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ORIGINAL ARTICLE

Tool wear condition monitoring based on continuous wavelet transform and blind source separation

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Abstract

Prognostics and health management (PHM) for condition monitoring systems have been proposed for predicting faults and estimating the remaining useful life (RUL) of components. In fact, in order to produce quickly, economically, with high quality and reduce machine tool downtime, a new intelligent method for tool wear condition monitoring is based on continuous wavelet transform (CWT) and blind source separation (BSS) techniques. CWT is one of the most powerful signal processing methods and has been widely applied in tool wear condition monitoring. The CWT used to transform one set of one-dimensional series into multiple sets of one-dimensional series for preprocessing. After that, BSS was applied to analyze the wavelet coefficients. The signal energy evolution of each independent source obtained by BSS was used for health assessment and RUL estimation, the idea is based on the computation of a nonlinear regression function in a high-dimensional feature space where the input data were mapped via a nonlinear function. Experimental results show that the proposed CWT-BSS method can reflect effectively the performance degradation of cutting tools for the milling process. The proposed method is applied on real-world RUL estimation for a given wear limit based on extracted features.

Keywords CNC milling · Tools wear · CWT · BSS · Feature extraction · RUL

1 Introduction

Machining process performances become a key issue for reliability improvement. In order to decrease the loss of production and probability of failure, condition-based maintenance (CBM) used condition monitoring technologies to detect and predict the risk failure of equipment working under different operating conditions [1–5]. In view of its importance in automation, modernization, sustainability, cost reduction, and control of manufacturing processes, extensive research has been carried out in the area of tool condition monitoring (TCM).

Several signal processing methods for failure prognostic are closely related to feature extraction from collected signals [6–8]. Many of these methods are analyzing the signal in time domain, frequency, and time-frequency domains [9, 10]. Lauro et al. [11] present a discussion for the first steps involved in choosing and defining various techniques that may be used to monitor machining processes. The limitation of these methods are sensitive to the cutting conditions and cannot be used to estimate the current state of the wear in the presence of different cutting conditions throughout the process [12]. The cutting force signals, vibration table, spindle power consumption, and cutting and acoustic emission are all shown to be correlated with tool wear [13, 14]. The force signal is the most widely used measurement in TCM. Due to the differences in the nature of sensors, each can extract different information from the machine [15]. Moreover, it has been shown that time-frequency analyses such as continuous wavelet analysis or wavelet packet decomposition can provide valuable information about the health state of the tool in different machining operations [16].

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When monitoring complex systems, mixtures of signals have been measure by sensors that are unique to component. The different signals collected from these components during operation contain information about the component conditions or machine. The isolating component signal from sensor signals can be a challenge. As an example, in condition monitoring of a rotating machine, if some components generate vibration signals at the same frequencies, they cannot be separated using traditional signal processing. The different signals collected by sensors (vibrations, forces, and acoustic emission) for TCM are defined by the combination of vibration energy produced by different components such as spindle, cutting tool, electric motor, workpiece, etc., in addition to the noise. In this mixture of signal measurements, it is difficult to obtain reliable monitoring criteria to identify in situ tool failure during the machining process because the collected signals are usually contaminated with a great deal of noise. However, developing degradation signals from component sensors is an important issue to estimating the remaining useful life (RUL). However, in practice, the collected vibration signals are mixed with many vibration signals relevant to the cutting tool, which contaminate with each other in feature extraction processes and decrease the monitoring reliability. In this study, blind source separation (BSS) has been proposed for signal separation in milling operations for identifying different source collected data.

Therefore, it is important to develop a robust filtering scheme for improving the signal and feature extraction. A BSS proposed for recovering the various independent sources exciting a system was given only in the measurements of the outputs of that system [17–20]. BSS has become an appealing field of research with many technological applications areas such as medical, image processing, and communications. Lately, it was applied to condition monitoring of rotating machinery [21–24]. However, little has been investigated with the application of the BSS for tool wear condition monitoring. Shao et al. [25] developed BSS technique to separate those source signals in the milling process. A single-channel BSS method based on wavelet transform and independent component analysis (ICA) is used, and source signals related to a milling cutters and spindle are separated from a single-channel power signal. Zhu et al. [26] introduces a FastICA algorithm as a preprocessor to provide noise-free forces for later correlation to tool flank wear. It was identified that there exist both Gaussian and non-Gaussian noises. It applies the FastICA for these blind source separation and then discards the separated noise components. The BSS process is treated as signal denoising in this approach. Shi et al. [27] proposed an approach based on empirical mode decomposition and independent component analysis is presented to deal with the blind source separation problem of cutting sound signals in face milling with the objective of separating cutting oriented sound signals from those background noises. Gandini et al. [28] developed a convolutive version of ICA to overcome technical and metrological problems arising. This convolutive modification of ICA was used to demix the recorded signal and to recover the technological fingerprint over it.

The purpose of this research is focused on the separation of dependent sources and proposes an algorithm combining continuous wavelet transform (CWT) and BSS. The CWT is used to reduce the computational cost of covariance estimation.The method consists of three processing stages. In stage one, the sensor signal collected from milling cutters decomposed into several groups of signals based on CWT. In stage two, the BSS algorithm is used to deal with these CWT signals, and hence to complete the separation process. In addition, the proposed CWT-BSS algorithm processes the multi-channel cutting signals [29]. Finally, the health state of cutting tools was identified by health state calculation of cutting tools, the health indicator obtained by computing signal energy of independent signals.

The main investigation objectives of this paper are as follows:

– Proposes a new data-driven approach for prognostics based on CWT and BSS
– The model parameters are optimized by testing different techniques for BSS that facilitates the application of the proposed method
– The combination of CWT and BSS techniques is very significant
– The degradations dataset [29] and comparisons with the related state-of-the-art results validate the effectiveness and superiority of the proposed method
– The BSS method-based CWT is developed, and source signals related to a milling cutter and machine are separated
– To the best of our knowledge, the BSS method based on CWT is applied to predict tool wear for the first time
– Experimental results shown that the predictive model trained by CWT and BSS is very accurate
– The experiments with different cutting tools illustrate that the separation strategy is robust and promising for cutting process monitoring.

