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Singularity Analysis of Cutting Force and Vibration for Tool Condition Monitoring in Milling

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ABSTRACT Tool wear is inevitable in manufacturing and affects the surface quality and geometric tolerance significantly. A robust and efficient tool condition monitoring (TCM) system is needed to maximize tool life, ensure work-piece quality, and benefit the cost control of manufacturers. This paper presents a systematic singularity analysis approach of cutting force and vibrations for feature extraction of TCM in milling. The singularity of sensory signals is estimated by Holder Exponents (HE), which are determined by wavelet transform modulus maxima (WTMM). A comprehensive wavelet basis selection approach is proposed to choose the appropriate wavelet basis for different sensory signals. A de-noising algorithm based on WTMMs' estimation was used as a pre-processing technique to improve noise reduction and preserve the singularities. The mutual information method was employed to rank HE features. The effectiveness of the singularity analysis approach is validated through the Support Vector Machine (SVM) models trained by these ranked features. The estimating results of case studies confirm the efficacy and efficiency of the proposed approach.

INDEX TERMS Force, vibrations, tool condition monitoring, singularity, holder exponents, wavelet basis selection, support vector machine.

I. INTRODUCTION

Manufacturing sectors play an essential role since they are among the largest energy consumers in modern societies [1]. Especially, the high-end manufacturing industry, such as aviation and aerospace fields, has always been the vane of manufacturing development due to its technological advantages. In these fields, materials with excellent properties such as titanium alloys and nickel-based alloys are widely applied. During machining these difficult-to-machine materials, the interactions between the cutting tools, work-pieces, and chips put cutting tools in extreme working conditions and result in the shape change of tools, such as gradual tool wear, or tool breakage [2]. Moreover, surface quality and geometric tolerance are highly related to the tool conditions, especially when high-added-value components like aeronautical engine blades and monolithic parts, are manufactured. However, tool replacements in most factories still rely heavily on workers' experience. Premature tool replacements can lead to wasting of resources and increasing of economic costs. And late replacement of worn tool may cause unpredicted machine breakdown and affect the machining quality. To ensure the machining quality of high value-added components, workers often tend to adopt conservative tool replacement strategies. Therefore, a robust and efficient tool condition monitoring (TCM) system is needed to maximize tool life, ensure work-piece quality, and benefit the cost control of manufacturers [2].

For the implementation of monitoring schemes, most of the current studies on TCM are based on empirical analysis [3],

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or sensing-oriented approaches such as cutting forces [4]–[8], motor current analysis [9], [10], vibration analysis [11], [12], and acoustic emission (AE) [13], [14]. Several comprehensive surveys of these works have been published [15], [16]. Essentially, the core issue of TCM could be seen as a pattern recognition problem, in which the vital procedure is to obtain appropriate features from sensory data by the adequate signal processing means. The milling process is discontinuous, and this produces highly nonstationary signals. Wavelet analysis has a strong capacity in coping with nonstationary signals and is sensitive to tool conditions in milling TCM [17], [18].

In the signal processing, singularities can be thought of as either an abrupt change or a sudden shift of the signal's mean value to a different level. For condition monitoring, singularities can be found in sensor signals captured during machining, such as when chipping and tool breakage occur. There is an excellent time-frequency localization property provided by singularity analysis in wavelets [19]. The original goal of singularity analysis is to estimate the localization and degrees of abrupt changes in a signal or image edges [20]. It has been studied in machinery condition monitoring lately [21], [22], but little is studied in TCM of milling. Because it is robust and stable in capturing signal changes, it can be expected that these singularity-based features will provide valuable studies in TCM.

The singularity analysis with wavelet for TCM was first introduced by Chen and Li [23]. They chose the wavelet coefficient norm and their statistics as features to indicate the tool conditions. Their wavelet features are robust in case of noise, but they are still subject to the limitation in choosing threshold, which also varies with working conditions. Some other studies applied fractal features to describe the signal singularities. Fractals are objects that display self-similarity over scales [24]. Fractal features were applied to characterize the tool states [25]. Bukkapatnam *et al.* [26] studied the fractal properties of force and vibration for turning TCM. The flank wear is estimated by associating the fractal properties of machining dynamics and flank wear through a recurrent neural network. Zhu *et al.* [27] estimated tool conditions from probability densities of force waveform singularity measurements in micro-milling. However, there is still a lack of systematic research on the difference of singularity analysis on various sensory signals in milling at present.

The goal of this paper is to provide a systematic singularity analysis of cutting force and vibration which could be employed for TCM in milling. Its underlying assumption is that a new tool produces various signal waveforms and singularities from a worn-out one, then HE as a direct index of singularity is estimated based on WTMM [27]. The main contributions of this paper include the following 3 points:

1. A comprehensive wavelet basis selection approach is proposed to decide which order vanishing moment is appropriate for the different sensory signals without any knowledge of their singularity properties beforehand. The wavelet basis with 1 vanishing moment is found quite efficient to analyze cutting force signals, and the wavelet basis with 2 vanishing moments is most suitable for vibration signals.

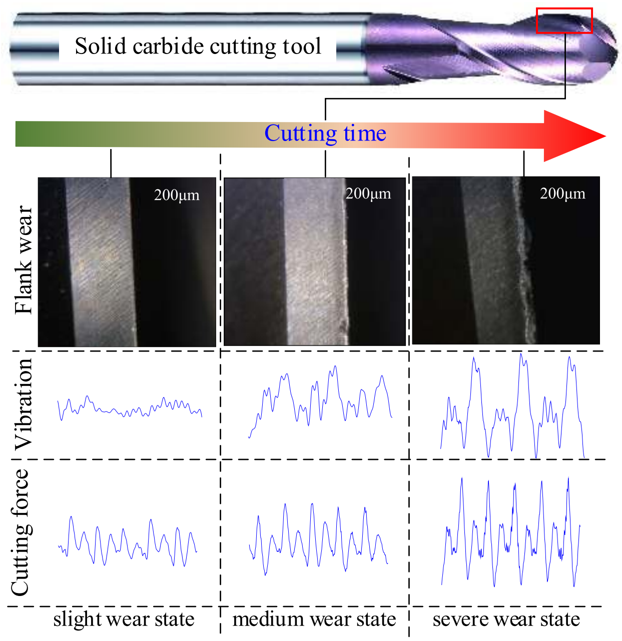

FIGURE 1. Signal waveform shapes of different tool conditions.

