Hierarchical Dirichlet process hidden semi-Markov model-based method for tool wear estimation

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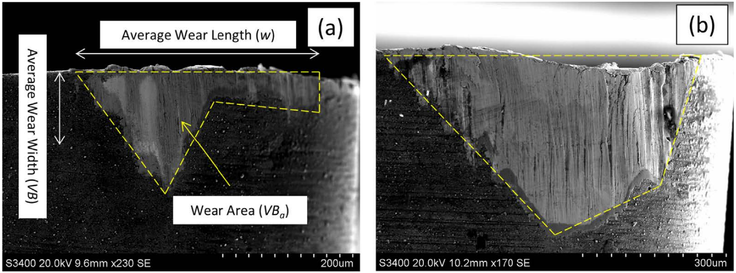
Outline

Problem Definition

Ti-6Al-4V alloys have been used widely in the aerospace, chemical and petroleum industry. However, the machinability of Ti alloys is characterised by **extremely rapid tool wear** and **short tool life** due to the high cutting temperature and the strong adhesion at the tool-chip and tool-workpiece interface.



Tool condition monitoring

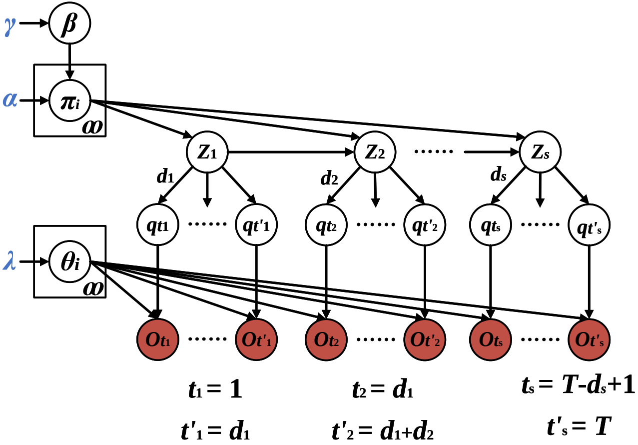
Monitoring the cutting tool performance during high speed milling of Ti-6Al-4V alloy is a critical factor since titanium alloy is a typically difficult-to-cut material, besides the quality of the end-product and productivity rate are highly dependent on the functional state of the tool.

Key Contributions

A flexible tool wear state recognition method based on HDP-HSMM that

- **provides** a powerful framework for inferring arbitrarily state complexity from data.
- **does not restrict** tool wear state duration distribution to a exponential form.
- **achieves** higher prediction accuracy than other published methods and promising results in detecting the severe wear state.

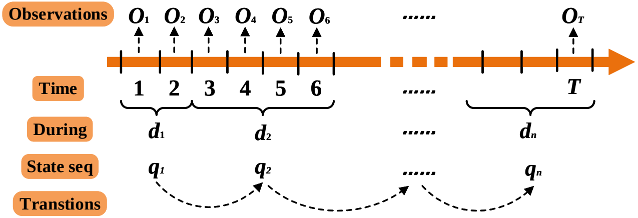
HDP-HSMM Archircture



HDP-HSMM based method consists of two steps:

State duration distribution and Observation distribution are constructed in a Hierarchical Dirichlet Process first, then weak-limit approximate sampler is used during sampling inference to get all parameters.

HSMM: $\boldsymbol{\theta = (\pi, A, B, D)}$

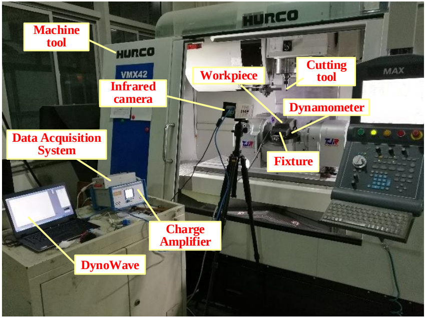


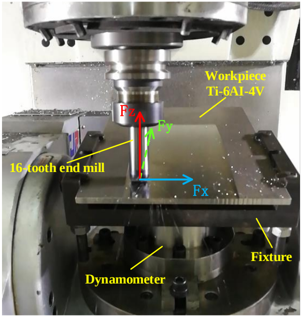
Parameters of HSMM:

1. State Assuming the set of all the possible tool wear states is S$=[1, 2, q_n]$.
2. Initial state probability vector $\pi = [\pi_i]$ π_i represents the probability of being in state q_i at time $t = 1$ and satisfies $\sum_{i=1}^{n} \pi_i = 1$.
3. State transition probability matrix $A = [a_{ij}]$ a_{ij} represents the probability of transition from state q_i at time t to state q_j at time $t + 1$ and satisfies $\sum_{j=1}^{n} a_{ij} = 1$.
4. Observation distribution $B = [b_i(O_t)]$ The observed variable O_t at time t conditioned on the hidden state q_t is defined as observation distributions.
5. State duration distribution $D = p_j(d)$ The observed variable O_t at time t conditioned on the hidden state q_t is defined as observation distributions.