The paper is organized as follows: Section 2 gives a description of the proposed method; we describe the CWT-based BSS algorithm for dependent sources in detail. In Section 3, CWT-based BSS algorithm and the procedure of the proposed BSS algorithms are given. Simulations illustrate the good performance of the proposed method, a case study utilizing a real data to validate the proposed method. Finally, Section 4 concludes the paper.

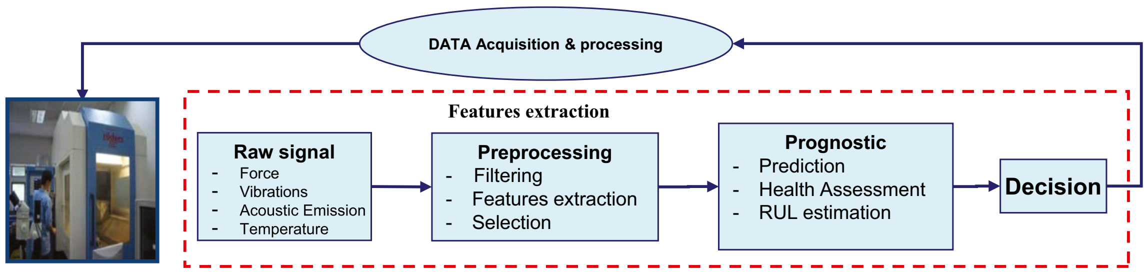

Fig. 1 Steps of the proposed method

2 Description of the proposed method

Various prognostic research works have been conducted for predicting the RUL prediction. In Fig. 1, there exist three steps to be followed in the TCM process:

The data acquisition step is to collect the data related to system health; data preprocessing is to analyze the acquired signals including centering and filtering to remove the offset in the measured signals. In the preprocessing step, a CWT is used to decompose signals into coefficients for taking a certain scale of wavelet coefficients that contains information about sources as the input signal for BSS. The energy signal of independent source-based regression was used for the health assessment; in maintenance decision-making step, effective maintenance policies will be obtained based on information analysis.

2.1 Basics of continuous wavelet transformation

Wavelet transform is a mathematical tool that converts a signal into a different form. CWT was developed as an alternative to the short-time Fourier transformation in order to overcome typical resolution problems [30]. The wavelet used in CWT is defined by different wavelet basis function [31].
Given a mother wavelet function $\psi(t)$, a series of wavelet can be defined as:

$$\psi(t)_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a}), a, b \in \Re, a \neq 0 \tag{1}$$

where a is the scale parameter and b is the translation parameter.

Mathematically, a wavelet is a square integrable function $\psi(t)$ that should satisfy the condition:

$$C_\psi = \int_R \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty \tag{2}$$

where $\psi(\omega)$ denotes the Fourier transform of $\psi(t)$, and R represents the real number. The continuous wavelet transform of a signal $x(t)$ can be described as follows:

$$WT(a,b) = \sqrt{|a|} F^{-1}\left[X(f)\Psi^*(af)\right] \tag{3}$$

where $X(f)$ and $\Psi(f)$ are the Fourier transform of $x(t)$ and $\psi(t)$, respectively, and F^{-1} represents the inverse Fourier transform.

Accordingly, the CWT can be viewed as a filtering of the signal by a dilated version of the mother wavelet $\psi(t)$. The bandwidth and central frequency of the filter is determined by the scale parameter a of the wavelet function.

2.2 Background on blind source separation

BSS is a method for recovering the signal produced by individual sources from their mixtures (Fig. 2). In the simplest case, m mixed signals from m different sensors $x_i(k)$ are assumed to be linear combinations of unknown

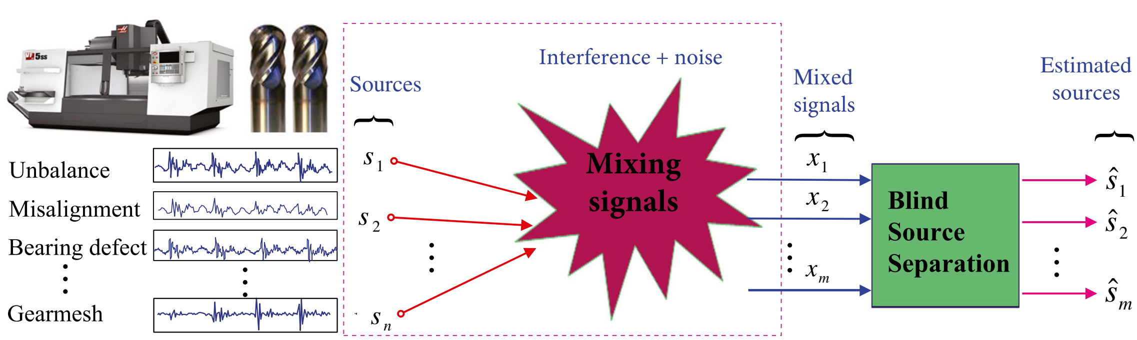

Fig. 2 Blind source separation model

mutually statistically independent signals from n vibrating components $s_j(k)$ with noise. This can be stated as:

$$X(t) = A.S(t) + N(t) \tag{4}$$

The mixed sources or the coefficients obtained by CWT, $S(t) = [S_1(t), ..., S_n(t)]^T$ is mixed using a matrix, $A = [a_{ij}] \in \Re^{m\times n}$ to produce a set of "mixed" source signals, $X(t) = [X_1(t), ..., X_n(t)]^T$ as follows, in this case $m = n$. If $m > n$, then the equations system is overdetermined and can be unmixed using a conventional linear techniques. If $n > m$, the system is underdetermined and a nonlinear techniques must be employed to recover the unmixed source signals (Fig. 2).

Several methods for BSS have been reported in the literature [32, 33]. These techniques can be classified into several major approaches: non-gaussianity, maximum likelihood, minimum mutual information, neural network modeling, and algebraic [34, 35]. Moreover, there are several famous algorithms which are based on the algebraic approach [24] such as FastICA, AMUSE, SOBI, JADE, and COMBI. Five algorithms implemented in this study were selected from the most used in the fault diagnosis [36] presented in this paper. The performance of each technique is tested and the results were shown from different mixed signals used (vibrations, force, and acoustic emission).

