Online Milling Tool Wear Monitoring Based on Continuous Hidden Markov Models

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Abstract. The health status evolving from normal to broken condition of wear tool are needed as an object of assessment in condition-based maintenance (CBM). This paper proposes a continuous Hidden Markov Models (CHMM) to assess the status of the wear tool online based on the normal dataset in the same case. A wavelet-packets technology is used to feature extraction and the CHMM is trained by Baum-Welch algorithm. Finally, we compute the log-likelihood based on the trained CHMM for abnormal detection and health assessment in real time during the milling process. Case study on the tool state estimation demonstrates the effectiveness and potential of this methodology.

1. Introduction

Tool wearing is getting more consideration in modern mechanical manufacturing systems such as milling process for the purpose of quality control. Tool wear is defined as the change of shape of the tool from its original shape during its working process and results from the gradual loss of the tool material. However, measuring the physical degradation variant such as flank wear, is not flexible and limited by the manufacturing equipment structures. It is hard to implement in the manufacturing process. Thus, the method focuses on the features extracted from the vibration signal or others and recognizing the dynamic undergoing health status by several data-driven models [1]. Among these models, Hidden Markov Models have been successfully applied to condition monitoring of manufacturing machines [2]. The common usage often follows three steps: first determine the degradation levels (i.e. good, partially worn, seriously worn, broken) through the all running cycle. Second, construct a HMM which fit the degradation pattern and train the models. Third, select the HMM that, on new incoming data, give the highest likelihood to get the actual level [3]. Rabiner proposed another methodology which trains a single HMM by using the sensor measurements corresponding to the entire lifetime of the system, maps each degradation phase to each state of HMM and obtain the condition assessment by calculating the Viterbi path on new incoming data [4].

This paper presents an online condition monitoring methodology of a milling process to determine the health status of the wearing tool based on Hidden Markov Model (HMM). The approach uses a continuous HMM to model one cutting pass and trains it by the data sampled under a normal status of the working tool. The condition monitoring is performed by inputting a new observation sequence into the trained model and calculating the log-likelihood value which specifies the current health status from the normal one.

2. Methodology

2.1. Continuous HMM

HMM is a popular tool in sequential data analysis and involves double-layer stochastic processes: the stochastic transition between one state to another state and the stochastic output symbol generated at each state. All the hidden states comprise a Markov chain by a set of transition probability between

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two states and the observation is assumed to be draw from the state chain by the observation probability named emission probability. Thus, the actual sequence of states is hidden and not directly observable while the observation sequence gives the evidence to infer and determine the actual sequence of the states [5]. The complete specification of an HMM consists of the following elements:

1) a set of hidden states $S=\{S_1,S_2\cdots S_N\}$ and initial state probability distribution:

$$\pi=\{\pi_1,\pi_2\cdots\pi_N\} \tag{1}$$

2) transition probability distribution $A=\{a_{ij}\}$:

$$a_{ij}=P\left(S_{t+1}=j\middle|S_t=i\right) \tag{2}$$

3) observation sequence $O=\{O_1,O_2\cdots O_N\}$, which defines the individual observation.

4) emission probability distribution $B=\{b_j(k)\}$:

$$b_j\left(k\right)=P\left(O_t\middle|q_t=S_j\right) \tag{3}$$

which defines the distribution in state S_j and O_t is the observation at time *t*.

An HMM can be represented by the following compact notation to describe the complete parameter set of the model:

$$\lambda=\{A,B,\pi\} \tag{4}$$

There are many structures such as ergodic HMM, left-right HMM, to adapt to the specific problem. From a physical point of view, we choose the left–right HMM to describe the milling process and set the HMM with three states: entry, in-progress, and exit [6, 7].

In our case, the observation features extracted from the signals are continuous and the structure of HMM is designed for modeling the cutting process. Gaussian mixtures (GM) are typically used in continuous HMM (CHMM) to model the feature vectors which correspond to a state due to its variability and accuracy. The observation $\{O_i\}$ is modeled as GMM as:

$$O_i=\sum_{j=1}^{K}c_{ij}N\left(\mu_{ij},\Sigma_{ij}\right) \tag{5}$$

where K is the number of Gaussians, μ_{ij} and Σ_{ij} are the mean and covariance matrix of each density function, the weights c_{ij} are all positive and sum to one. The number of mixture components controls the accuracy of the emission matrix *B*, and in turn influences the model. The Bayesian information criterion (BIC) helps to determine the number based on the observations. However the selection of this number should take the computation and efficiency in consideration.