Overview

The experimental setup & Direction indicators of three cutting force components





The machining parameters

Cutting speed (m/min)	Feed (mm/z)	Cutting depth (mm)	Cutting width (mm)
75	0.08	0.3	1.6

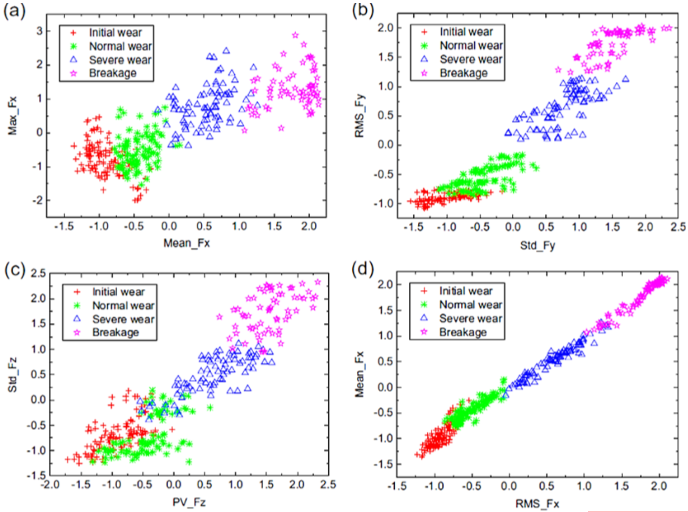
Categories of tool wear state

Tool wear state	Initial wear	Normal wear	Severe wear	Breakage
VB (mm)	0.1~0.2	0.2~0.25	0.25~0.3	>0.3
classification	1	2	3	4

Feature extraction

Type	Signal features	Mathematical expression
Time domain		
Mean	Mean-F_x, Mean-F_y, Mean-F_z	$\mu = E(\lvert x_i \rvert)$
Root mean square (RMS)	RMS-F_x, RMS-F_y, RMS-F_z	$x_{RMS} = \{E(x_i^2)\}^{1/2}$
Standard deviation (Std)	Std-F_x, Std-F_y, Std-F_z	$x_{Std} = \{E[(\lvert x_i \rvert - \mu)^2]\}^{1/2}$
Maximum (max)	Max-temp	$x_{Max} = max(\lvert x_i \rvert)$
Time-frequency domain (6-layer wavelet decomposition)		
Energy ratio mean (ERM) (625~1250Hz)	ERM-F_x, ERM-F_y, ERM-F_z	$x_{ERM} = E(x_i^2)/sum(x_i^2)$
Kurtosis mean (KM) (1250~2500Hz)	KM-F_x, KM-F_y, KM-F_z,	$x_{KM} = E[((x_i - E(x_i))/(Std(x_i))^2)^4]-3$

Space distributions of these normalized features(mainly)



1. It is obvious that the normalized features take on a certain degree of clustering propertity.
2. There are altogether 16 signal features constitute the feature vector(without dimension reduction) which further makes up the observed sequence.

Identifying the flank wear profile

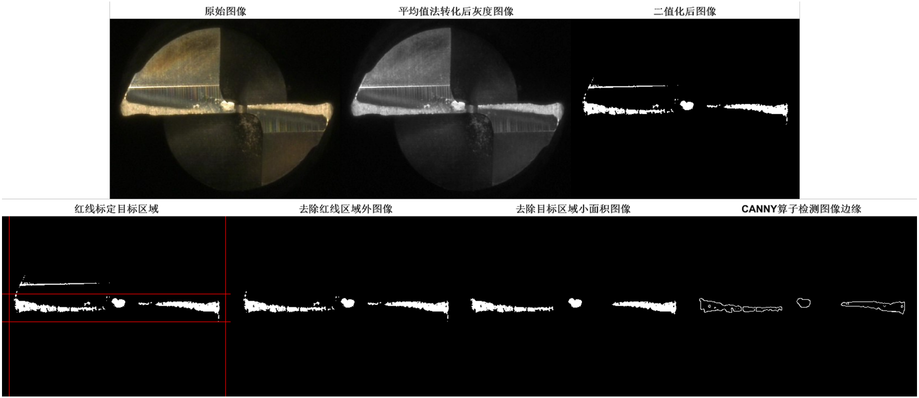
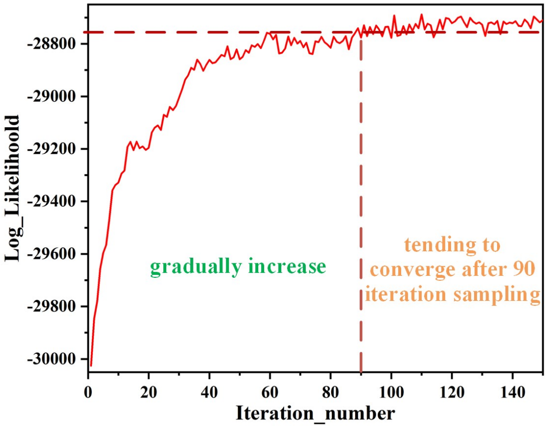


Image processing flow

- image collection(pictured by KEYENCE VHX-600)
- grayscale processing(grey-scale average method)
- binarization processing(set a threshold)
- extracting target zones(area,perimeter,horizontal length & vertical width,major axis & minor axis)