In order to obtain an accurate and quantitative measure of the performance of the algorithms, Chen et al. [37] examined various performance measures used in different BSS implementations. The performance measuring criteria used here are crosstalk, performance index, signal-to-interference ratio, and distance to the diagonal matrix.

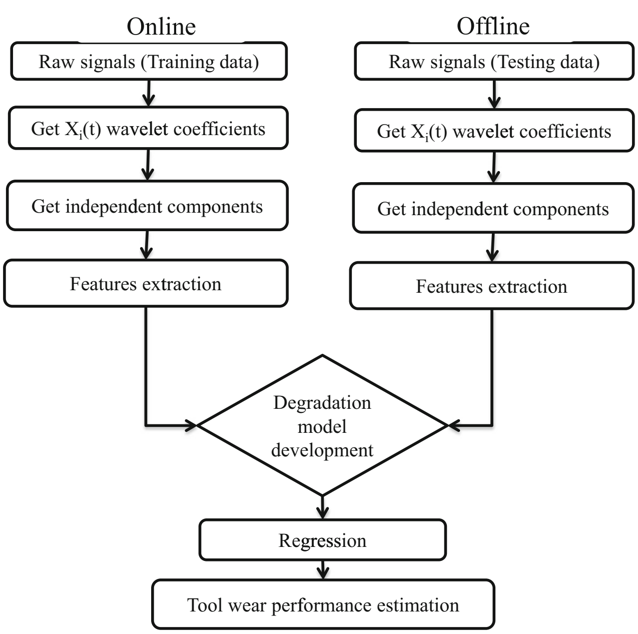

Fig. 3 The flowchart of the lean model for performance assessment

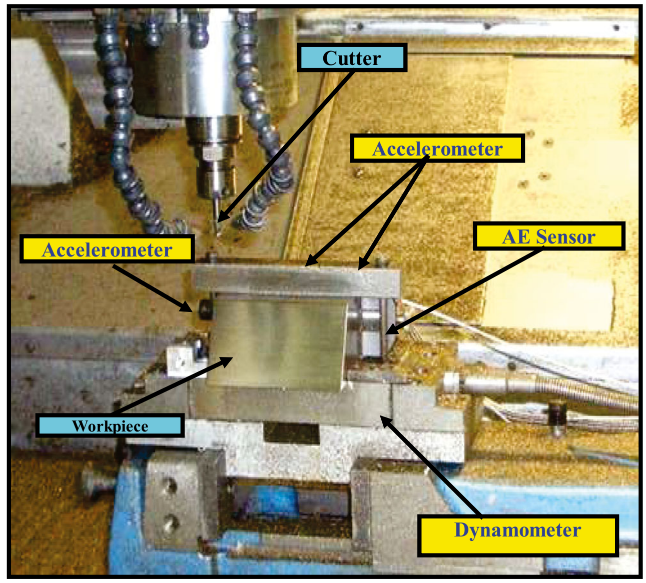

Fig. 4 Experimental setup

3 Proposed strategy of combining BSS with wavelet

The proposed method of the CWT-BSS for tool's wear estimation was given in Fig. 3. The method is decomposed into two main phases. The first phase is performed off-line and aims at generating an appropriate model that allows describing the behavior of the cutter's degradation. Specifically, the goal of this phase is to compute the model by regression. The second phase, which is achieved on-line, deals with the utilization of the model generated continuously to assess the health state of the tools and to predict its future one leading to a calculation of the RUL value.

3.1 Experimental setup

The experimental study shown in Fig. 4 is for tool wear condition monitoring in high-speed milling cutters [38]. Provided by Simtech Institute in Singapore is a high speed CNC milling machine (Roders Tech RFM 760) [29]. The data collected from three kinds of sensors (accelerometer,

Table 1 Cutting conditions

Cutters 6 mm	Ball nose tungsten carbide
Materials	Inconel 718 (Jet engines)
Spindle speed	10400 RPM
Feed rate	1.555 mm/min (50 μm/tooth)
Y cut depth (radial)	0.125 mm
Z cut depth (axial)	0.2 mm
Sampling data	50 KHz/channel

Table 2 Data acquisition files

Column	Measurement (unit)	Type
1	Force (N)	Kistler 9257BA dynamometer triaxial
2	Vibration (g)	Kistler 8762A50 ceramic shear triaxial
3	Acoustic emission-RMS (V)	Kistler 8152B121
4	Tool wear measurement	Olympic microscope
5	Data acquisition	PCI 1200 board

force, and AE) are attached to the workpiece shown in Table 2. Six individuals of three flute cutters (C1, C2,... C6). Each tool cutter completes 315 cuts with the same work piece, with identical condition, and with the same cutter; the cutting condition and the data acquisition (315 files have created a total of 6 sets) were shown in Table 1.

The proposed approach for data-driven prognostics was based on BSS and CWT, where $x_i = (F_x, F_y, F_z, V_x, V_y, V_z, AE)$. The input data description can be found in Table 2. The dynamometer consists of three-component force sensors in three dimensions. Each dynamometer sensor contains three pairs of quartz plates; in the z direction, the sensor is sensitive to pressure and in the x and y direction, the sensor is sensitive to shear. Three accelerometers with type Kistler 8762A50 ceramic shear triaxial, mounted on the workpiece, were used for vibration measurements in three perpendicular axes. An AE sensor was used to monitor a high-frequency oscillation, mounted on the workpiece. The data used in this study was obtained from [29, 39]. Some details of the experiment are presented in this section.

3.2 Source separation

Figure 5 show the sensor measurements of the first and last cycle of machining for different sensors (force, acceleration, and AE). The decomposed results of signals with degraded cutter by using CWT are given in Fig. 6. That has six levels. In general, the raw signals of healthy cutting tool are Gaussian in distribution for any value of speed and load; the kurtosis value is close to three .The appearance of wear degradation on the cutting surfaces resulted in kurtosis values that are greater than three; if the damage increases, the kurtosis values are back to three.

In this study, the wavelet Daubechies “$db4$” have been used to decompose cutting forces into six levels. The different frequency bands represent the force from different wear levels. In the process of signal analysis, the CWT is employed firstly to decompose the raw cutting signal by CWT and get the coefficients. Through CWT decomposition, the coefficients are obtained. Figure 6 shows the coefficients extracted from collected signals (vibrations, force, and AE).

