

Enhanced condition monitoring of the machining process using wavelet packet transform

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ABSTRACT: Tool wear in machining processes can have a detrimental impact upon the surface finish of a machined part, increase the energy consumption during manufacture and potentially, if the tool fails completely, damage incurred may require the part to be scrapped. Monitoring of the tools condition can therefore lead to preventative steps being taken to avoid excessively worn tools being used during machining, which could cause a part becoming damaged. Several studies have been devoted to condition monitoring of the machining process, including the evaluation of cutting tool condition. However, these methods are either impractical for a production environment due to lengthy monitoring time, or require knowledge of cutting parameters (e.g. spindle speed, feed rate, material, tool) which can be difficult to obtain. In this study, we aim to investigate if tool wear can be directly identified using features extracted from the electrical power signal of the entire Computer Numerical Control (CNC) machine (three phase voltage and current) captured at 50 KHz, for different cutting parameters. Wavelet packet transform is applied to extract the feature from the raw measurement under different conditions. By analyzing the energy and entropy of reconstructed signals at different frequency sub-bands, the tool wear level can be evaluated. Results demonstrate that with the selected features, the effects due to cutting parameter variation and tool wear level change can be discriminated with good quality, which paves the way for using this technique to monitor the machining process in practical applications.

1 INTRODUCTION

Tool wear and subsequent failure of tools during the manufacturing process will have a significant impact on the economics of machining, and about 25% of machine down time can be attributed to the direct results of tool wear failure (Altintas & Yellowley 1989). Moreover, the development of tool wear will give rise to inconsistencies in surface finishes and geometric tolerances, affecting the quality of manufactured products. Therefore, a series of studies have been devoted to monitoring systems detecting underperforming tooling and improving machining efficiency and productivity.

The monitoring techniques for tool wear can be divided into two categories, direct and indirect methods (Bhattacharyya & Sengupta 2009, Teti et al. 2010). With direct methods, tool wear is evaluated by analyzing the cutter itself, such as measuring the surface roughness and flank wear, etc. On the other hand, indirect methods apply either model-based or data-driven techniques to the measurements like cutting force, tool vibration and output power for evaluating tool wear conditions. It should be noted that due to the restrictions

of direct methods such as stopping requirements during production, indirect methods are more suitable for industrial applications (Zhu et al. 2009).

With indirect methods, different measurements can be collected and analyzed to evaluate the tool condition, including acoustic emission (Prickett & Johns 1999, Karimi et al. 2013, Hass et al 2013), cutting force (Dimla & Lister 2000, Li et al. 2006, Deng et al. 2013, Lee et al. 2006), vibration (Yesilyurt & Ozturk 2007, Zhang & Chen 2007, Lamraoui et al. 2014), temperature (Byrne 1987, Davoodi & Hosseinzadeh 2012), spindle power/current (He et al. 2017, Li et al. 2000, Simoneau & Meehan 2013), etc. However, several of these methods often require expensive sensing equipment (Nouri et al. 2015) and can be difficult to install due to the need for close proximity to the cutting tool and workpiece, meaning they can be impractical for large production environments. Additionally, the classification of tool wear from the collected data is challenging due to the high sensitivity of data to the cutting parameters (i.e. spindle speed, feed rate, depth and width of cut, material, tool type). Thresholding of time domain data has been used as a method of classifying tool wear (Shao et al.

2004), however, this requires large amounts of calibration and training data which is time consuming to collect and reduces the robustness of the system to a limited set of cutting conditions. Several studies of investigated frequency and time-frequency domain analysis to reduce the sensitivity to classification to cutting parameters (Kuljanic et al. 2009, Liao et al. 2007, Huang et al. 2010, Lauro et al. 2004], however, most of these methods require specialist monitoring equipment which pose the challenges described above.

Within this research we investigate the potential of a low cost, non-invasive sensing approach which is also cutting parameter agnostic to the problem of tool condition monitoring, which has so far not been identified within existing literature. The investigated solution uses current and voltage sensors across electrical three phase input to the machine to monitor the overall machine power consumption, whilst classification of the signal is conducted through time-frequency analysis using wavelet packet transform.