2. The de-noising algorithm based on the estimation of WTMMs with appropriate wavelet basis could improve de-noising effect and preserve the singularities in signals compared with traditional filters.

3. The statistical features extracted from HE values selected by the mutual information method could obtain higher machine learning classification rate; the singularity characteristics of the cutting force are more correlated to the tool conditions than the vibration signal.

The following Section II discusses the theoretical basis of waveform analysis for TCM. The experiment and results are then presented in Section III. The singularity analysis and discussion are then presented in Section IV. Section V concludes the results.

II. SINGULARITY ANALYSIS

A. SIGNAL WAVEFORM SHAPES AND TOOL CONDITION

Cutting force and vibration signals are the most widely acquired process signals in milling, which have been found quite sensitive to different tool conditions and extremely suitable for TCM [12]. As mentioned above, the basic idea of this paper is that changes of tool conditions are strongly associated with the variations in signals' waveforms, which show various singularity or disorder, with the proceeding of milling process [27], which is briefly described in Figure 1. These disorders or singularities could be estimated by Holder Exponent (also named Lipschitz Exponent in mathematics) [28].

B. HOLDER EXPONENT

The singularity means discontinuity; if a function $f(t)$ is not differentiable at v, we say the $f(t)$ is singular at v. From the perspective of signal processing: During machining, singularities can generally be found in the sensor signals when chipping and tool breakage occur. When the signals' waveform undergoes slow variation without abrupt changes, the singularity degree measures how close the signal is related to the singularity and also provides abundant information on the tool condition variations [27]. We qualitatively describe the geometrical characteristics of signals with discontinuity, disorder, smoothness, etc. In mathematics, the Holder Exponent (HE) α is a good index for this characterization [29]. Usually, a large HE indicates a regular point in the signal while a small HE indicates a singular point.

A function $f(t)$ is said to be Holder Exponent $\alpha \geq 0$ at $t = v$ if there exists $A > 0$ and a polynomial p_v of degree m(m is the largest integer satisfying $m \leq \alpha$) such that

$$f(t) = p_v(t) + \varepsilon_v(t) \tag{1}$$

$$|\varepsilon_v(t)| \leq A\,|t - v|^{\alpha} \tag{2}$$

As A is a constant, this upper bound is decided by the exponent α. The HE of $f(t)$ at t_0 is the supremum of α for which (2) holds. Higher α means that the function $f(t)$ is more regular. With $n < \alpha < n+1$, then $f(t)$ is n-time differentiable, but the nth derivative is singular at t_0, where α characterizes this singularity.

However, the estimation of HE is nontrivial. Mallat and Wen [19] have shown that the HE of a signal can be estimated from its wavelet maxima and the decay of the WT modulus in the time-scale plane.

The local extrema along the scale are first obtained by setting the partial differentiation of wavelet transform $W_{\psi}f(u, s)$ of signal $f(t)$ at position u to zero

$$\frac{\partial WTf(u, s)}{\partial u} = 0. \tag{3}$$

Along the modulus maxima line, the wavelet coefficients have the scaling behaviors in the vicinity of t as follows [19]:

$$|WTf_s(t)|\,A \leq s^{\alpha+1/2}. \tag{4}$$

where A is a constant ($A > 0$) related to the wavelet $\psi_{u,s}(t)$. By taking the discrete scale $s = 2^j$ along the modulus maxima line, the wavelet coefficients have the scaling behaviors as follows:

$$\log_2\left|WT_{2^j}f(t)\right| \leq \log_2 A + j\left(\alpha + 1/2\right). \tag{5}$$

A and α can be computed by setting the equality in (5). This function connects the wavelet scale j and the HE α. The function also shows the relationship between WTMM and the wavelet scale j (or s in CWT). A higher α means that the function $f(t)$ is more regular or smoother. For instance, white noise with HE $= -0.5 - \varepsilon(\varepsilon > 0)$; ramp signal is piecewise linear, 1st order differentiable, with HE $= 1$; the 1st derivative of a ramp signal is a step function with HE $= 1 - 1 = 0$; and the 2nd derivative of ramp signal is impulse signal with HE $= 1-2 = -1$. The HE with WTMM estimation was initiated to analyze self-similar phenomena in physics [30], [31] and also have been studied for machinery diagnostics [32], [33], which are similar to the task of TCM in principle.

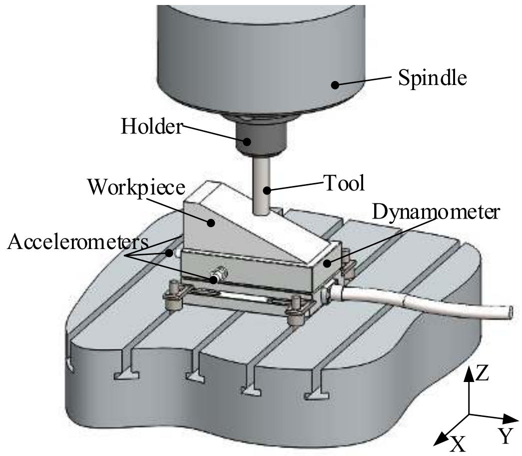

FIGURE 2. Experimental setup.

III. EXPERIMENTS

The experiment data is extracted from the "prognostic data challenge 2010" database [34], which contains several histories of high-speed CNC milling machine 3-flute cutters used until a significant wear stage (Figure 3).

The authors recorded the vibration data from accelerometers during the cut process and measured the amount of wear after each cut for three experiments (a total of three sets of 315 cut files). Three Kistler piezo accelerometers were mounted on the workpiece to measure the vibration of the cutting process in X, Y, Z direction respectively. The Kistler dynamometer (9257B) was employed to measure the cutting force in X, Y, Z directions. The outputs of these sensors were conditioned through corresponding signal conditioning accessories such as charge amplifiers or couplers. The voltage signals were captured by a NI DAQ PCI 1200 board with 12 kHz frequency. These histories were named as cutter1, cutter2, and cutter3.

