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SENSOR FUSION FOR REAL-TIME CONDITION MONITORING OF TOOL WEAR IN SURFACING WITH FLY CUTTERS

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Abstract
A coherent artificial neural network, ANN, software program capable of real time analysis and decision-making is utilized in this work for the automatic detection and diagnostics of tool wear during a surfacing milling operation using a fly cutter. Several sensors were utilized to collect data indirectly related to wear: current measurements from the spindle and two (x, y) drive motors, three (*x, y, z*) components of cutting force, and acoustic emission. Furthermore, direct wear measurements were collected using image capturing and dimensional measurements of the worn location (not performed in real-time). As the inputs from these sensors were 'fused', the ANN utilized this multiple-sensor data to yield reasonable predictions of 'good', 'used', and 'worn' tools.

Keywords:
Milling, fly cutter, artificial neural network, ANN, wear, automatic, condition monitoring.

1. INTRODUCTION

Typically, fly cutters perform surfacing operations using small depths of cut. Due to issues relating to their salient features and geometry, and peculiar mounting, the cutting action with such cutters may cause dramatic tool wear and, often, catastrophic tool breakage. Therefore, the study of tool wear of fly cutters is of interest to the machining community at large as evidenced by the studies of wear inflicting fly cutters that have been reported in the literature ([e.g.,1,2]).

The successful implementation of tool condition monitoring (TCM) is critical to the success of fully automated cutting operations. To monitor and detect tool wear in metal cutting operations, several types of sensors have been utilized over the years including direct and indirect measurements with both being correlatable to the condition of the tool. Direct measurements rely on visual and computer vision methods with the latter being made while the cutter is rotating [3]. Indirect sensors include a host of techniques including: vibration / noise detection [4], spindle motor / feed drive current measurements [5], and measurements of cutting forces [2]. In the latter, it was concluded that 'tool wear can be properly estimated by knowing the average cutting force coefficients and cutting parameters when fly cutting aluminum with a single cutter and workpiece geometry'.

Since obtaining exact mathematical functional relationships between these signals and tool wear is challenging, and in order to combine the data from these signals resulting in a functional classification or decision regarding tool go/no go decision, artificial neural network (ANN) presents an attractive solution. Typically, the network is trained in the first stage where sensor data is fed to the diagnostics software. Once the software has been 'taught' to distinguish a good (sharp) tool from a partially worn one and from a completely dull one, the diagnostic capabilities of the software become automatic resulting in the real-time correct identification of the drilling tool condition by the software. For example, Lin and Lin [6] utilized ANN to study the closely related problem of tool wear in face milling cutters using force signals only. ANN has been recently utilized by Patra et al. [7] where the root mean square (RMS) value of the spindle motor current was used as input to a multilayer neural network. Also in [7], it was demonstrated that ANN yield more accurate results as compared with traditional techniques such as regression models.

2. EXPERIMENTAL PROCEDURES

A fly cutter with a brazed insert was used to surface blocks of an aluminum alloy, Alumec. The tool is shown in Figure 1 from the side while cutting (l.h.s) and from the end (r.h.s.).

Figure 1. The fly cutter shown in side (l.h.s.) and end (r.h.s.) views.

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The cutting was performed on a Haas V6 vertical machining center. The (compact) test matrix is conducted according to the cutting parameters in Table 1. Specifically,

- Speeds and depths of cut are as in Table 1.
- All feeds are fixed at = 0.0125 mm/rev.
- Blown air is used for cooling (no coolant).

Table 1. Test matrix showing speeds and depths of cut used in milling experiments.

		1	2
	depth of cut (mm)	0.5	1
	Speed (rpm)		
A	4000	x	x
B	5000	x	x

Indirect sensors utilized in this study are: force dynamometer, acoustic emission sensor, and current transducer. The direct sensor utilizes a high-resolution camera suitable for computer vision applications.