In Section 2 the diagnostic approach using the wavelet analysis is described. Section 3 details the experimental methodology and results, and Section 4 concludes the findings and highlights limitations and future work.

2 DIAGNOSTIC APPROACH

Although several studies have been performed for condition monitoring of the milling process using wavelet transform [Choi et al. 2004, Li et al. 2008, Zhong et al. 2010], these have mainly used vibration or cutting force measurements in the analysis instead of electrical power consumed by the machine. Moreover, the effectiveness of wavelet transform in discriminating tool wear level operated at varying cutting parameters still requires further investigation.

In this study, wavelet packet transform (WPT) is selected to evaluate the tool wear level. The reason of using WPT is that compared to wavelet transform, which only filters the signal to get the low-pass results (approximation), WPT can filter the signal to obtain both low-pass and high-pass (detailed) results (depicted in Figure 1). Therefore, more information can be extracted from the original signals using WPT [Torrence & Compo, 1995]. The extracted wavelet coefficients $C_{j,k}$ can be expressed using Eq. (1).

$$C_{j,k} = \int f(t)\psi_{j,k}(t)dt \quad (1)$$

where $f(t)$ is the original signal, $\psi_{j,k}$ is the wavelet function, j and k are the scale and shift parameters, this can be expressed in Eq. (2).

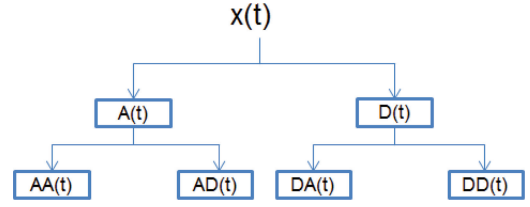


Figure 1. Two-level wavelet packet transform, where A and D are the approximation and detail by filtering the signal at the previous level.

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{j}}\Psi\left(\frac{t-k}{j}\right) \quad (2)$$

It can be seen from Figure 1 that the application of WPT provides a sub-band filtering of the original signal into progressively finer equal-width intervals with the extracted packets of wavelet coefficients, i.e. the j^{th} packet of wavelet coefficients at j^{th} level represent the information of original signal within the frequency sub-band of $[iF_s/2^{j+1}, (i+1)F_s/2^{j+1}]$, where F_s is the sampling frequency.

With wavelet coefficients, the time-history of signals at different frequency sub-bands can be reconstructed using Eq. (3).

$$f_j(t) = C \sum_k C_{j,k}\Psi_{j,k}(t) \quad (3)$$

where C is a constant independent of signals.

With these constructed signals, energy and entropy are calculated from each signal using Eqs. (4) and (5).

$$E_s = \int |f(t)f(t)|dt \quad (4)$$

$$H_s = -\sum_{i=1}^N p(x_i)\log_{10} p(x_i) \quad (5)$$

where E_s and H_s are the energy and entropy of the signal, $p(x_i)$ in Eq. (5) is a probability of the signal with value of x_i .

The energy of reconstructed signals represents the amount of information within different frequency sub-bands, while entropy of reconstructed signals can indicate the signal disorganization at the frequency sub-bands. It is expected that these two features would be sensitive to the change of cutting parameters and cutting tool wear level, thus can be used for the discrimination of cutting tool levels. This will be further investigated in the following section.

It can be seen that with the use of WPT, the original signals can be decomposed and reconstructed

at different frequency ranges, from which the frequency information can be related to the signals in the time domain, and better used for the feature extraction and fault diagnosis.

3 PERFORMANCE OF DIAGNOSTIC APPROACH

3.1 Experiments

In the study, HSS-Co8 is selected as the end milling tool due to its ease of wear measurement, which is a high speed steel containing 8% cobalt with 4 flutes. Two end milling tools with different diameters are selected herein for the analysis. Table 1 lists the characteristics of these end milling tools, where LOC refers to the tool's length of cut.

In the experiments, each end mill was assigned a work piece of dimension 150 mm × 120 mm × 30 mm, and the plate material was selected as commercial aluminum grade 6082 T651, which is a common alloy used in manufacturing.

Cutting parameters used in the tests were selected according to the manufacture's recommendation, which are listed in Table 2.