2.2. The HMM algorithms

There are three main problems in implementing the HMM applications. But the issues we have to solve concerning the condition monitoring of tool wear are:

1) the estimation of the model $\lambda=\{A,B,\pi\}$ to maximize $P\left(O\middle|\lambda\right)$, given the observation sequence $O=\{O_1,O_2\cdots O_T\}$.

2) the evaluation of the probability of observation sequence $P(O|\lambda)$, given the observation sequence $O=\{O_1,O_2\cdots O_T\}$ and the model parameters $\lambda=\{A,B,\pi\}$.

The following two basic algorithms are proposed to solve the corresponding problems: the Baum-Welch algorithm and Forward-backward algorithm. The former solves the problem of HMM training. This algorithm makes use of the observation sequence O and adjusts the model parameters to maximize the probability $P(O|\lambda)$, given an initialization of the model. And the latter efficiently computes $P(O|\lambda)$, given a trained model $\lambda=\{A,B,\pi\}$ and input observation $O=\{O_1,O_2\cdots O_T\}$.

3. Case study

Since the CHMM has the capability in modeling the dynamic character of the sequence, we train a single CHMM using the observations sampled in the normal pattern of the wearing tool, and then send the observation sequence under a unknown wearing status into this normal-trained CHMM to compute the log-likelihood probability. We use a mill data set to test this condition monitoring methodology under one working condition and suppose the speed run at 200m/min; the depth of cut is 1.5mm; the feed is taken at 0.5mm/rev, and the material is chosen as cast iron. There are 17 runs in this case and 9000 samples in each cut.

3.1. Feature Extraction

Signal preprocessing is then performed to extract the features. We choose a vibration signal collected by an accelerometer in one cut pass and extract the features in frequency domain. In order to filter the noise, a wavelet-packet method is used to decompose the vibration signal into 3 levels and obtain a vector consist of the energy information in each frequency bands because different frequency bands have been proven to represent the effect of the force on different wear level.

3.2. Construction of CHMM

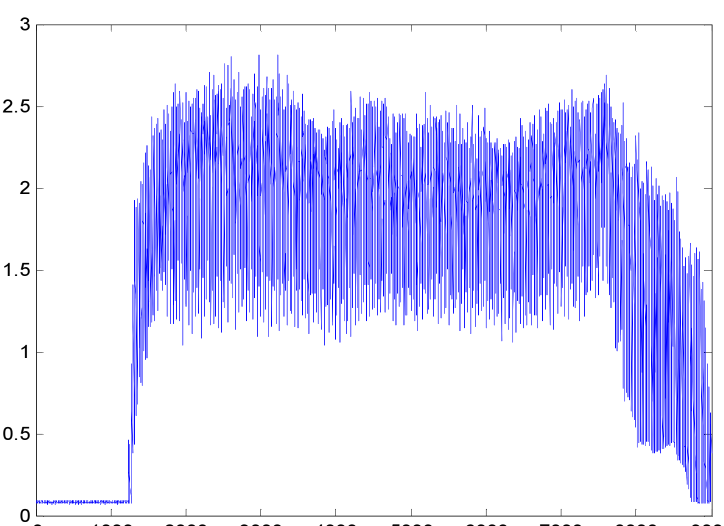

Figure 1. The vibration signal in one cutting pass.

Fig. 1 shows the vibration signal through one cutting pass. In order to model this time series, we choose a left-right CHMM and set the number of the hidden states as 3 to model the cutting pass with three states: entry, in-progress, and exit. A 3-state left–right HMM is shown in Fig. 2. This transition matrix and the initial state of the left–right HMM are initialized as:

$$A = \begin{bmatrix} a_{11} & a_{12} & 0 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} and\ \pi = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \tag{6}$$

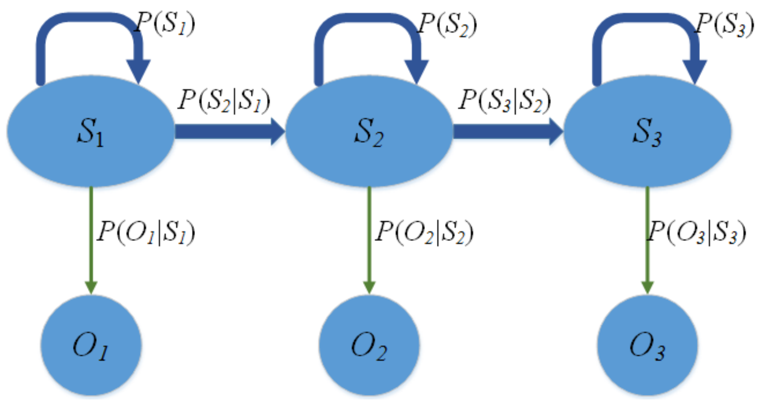

Figure 2. Left–right HMM tool state model.

