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

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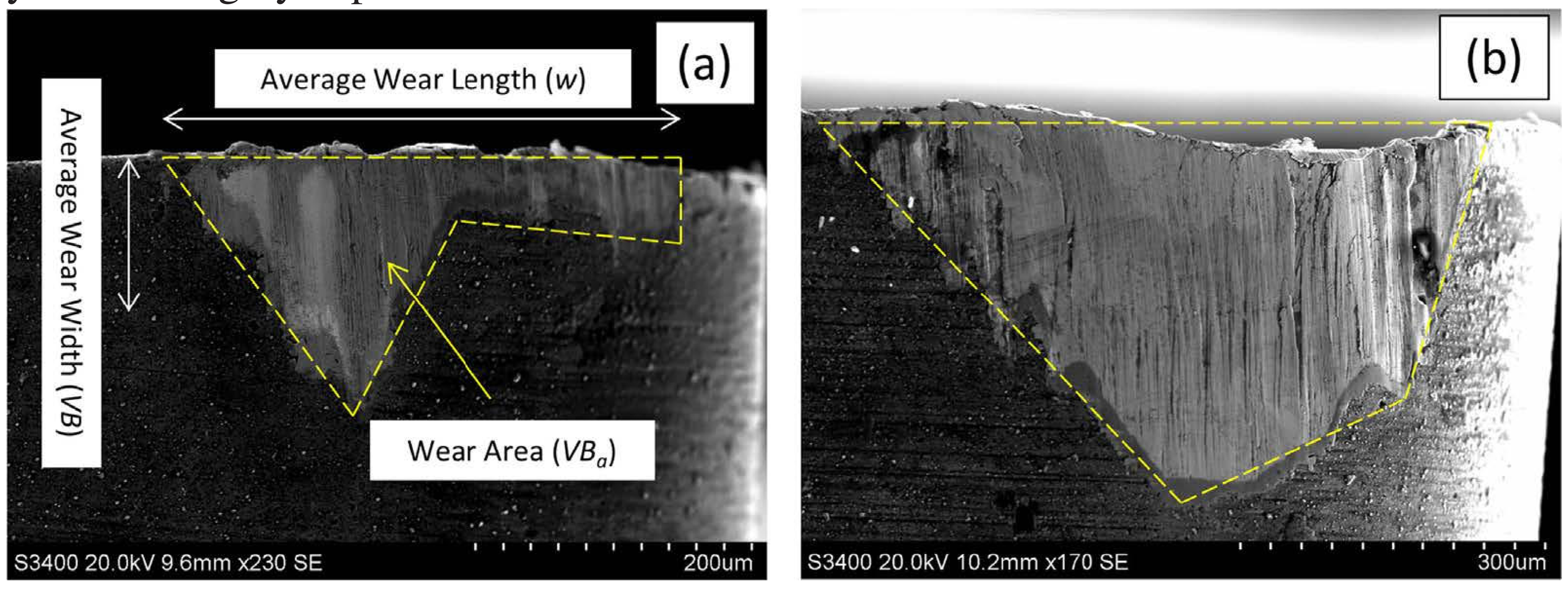
Problem Definition and Contribution

Goal: 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.