The experimental records from these tests were obtained under constant conditions. The cutting parameters were: the spindle speed of the cutter was 10400 r/min, the feed rate was 1555 mm/min, the Y depth of cut (radial) was 0.125 mm, and the Z depth of cut(axial) was 0.2 mm. The data were acquired at 50 kHz/channel; the experimental setup is shown in Figure 2.

IV. RESULTS AND DISCUSSIONS

A. SIGNAL DE-NOISING AND WAVELET BASIS SELECTION APPROACH

Raw cutting force and vibration signals are highly contaminated by noises. At the positions where the signal has positive HEs, the noises would add negative singularities. In turn, the sum would present as a signal with negative HEs. Therefore, the raw cutting force signal needs careful preprocessing before estimating singularities. In practical

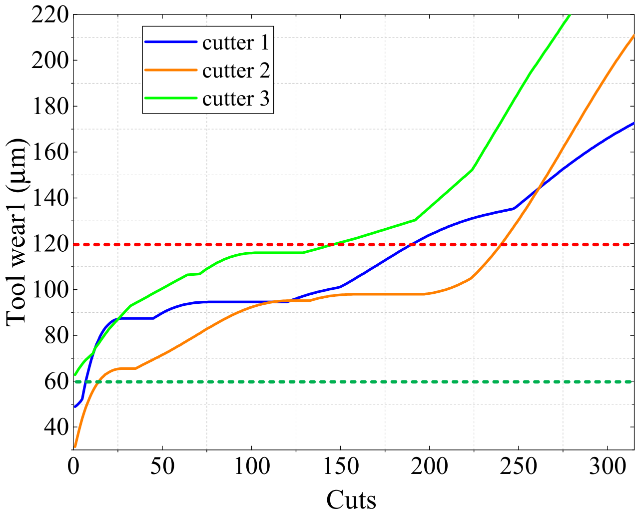

FIGURE 3. Variation of flank wear with cuts.

applications, the useful segment of the signal usually appears as a low-frequency signal or relatively stable signal, but noise shows a high-frequency nature. Based on the above characteristics of the noisy signal, the traditional low-pass filter, band-pass filter or wavelet filter can effectively improve the signal-to-noise ratio, but they would blur the singular features in signal, as shown in Figure 4 (b) and Figure 5 (b). Therefore, how to remove noise while preserving singularities of cutting force signal becomes an urgent problem before the detection of singularity.

Since noise produces negative HE values [19], we could distinguish the WTMM generated by noise from the one created by signal, by checking the development of their values along with scales. If the WTMM has a value, which increases considerably when the scale decreases, it indicates that the corresponding singularities have negative HEs. These WTMMs are mostly dominated by noise and are thus removed. After the WTMM selection, we reconstruct a "de-noised" signal with Mallat's approach. By comparing Figure 4 (b) and (c), it could be found that the WTMM de-noising algorithm could significantly improve the noise reduction effect and acquire a smoother curve.

However, the choice of wavelet basis is especially important when estimating WTMMs. So far, there is still no uniform selection criteria for the wavelet basis for singularity detection. Based on lots of applied researches [19], [27], [29], [33], the wavelet basis used for singularity detection should have the following properties: continuously differentiable, with suitable vanishing moments and small effective support, regular, symmetry or anti-symmetry. Among them, the vanishing moment is critical, which should fit with characteristics of the signal. A wavelet $\psi(t)$ is said to have n vanishing moments, if and only if for all positive integer $k < n$, it satisfies

$$\int_{-\infty}^{+\infty} t^k \psi(t)\, dt = 0. \tag{6}$$

In the analysis of real signals, there are two types of singularities: Type I, which is a discontinuity of the signal at point a; Type II, which is the discontinuity of the nth order derivative of the signal at point a. Only by selecting the wavelet basis with appropriate vanishing moments we can effectively detect different types of singular points. If wavelet ψ has exactly n vanishing moments and a small compact support, then there exists θ of compact support such that $\psi = (-1)^n \theta^{(n)}$ with $\int_{-\infty}^{+\infty} \theta(t)dt \neq 0$. The wavelet transform is rewritten in (7) as a multiscale differential operator

$$Wf(u, s) = s^n \frac{d^n}{du^n} \left(f * \bar{\theta}_s\right)(u). \tag{7}$$

If $\psi = -\theta'$, it has only one vanishing moment, wavelet modulus maxima are the maxima of the 1st order derivative of f smoothed by $\bar{\theta}_s$, as illustrated by Figure 3. These multiscale modulus maxima are used to locate sharp variation points. If $\psi = \theta''$, the modulus maxima of $W_2 f(u, s) = s^2 \frac{d^2}{du^2}\left(f * \bar{\theta}_s\right)(u)$ corresponds to Type II singular points and local maximum curvity around Type I singular point, and it can be observed that modulus maxima of local maximum curvity are also closely related to the singularity of sharp variation points. Therefore a wavelet basis with n vanishing moments can detect the singularity till HE = 0 in the $n - 1$ derivative of the signal.

However, we don't know in advance which kind of singularity the signal has. Therefore, we propose a quite comprehensive approach to select the wavelet basis. Firstly, we employ several wavelet bases with the different vanishing moment to de-noise the signal; then we check the smoothness of the de-noised signal and frequency spectrum analysis is performed to compare the effect of noise reduction. However, the number of maxima at a given scale often increases linearly with the number of moments of the wavelet [29]. In order to ensure the efficiency of the calculation at the same time, computational efficiency is another crucial factor.

To better compare the effects of different vanishing moments on signal singularity analysis, it is necessary to use the wavelet bases of same wavelet family. The Gaussian derivatives family is built starting from the Gaussian function by taking its n^{th} derivative, and this n^{th} derivative is a wavelet basis with n vanishing moments [19], so Gaussian derivatives family is employed as the wavelet basis in this paper.

Figure 4 and Figure 5 show the de-noised vibration, cutting force signal of one rotation by different wavelet bases and their corresponding frequency spectrums.

