Experimental study of vibration signal for a prognostic system to prevent tool breakage in micro gun drilling

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Abstract
Unexpected drill breakage can be foreseen and prevented. We observed a factory and identified the warning signs of tool breakage for micro gun drills, as well as a laboratory experiment for micro drills. The vibrations of stable drilling and the vibrations that warn of tool breakage were analyzed based on the time and frequency domain features. We developed a prognostic model. We conducted physical drilling experiments on a Swiss turning machine and a laboratory research platform. Stainless steel was drilled with two types of 0.9-mm-diameter tools: 125-mm-long micro gun drills on Swiss turning machine and 25-mm-long micro drills. In both types of testing, two accelerometers were installed on the tool holder to collect two-directional vibration signals; a linear discriminant function processed the Z-axis and Y-axis signals for the telltale warning signs of impending tool breakage, and obtained a 100% classification rate. To confirm the effect of drilling disturbances on the prognostic system, the entries and exits of tools to and from workpieces were studied. The results demonstrate that both types of signal features can be used without causing any misclassification.

Keywords Tool breakage prognosis · Vibration signal · Micro drilling · Gun drilling

1 Introduction

The demand for microfeature fabrication on products has increased drastically, and various techniques have been proposed to achieve feature sizes between 1 µm and 1 mm [1–3]. In the manufacturing of medical devices, such as bone screws and corresponding surgical tools, a high-aspect ratio drilling technique is required to produce high-quality equipment and devices.

In the micro gun drilling process, unexpected tool breakages, mostly caused by chip clogging or tool wear, are a challenge for process development. Therefore, a prognostic system is required to prevent tool breakage. Effective prognosis plays a crucial role in improving efficiency and reducing the cost in a mass production line because of the high cost of micro gun drills and related equipment. Tool condition monitoring systems for conventional cutting processes have been reported for the past 40 years [4–9]. A number of studies related to condition monitoring of drilling tool have been reported lately with various sensors including drilling torque, cutting force, vibration, current/power, and acoustic emission signal [10–14]. Jantunen [10] made a summary of studies for tool condition monitoring in drilling. Abu-Mahfouz [11] used the vibration signals on the workpiece to study the performance of drilling wear detection based on different artificial neural networks. The results demonstrate the effectiveness and robustness of using the vibration signals in a supervised neural network for drill wear detection and classification. For the deep hole drilling, Messaoud and Weihs [12] used the torque signal to detect the chatter in deep hole drilling. Harun et al. [13] studied the drilling force and vibration signal in monitoring tool wear condition in deep drilling. The results indicated that both sensors are capable of monitoring tool conditions, but data produced by vibration sensors are more appropriate to detect initial conditions before tool failure. Ramirez-Nunez et al. [14] used infrared technology to detect tool breakage in milling based on the analysis of thermograms obtained during the cutting process. Xu [15] proposed an indirect electric data decomposition-based tool breakage monitoring (TBM) method along with support vector machine (SVM) algorithms to detect the tool breakage in milling. For the tool breakage monitoring in drilling, Szalay et al. [16] demonstrate that measuring thrust
force is an efficient way to recognize the tool breakage. Hsu and Lu [17] studied the cutting parameter effect including tool diameter and feed rate on the spindle vibration signal for tool breakage monitoring. The results demonstrated that tool breakage in drilling could be detected by linear discriminant function with properly choosing wavelet coefficient as features.

A number of studies have confirmed that the tool breakage in drilling could be monitored; however, tool-breakage monitoring systems do not prevent the loss of high-cost micro gun drills and high-value products. Studies have focused now on the development of prognostic systems to considerably decrease tool breakage in the drilling process. On the basis of conventional cutting tool condition monitoring research, a prognostic system can be developed that observes the features generated just before tool breakage occurs; the drill operator can monitor the prognostic system and can shut down the drilling process before the drill breaks.

