Chapter 11
A Temporal Probabilistic Approach for Continuous Tool Condition Monitoring

Omid Geramifard
National University of Singapore, Singapore

Jian-Xin Xu
National University of Singapore, Singapore

Junhong Zhou
Singapore Institute of Manufacturing Technology, Singapore

ABSTRACT

In this chapter, a temporal probabilistic approach based on hidden semi-Markov model is proposed for continuous (real-valued) tool condition monitoring in machinery systems. As an illustrative example, tool wear prediction in CNC-milling machine is conducted using the proposed approach. Results indicate that the additional flexibility provided in the new approach compared to the existing hidden Markov model-based approach improves the performance. 482 features are extracted from 7 signals (three force signals, three vibration signals and acoustic emission) that are acquired for each experiment. After the feature extraction phase, Fisher’s discriminant ratio is applied to find the most discriminant features to construct the prediction model. The prediction results are provided for three different cases, i.e. cross-validation, diagnostics, and prognostics. The possibility of incorporating an asymmetric loss function in the proposed approach in order to reflect and consider the cost differences between an under- and over-estimation in tool condition monitoring is also explored and the simulation results are provided.

INTRODUCTION

Tool Condition monitoring (TCM) is a challenging task in industrial environments. TCM reduces the downtime of machinery for maintenance purposes (Jun-Hong, Chee Khiang, Lewis, & Zhao-Wei, 2009). Consequently, TCM reduces the maintenance cost while improving the performance of the machine. Furthermore, TCM increases the quality of the product.

The idea of Continuous TCM is to regularly assess the health status of the tool based on a continuous metric. In other words, instead of setting some thresholds and differentiating dis-
distinct health states as various (ordinal) classes, we would like to monitor the health status of the tool using a continuous measure. This task allows us to have a smoother decision maker system for the condition based maintenance. It also enables us to incorporate different quality thresholds for different applications using the same condition based maintenance system e.g. to satisfy and guarantee different qualities in various products.

Temporal probabilistic models can be identified as a group of probabilistic graphical models which can be unrolled over time. They take into account the dependencies among the states as well as observations over the time, and use the conditional independencies to make inferences (Neapolitan, 2003; Russell & Norvig, 2009). The essential motivations for applying these models to the tool condition monitoring are as follows. Firstly, the tool condition prediction based on the non-intrusively sensed information from the machines, is a task which is inherently uncertain and probabilistic (Rao, 1996). Secondly, there is temporal information lying in the sequentially sensed data which can be captured using temporal models. Last but not least, the output of these models is a probability distribution over states that can be directly used either to do the decision making or to find the expected value of the tool condition.

One of the simplest temporal probabilistic models, commonly used for discrete TCM, is called hidden Markov Model (HMM) (Atlas, Ostendorf, & Bernard, 2000; Zhu, Hong, & Wong, 2008). In (Geramifard, Xu, Zhou, & Li, 2010), a single HMM-based approach is used to do the continuous health assessment in a CNC-milling machine. However, one of the deficiencies of using the HMM is its fixed duration distribution (Geometric distribution). The duration distribution indicates the probability of staying in one state for different possible durations. Having a fixed duration distribution may lead to unsatisfactory prediction results in cases that the assumption of having a geometric duration distribution does not hold. In lots of real applications, the duration distribution is not geometric. Hence, to improve the prediction performance in TCM, a more complex temporal probabilistic model, namely, hidden semi-Markov model (HSMM) can be used to dissolve the aforementioned fixed duration distribution problem in the HMM-based approach.

In HSMM, the idea is to use temporal information in a more effective way than in HMM by keeping track of the duration of staying at each state (Yu, 2010). Both HMMs and HSMMs are previously used in (Atlas, et al., 2000; Dong & He, 2007; Zhu, et al., 2008) to recognize different fault types and states (discrete TCM). However, in the way these models are used, they do not provide any relation between the actual physical states and the hidden states in them. Contrary to the existing approaches based on HMM or HSMM, the HSMM-based approach introduced in this chapter provides an explicit relationship between the actual physical states and its hidden state values. Using the HSMM, the aforementioned deficiency of HMM-based approach is also remedied.

Another issue that we would like to address in this chapter is how to incorporate an asymmetric loss function into our approach, to consider the dramatic cost differences between an over- and an under-estimation of the tool condition. To this end, we can take the advantage of having flexible duration distributions in the HSMM and try to modify the overall skewness of the duration distributions based on a given asymmetric loss function and training dataset.

This chapter is organized as follows. In section II, HMM and its graphical concept used in tool condition monitoring are introduced. In section III, a single HSMM-based approach for continuous health assessment is proposed. Then a computationally efficient version of forward-backward algorithm for inference in the implemented HSMM as well as state estimation variables is given in section IV. Diagnosis and Prognosis procedures using