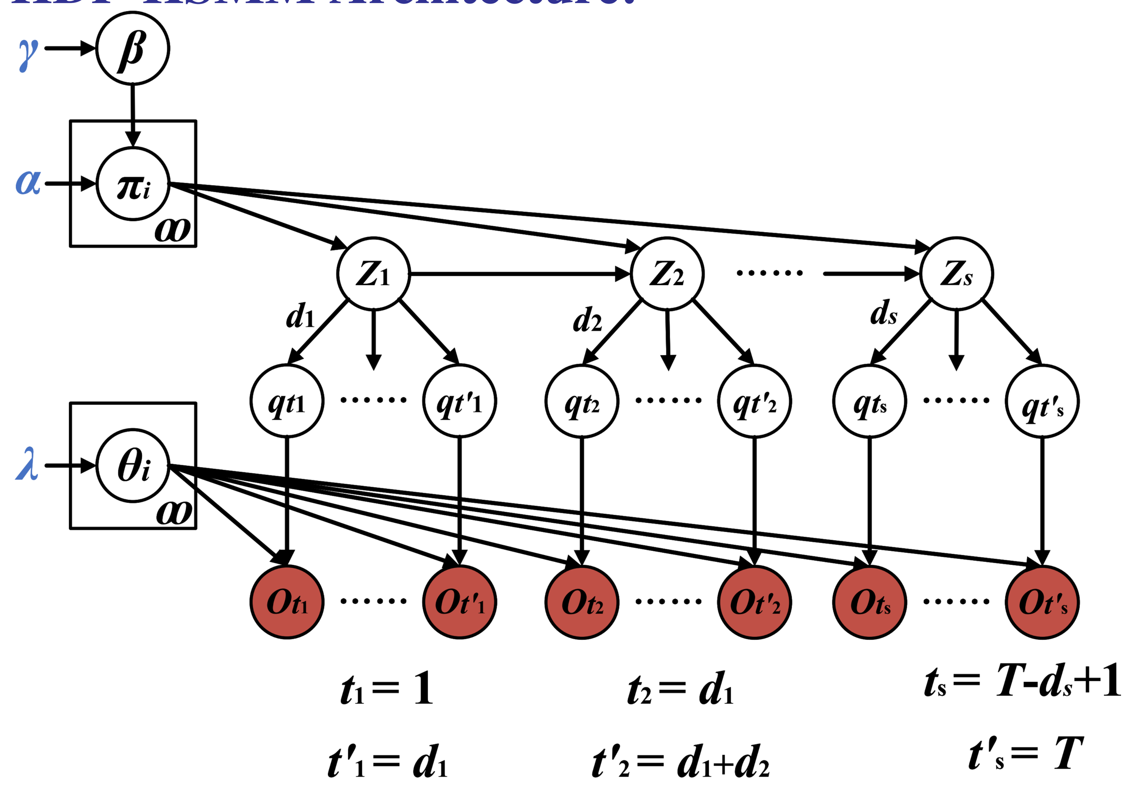


Key Contributions: A flexible tool wear state recognition method based on HDP-HSMM that

- provides a powerful framework for inferring arbitrarily large state complexity from data.
- does not restrict state duration distributions to a geometric form.
- presents an efficient sampling inference method: weak-limit approximate sampler.
- achieves higher prediction accuracy than other published methods and promising results in detecting the severe wear state.