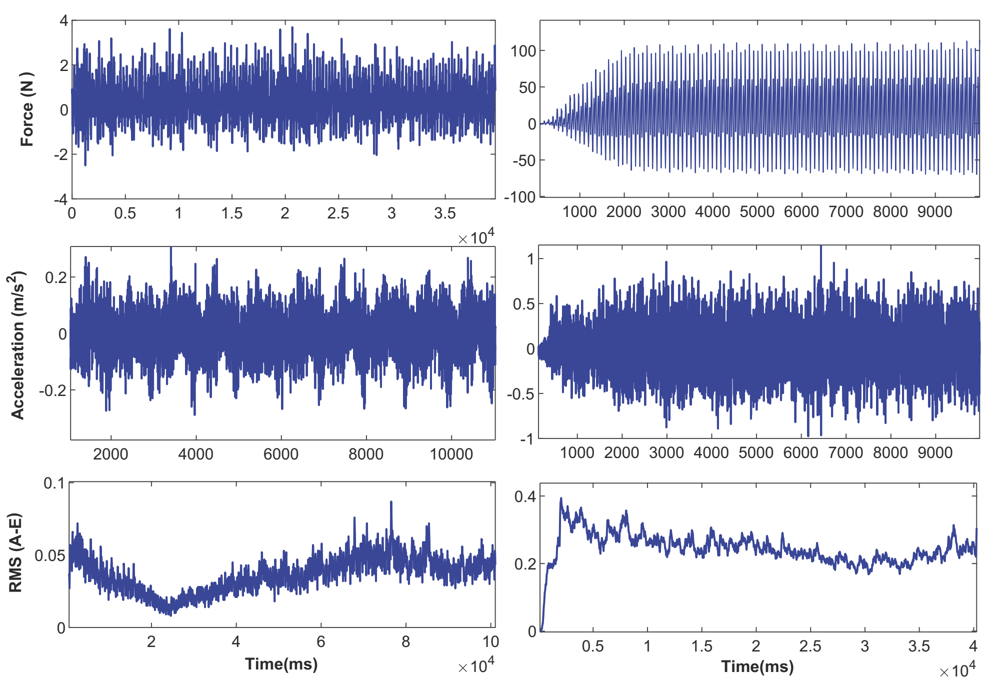

Fig. 5 Sensors measurement for the first cycle (right) and last cycle (left) of machining

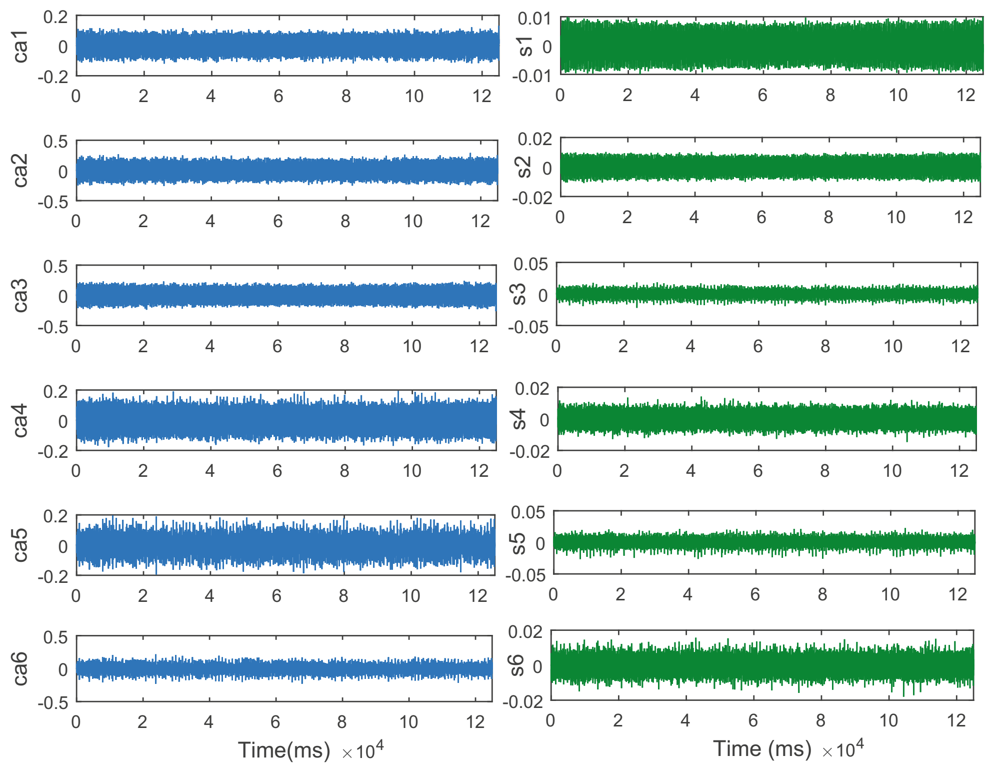

Fig. 6 CWT coefficients of force signal in x dimension (left), source separation using WASOBI (right)

Separated signals based on Ewasobi [40, 41] are shown in Fig. 6. The proposed algorithm was performed on multiple channel cutting signals. Cutting force signals in the milling process had been collected using three kinds of sensors in three dimensions (Fig. 4).

The force signal correlates well with tool wear condition monitoring [26]. However, the noise component in the signal is very difficult to separate. The noise component in the signal for TCM is usually very high and difficult to separate [9]. Figure 6 shows a force signal and noise. It can be observed that the force signal is very highly non-stationary.

3.3 Statistical dependence

In order to confirm the validity of the proposed method CWT-BSS, the source correlation values of different sources obtained by CWT coefficients are shown in Table 3 for the vibration signal in Z dimension at the cycle 150.

Separated signals based on efficient weights-adjusted second-order blind identification algorithm (EWASOBI) that are shown in Fig. 6 have high dependent; the other BSS technique does not have a good separation of the original source signals, but the proposed approach based CWT can separate the desired signals properly and given a good correlation. The proposed CWT-BSS algorithm can separate the signals properly. Next, for comparison between different BSS algorithms along the performance criteria that are statistical, the results are shown in Table 1.

In order to verify the advantage of the proposed CWT-BSS method, signal processing with BSS only was carried out in the present work. The signal collected in milling process had been collected using three sensors (vibrations, force, and acoustic emission) shown in Fig. 4. The observed signals obtained by computing the wavelet coefficients have been selected as the mixtures for BSS only. Figure 6 shows the separated results with EWASOBI.