For the duration of each cutting session the energy monitoring device was connected to the system, which collected the current and voltage measurements at a sampling frequency of 50 kHz. During each session, the tools were used to per-

form climb milling on the work pieces. The number of passes, cut depth and cutting radius are selected as 10, half of the cutter diameter, respectively.

It should be mentioned that after each cutting session, the tools were used to machine the carbon steel to induce wear (40 min initially, subsequently 20 min), and this process was repeated until 100 min, where full tool wear was observed. Table 2 lists the cutting parameters used for different cuts and corresponding wear measurements.

3.2 Discrimination of different cutting tools with different wear level

In this section, the current and voltage from two end milling tools with 8 mm and 10 mm cutting diameters are collected at 0 min and 100 min, which represents the intact and fully worn tools. The reason of selecting these measurements is that the collection process will not interrupt the machining process, and the installation of sensors will not add complexity of monitoring systems, thus the results can be better applied in the practical machining process. With current and voltage measurements, the instantaneous power can be calculated using the following equation.

$$P_{ins}(t) = v(t)i(t) \quad (6)$$

where $v(t)$ and $i(t)$ are the collected voltage and current measurements at time t .

Figure 2 depicts the instantaneous powers for 8 mm and 10 mm tools at intact and fully worn conditions. It should be mentioned that only power from single pass cutting is illustrated herein, as the powers of 10 passes have a similar trend. In the current study, only the power from a single pass is analyzed. Table 3 lists the average and maximum instantaneous power at each condition. It can be seen from the table that the instantaneous power will be increased with cutting tool wear.

From the instantaneous powers shown in Figure 2, the cutting tools with different diameters and cutting parameters, and the same tool with different wear levels cannot be discriminated easily in the time-domain, as the signals from different conditions have a similar shape, thus the four different conditions cannot be discriminated using only the power amplitude variation.

As described in section 2, WPT is applied to the instantaneous power to extract wavelet coefficients and reconstruct signals at different frequency sub-bands. In the current study the WPT is used to decompose the original signal over 8 levels. This decomposition level is selected by considering both the range of frequency sub-band and computational time. In the current study the Shannon wavelet

Table 1. Characteristics of end milling tools.

Mill Dia. (mm)	Shank Dia. (mm)	LOC (mm)	Overall length (mm)	No. teeth/flutes
8.0	10	19	69	4
10.0	10	22	72	4

Table 2. Cutting parameters and corresponding wear measurements.

Dia. (mm)	Cut no.	Time (min)	Spindle speed (RPM)	Feed rate (m/min)	Localized tool wear (mm)
8	1	0	4000	580	0
8	2	40	4000	580	0.182
8	3	60	4000	580	0.279
8	4	80	4000	580	0.327
8	5	100	4000	580	0.493
10	1	0	3100	600	0
10	2	40	3100	600	0.185
10	3	80	3100	600	0.434
10	4	100	3100	600	0.582

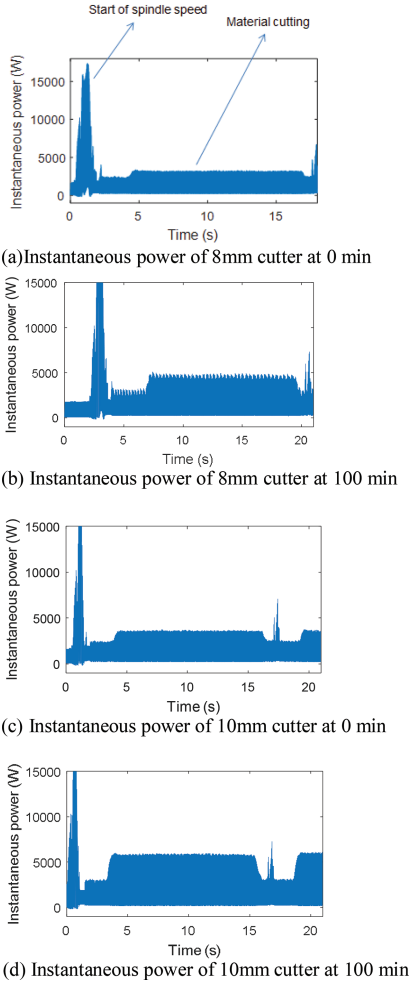


Figure 2. Instantaneous power of two cutters at intact and fully worn conditions.