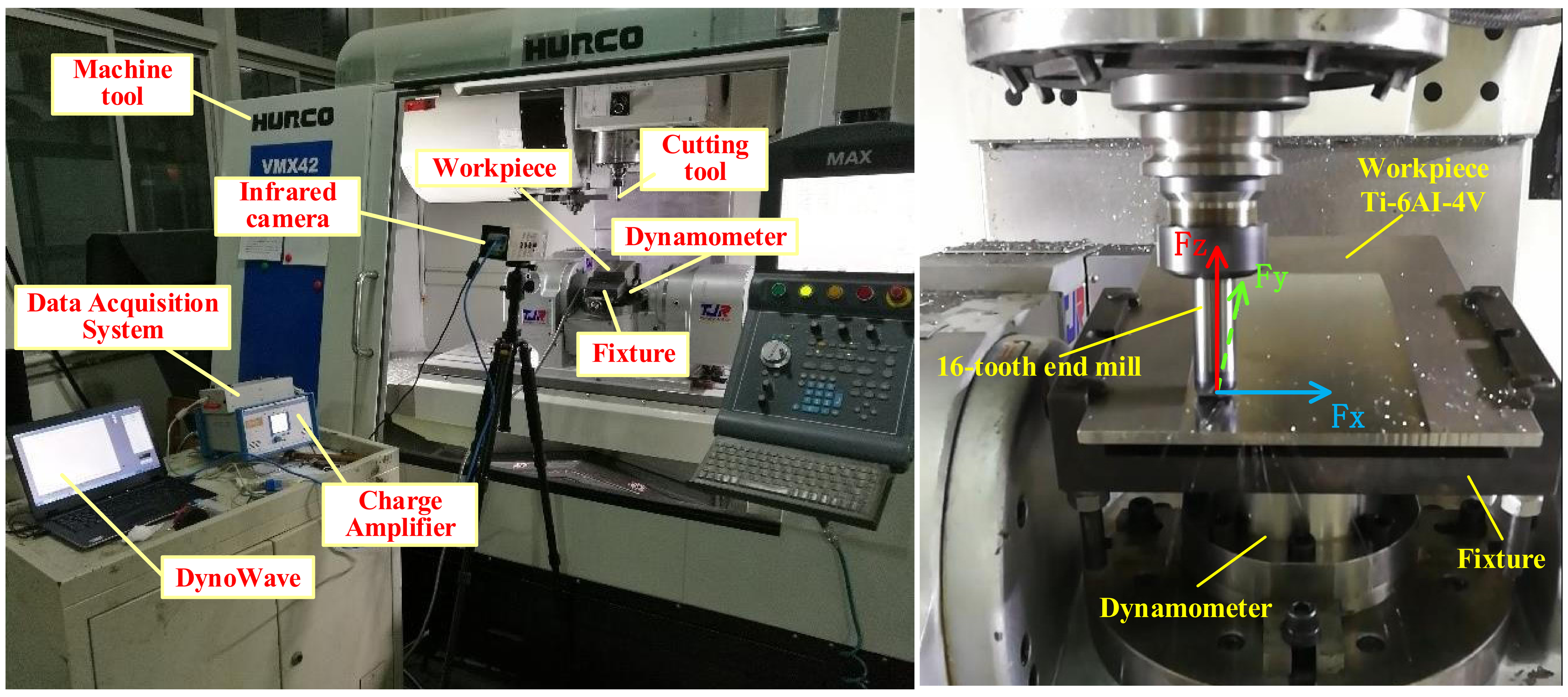
Method

HDP-HSMM Architecture:



- HDP-HSMM based method consists of two steps: HSMM parameters are sampled in a Dirichlet process[1] first, then the Gibbs sampling algorithm[2] is used during sampling loop to get all potential variables.