We suppose this online condition monitoring methodology implements in the situation where the data are hard or expense to acquire. The data from the first three run pass at the beginning are extracted to the feature vectors using wavelet-packets as the ‘normal’ dataset. The emission probability distribution can be estimated by the GMM and *k*-means algorithm based on the training features. The CHMM is trained by the Baum-Welch algorithm.

3.3. Online condition monitoring

Once the CHMM is trained, we can use this model to assess the health status of the wear tool through the life time. The health status is defined based on the log-likelihood between the normal condition and the wear condition:

$$\log - likelihood = \log P\left(O_1 O_2 \cdots O_t \,|\, \lambda\right) \tag{7}$$

where λ is the ‘normal’ model. This value can be calculated by the forward-backward algorithm quickly. So input the feature sequence $\left\{O_1 O_2 \cdots O_T\right\}$ extracted from the data acquired under an unknown condition to the CHMM and compute the corresponding log-likelihood value which represents the current health status.

3.4. Experimental results

The flank wear VB is measured as the distance from the cutting edge to the end of the abrasive wear on the flank face of the tool. All the measurements of VB in this experiment is displayed in Fig. 3. Fig.4 shows the each log-likelihood value in every cutting pass through the whole life time of the wearing tool. The experiment result shows that as the frank wear VB increases, the log-likelihood value decreases over the whole life time of the tool. This means the health status of the wearing tool is getting far from the ‘normal’ one.

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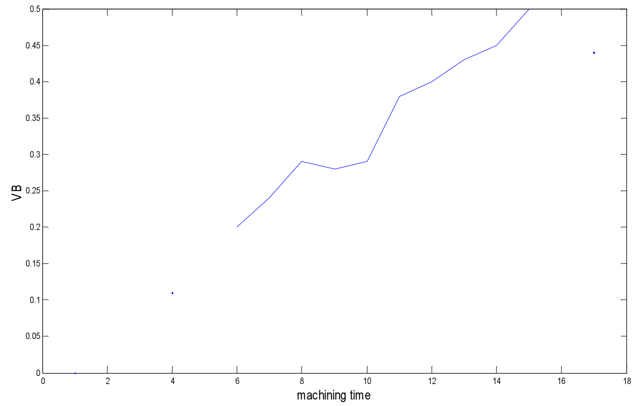

Figure 3. Tool wear VB over time.

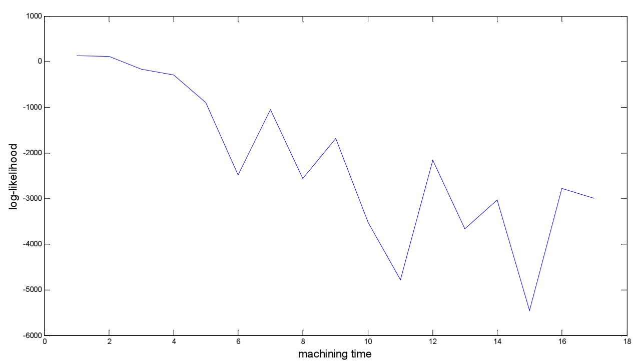

Figure 4. The log-likelihood over time.

4. Conclusion and future work

In this paper an online condition monitoring methodology base on CHMM for assessing the unknown health status of the wear tool is presented. In the CHMM, the data from the normal status is used to train the model instead of the historical data and the new observation sampled under the same case is sent into the model. The output of CHMM, log-likelihood, is regarded as the index to quantize the current health status compared with the normal status. However, this model is still need to improve to robustness and a failure threshold may be necessary.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (Grant Nos. 61074083, 50705005 and 51105019), as well as the Technology Foundation Program of National Defense (Grant No. Z132010B004).

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