1) VIBRATION

Comparing Figure 4 (c) and (d), it could be observed that the signal de-noised by wavelet basis with 2 vanishing moments is much smoother. It is because that the 2nd derivative of Gaussian wavelet with 2 vanishing moments can locate both Type I and II (discontinuities in the 1th derivative of signal) singular points and create more WTMMs. Then we can evaluate more points which are dominated by noise or not. Preserving more real signal points, and eliminating more noise makes

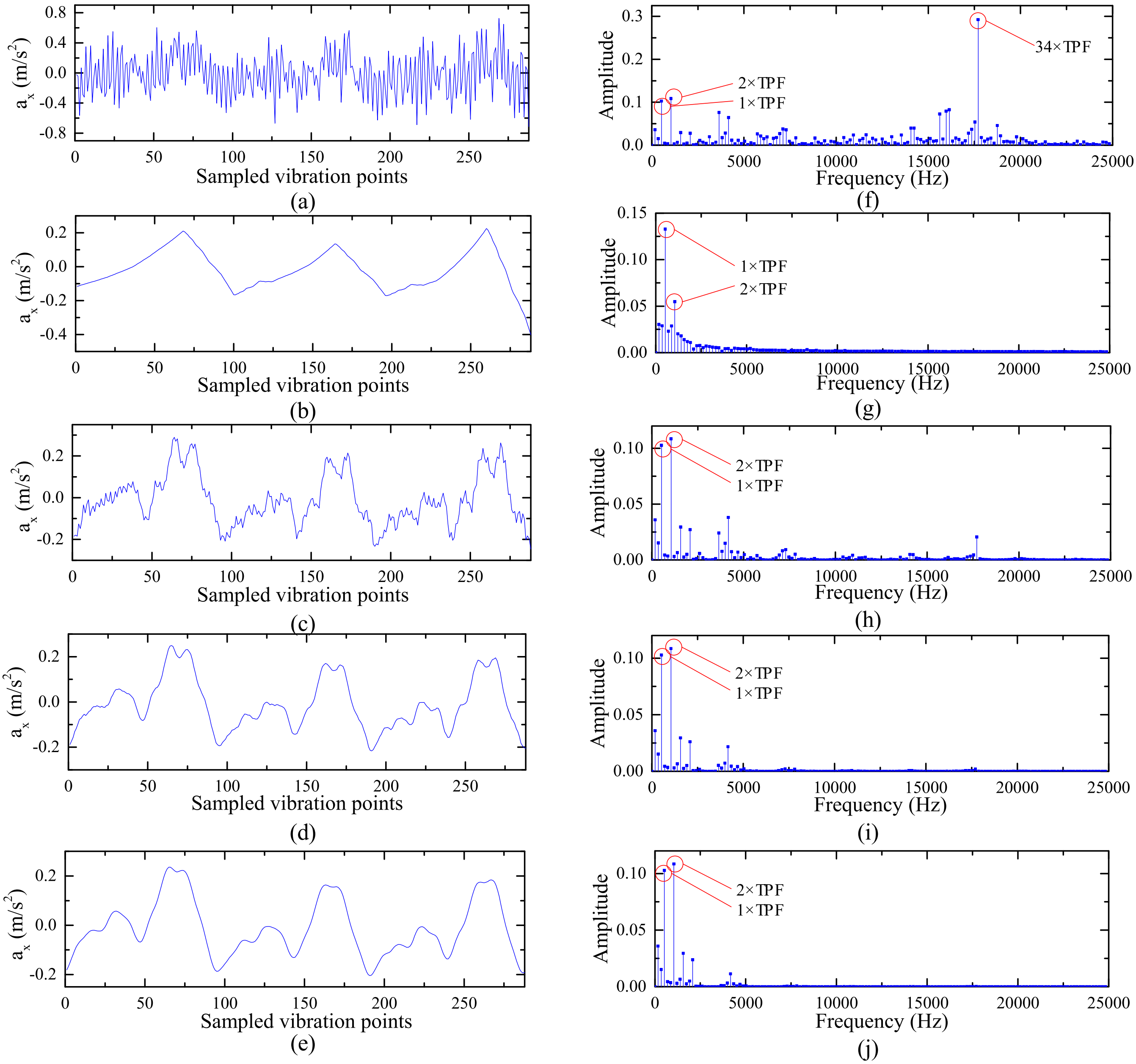

FIGURE 4. (a) Noisy vibration signal of cutter1 in the feed direction. (b) Signal de-noised by wavelet filter. (c) Signal de-noised by WTMM by the 1st derivative of Gaussian wavelet with 1 vanishing moment. (d) Signal de-noised by WTMM by the 2nd derivative of Gaussian wavelet with 2 vanishing moments. (e) Signal de-noised by WTMM by the 3th derivative of Gaussian wavelet with 3 vanishing moments. (f), (g), (h), (i), (j) are the corresponding frequency spectrum of (a), (b), (c), (d), (e).

the curve smoother. To further evaluate the de-noising effect of noise reduction, we conducted the frequency spectrum analysis to signals. The energy of vibration signal should be distributed at the integral multiples of the tooth passing frequency (*TPF*) [35].

$$TPF = N \times \frac{n}{60} = 3 \times \frac{10400}{60} = 520\,(Hz)\,. \tag{8}$$

where N and n are quantities of tool cutting edges and spindle speed (r/min), which are 3 and 10400 respectively.

From Figure 4 (h), (i), and (j), it can be observed that wavelet basis with 2 vanishing moments can preserved energy of vibration signal at integral multiples of *TPF* while eliminating noise energy at high frequencies significantly. Therefore, this means that both the Type I and Type II singularities exist in the milling vibration signal.