Table 3 The correlation values between sources

CWT coefficients	$\hat{S}_1$	$\hat{S}_2$	$\hat{S}_3$	$\hat{S}_4$	$\hat{S}_5$	$\hat{S}_6$
Source 1	−0.9997	0.0087	0.0222	−0.0165	−0.0058	0.0358
Source 2	0.0442	−0.9984	−0.0473	−0.0304	0.0265	0.0150
Source 3	0.0130	−0.0227	−0.9922	−0.1838	0.0970	0.0067
Source 4	0.0012	−0.0062	−0.1048	0.9847	0.0206	−0.1125
Source 5	0.0205	−0.0177	−0.0929	−0.0250	0.9918	−0.0009
Source 6	0.0212	0.0270	−0.0051	0.0944	−0.1317	−0.9997

Table 4 Performance criteria for various BSS algorithms

Algorithm	SOBI	JADE	FastICA	COMBI	FPICA	EWASOBI
PI	0.2856	0.2589	0.2748	0.2345	2.9865	0.02468
SIR	18.4563	33.1525	29.5452	9.4672	12.6003	15.3135
$\Omega(D)$	0.2654	0.3156	0.3138	0.2439	0.2397	0.2133

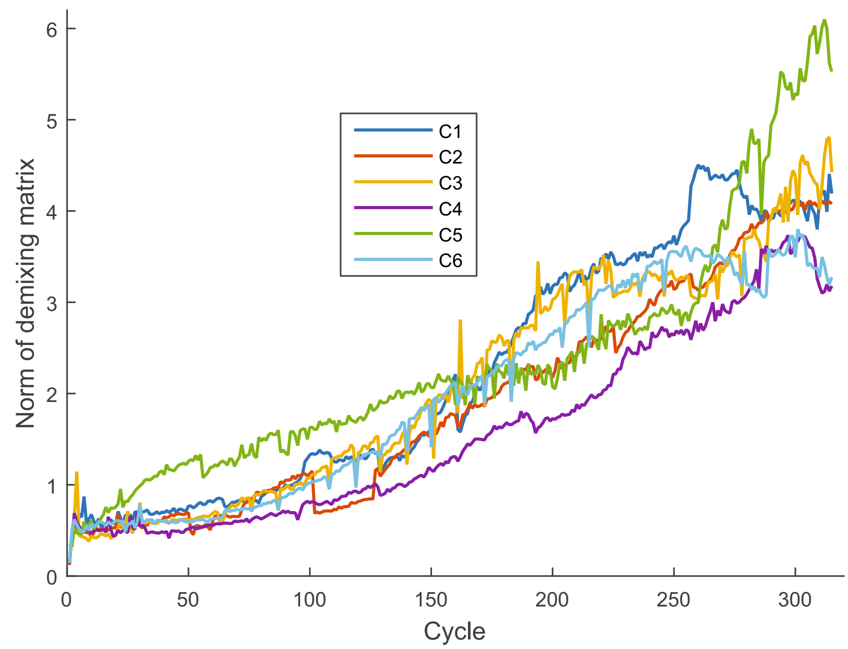

Fig. 7 Norm of demixing matrix of all cutters

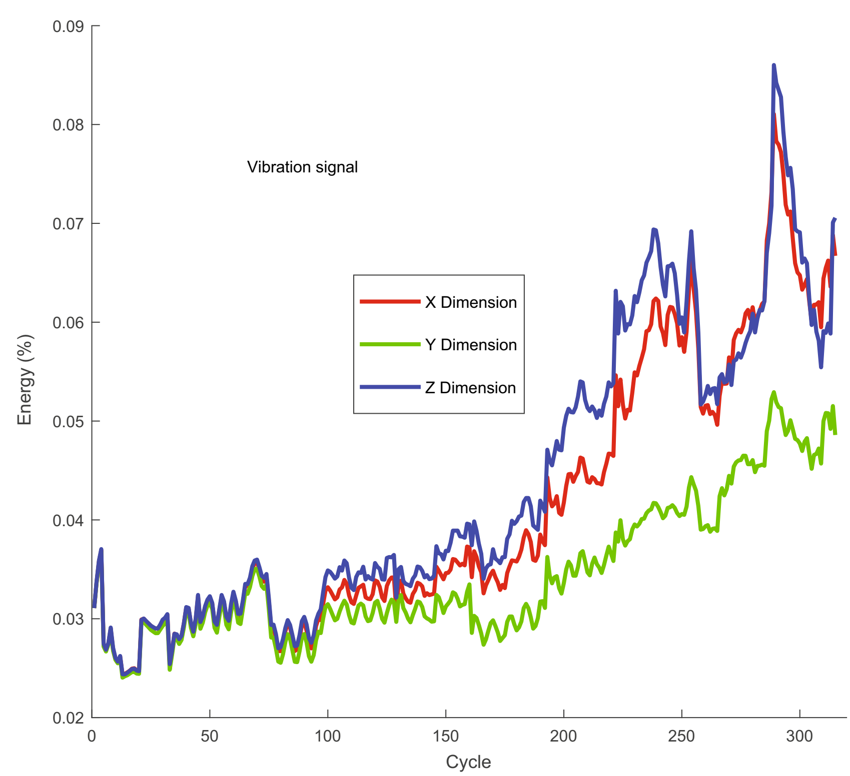

Fig. 8 Vibration signal energy for the cutter C1 in three dimensions

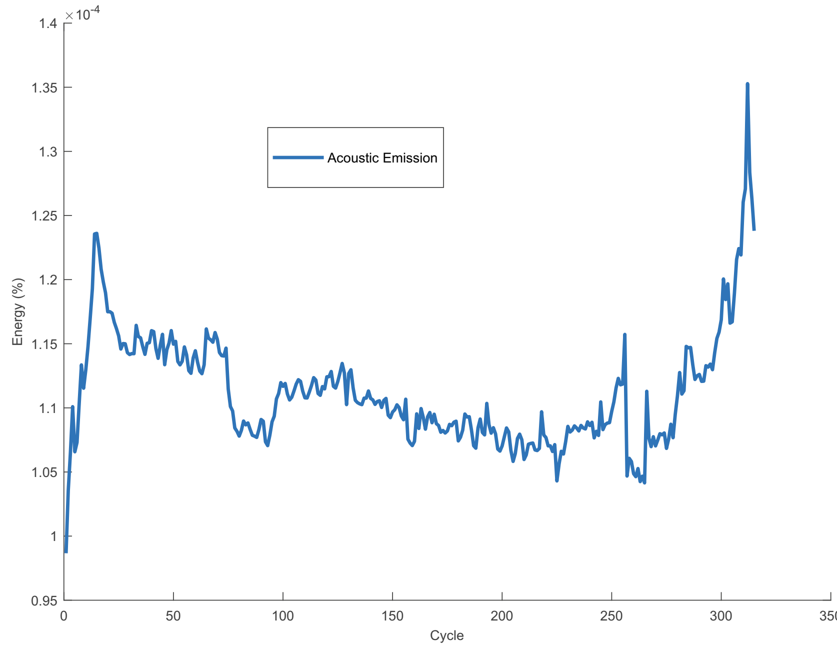

Fig. 9 AE signal energy for the cutter C1

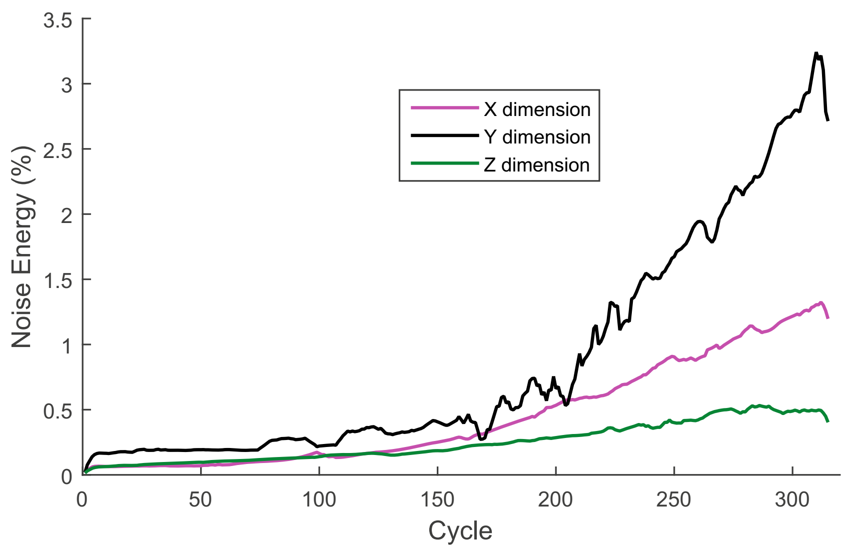

Fig. 10 Force noise energy for the cutter C1 in three dimensions

Table 5 Feature extraction

Norm of demixing matrix (Frobenius norm)	$\|A\|$
Eigenvalue trace of demixing matrix	$Trace(A) = \sum_{i=1}^{n} A_{ii}$
Root mean square (energy of mixed sources)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x(t)_i^2}$
Root mean square (energy of estimated sources)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s(t)_i^2}$
Root mean square (noise energy)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} N(t)_i^2}$

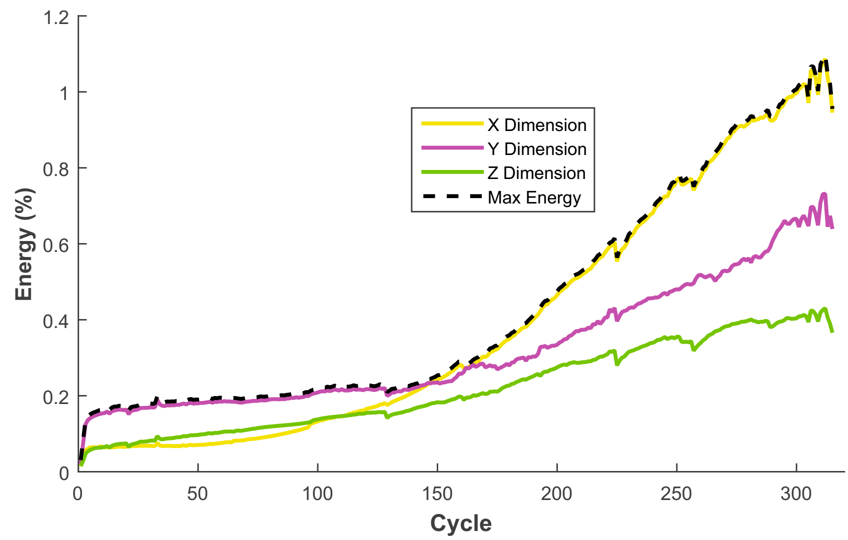

Fig. 11 Force signal energy for the cutter C1 in three dimensions

In order to confirm the validity of the proposed method CWT-BSS, the dependence between estimated sources can be measured by using some performance criteria shown in Table 4 of various algorithms [42].

Table 4 shown the performance evaluation of source separation; the value of performance index (PI) is less than 5% and the techniques COMBI and WASOBI give a good separation with a small time computing, whereas JADE, FastICA, and SOBIRO has the lowest performance (Figs. 7, 8, 9, and 10).

3.4 Feature extraction

In this section, we present the feature generation from CWT-BSS for the force signals. More advanced prognostics are interested in performance degradation assessment, so that failures can be predicted and prevented. The concept of feature extraction for accurately assessing the cutting tool performance degradation is a critical step toward realizing an online tool condition monitoring platform. Many original features that can be extracted from raw signals have been investigated. This section presents a comprehensive discussion of feature extraction from time domain signal separation shown in Table 5.

In this study, the energy signal of each level was used in regression for performance degradation assessment. In this combination strategy, the raw signal is first decomposed in different scales by CWT with the given scaling function and wavelet function. Accordingly, it is expected that the proposed CWT-BSS model can more accurately model and compensate the performance degradation of the raw signal characteristic.

