predict the tool degradation condition in the desired prediction horizon. Depending on the system type and noise assumption, different methods including Kalman filter (for linear system and Gaussian noise) [9], extended Kalman filter (for weak nonlinear system and Gaussian noise) [10], and particle filter (for nonlinear system and non-Gaussian noise) [11] have been investigated to implement model based prognosis.

Particle filter is a numerical approximation method based on Bayesian inference using point mass (or 'particle') representation of probability densities to tackle the nonlinearity and non-Gaussianity in modeling dynamic systems [11]. It has been investigated for condition prognosis and remaining useful life prediction in different applications. In [12,13], a particle filter framework is investigated to analyze the axial crack growth in a planetary carrier plate and predict degradation condition of a thermal processing unit in semiconductor manufacturing, respectively. A regularized auxiliary particle filter is presented for battery remaining life prediction in [14].

When signal-to-noise ratio (SNR) of measurement is low, it is usually difficult to model the relationship between raw online measurement and tool wear state. To address this problem, virtual sensing technique based on artificial intelligence model, which bridges the gap between offline measurement and online monitoring, is investigated to estimate tool degradation condition. Moreover, SVR model is also investigated to define the measurement function that represents the relationship between tool wear state and the condition indicators (CIs) in a general analytical expression. It is then integrated with particle filter for tool condition prognosis. Afterwards, tool degradation condition is predicted by recursively updating the physical model with virtual measurement through virtual sensing technique, following Bayesian inference scheme. Tool life test data from ball nose cutters in a CNC milling machines is analyzed to evaluate the performance of presented method.

The rest of the paper is constructed as follows. After introducing the theoretical background of particle filter and virtual sensing technique in Section 2, details of the mathematical framework of an augmented particle filter is discussed in Section 3. In addition, the construction of state space model based on physical knowledge and in-process measurement is also discussed respectively. The effectiveness of the presented prognostics method is experimentally demonstrated in Section 4, based on run-to-failure data acquired using a ball nose tungsten carbide cutter in a CNC milling machine. Finally, conclusions are drawn in Section 5.

2. Theoretical framework

2.1. Virtual sensing technique

In the context of tool condition monitoring, a variety of sensing techniques have been instrumented to acquire machining tool conditions. According to the correlation between sensing parameters and tool conditions, these sensing techniques can be categorized into direct sensing and indirect sensing methods [15].

It is recognized that indirect sensing techniques (e.g. force, vibration, and acoustic emission, etc.) measure in-process auxiliary parameters during machining operations. The indirect sensing parameters are less accurate to indicate tool conditions, but the rugged senor design makes them more suitable for practical applications. On the other hand, direct sensing techniques (e.g. microscope, CCD camera, etc.) measure actual quantities of tool conditions and have a high degree of accuracy. Due to the practical limitations caused by access problems during machining, illumination and the use of cutting fluid, direct sensing techniques are commonly used for offline measurement or as laboratory techniques.

To bridge the gap between direct sensing and indirect sensing, virtual sensing, as a complement to physical sensing, has emerged as a viable, non-invasive, and cost-effective method to infer difficult-to-measure or expensive-to-measure parameters in dynamic systems based on computational models [16]. It has been investigated for active noise and vibration control [17], industrial process control [18], and tool condition monitoring [19,20].

Virtual sensing, which utilizes the advantage of indirect sensing, can model the nonlinear dependencies between in-process measurements and actual quantities of tool conditions based on artificial intelligence models. And its performance is expected to be comparable to direct sensing. The rationale of virtual sensing is described in Fig. 1. The developed virtual sensing model in this work mainly consists of four modules: (i) a data acquisition system capable of measuring multi-sensory data from machining processes, (ii) a feature extraction module to extract tool condition indicators (CIs) by preprocessing raw noisy measurements, (iii) a feature fusion module to select and fuse the extracted features for dimension reduction, and (iv) a SVR based artificial intelligence model to infer tool wear conditions from the fused features. The developed virtual sensing model is a complement to physical sensing, and can be used for tool wear monitoring and maintenance actions guidance. The deduced virtual sensing parameters are compared to actual quantities of tool wear for performance comparison.

2.2. Bayesian framework

In tool condition prediction, tool wear condition is usually difficult to be observed unless it is measured offline by costly equipment (e.g. microscope, CCD camera, etc.). On the other hand, online sensing techniques, such as force, vibration and dynamic force, are readily measured in process. Such scenario can be well described using mathematical model in Bayesian framework [21] as follows.

The mechanical system can be represented by following state-space model:

$$x_k = f(x_{k-1}, u_{k-1}) \tag{1}$$

$$z_k = h(x_k, v_k) \tag{2}$$

where k is the time index, x_k is the tool wear state at time k, $f(\bullet)$ is the state transition function from state x_{k-1} to x_k considering order-one Markov process, u_{k-1} is an independent and identically distributed (*i.i.d.*) process noise at time k-1; z_k is the available measurement at time k, v_k is an *i.i.d.* measurement noise at time k, and $h(\bullet)$ is a possibly nonlinear measurement function representing the relation