From Figure 4 (d), (e), (i) and (j), we could find that the signal de-noised by wavelet basis with 3 vanishing moments becomes smoother, but not so noticeable. And a tiny difference in the frequency spectrums illustrates the same condition. Considering the computational efficiency

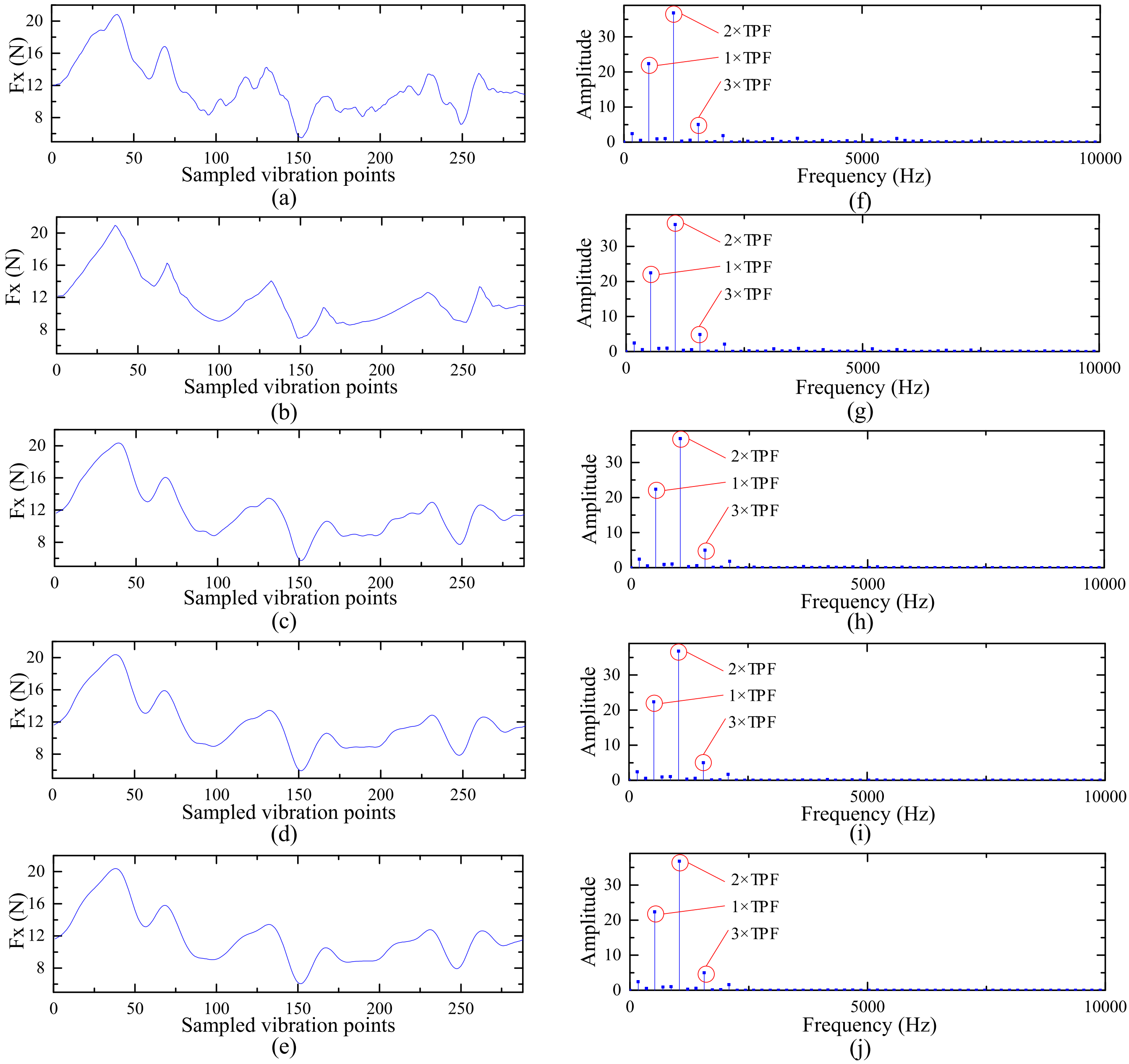

FIGURE 5. (a) Noisy cutting force of cutter1 in feed direction. (b) Signal de-noised by wavelet filter. (c) Signal de-noised by WTMM by 1st derivative of Gaussian wavelet with 1 vanishing moment. (d) Signal de-noised by WTMM by 2nd derivative of Gaussian wavelet with 2 vanishing moments. (e) Signal de-noised by WTMM by 3th derivative of Gaussian wavelet with 3 vanishing moments. (f), (g), (h), (i), (j) are the corresponding frequency spectrum of (a), (b), (c), (d), (e).

and de-noising effect, the wavelet basis with 2 vanishing moments is efficient to analyze the singularity of milling vibration signals.

2) CUTTING FORCE

Comparing Figure 4 (c), (d) and (e), it could be observed that the smoothness of the de-noised signals by wavelet basis with 1-3 vanishing moments is almost the same. The same condition happens to the frequency spectrums. Therefore, it can be perceived that the singularity in the cutting force signal is dominated by the Type I singularities. Then the wavelet basis with 1 vanishing moment is efficient to detect these singularities.

By comparing the singularities of the vibration and cutting force, it could be concluded that it needs to employ different wavelet bases to meet the singularity detection requirements of different signals. Otherwise, some useful information in the signal would be ignored.

B. HE ESTIMATION PROCEDURE

In this paper, both the HE estimation and the signal de-noising need to calculate WTMM. In order to improve the

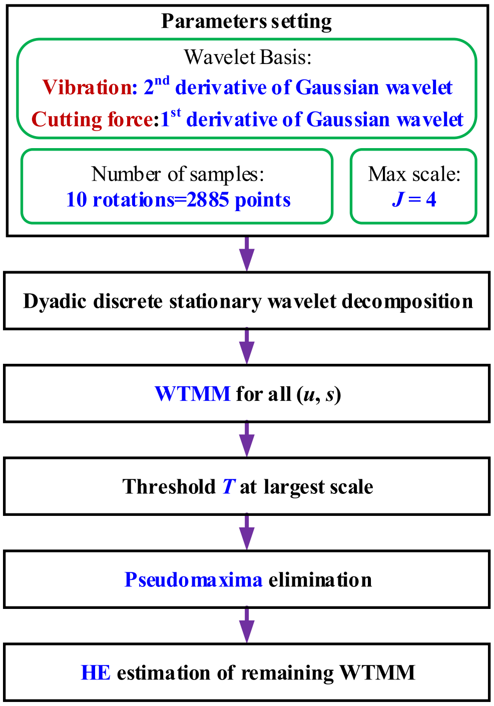

FIGURE 6. HE estimation procedure.

computational efficiency, the de-noising algorithm is integrated into HE estimation. The numerical implementation of HE estimation of signal $f(t)$ is shown in Figure 6.