Table 3. Average and max instantaneous power.

Condition	Average power (W)	Max power (W)
8 mm tool at 0 min	1593.7	3277.4
8 mm tool at 100 min	1989.6	4890.1
10 mm tool at 0 min	1712.3	3827.7
10 mm tool at 100 min	2537.5	5971.5

function is used in the WPT analysis, which can be written as follows:

$$\Psi_{j,k}(t) = \sqrt{j} \text{sinc}(jt) e^{2\pi i k t} \quad (7)$$

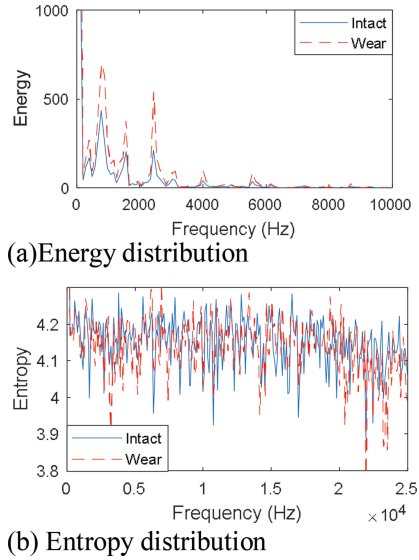


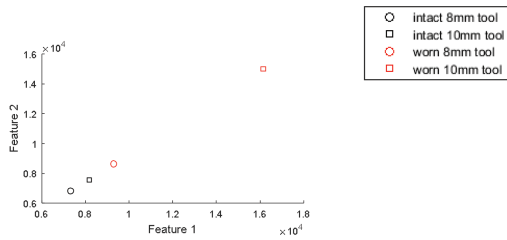
Figure 3. Energy and Entropy distributions of 8 mm cutter at intact and worn conditions.

Energy and entropy are then calculated from each reconstructed signal. Figure 3 depicts the distribution of energy and entropy over the whole frequency range. It should be noted that as the distributions are similar for the two end milling tools, only energy and entropy distribution from the 8 mm tool are illustrated herein.

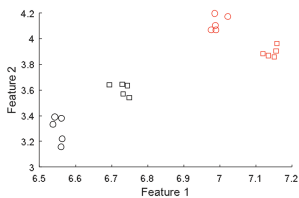
It can be seen from Figure 3 that the energy distribution shows similar trends for both intact and worn conditions, and the maximum energy is concentrated at around 700 Hz. However, the entropy distributes well along the whole frequency range, and the entropy distribution at intact and worn conditions shows clear variation. This indicates that the energy features can provide more consistent results, while entropy features are more sensitive to the change in the cutting parameters.

In this study, the two highest energies and entropies at the intact condition are selected for the discrimination, as they represent the most information and disorganization in the original signal. Figure 4 depicts the discrimination results. It should be noted that each point in Figure 4 represent the feature calculated with a two-second length instantaneous power signal.

From Figure 4, it can be seen that with selected energy and entropy features, all four different states, i.e. two end milling tools with two wear levels, can be discriminated with good quality, indicating that not only the worn condition can be identified clearly for the same cutting tool, but the different cutting tools with similar worn levels can also be separated accurately.



(a) Discrimination results using two highest energies



(b) Discrimination results using two highest entropies

Figure 4. Discrimination results using two highest energies and entropies.

When this approach is used in practical applications, the state of the end milling tool can be determined with the minimum Euclidean distance between features (two highest energies or entropies) of instantaneous power from the unknown state and the features shown in Figure 4. It should be mentioned that as the analysis is computational efficient (only taking about 20 seconds to gain the results), this approach can be used in the practical application for on-line monitoring purposes.

3.3 Discrimination of different cutting tools with different wear level and similar instantaneous power

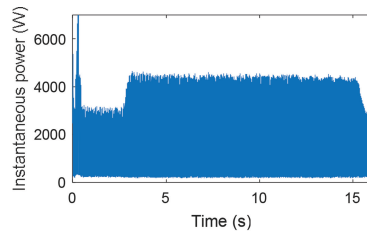
The performance of WPT in discriminating cutting tool conditions is further investigated using the data from the end milling tools at different cutting parameters but having similar instantaneous power, which makes it extremely difficult for discrimination using time-domain techniques.

