Applied Soft Computing 64 (2018) 454–467

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Tool condition prognostics using logistic regression with penalization and manifold regularization

Jianbo Yu

School of Mechanical Engineering, Tongji University, Shanghai, 201804, PR China

ARTICLE INFO

Article history:
Received 27 August 2015
Received in revised form 5 December 2017
Accepted 27 December 2017
Available online 28 December 2017

Keywords:
Tool condition prognostics
Remaining useful life
Logic regression
Penalization regularization
Manifold regularization

ABSTRACT

Appropriate and timely maintenance decision for tool health degradation (i.e., wear) is significantly required to prevent severe degradation in product processing quality. Multiple sensor signals (e.g., vibration, acoustic emission) collected from tools contain much valuable information about their health states. However, information fusion of multiple sensor signals for assessing and predicting the tool health presents a big challenge. In this paper, logistic probability (LP) generated by logistic regression with manifold regularization (LRMR) is used to serve as a comprehensible indication to assess tool health state. Prognostic features are selected firstly by logistic regression with penalization regularization (LRPR) to improve the performance of the proposed tool health prognostics system. Based on the health indication values (i.e., LPs) and tool ages, the LR model is further developed to online construct the interior relationship between the tool health state and its ages, and then predicts the remaining useful life (RUL) of tools subjected to condition monitoring. The proposed prognostics system provides an adaptive learning scheme for assessment and prediction of tool health, and hence is easier to use in real-world applications. The experimental results on a tool life test-bed illustrate the potential applications of the proposed system for tool health prognostics.

1. Introduction

Tool condition monitoring (TCM) is crucial to improve the quality of unmanned manufacturing systems where the tools are subjected to continuous wears. TCM aims to use tool health assessment and prediction techniques to identify and estimate the health state of the cutting tools, so as to reduce time and production loss brought about by tool wears or failures [1–3]. Basically, the tool wear procedure consists of several typical stages, i.e., an initial wear stage, a progressive wear stage, and a rapid wear stage. In the last stage, the presence of a large wear drastically increases the temperature and triggers some complicated changes in the tool, causing rapid deterioration (or breakages) [4]. Therefore, it is of prime importance to assess and predict accurately the health degradation (i.e., wear) of tools to prevent the sequent damages and to reduce the costly downtime.

Recently, some effective TCM systems have been developed and can be categorized mainly into two fundamental methods: direct and indirect methods [2,7,8]. Video-based and laser-based vision is often used for direct TCM [5,6]. But high cost and measurement inconsistency due to the big variation in illumination have prevented those direct methods from being performed widely in real-world applications. Although the direct methods could be more accurate than the indirect methods, some indirect methods that rely on changes in the signals of sensors associated with tool wears, are more commonly used for TCM. These measurement signals are often from cutting force [7], machine vibration [8], motor current [8], acoustic emission (AE) [9], or various combinations of these signals [10]. Thus, various methods such as support vector machine (SVM) [10], artificial neural network (ANN) [11], hidden Markov model (HMM) [12], adaptive Gaussian mixture model (AGMM) [13], time-frequency analysis [1,14], etc., using these sensor signals, have been developed for TCM.

However, recent attempts in designing TCM systems did not consider multiple sensor fusion techniques [4,15], since single particular sensor could not work well in quantifying the tendency of the tool health degradation. As for example, use of AE signal has been reported as not being that helpful for cutting processes [16,17]. Multiple sensor fusion [15,18] at various system levels is known to provide more accurate estimation of tool health (i.e., wear) than those methods using single sensor. Various sensor

E-mail address: jbyu@tongji.edu.cn

https://doi.org/10.1016/j.asoc.2017.12.042
1568-4946/

fusions, e.g., fusion of force and AE signals [19], fusion of force and vibration signals [10], fusion of force, vibration and sound signal [20] have been attempted and obtain some successes in some cases. These multi-sensor signals have been used as inputs of those machine learners, (e.g., ANN, SVM, GMM) to implement tool health prognostics [10,11,13]. Therefore, the study has occurred that efforts in future centers on fusing the most valuable information from the multiple sensor signals.

Mainly, the degrading behavior of aging component or system is reflected by those original features derived from various sensor signals. The features (or variables) affect the performance of the diagnosis and prognostics system significantly [21–24]. Thus, it is important to evaluate these original features by those appropriate methods to detect the degradation and then to predict the remaining life of tool. We aim to select those features with monotonic trends that properly correlate to degradation phenomenon and may lead to simple and accurate prognostics systems. Zhou et al. [22] proposed a method for diagnosis and prognosis of tool wears, where a time series prediction method based on the selected prognostic features was applied to estimate the tool wears. Yu [23] proposed a contribution analysis method to select the prognostic features to improve the effectiveness of machine health assessment system. Actually, it is still sparse for studying of prognostic feature selection in the construction procedure of TCM systems.