Experiment setup



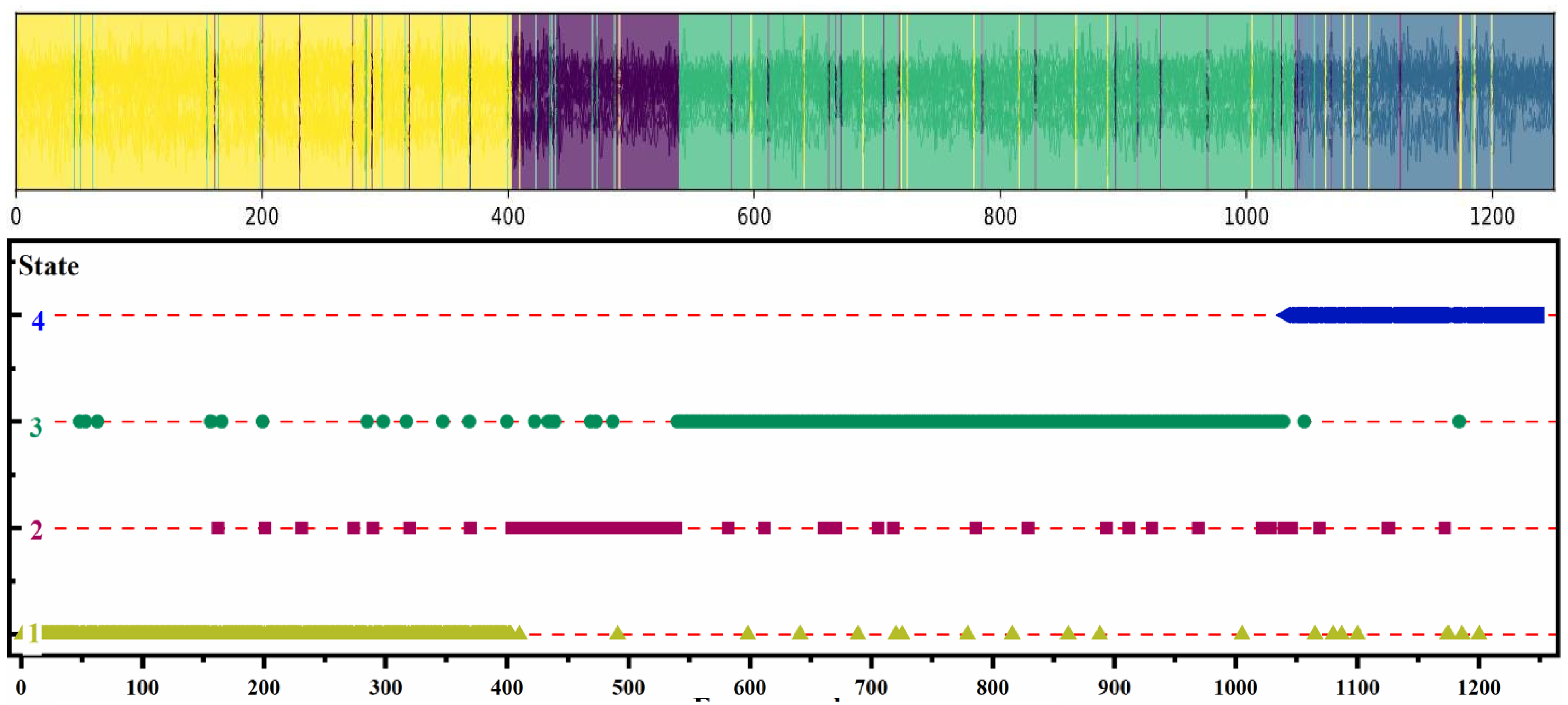
The machining parameters

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

Feature extraction

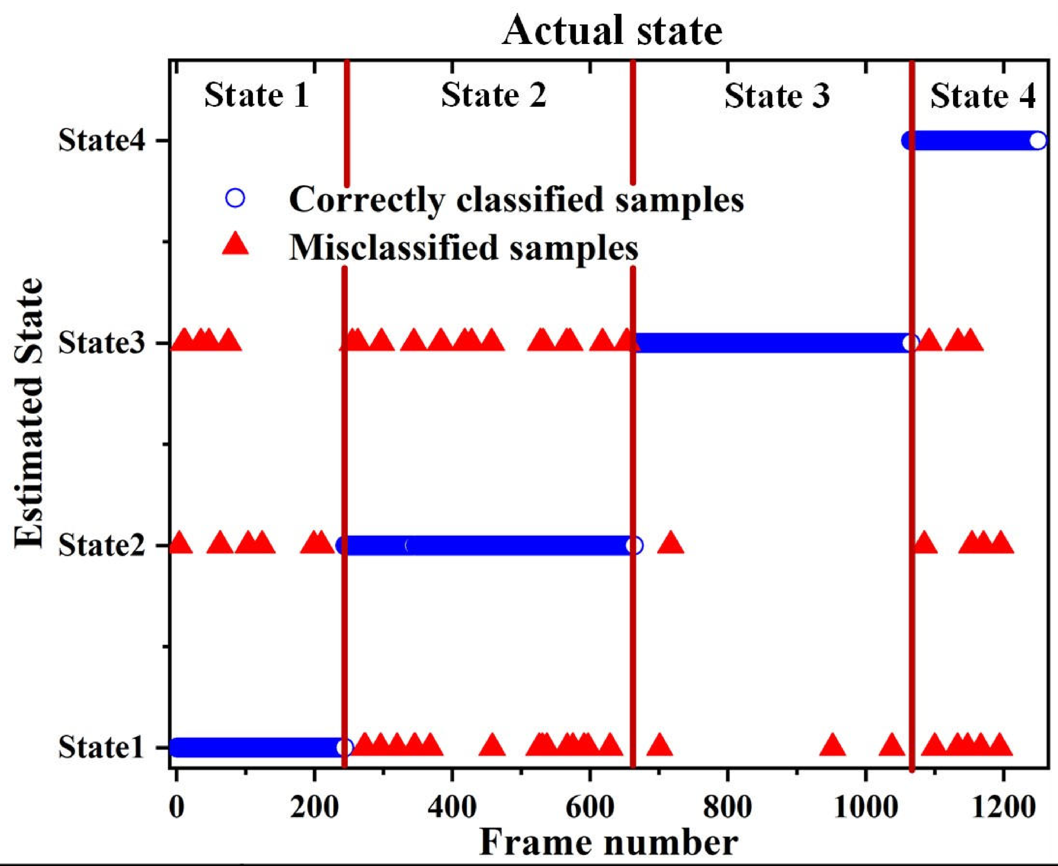
Type	Signal features	Mathematical expression
Time domain		
Mean	Mean-F_x, Mean-F_y, Mean-F_z	$\mu=E(\lvert x_i\rvert)$
Root mean square (RMS)	RMS-F_x, RMS-F_y, RMS-F_z	$x_{RMS}=\{E(x_i^2)\}^{1/2}$
Standard deviation (Std)	Std-F_x, Std-F_y, Std-F_z	$x_{Std}=\{E[(\lvert x_i\rvert-\mu)^2]\}^{1/2}$
Maximum (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	$x_{KM}=E[((x_i-E(x_i))/(Std(x_i))^2)^4]-3$