Some studies have reported development of prognostic systems for machine tools and components such as gears and bearings [18]. Yan et al. [19] developed an autoregressive moving average (ARMA)–based model to predict the machine performance and estimate the remaining life for maintenance. Pandian and Ali [20] reviewed the algorithms in machine diagnosis and prognosis including Markov process, ARMA model, and artificial intelligence algorithms. Machining processes have been investigated in some studies, but they are still in the early stages of development and focused on the prognosis of tool wear conditions. Most of the studies reported the results for the tool wear life estimation in milling process, and the cutting force collected from the dynamometer is well investigated due to its high sensitivity to tool wear conditions. However, high-cost dynamometer is not a proper sensor to be installed in the production line. Zhou et al. [21] focused on the selection of dominance features to predict the tool wear based on force signal. Oentaryo et al. [22] used the cutting force and fuzzy-neural network to solve the tool wear prognosis problem in milling of Inconel 718. Javed et al. [23] also used the cutting force collected from dynamometer to estimate the remaining useful life of milling tool based on neural network algorithm. Geramifard et al. [24] studied the PS-HMCO approach for tool wear prediction based on force, AE, and vibration signals collected from the sensors installed on workpiece. Wang and Wang [25] presented the estimation of remaining useful life of milling tool based on cutting force and the integration of continuous hidden Markov model (CHMM) and Gaussian regression algorithms. Wu et al. [26] reported a strategy to estimate tool wear. The on-line cutting force prediction was made first with the collected cutting force, followed by the tool wear estimation base on the predicted cutting force in milling. Zhu and Liu [27] studied the hidden semi-Markov model (HSMM) with dependent durations for the remaining useful life (RUL) estimation of tool based on cutting force as well. Instead of adopting cutting force for RUL estimation of tool, Kondo et al. [28] investigated effectiveness of the thrust force, the motor current of spindle, and the acoustic emission (AE) signals from workpiece for the monitoring of the pre-failure phase and the detection of the tool breakage in drilling holes through a thin stainless-steel plate. The results revealed that the thrust force and motor current is the most suitable for the monitoring of the pre-failure phase of the tool breakage. Zhang et al. [29] reported that the combination of the vibration signal and particle learning algorithm could be used for tool wear prognosis. Das et al. [30] presented a framework for tool wear prognosis in turning when the degradation data is limited. The vibration, temperature, current, and AE signals were used for the system development. Limited studies have been conducted in the prognosis of tool breakage in micro gun drilling. In the prognosis of tool breakage in conventional size, tool wear monitoring is the basis to estimate the tool failure mode in drilling. Yan and Lee [31] presented a hybrid method of combining logistic regression analysis and maximum likelihood to evaluate the remaining tool life in conventional drilling operation based on the vibration signals. Ao and Qiao [32] presented a strategy to monitor tool condition for drilling machine using wavelet packet decomposition of spindle current signature. Logistic regression combined with autoregressive moving average models was used to evaluate the remaining life of the drill bit. Chinnam and Baruah [33] demonstrated the ability of this method to estimate on-line the remaining-useful-life of a drill bit by employing an unsupervised competitive learning algorithm to perform hidden Markov model (HMM)–based clustering of multivariate temporal observation sequences derived from torque signals. Heinemann and Hinduja [34] presented a strategy to predict an imminent tool failure by using features extracted from the spindle power and AE-RMS signals when drilling small deep holes using twist drills. Average of 84% tool life could be achieved. Patra et al. [35] studied the artificial neural network (ANN) model which was developed to fuse thrust force, cutting speed, spindle speed, and feed parameters to predict the drilled hole number. Corne et al. [36] evaluated spindle power data for real-time tool wear/breakage prediction during drilling of a Ni-based Inconel 625. Jeong et al. [37] proposed a new method to monitor wear condition and predict drill breakage by measuring reflected infrared light from the drill bit outer corner when drilling a titanium workpiece. Based on aforementioned studies, tool breakage can be caused by tool wear over a long period of time. However, instantaneous tool breakages have also been reported because of the chip clogging. In theory, if the signals corresponding to the situation with tangled chip just before tool breakage can be identified, then both damage on the workpiece and downtime for the machining operation can be reduced drastically. Otsu and
Fujyama [38] reported that the severe adhesion and deposition of chips were observed before tool breakage and the prediction of drill breakage in small-diameter drilling could be achieved by monitoring the number of AE events. In this study, we first visited a factory and investigated vibration signals obtained from the tool holder in micro gun drilling occurring on a mass production line. To evaluate the generality of observed features related to micro-tool breakages, micro-drilling experiments were conducted in the laboratory to simulate the conditions in production line for various types of microtools. Signal analysis was performed and feature extraction for both experiments was discussed, in addition to classifier design and system evaluation of the prognostic system for micro gun drill breakage. Finally, the signals corresponding to the conditions of tool entering and leaving the workpiece were applied to the developed system to confirm that these two signals do not impair the accuracy of the developed system in industrial applications.