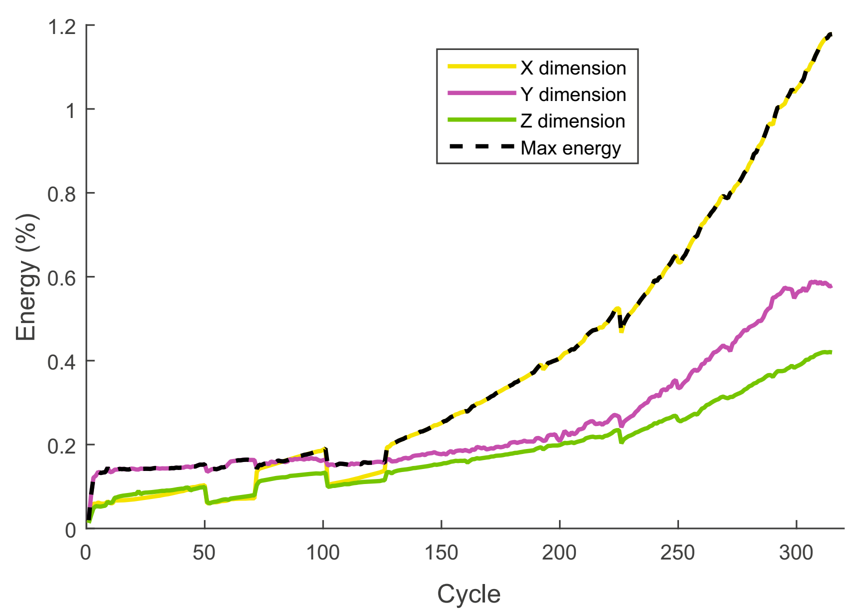

Fig. 12 Force signal energy for the cutter C2 in three dimension

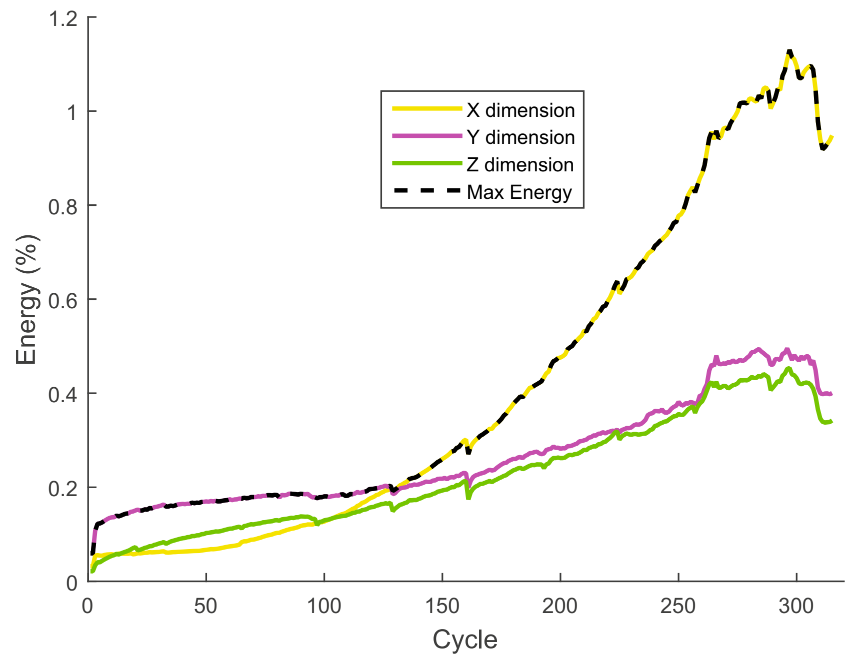

Fig. 13 Force signal energy for the cutter C4 in three dimension

The feature evolution is represented by the node energy of the respective CWT node shown in Figs. 11, 12, 13, and 14.

The node energy value has been used to follow up the level or the system severity. In experimental setup, this value is used to monitor the overall signal force level. The RMS value of the signal force is a very good temporal descriptor of the overall condition for the other monitor signal vibration in Fig. 9 and AE in Fig. 9.

The estimated wear value shown in Fig. 15 based on typical training sets of the force signals of the six datasets reflects high accuracy and dependencies of the obtained models by CWT-BSS. The computing errors obtained only in the final part of the models that were the observed wear values are great. From the results, it is seen that all the predictors perform very well.

In Fig. 15, in the maximum node energy of force signal, we can observe three different regions. The first region