In recent years, health prognostics techniques that aim to realize near-zero downtime, maximum productivity and proactive maintenance, have received more and more attentions [25–27]. The research emphasis in this studying field has been centered on system (or machine) health assessment and prediction, so the final failure can be predicted and prevented. HMM-based prognostics system was developed to track and predict the evolution of health-states and remaining useful life (RUL) of cutting tools [11]. Lee et al. [28] proposed a modified HMM for online degradation assessment and adaptive fault detection of multiple failure modes in tools. Yu [12] proposed an AGMM for online monitoring of tool health. However, these proposed models generally do not consider the intelligibility of the proposed health indication (HI) to improve their effectiveness significantly. Logistic regression (LR) has shown its power in assessment of machine health because its logic curve (e.g., S-curve) is similar to the procedure of machine health degradation [29]. However, LR in applications of tool health prognostics (e.g., prognostic feature selection, health degradation assessment and prediction) is still worth studying.

Driving by the desire of improved production quality and near-zero breakdown productivity, we develop a novel prognostics system to implement on-line tool health assessment and prediction. In this system, LR with penalization regularization (LRPR) is developed to select prognostic features, and LR with manifold regularization (LRMR) is further proposed for tool health assessment and prediction online. Logistic probability (LP) derived from the baseline LR constructed by LRMR is developed to provide an HI based on failure risk probability once the tool is in degraded state. Based on LPs on time series flow, LR is constructed online to perform RUL prediction of tools. With the health assessment and RUL prediction, users will know clearly the tool health states, and then take correct and timely maintenance measurements to recover the tool health. Thus, the proposed prognostics system provides an effective methodology of enhancing the assessment and prediction of tool health: (1) A new LRPR-based prognostic feature selection method is developed for improving the prognostics performance of the proposed method, which is rarely considered in most tool prognostics methods; (2) A probability-based HI is developed to quantify tool health state, which provides some unique features, e.g., consistent range (0–1), very few false alarms, and quick calculation, to enable it to possess high applicability in real-world cases; (3) An LRMR-based model is developed to predict tool health state, which is capable of estimating the failure time point of the tool with high accuracy and calculation efficiency. A tool life test on a test-bed was implemented to collect multiple sensor data over the whole life time of tools. Experimental results validate the feasibility and validity of the proposed system for tool health prognostics.

The rest of the paper is organized as follows. Section 2 proposes a tool health prognostics system based on LRPR and LRMR. A real-world milling case is used to verify the effectiveness of the proposed prognostics system in Section 3. Conclusions are given in Section 4.

2. Methodology

This section proposes a tool health prognostics system (see Fig. 1), which includes two key parts, i.e., off-line system modeling and on-line tool health prognostics. We need to collect historic data to select the prognostic features by using LRPR and to construct a baseline LR by using LRMR for tool health assessment, and then to use LR with online learning scheme to implement tool RUL prediction. The proposed prognostics system consists of two parts, i.e., off-line modeling and on-line health prognostics. In the offline modeling phase, the data collected from the historic tools are used to construct the baseline LR, where the original feature generation and LRPR-based feature selection are firstly implemented. In the online health prognostics phase, LR-based LP is developed to quantify tool health degradation. Then, an LR with LRMR algorithm is established for modeling the dynamic propagation of the tool

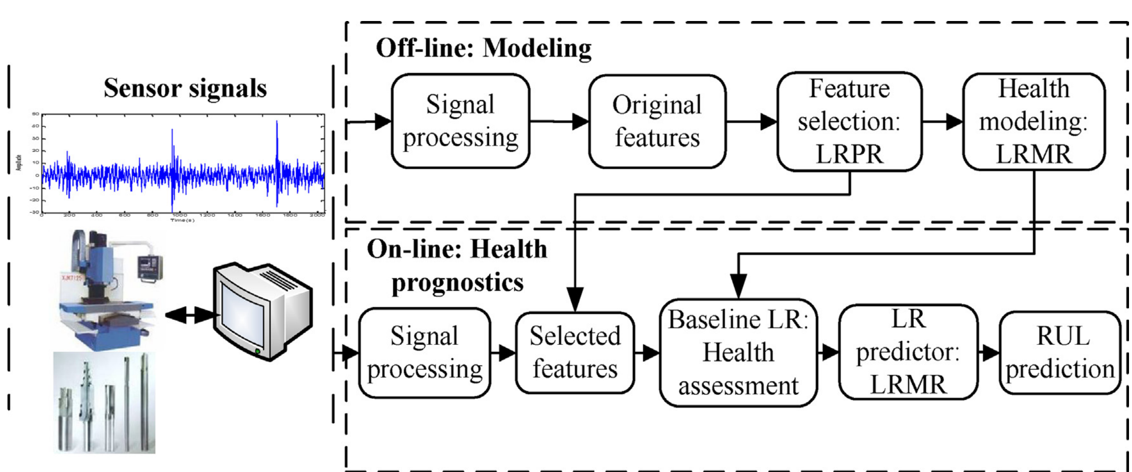

Fig. 1. System framework for tool health prognostics.