2 System development

2.1 System structure

The design structure of a tool breakage prognostic system is presented in Fig. 1. The tasks in the system include signal transformation, feature extraction, and classifier design. A fast Fourier transform (FFT) was used in this study to obtain the frequency-domain signal. Feature extraction was then used to select features closely related to the monitoring target according to the class-mean criteria. In the classifier design, a Fisher linear discriminant function with very short computing time classified the tool condition for each period of time. Because this function requires very little time, the monitoring was fine-grained and collected precise data for each instant of time.

2.2 Feature extraction

It was necessary to monitor subtle changes, to predict impending tool breakage, and to react within very short time intervals. Raw signals from the time domain were transformed into the frequency domain because some frequency features of signals are sensitive to the changes in conditions just before tool breakage and are considered valuable features for identifying tool condition. However, a number of frequency features are not related to the target event, such as material and system variation, and are affected by the other parameters as well as the noise generated from the machine or environment. Therefore, system efficiency decreases drastically with full feature selection because of the high computing load, especially for any very short time period. At the same time, if the system inputs noise from features irrelevant to tool breakage, the reliability of the system can decline.

To evaluate the sensitivity of each frequency-domain feature for the condition that leads to drill breakage and to select the correct features for system development, the class-mean scatter criterion was adopted for this study. The cost function is defined as follows:

$$J = \frac{R_c}{R_t(k,k)}$$

where

- $R_c$ is the within-class scatter
- $R_t(k,k)$ is the between-class scatter

The between-class scatter $R_c$ and within-class scatter $R_t$ are defined as follows. First, the feature mean for each class, $\bar{Y}(k)$, can be obtained from individual features $Y_j(k)$

$$\bar{Y}(k) = \frac{1}{M_i} \sum_{j=1}^{M_i} Y_j(k)$$

where

- $i = i^{th}$ class
- $j = j^{th}$ pattern in a class
- $k = k^{th}$ feature
- $M_i$ = the number of patterns in class $C_i$

The overall system mean, $\bar{Y}$, is determined as follows

$$\bar{Y}(k) = \frac{1}{M} \sum_{i=1}^{C} p_i \bar{Y}(k)$$

where

- $p_i$ = a priori probability of class $C_i$
- $C$ = number of classes

The scatter within each class is obtained by calculating the covariance for each feature as follows:

$$R_c(k) = \frac{1}{M_i} \sum_{j=1}^{M_i} (Y_j(k) - \bar{Y}(k))(Y_j(k) - \bar{Y}(k))^T$$

and scatter between the individual classes is defined as follows:

$$R_t(k) = \sum_{i=1}^{C} p_i (\bar{Y}_i(k) - \bar{Y}(k))(\bar{Y}_i(k) - \bar{Y}(k))^T$$

![Fig. 1 Schematic of the system for tool breakage prognosis](image-url)
The feature selection criterion, a cost function, is defined as follows:

\[ J(k) = \frac{R_c(k)}{R(k)} \]  

where

\[ R(k) = \sum_{i=1}^{c} R_i(k) \]

2.3 Classifier design

For the classifier design, Fisher’s linear discriminant analysis was conducted in this study because of its simple structure with a relatively low computing loading compared with other classifiers such as neural network or hidden Markov model–based classifiers. In the model development, the transformation matrix that provides the largest distance between different classes of features on the projection plane can be obtained. The relationship between the original data space and feature space can be expressed as follows [40]:

\[ y = w^T x \]  

In which, \( x \) is the original data space, \( w^T \) is the transformation matrix, and \( y \) is the feature space after transformation.

The transformation matrix \( w \), also called Fisher discriminant function, can be obtained as follows:

\[ w = S_w^{-1}(m_2 - m_1) \]  

\[ m_i = \frac{1}{n_i} \sum_{x \in D_i} x \]

where \( m_i \) is the mean value for each class, \( n_i \) is the number of features in the \( i \) th class, and \( D_i \) is the \( i \) th class.