In this study, two sets of data are used for the analysis, including end milling tools with diameters of 6 mm and 10 mm at different wear levels and cutting parameters. Table 4 lists the cutting parameters of these two end mill tools and the corresponding wear measurements.

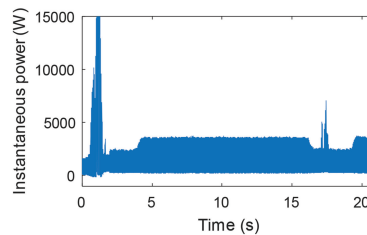
Figure 5 depicts the instantaneous powers from these two end milling tools. Similar instantaneous power can be observed due to the combination of different wear levels and cutting parameters. The average instantaneous powers from these conditions are listed in Table 5. It can be seen that these two conditions will provide similar average instantaneous power, while clear

Table 4. Cutting parameters and corresponding wear measurements.

Dia. (mm)	Spindle speed (RPM)	Feed rate (m/min)	Time (min)	Wear measurement (mm)
8	4000	580	60	0.279
10	3100	600	0	0



(a) Instantaneous power from 8mm cutter



(b) Instantaneous power from 10mm cutter

Figure 5. Instantaneous powers from 6 mm and 10 mm diameter end mill tools.

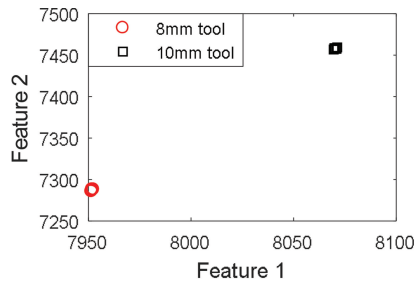
Table 5. Average and max instantaneous power.

Condition	Average power (W)	Max power (W)
8 mm tool at 60 min	1810.1	4461.2
10 mm tool at 0 min	1712.3	3827.7

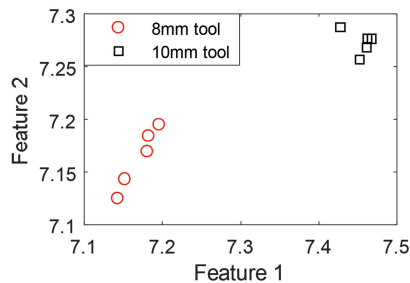
variation is observed in the wear level, which is listed in Table 4.

WPT described in section 2 is applied to extract the wavelet coefficients over 8 levels, and signals at different frequency sub-bands are reconstructed. The two highest energies and entropies are then selected for the discrimination. Results are depicted in Figure 6.

It can be seen from Figure 6 that with the selected energy and entropy, the two end milling tools can be discriminated with good quality, indicating the effectiveness of the proposed approach in identifying the states of different end mill tools at varying cutting parameters.



(a) Discrimination using energies



(b) Discrimination using entropies

Figure 6. Discrimination results of 6 mm and 10 mm tools at different conditions.

4 CONCLUSIONS

In this paper, the discrimination of end mill tools with different diameters, wear levels, and cutting parameters is investigated. Wavelet packet transform is applied to extract wavelet coefficients from the original signal. Signals at different frequency sub-bands are then reconstructed using wavelet coefficients from which energy and entropy are calculated. The two highest energies and entropies are selected to discriminate different cutting tool states.

Two cases are used in this study to investigate the performance of the proposed method; cutting tools with different diameters and wear levels, and cutting tools with different diameters and wear level but similar instantaneous powers. Results demonstrate that with the proposed approach, the state of the cutting tool can be discriminated with good quality, both the tool wear level and cutting parameters can be discriminated.

Whilst these initial results are promising further work is required to expand the analysis over a wider range of cutting parameters to establish if the methodology holds. Additionally, refinement of the sensor measurement and tool monitoring service is required. At present signal analysis is performed off-line, whilst data is captured at higher frequency (50khz) increasing the cost of equipment and time of analysis. Optimization of this

methodology is required in order to enable on-line monitoring.

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