In the de-noising algorithm based on wavelet modulus maxima, since the density of modulus maxima of noise decreases as the scale (2^j) increases [29], so we need choose a relatively large scale to make the useful signal dominant, but too large scale would lose some important local singular points, $j = 4 - 5$ is chosen generally [27]. After WTMM for all (u, s) is computed, we would search the modulus maxima dominated by the noise through setting the threshold T of the modulus maxima at the largest scale. The modulus maxima below T will be eliminated. After removing pseudo-maxima at different scales, HE of remaining WTMM would be calculated. The T is set as

$$T = \log_2 \frac{\left(1 + 2\sqrt{P_N}\right)}{J + Z} \times M. \tag{9}$$

where Z is a constant, is set as 2 [27]. The discrete scale $s = 2^j (j = 0, 1, 2 \ldots J)$, J is the maximum.

M is the maximum modulus, $M = \max \left|W_{2^J}(x_i)\right|$

C. HOLDER EXPONENT ANALYSIS

In the TCM research of micro-milling [27], [36], Zhu et al. found that the HE values of three force components all are located within narrow bands and their variation areas overlap a lot, which means the HE values alone could not be used as features for TCM. However, they noticed that the probability densities of HE values were well approximated with Gaussian densities and the HE ranges could be divided into three separate areas corresponding to three tool states.

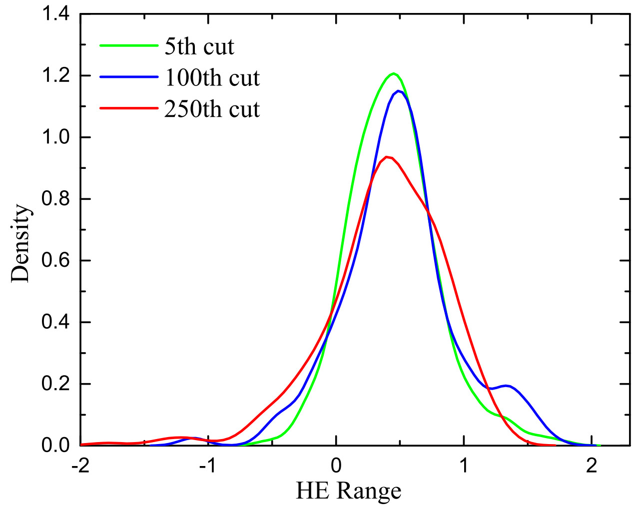

FIGURE 7. HE probability densities of vibration estimated by 2nd derivative of Gaussian wavelet.

Figure 7 and Figure 8 show HEs' probability densities of three typical tool wear states (corresponding to 5th, 100th and 250th cut according to Figure 3) calculated from axial vibration A_x and axial force F_x samples of cutter 1. It is perceived that Gaussian densities can estimate all these probability densities of HEs, but the distributions of three tool states are extremely overlapping, which is a totally different scenario from the micro-milling. Moreover, the same case happens to the HEs' probability densities of A_y, A_z, F_y and F_z. So the conditional probability density ratio employed in [27] cannot be used in this case. This means that only the basic parameters μ (means), and σ (standard deviations) of the Gaussian distribution are insufficient to distinguish the distributions of different tool states. However, it is also observed that the probability densities of different tool wear states are different in shapes and ranges significantly. Therefore, we extracted Maximum, Minimum, Skewness, Kurtosis of HE values to describe the distribution further. In the estimation of WTMMs, we found that in the case of the same amount of data, different tool states would cause significant variations in the quantities of singular points. Then we extracted these 7 statistical features from every component of cutting force and vibration, 42 features in total.

D. HE FEATURES SELECTION

Now we have a lot of features extracted from HE values, including some redundant and irrelevant features. If we don't choose the most relevant ones, it will increase the complexity of machine learning models and lead to problems of overfitting and dimension disaster. In this paper, we employed the Mutual Information based feature selection method, which has been proved effective to rank the class-discriminant capability of features [37], [38]. Since the mutual information method is only applicable to discrete variables, but the HE features extracted are continuous variables, then the

TABLE 1. SU of different cutting force HE features.

Ranks	Force components	Vanishing moments	HE Features	SU
1	F_y	1	Quantity	0.917352
2	F_x	1	Mean	0.866184
3	F_x	1	Standard deviation	0.810899
4	F_y	1	Kurtosis	0.772619
5	F_y	2	Quantity	0.735685
6	F_z	1	Standard deviation	0.67228
7	F_y	2	Mean	0.666663
8	F_y	1	Standard deviation	0.662071
9	F_y	2	Standard deviation	0.604848
10	F_z	1	Quantity	0.564192

TABLE 2. *SU* of different vibration HE features.

Ranks	Vibration components	Vanishing moments	HE Features	SU
1	A_x	2	Mean	0.51821
2	A_y	2	Skewness	0.408881
3	A_y	1	Mean	0.369572
4	A_y	1	Quantity	0.314091
5	A_z	2	Standard deviation	0.284548
6	A_z	2	Kurtosis	0.277857
7	A_y	1	Kurtosis	0.276967
8	A_x	2	Kurtosis	0.270136
9	A_y	2	Quantity	0.254382
10	A_z	2	Mean	0.254382

Minimum Description Length Principle (MDLP) [39], [40] is employed to discretize these continuous features firstly.

The mutual information could quantitatively characterize the relationship either between any two features or between a feature and a class variable. The mutual information of 2 discrete variables X, Y could be described as:

$$I(X;Y) = H(X) - H(X|Y). \tag{10}$$

where $H(X)$ is the entropy measure of X:

$$H(X) = -\sum_{X\in\Omega_X} p(x)\log_2(p(x)). \tag{11}$$

and $H(X|Y)$ is the conditional entropy of variable Y given the occurrence of variable X, is estimated as:

$$H(X|Y) = -\sum_{X\in\Omega_X}\sum_{X\in\Omega_Y} p(x,y)\log_2(p(x|y)). \tag{12}$$

where Ω_X and Ω_Y are the variable spaces of X and Y. And $p(x)$, $p(y)$, $p(x, y)$ are the probability density functions of X, Y and (X, Y). $p(x|y)$ is calculated as:

$$p(x|y) = \frac{p(x,y)}{p(x)p(y)}. \tag{13}$$

After the mutual information is estimated, the symmetric uncertainty (SU) analysis is employed to score different features. $SU(X, Y)$ is calculated as:

$$SU(X;Y) = 2\frac{I(X,Y)}{H(X)+H(Y)}. \tag{14}$$

To further illustrate the influence of wavelet base selection on HE estimation, the SUs of HE features estimated from wavelet bases with vanishing moments of 1 and 2 are calculated. The top 10 results of SU analysis of cutting force and vibration HE features are shown in Table. 1 and 2.