3 Experimental setup

For the establishment and evaluation of the tool breakage prognostic system in the micro gun drilling, the signals corresponding to the tool condition just before tool breakage were analyzed. To achieve this, an experiment was implemented on a Swiss turning machine in a production line. The system setup is depicted in Fig. 2. The gun drilling tool was installed on the holder, and two Kistler vibration sensors (8141B) with a linear frequency range up to 6 kHz were installed on a fixture connected to the tool holder. In this gun drilling test, the gun drill was fixed on a holder and the workpiece rotated to generate the cutting action (Fig. 3a). To repeat and confirm the signal features provided by the vibration signal for the prognosis of tool breakage in micro gun drilling, another experiment was implemented on a micromachining research platform developed by Micromanufacturing Laboratory in NCHU as well. Based on the same structure as the gun drilling test in a production line, the tool and vibration sensors were installed on a holder fixed to the X–Y table and the workpiece was installed on the spindle as depicted in Fig. 4 to simulate the condition in the Swiss turning machine. The tool in the laboratory experiment is illustrated in Fig. 3b. The specification of the gun drill and microdrill used in both tests are listed in Table 1, and the workpiece and the cutting condition for both experiments are listed in Table 2. In the experiments, seven gun drills and eight microdrills were used to collect data in both tests, respectively. For the tests, a new drill was used for each test and the drilling process was not stopped until the broken tool was observed. In the process, the vibration signals were collected simultaneously and stored in the computer by using the NI 6251 DAQ card. To investigate vibration signals higher than 6 kHz (higher than the linear range), a
A sampling rate of 60 kHz was set up with antialiasing filter in this study.

4 Results and discussions

4.1 Signal analysis

The features of the signals corresponding to the conditions that lead to tool breakage are crucial for the development of the tool breakage prognostic system. Therefore, the signals during stable cutting and the period just before the tool breakage in the test were analyzed first, followed by feature generation and classifier design. The new and broken tools, as well as workpiece, for the gun drill test are illustrated in Fig. 5, and the Z- (axis) and Y-(radial) direction time-domain vibration signals are depicted in Fig. 6. In Fig. 6, stable cutting, before tool breakage, and during tool breakage cases are marked for the following analysis of the frequency-domain feature. Based on the observed signals, the amplitudes of signals at Sects. 1, 2, and 3 refer to stable cutting, and the amplitude of the vibration signal is at the same level as the signals corresponding to the moment just before tool breakage. The amplitude of the vibration signals increased drastically when the tool was broken. The results demonstrated that the condition before the occurrence of tool breakage is not easy to be detected based on only the time-domain signal. To identify the features useful for detecting the tool conditions other than time-domain signals, the time-domain signals were transformed into frequency-domain signals using FFT. Figure 7 illustrates the Z- and Y-direction frequency-domain signals corresponding to the four sections presented in the time-domain signals in Fig. 6. In Fig. 7, the amplitude and distribution of the frequency-domain signals corresponding to the first three sections for stable cutting matched for both direction signals. However, the frequency-domain signals obtained from Sect. 4 refer to the moment just before tool breakage. These signals exhibit different energy distribution over the frequency range compared with the first three sections. The signals between 5 and 6 kHz provide several features to represent the case before breakage and provide the prognostics of tool breakage.

To verify the features observed in the micro gun drilling test, other experiments were implemented in the laboratory.

Table 1 Specifications of the micro gun drill

| Material       | Diameter (mm) | Length (mm) |
|----------------|---------------|-------------|
| Gun drill      | Solid carbide | 0.9         | 125         |
|                | AITn coated   |             |             |
| Micro drill    | WC            | 0.9         | 50          |

Table 2 Workpiece and cutting condition

| Workpiece material | Workpiece diameter (mm) | Feed rate (mm/rev) | Max cutting length (mm) | Spindle speed (rpm) |
|--------------------|-------------------------|--------------------|-------------------------|---------------------|
| Gun drill          | Stainless 316L          | φ5                 | 1.1–2.5                 | 50                  | 7200                |
| Micro drill        | Stainless 316L          | φ5                 | 1.1–1.39                | 5                   | 7000                |
to confirm the observation that the high-frequency vibration features can be potential candidates to predict the occurrence of tool breakage in micro drilling. The conditions of the normal and broken tools in the laboratory tests are depicted in Fig. 8. The time- and frequency-domain signals are depicted in Figs. 9 and 10, respectively. Similar to the observation in the gun drill test, the time-domain signals provide no clear features to detect the condition before tool breakage. However, the high-frequency signals from 10 to 12 kHz represent a potential feature to identify the condition to prevent tool breakage. This result confirmed that the high-frequency signal features that were out of the linear range of the normal accelerometer could be potential candidates for tool breakage prognosis in micro drilling. Thus, the change of the frequency range for the potential features between micro gun drilling and conventional micro drilling can be caused by the structure of the drill and holding system.