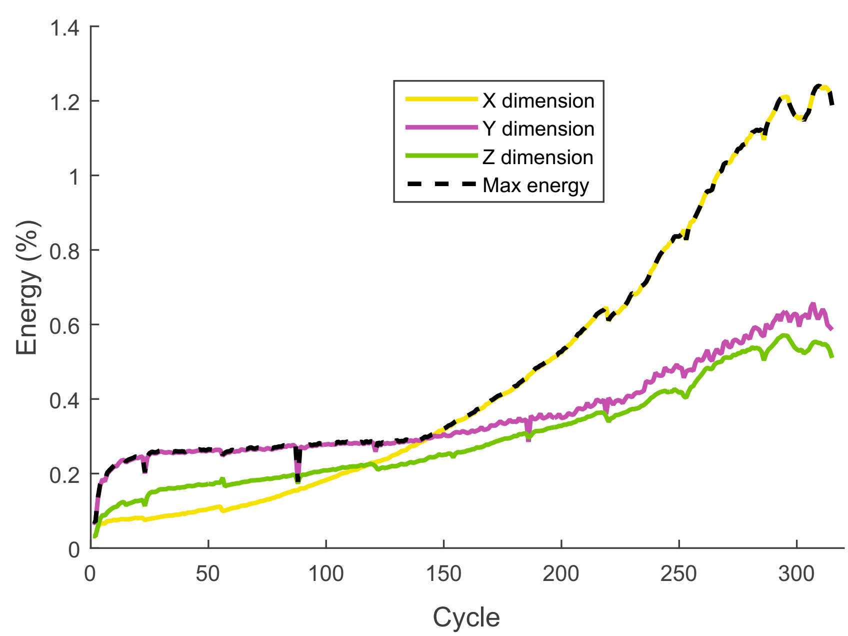

Fig. 14 Force signal energy for the cutter C5 in three dimension

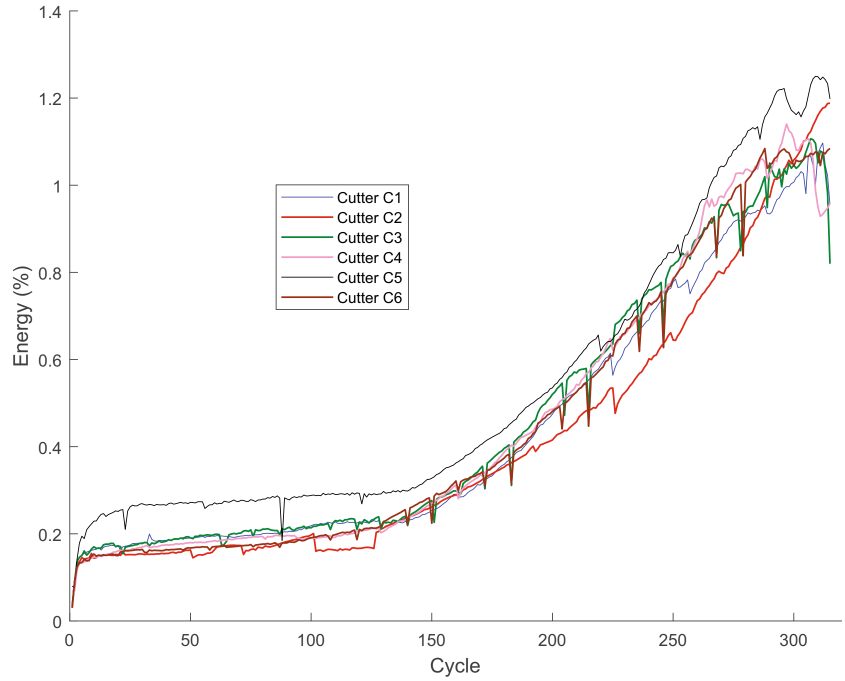

Fig. 15 Maximum energy of force signals of each cutter

between zero and six cycles of machining is representing the normal cutting operation. The second region between 6 and 150 machining cycles is characterized by fluctuating the energy with a mounting development; this region is associated with wear initiation and propagation along the three flutes of cutters; the last region, an extends exponential behavior at the time of damage initiation to until total failure (Fig. 16).

3.5 RUL estimation

The collected signals were used in this paper [29]. The experimental datasets are generated from cutting tool run-to-failure tests under constant load conditions. In order to prove the effective prediction of the CWT-BSS method, six datasets were used with the same operating condition of the machining process.

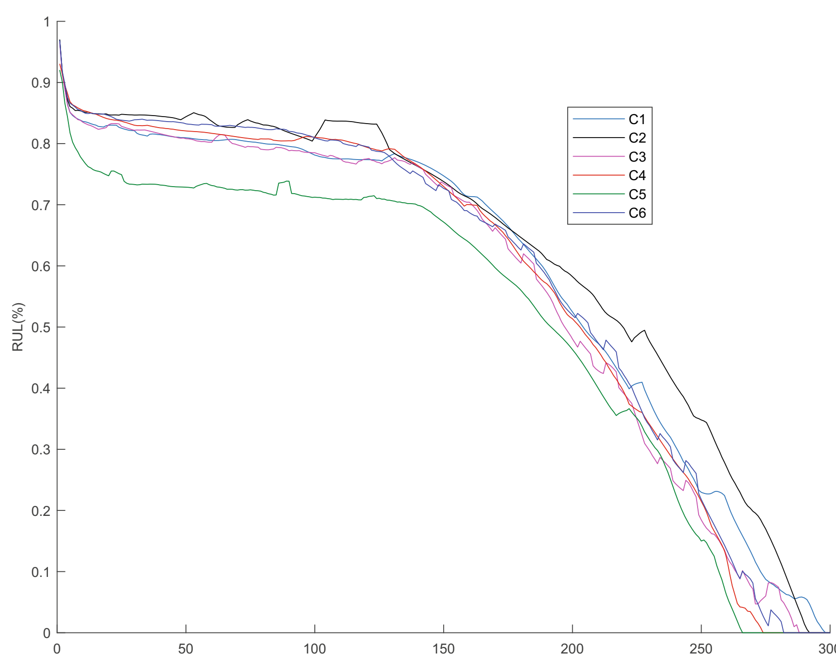

Fig. 16 RUL for all cutters

Table 6 Prediction performance

Cutter	Regression function : $f(x) = a * x^b + c$	SSE	RMSE	R^2
C1	$f(x) = 4.259e - 07 * x^{2.549} + 0.1561$	0.3959	0.03562	0.9853
C2	$f(x) = 2.175e - 08 * x^{3.077} + 0.1485$	0.0750	0.01550	0.9974
C3	$f(x) = 1.302e - 06 * x^{2.362} + 0.1492$	0.6888	0.04699	0.9770
C4	$f(x) = 9.708e - 07 * x^{2.421} + 0.1351$	0.8946	0.05355	0.9726
C5	$f(x) = 9.179e - 08 * x^{2.839} + 0.2332$	0.4813	0.03927	0.9858
C6	$f(x) = 6.336e - 07 * x^{2.496} + 0.1340$	0.4113	0.03631	0.9873

The regression results are presented in Table 6 in terms of the factors of determination R^2 for the different training models. The R values indicating the fraction of the total variance that could be explained by the model are very high. From the results, it is seen that all the predictors perform very well. The objective is to apply the best exponential fit on the degradation model. The validation of these results is shown in Table 6 by computing of the sum square error (SSE), R^2, and root mean square error (RMSE).

The goal of this technique is to analyze prediction capabilities by using CWT-BSS for TCM. A comparative study between different algorithms used in BSS on reliability performance analysis was summarized in Table 4.

4 Conclusion

In this paper, the tool wear prediction in milling operations was conducted using CWT and BSS. The dataset collected from 315 milling tests was used for the performance evaluation of the proposed approach including $RMSE$, R^2, and SSE. The study of tool wear degradation assessment is done by using the multisensory signal (force, vibrations, and acoustic emission) in milling operations. The features were extracted from separated sources by computing the signal energy for the performance degradation assessment. The potential of CWT-BSS was shown in this paper for performance degradation assessment. It is expected that with additional development, CWT-BSS can drastically improve the accuracy of RUL estimation-based tool wear condition monitoring across the full range of the machining process. In this study, we demonstrate that the health indicator can reflect effectively the tool wear.

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