1) CUTTING FORCE

From Table.1, it could be observed that in the Top 10 features, the ones estimated by wavelet basis with 1 vanishing moment score a higher SU value than that with 2 vanishing moments. The Quantity and Kurtosis of F_y, the Mean and Standard deviation of F_x are highly correlated with the tool conditions, and these features could be used to train the machine learning models. In addition, it could be found that the HE features estimated by wavelet basis with 2 vanishing moments also have a correlation with the tool conditions; it could be perceived that the HE features estimated with different vanishing moments all can obtain some useful information. Only by selecting the most suitable wavelet base, the obtained HE features can extract as much useful information as possible from the original signal.

2) VIBRATION

From Table.2, the same scenario happens to the vibration; the difference is that the wavelet basis with 2 vanishing moments is more suitable for vibration. The Mean of A_x and the Skewness of A_y score higher SU value than other features.

By comparing Table.1 and Table.2, it can be found that the SU values of the HE features of the cutting force are much higher than that of the vibration. This is because the cutting force is a direct indication of the tool-workpiece interactions [2], and it has been found the most effective sensory signal for TCM. And due to the limitations of accelerometers' installation, the collected vibration signal is far away from the cutting zones and is contaminated by lots of interference. This phenomenon is consistent with the literature on TCM with different signals [4], [17].

Figure 9 shows the variations of the top features ranked by mutual information algorithm of cutting force and vibration (Quantity of F_y and Mean of A_x) throughout the tool life. By observing the trend and distribution of these two features, it can be easily seen that there is a higher correlation between the cutting force HE features and the tool conditions, which is consistent with the result of mutual information.

Considering the calculation efficiency and the correlation of features, this paper selects the Top 2 HE features of cutting force and vibration respectively as input features of the machine learning models detailed in the following section.

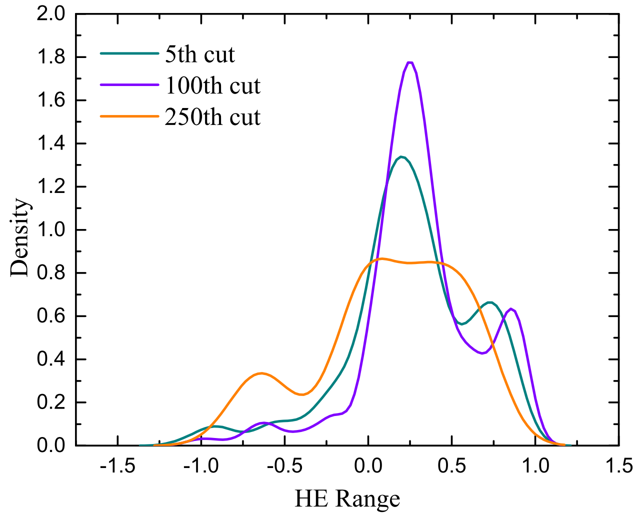

FIGURE 8. HE probability densities of cutting force estimated by 1st derivative of Gaussian wavelet.

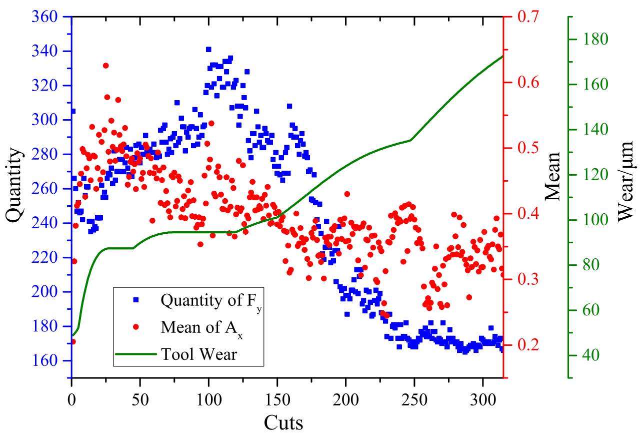

FIGURE 9. HE probability densities of cutting force estimated by 1st derivative of Gaussian wavelet.

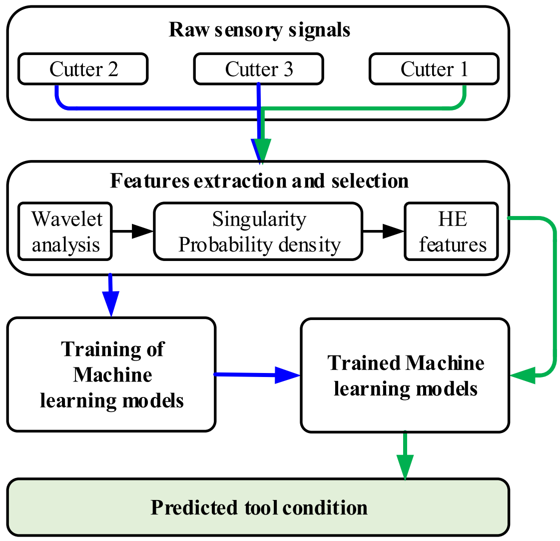

FIGURE 10. Scheme of the Tool condition estimation approach.

E. TOOL CONDITION ESTIMATION WITH HE FEATURES

1) TOOL CONDITION ESTIMATION APPROACH

In this paper, to ensure the repeatability and generality of machine learning models, models are generated using the "Classification learner" toolkit provided by MATLAB. Several classical machine learning models were trained including Support vector machine (SVM), k-Nearest Neighbor (KNN), Decision Tree, Ensemble Learning, Artificial Neural Networks (ANN) and Hidden Markov Model (HMM), etc. Input features of two experiments (cutter2 and cutter3) are selected as training samples; the data of cutter1 is used as test samples.