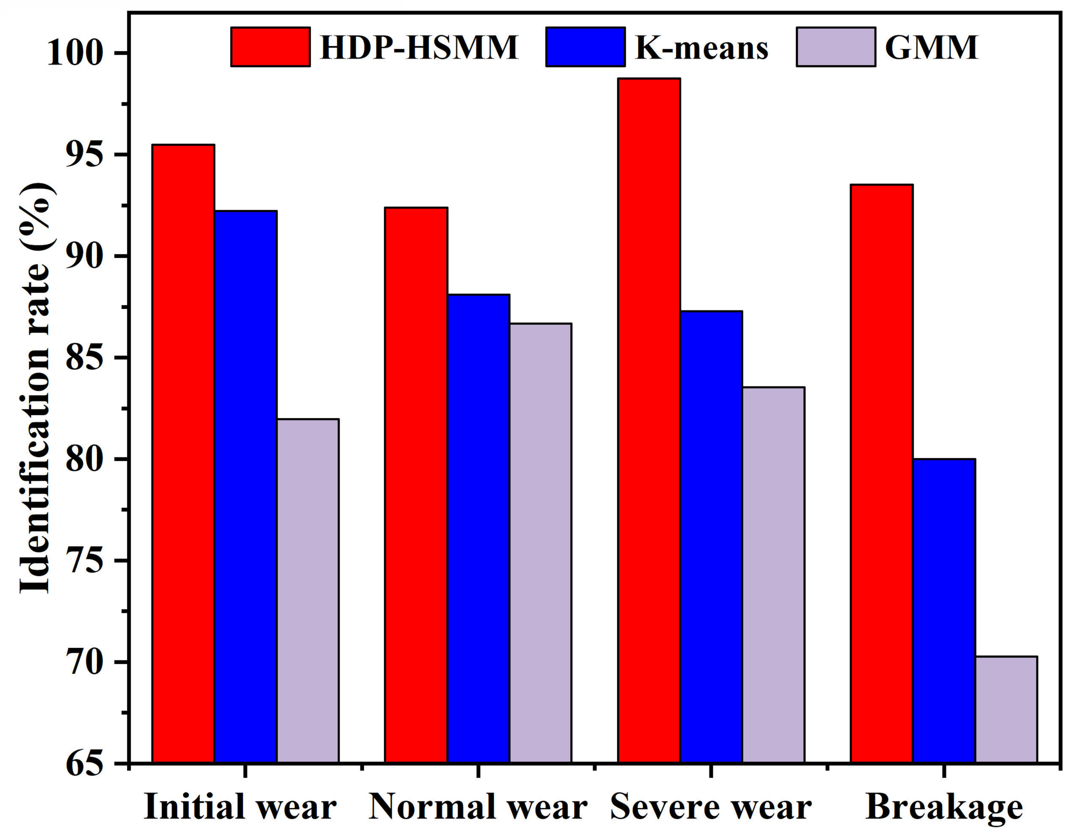
Results



Training results:

- The deeper the color, the higher the number, the more serious the tool wears.
- Although there are some abnormal state changes in these sequences, the overall state division is still very clear.



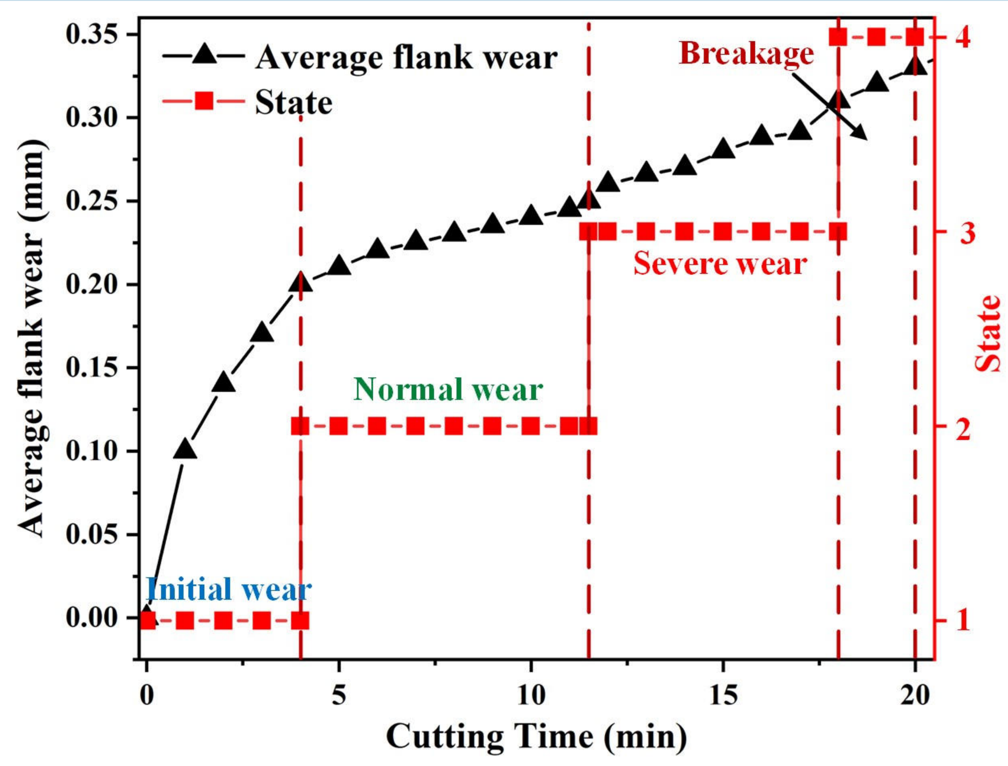


Method	Initial wear	Normal wear	Severe wear	Breakage	Avg.
HDP-HSMM	0.954	0.924	0.988	0.935	0.95
K-means	0.922	0.881	0.873	0.804	0.87
GMM	0.820	0.867	0.835	0.703	0.806

Testing results & Comparsion with other published methods:

- The numbers represent the classification rate (the higher the better).

Testing dataset visualization



Conclusion and Future work

We present a **new real-time** tool wear monitoring system for high speed milling of TC4 alloy.

Future work: Collect signals from other machining parameters to further investigate **generalization capability**.

References

[1] J. Springenberg, A. Dosovitskiy, T. Brox, and M. Riedmiller, "Striving for simplicity: The all convolutional net," *arXiv:1412.6806*, 2014.

[2] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, no. 285-296, pp. 23–27, 1975.

Project Webpage: Code&Dataset&Model