4.2 Feature analysis and selection

To quantify the correlation of features and condition just before the tool breakage for selecting the best features for the tool breakage prognosis, the class scatter criteria discussed in Sect. 2 were applied to all frequency features. The index $J$, which is the ratio of between-class scatter to in-class scatter, was used as the criteria to estimate the level of features for the feature selection. The index $J$ for the Z-direction vibration signals covering the frequency of interest from 5 to 6 kHz are illustrated in Fig. 11 with various bandwidth selections. Each of the average energy values referring to a selected frequency was considered a feature, and the width of the frequency for the calculation of each average energy of the signal was considered the bandwidth in this study. From the data illustrated in Fig. 11, the features between 5.7 and 6 kHz exhibit a better chance to identify the tool condition before the occurrence of tool breakage. The results concur with the frequency-domain signals depicted in Fig. 7. The first two highest values of index $J$ varied with the change in the bandwidth size. The 15-Hz bandwidth appeared to provide superior features for tool breakage prognosis. However, the difference was not considered to be large enough. For the signals obtained for the test in the laboratory for micro drilling, the features with the highest index $J$ were between 9 and 9.5 kHz (Fig. 12). However, the application of the 150-Hz bandwidth appeared to achieve a better index $J$ than the other bandwidths.

4.3 System development and evaluation

To avoid data loss during the monitoring of tool condition because of instantaneous occurrence of tool breakage, the developed system requires minimized computing time. Therefore, a simple Fisher linear discriminant classifier was adopted with two selected features in this study. To develop and evaluate the system for the prognostics of tool breakage, two features with the highest index $J$ were selected for further processing. Data obtained from the first two tests were selected as the training data for developing the Fisher linear discriminant classifier model and the other four sets of data were used to verify the performance of the developed model. The discriminant functions developed with two selected features are depicted in Fig. 13 for Z-direction vibration signals. The scattering of features for the signals corresponding to the conditions just before the tool breakage is clearly higher than that for the tool in stable cutting. A similar result can be obtained for the Y-direction vibration signals.
signals. These results could be attributed to the lower variance in stable cutting than that in the case of chip clogging, which is the primary cause of tool breakage. For solving this problem and improving system reliability, the modified discriminant function, depicted as a solid line in Fig. 13, was implemented in this study to evaluate the performance of the developed system.

The evaluation results for both gun drill and microdrill cases are listed in Tables 3 and 4 with Z-direction and Y-direction vibration signals, respectively. Based on the results with the Z-direction vibration signal, 100% classification rate can be obtained for the tool breakage prognosis along with various feature bandwidth selection in the gun drill case. For the microdrill case, 100% classification rate could be obtained with bandwidths of 50 and 150 Hz. Considering the results listed in Table 4, by applying the Y-direction signal to the developed model, the classification rate can be improved as the bandwidth increases from 15 to 50 Hz and 100% classification rate can be obtained for tool breakage prognostics in gun drilling on the production line and conventional microdrilling in the laboratory.

4.4 Confirmation of signal effect during the entering and leaving of micro gun drill

For the development of any tool breakage prognostic system, it is paramount to confirm that all the signal features collected during normal processes do not match the signal features corresponding to the condition just before tool breakage. In section of signal analysis, the signals referring to the situation when the tool is entering and leaving the workpiece were not analyzed. In this section, both the signals corresponding to entering and leaving processes in the micro gun drilling case are analyzed and applied to the developed prognostic system to evaluate their effects. The time-domain vibration signals in both directions corresponding to the entering of the tool in the workpiece are depicted in Fig. 14; in particular, four drilling periods are highlighted with blue boxes. The corresponding frequency-domain signals are illustrated in Fig. 15. Compared with the signals regarding the normal drilling operation (Fig. 6), the signal amplitude increased gradually, and exhibited more oscillations. The analysis of the frequency-domain signals indicated that the pattern varies from the first drilling period to the fourth drilling period for two-direction signals. These results concur with the drilling behavior during the beginning of tool/workpiece contact because of the geometry of the drill bit and the lower stability of the drilling dynamic in this period. Moreover, the frequency-domain signals lower than 3 kHz for the fourth drilling period exhibited a pattern similar to the stable drilling depicted in Fig. 7. It can be considered by the full contact of cutting edge to the workpiece in the fourth drilling period. Considering the frequency range for the selected features in model development, signal energy higher than 3 kHz was not observed. This suggests that the variation of the frequency-domain signal pattern at the entering period does not deteriorate the performance of the developed prognostic system if the selected feature is located in the frequency range between 4 and 6 kHz.