To collect thrust and x,y force data, Kistler's CompacDyn 3-Component Dynamometer (Type 9254) was used. The Kistler 9254 can measure forces up to 0.5 kN in the X- and Y-Directions, and forces of up to 1 kN in the Z-Direction (but not torques). The Kistler 5070A Charge Amplifier was used to acquire and amplify the signal emanating from the dynamometer. This was then processed through the Dynamometer's Dynoware data acquisition software (also from Kistler).

Acoustic emissions measurements were made using a small diaphragm, directional microphone placed at a constant distance of 0.20 meter from the cutting zone. The audio signal is interfaced to the PC through the PC soundcard, and run through LabVIEW for signal analysis. The signal is divided into three frequency ranges namely:

- 50Hz – 100 Hz (contains the frequency of the tool's rotational speed for all test cases in Table 1).
- 5kHz – 10kHz (chosen as a representative of mid-range frequency).
- 15kHz – 22kHz (chosen as a representative of high-range frequency).

After filtering, the root mean square (RMS) of the signal in each frequency range is extracted as one representative feature for ANN processing. Also a power spectral analysis program was used to observe and identify resonant or predominant frequencies in the auditory range.

The setup for the spindle motor and x,y drive motors current measurement was as follows:

- Texas Instruments (TI) Transformer: Transforms the primary current emanating from each motor into a secondary current.
- IMA AC current transducer (Input: 0-5 A, Output: 0-10 V): Takes as input the scaled down current coming out of the transformer and outputs a voltage signal.
- National Instruments (NI)-USB 6251: Data Acquisition board, which takes as input the voltage signal coming out of the transducer and outputs the signal to the Lab VIEW software for data Acquisition.
- PC: LabVIEW program writes the data coming from the main spindle motor onto excel sheets. The sampling was done at 10 kHz.

The role of the computer vision system is to give a direct method to complement the other sensors in the measurement of tool wear. Of the many modes of wear investigated, flank wear, VB_{max}, is by far the most popular, and as such, was studied in this work. All images were captured using a Canon 1000D camera and all image analyses were performed using Matlab. The Hough transform is a feature extraction technique commonly used [8] so that the pictured image need not be taken from exactly the same position and orientation for correct image analysis. In this work, three Matlab built-in functions related to the Hough transform (hough, houghlines and houghpeaks) were used in combination so that extraction of the wear region from the image was made possible.

Table 2 summarizes the extracted features from the various sensor signals.

Table 2. Extracted Features from sensor data

Features Extracted	Dynamometer	AC Current Sensor	Audio Sensor
Root Mean Square (RMS)= $\sqrt{\sum_{i=1}^{n}\frac{1}{n}x_i^2}$	✓	✓	✓
Signal Power (P) = $\sum_{i=1}^{n}\frac{1}{n}x_i^2$	✓	✓	
Peak-to-Peak Amplitude (pp) = Max (x_i)- Min (x_i)	✓	✓	
F_{net} (mean) = $\sqrt{F_x^2+F_y^2+F_z^2}$	✓		

3. IMPLEMENTATION AND RESULTS

As cutting progressed, so did tool wear causing the tool to go from a 'sharp' condition, through a partially worn condition, and ultimately to a dull condition where catastrophic failure is likely to occur if cutting commences with a dull tool.

3.1. Direct measures of tool wear

Computer vision and optical dimensional measurements yielded VB_{max} vs. cutting time (or distance) histories such as that shown in Figure 2. From the figure and from other similar results, the following reference critical wear criterion was adopted where classification of tool wear is according:

$$0mm < flank\ wear < 0.1mm \ \rightarrow good\ tool$$

$$0.1mm < flank\ wear < 0.4mm \ \rightarrow used\ tool$$

$$0.4mm < flank\ wear \rightarrow dull\ tool \qquad (1)$$

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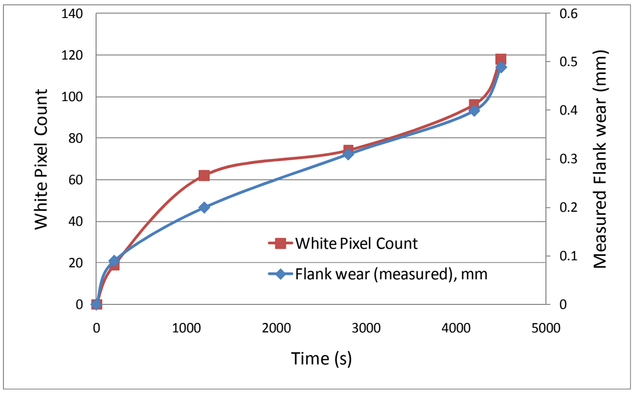