Cutting tools experience several wear mechanisms during machining, namely abrasion, adhesion, diffusion, fatigue, and chemical wear [41]. Typical wear situations usually involve more than one of these types of wear. However, from the process point of view, flank wear is the most important and VB, the width of the flank wear land, is the most recommended variable used to evaluate tool wear states. This article divides the tool conditions into three categories: State 1 is the slight wear state with wear range 0-60 μm; State 2 is medium wear state with wear range 60-120 μm; State 3 is severe wear state with wear larger than 120 μm. The boundaries between different wear states are decided by the closest 10 μm of cross-over points of 2nd derivative of the Taylor tool life curve [42].

The scheme of the tool condition estimation approach is illustrated in Fig.10. The training accuracies of selected models are listed in Table. 3. From Table.3, it can be observed that the SVM models could achieve higher training accuracies in both conditions with 97.1% and 86.2%. The SVM is a classic small sample learning method with a solid theoretical basis, which is quite suitable for the situation in this study. Afterward, these models are used to classify the corresponding HE features of cutter1. Besides, it also can be seen that the training accuracies of the machine learning models trained by the cutting force HE features are much higher than those of the vibration HE features, which demonstrates the stronger correlation between the cutting force and the tool conditions again.

2) TOOL CONDITION ESTIMATION RESULTS

Figure 11 and Figure 12 show the classification results. By comparing the defined tool conditions and measured flank wear, the classification rate of the SVM model trained by cutting force and vibration HE features could reach 94.9% and 69.8% respectively (the classification rate is based on counting the ratio of correctly classified samples over all testing samples). We could find that the cutting force HE features could have more accurate classification results. This result is comparable to the classification efficiency in up-to-date published studies [27], [42]–[45] on the tool condition monitoring with different cutting force features in milling operations, as shown in Table 4. From the perspective of

TABLE 3. Training accuracy of machine learning models.

Machine learning models	Training accuracy of cutting force		Training accuracy of vibration	
	Total	Each wear states	Total	Each wear states
Gaussian Support Vector Machine	97.1%	14.3%	86.2%	0.0%
		100%		94.2%
		92.8%		80.2%
Cubic Support Vector Machine	92.9%	0.0%	85.7%	14.0%
		96.1%		88.0%
		93.4%		84.0%
k-Nearest Neighbor	94.8%	0.0%	85.7%	0.0%
		97.8%		88.0%
		95.7%		87.1%
Decision Tree	92.5%	28.5%	84.9%	14.0%
		92.9%		86.1%
		95.5%		85.9%
Quadratic Discriminant Analysis	93.5%	0.0%	82.2%	71.0%
		93.7%		68.2%
		98.4%		92.8%
Ensemble Learning	94.9%	28.5%	85.9%	0.0%
		94.5%		80.1%
		98.9%		95.7%
Artificial Neural Networks	89.7%	0.0%	82.1%	14.3%
		87.8%		85.1%
		93.6%		81.5%

TABLE 4. Studies published on tool condition monitoring with cutting force in milling. TD: Time domain. FD: Frequency domain. WD: Wavelet domain.

Authors	Sample featrues	Results
Zhu et al. [27]	Singularity probability density functions	95%
Zhu et al. [43]	WD	97.14%
Shi et al. [44]	TD, FD, WD	93.18%
Kong et al. [45]	TD, FD, WD	95%
Xie et al. [46]	TD, WD	90%

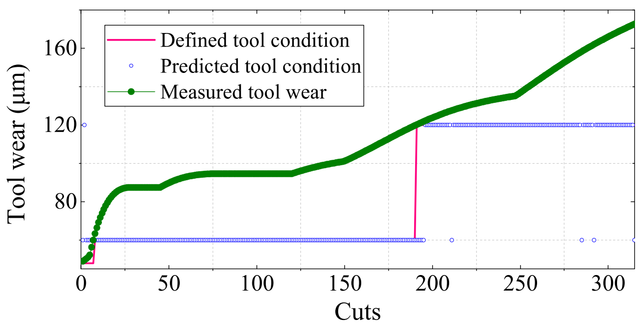

FIGURE 11. Tool condition estimation of cutter1 with cutting force HE features.

model classification results, the singularity analysis with suitable wavelet bases could extract as much useful information as possible from the original signals, which helps to obtain a higher classification rate.

It also could be observed that most misestimated points with cutting force HE features occur at transitions of different wear states. This phenomenon also happens in [27], [36], These may be due to the fact that the 3 identical tools in the public database have different tool wear trends under the same cutting conditions, as shown in Fig. 3.

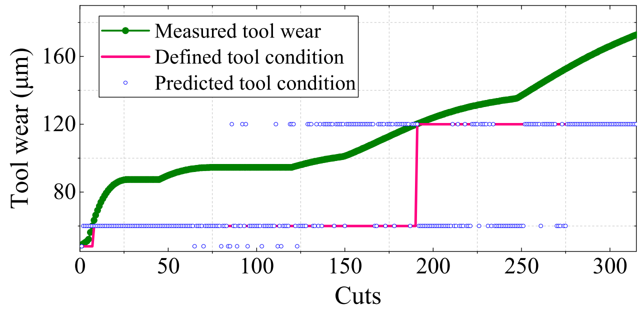

FIGURE 12. Tool condition estimation of cutter1 with vibration HE features.

V. CONCLUSION

A systematic singularity analysis method has been proposed for the feature extraction of TCM in milling in this paper. A comprehensive wavelet basis selection approach is proposed to decide which order vanishing moment is appropriate for different sensory signals without any knowledge of their singularity properties. The wavelet basis with 1 vanishing moment is found quite efficient to analyze cutting force signals, and the wavelet basis with 2 vanishing moments is most suitable for vibration signals. As a preprocessing of the raw signals, the de-noising algorithm based on the estimation of WTMMs with appropriate wavelet bases was employed, which could improve de-noising effect and preserve the singularities in signals compared with traditional filters. The statistical features extracted form HE values were ranked by the mutual information method, the singularity characteristics of the cutting force were found more correlated to the tool conditions than the vibration signal. The SVM model trained by the ranked HE features of cutting force could reach a 94.9% classification rate, and this result shows that the proposed method is capable of providing practical guidance on tool replacement.

Future studies will be carried out on optimizing the adaptability of this method to accommodate other machining methods such as turning, drilling, etc.

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