The time- and corresponding frequency-domain signals for the tool leaving the workpiece after completion of the drilling process in the stable condition are illustrated in Figs. 16 and 17, respectively. The signals are more stable than the case with the tool entering the workpiece. Similar to the tool entering the workpiece, no high-frequency energy was observed. This suggests that the tool leaving motion does not affect the performance of the developed tool breakage prognostic system.

The selected feature distributions for the tool entering and leaving cases and the modified linear discriminant
Fig. 9 Time-domain vibration signals for micro gun drilling in the a Z-direction, b Y-direction

(a) 
(b) 

Fig. 10 Frequency-domain vibration signals for micro gun drilling in the a Z-direction, b Y-direction

(a) 
(b) 

Fig. 11 Classification index for features with bandwidth a 1 Hz, b 15 Hz, c 50 Hz, d 150 Hz (Z-direction, 5 kHz-6 kHz)

(a) 
(b) 
(c) 
(d)
**Fig. 12** Classification index for features with bandwidth a 1 Hz, b 15 Hz, c 50 Hz, d 150 Hz (Z-direction, 9 kHz-15 kHz)

**Fig. 13** Linear discriminant function and feature distribution for the Z-direction vibration signals with bandwidth a 5 Hz, b 15 Hz, c 50 Hz, d 150 Hz
Table 3 Classification rate for the prognosis of tool breakage (Z-direction vibration)

| Bandwidth (Hz) | Tests          | Stable cutting (%) | Before tool breakage (%) | Average (%) |
|---------------|----------------|--------------------|--------------------------|-------------|
| 5             | Gun drill 100  | 100                | 75                       | 87.5        |
|               | Micro drill 50 | 50                 | 87.5                     | 68.75       |
| 15            | Gun drill 75   | 100                | 100                      | 87.5        |
|               | Micro drill 75 | 100                | 100                      | 87.5        |
| 50            | Gun drill 100  | 100                | 100                      | 100         |
|               | Micro drill 100| 100                | 100                      | 100         |
| 150           | Gun drill 100  | 100                | 100                      | 100         |
|               | Micro drill 100| 100                | 100                      | 100         |

Table 4 Classification rate for the prognosis of tool breakage (Y-direction vibration)

| Bandwidth (Hz) | Tests          | Stable cutting (%) | Before tool breakage (%) | Average (%) |
|---------------|----------------|--------------------|--------------------------|-------------|
| 5             | Gun drill 100  | 100                | 75                       | 87.5        |
|               | Micro drill 50 | 50                 | 87.5                     | 68.75       |
| 15            | Gun drill 75   | 100                | 100                      | 87.5        |
|               | Micro drill 75 | 100                | 100                      | 87.5        |
| 50            | Gun drill 100  | 100                | 100                      | 100         |
|               | Micro drill 100| 100                | 100                      | 100         |
| 150           | Gun drill 100  | 100                | 100                      | 100         |
|               | Micro drill 100| 100                | 100                      | 100         |

Fig. 14 Time-domain vibration signals at the entering of the tool to workpiece a Z-direction, b Y-direction

Fig. 15 Frequency-domain vibration signals at the entering of tool to workpiece a Z-direction, b Y-direction
function are illustrated in Fig. 18. The results indicated that the selected features for both cases are far from the classification line and do not lead to misclassification. In the microdrilling case in the laboratory, the same results were obtained.

5 Conclusions

A micro gun drilling experiment was conducted on a Swiss turning machine, as well as an evaluation experiment setup in the laboratory through simulated micro drilling. The two-directional vibration signals were analyzed for both directions to develop a microdrill breakage prognostic system to identify any conditions that lead to tool breakage. The results proved that the high-frequency features of the two-directional vibration signals provided valuable features to identify the conditions that lead to unexpected tool breakage. With the proper selection of features that are closely related to tool conditions before tool breakage, the proposed prognostic system can detect the danger of tool breakage successfully before the tool breaks; thus, costly losses can be prevented. This prognostic system can use Y- or X-direction vibration signals on a production line or in a laboratory. To confirm the effects of drilling disturbances on the prognostic system, the signal features of the entries and exits of tools to and from workpieces were studied. The results demonstrate that both types of signal features can be used without causing any misclassification.

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Author contribution Ming-Chyuan Lu contributes to the conceptualization, methodology, signal analysis, and writing. Li-Yu Hsu contributes to the development, the conduction of experiments, and the data process and analysis.

Availability of data and material The data will not be shared publicly.

Declarations

Ethical approval None.

Consent to participate All authors consent to participate.

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Conflict of interest The authors declare no competing interests.

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