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# Adaptive hidden Markov model-based online learning framework for bearing faulty detection and performance degradation monitoring

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ABSTRACT

This study proposes an adaptive-learning-based method for machine faulty detection and health degradation monitoring. The kernel of the proposed method is an “evolving” model that uses an unsupervised online learning scheme, in which an adaptive hidden Markov model (AHMM) is used for online learning the dynamic health changes of machines in their full life. A statistical index is developed for recognizing the new health states in the machines. Those new health states are then described online by adding of new hidden states in AHMM. Furthermore, the health degradations in machines are quantified online by an AHMM-based health index (HI) that measures the similarity between two density distributions that describe the historic and current health states, respectively. When necessary, the proposed method characterizes the distinct operating modes of the machine and can learn online both abrupt as well as gradual health changes. Our method overcomes some drawbacks of the HIs (e.g., relatively low comprehensibility and applicability) based on fixed monitoring models constructed in the offline phase. Results from its application in a bearing life test reveal that the proposed method is effective in online detection and adaptive assessment of machine health degradation. This study provides a useful guide for developing a condition-based maintenance (CBM) system that uses an online learning method without considerable human intervention.



## 1. Introduction

Degradation and failure of machines and systems occur in many settings every day, which lead to considerable added cost, wasted time, and security problems for both company employees and customers. Condition-based maintenance (CBM), which implements preventive maintenance actions based on sensor information, is crucial to the efficient operation of machine running procedures that are subject to continuous health degradation. The primary goal of CBM is to use suitable sensor signals and monitoring techniques to identify and predict the health states of machines in order to reduce economic loss as a result of degradation or failure [1–7].

In recent years, CBM-based health degradation detection, assessment, and prediction in machines have received increased attention. However, conducting a health degradation assessment model is more difficult than conducting a fault diagnosis model [6]. Some machine degradation assessment approaches have been proposed recently. Huang et al. [7] developed a self-organize-mapping (SOM)-based minimum quantifying error (MQE) and back-propagation network (BPN)-

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based model for residual life prediction of bearings. Camci et al. [8] proposed a hidden Markov model (HMM)-based machine health state estimation and prognostics system, in which the health estimation and residual life prediction of machine tools were realized. Yu [9] proposed a manifold learning algorithm, known as a local and nonlocal preservation projection (LNPP)-based method for faulty detection and health assessment of bearings. The results show that LNPP performs better at feature extraction than do other feature extraction methods. Yu [10] developed a generative topographic mapping (GTM)-based machine health assessment model, in which a contribution analysis method was employed to conduct prognostic feature selection. He [11] proposed a time–frequency manifold-based nonlinear feature extraction method for machinery fault diagnosis. Liao and Lee [12] proposed a genetic programming-based feature selection method for bearing health assessment and prediction. Golafshan and Sanliturk [13] proposed a singular value decomposition (SVD) and Hankel matrix based de-noising method for bearing fault detection and assessment. He et al. [14] developed a wavelet filter for early detection of faults occurring in fan bearings and to assess their fault severity. Zhou et al. [15] used neighborhood component analysis and coupled HMM (CHMM) for bearing fault recognition. However, in machine running processes, the operation condition drift and/or shift often happens as a result of the following: different locations of sensors, preventive and corrective maintenance, and running condition changes of machines. These dynamic operation conditions often generate healthy data to present complicated distributions (e.g., multimodal or nonlinear distribution), which represents a major challenge for machine learning models to describe these distributions. Furthermore, these health monitoring models will be fixed once they are constructed offline, which could prevent them from being adapted to the dynamic and complicated changes of machine health online. Recently, HMM-based faulty detection and recognition models were developed for CBM [16–19]. However, these HMM-based monitoring models did not consider online learning schemes for machine health changes to improve their industrial applicability.

More recently, some health monitoring models that employ adaptive learning schemes have been proposed for online monitoring of machine health. An adaptive learning-based framework using principal component analysis (PCA) and a clustering method was proposed for autonomous monitoring of industrial equipment based on novelty detection [5]. Ni et al. [20] proposed an adaptive approach based on kernel PCA (KPCA) and support vector machine (SVM) for real-time fault diagnosis of high-voltage circuit breakers (HVCBs). An adaptive Gaussian mixture model (AGMM)-based Kullback–Leibler (KL) divergence was used for online quantifying the health states of machine tools [21]. Lee et al. [22] developed an online degradation assessment and adaptive fault detection model based on a modified HMM. Cartella et al. [23] proposed a methodology based on online adaptive learning of left–right continuous HMM combined with the change point detection algorithm to recognize unknown health states and perform fault diagnosis of machines. Although these adaptive learning-based machine monitoring methods have been investigated recently, several important issues must be further resolved. The first is to improve the comprehensibility of the health index (HI) based on the physical means and certain range (e.g., 0–1), which are important to improve HI's industrial applicability. The second concern is that adaptive learning models should be capable of learning both abrupt and gradual health changes in machines online. The third issue is that the monitoring model should be capable to detect and quantify unknown (new) health states of machines over a time series flow.

Based on our desire to improve machine uptime and reduce human intervention, an adaptive learning-based CBM system is developed to online quantify the machine health state as well as to recognize the emergence of unknown health degradations at an early stage. An adaptive HMM (AHMM) that includes updating of model parameters, merge/split of Gaussian components, and add of hidden states is developed to learn online the dynamic health degradations, including gradual and abrupt changes. Once the proposed CBM system is running online, AHMM will adaptively learn machine health changes. A statistical indication extracted from the AHMM is further used to detect abrupt changes of machine health. An HI based on similarity between two Gaussian components from the AHMM is further proposed to online quantify machine health states. The monitoring system accounts for lack of knowledge of structural and dynamic properties of the machine and its failure modes, reduces the need for extensive data, and recognizes that information is limited. In addition, it reduces human intervention and ensures low tolerance for false alarms. The proposed monitoring system is also novel in its attempt to detect faults and quantify the health degradation of machines based on its support of online learning and its adaptation to different complicated running conditions. Thus, the major contributions and innovations of this study include:

(1) A new AHMM with parameter and structure updating is developed for online learning of machine health states. In comparison with other adaptive HMM algorithms [22–27], which generally consider only parameter updating or structure updating, AHMM is capable of online learning both gradual and abrupt changes of machine health.
(2) A health change detection method is proposed to recognize those abrupt health changes, and the adaptive learning scheme (by adding hidden states in AHMM) is provided to respond to these health state changes quickly and effectively.
(3) A new HI based on a similarity measurement is developed to quantify machine health states, which provides some unique features (e.g., consistent range (0–1), minimal false alarms, and quick calculation) to endow it with high applicability in real-world cases.
(4) A whole fault detection and health monitoring system is developed, which includes three monitoring charts (i.e., the Mahalanobis distance (MD) chart, hidden state chart, and HI chart) to online quantify machine health states, and then provides important health information to users to perform necessary maintenance.

Experimental results on a bearing life test-bed illustrate that the proposed CBM system is effective at adaptive faulty detection and health monitoring of machines.