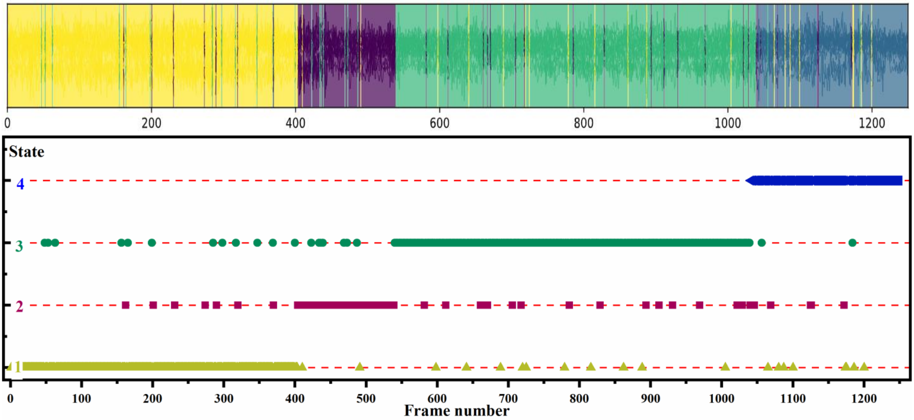
Training curve: Log_Likelihood vs iteration number



HDP-HSMM can learn and converge quickly

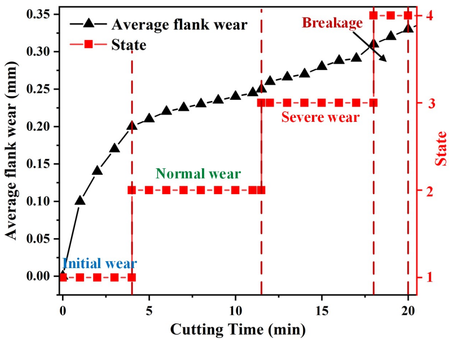
The convergence of the EM algorithm for HSMM requires only 90 iterations and the total training time is $3.56s$ ($2.848ms$ per sample point).

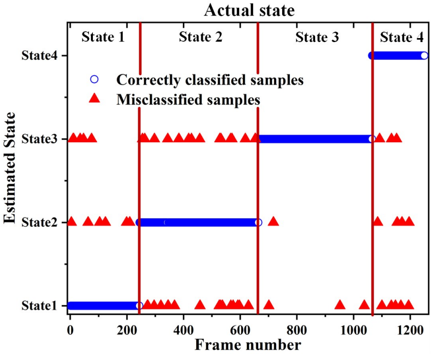
Training results



- **The deeper the color, the higher the number, the more serious wear state the tool in.**
- **Although there are some abnormal state changes in sequence(1250 samples), the overall state classification is still very obvious.**

Testing dataset visualization & Testing results

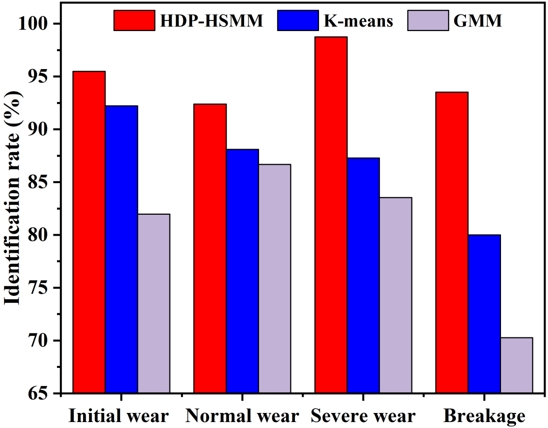




Summary

- The average prediction accuracy for four kinds of tool wear state in testing samples reaches up to 95%.
- The misclassified points gathering partly in the transitions between consecutive states.
- However,error rate on severe state (namely state 3) samples is relatively low.

Comparsion results



Method	Initial wear	Normal wear	Severe wear	Breakage	Avg.
HDP-HSMM	0.954	0.924	0.988	0.935	0.95
K-means	0.922	0.881	0.873	0.804	0.87
GMM	0.820	0.867	0.835	0.703	0.806

Conclusion

Hindsight is Clearer than Foresight

This paper presents a new tool wear monitoring system based on the Hierarchical Dirichlet process hidden semi-Markov model (HDP-HSMM)

- The experimental results reveal that the prediction accuracy of HDP-HSMM model under the Poisson distribution with a conjugate Gamma prior reaches 95% in testing dataset.
- Comparison results reveal that the proposed method has relatively higher identification rate than K-means and GMM in different tool wear state, especially in the severe state.
- Besides, the model structure of HDP-HSMM needs fewer pre-determined parameters, which greatly reduce the time cost for practical application in industrial environment.

Further work

1. generalization capability on other machining parameters should be investigated.
2. Workpiece surface texture & Spindle current(power) are important features in describing a maching process model.
3. Surface integrity, Chip conditions, &Chatter detection are interesting fields.

Questions

THANK YOU

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