Figure 2. Typical flank wear history (test case B1).

3.2. Forces

Figures 3 (a, b, c) contrast the collected F_x, F_y, and F_z force components for a dull tool with those for a sharp tool (for test case A1) where significant increases in force components are recorded.

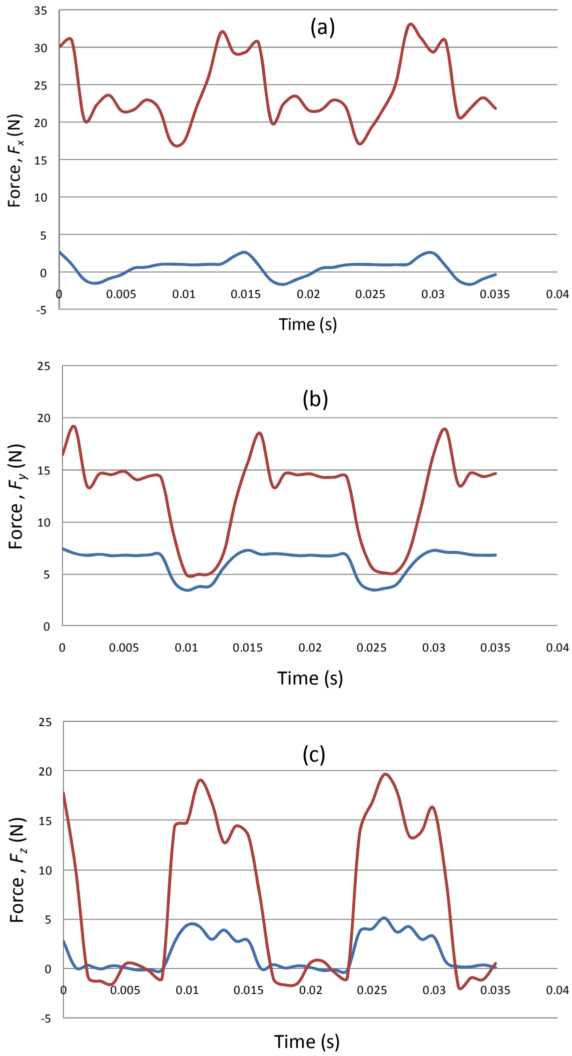

Figure 3 (a, b, c). Plots contrasting the F_x , F_y , and F_z force components (a, b, and, c, respectively) for a dull tool with those for a sharp tool (test case A1).

Figure 4 illustrates the increase, over total cutting time, in *x*- and *y*- force components (shown RMS values for F_x and peak-to-peak for F_y).

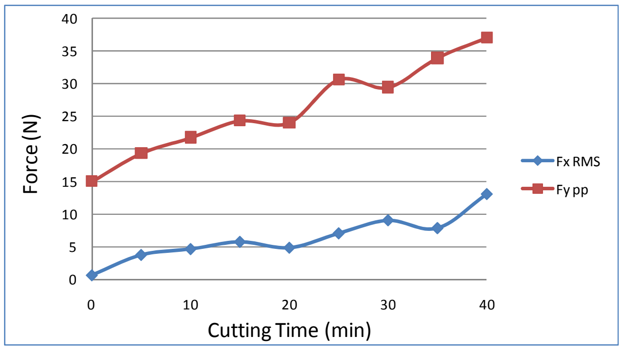

Figure 4. Increase, over total cutting time, in *x*- and *y*-force components. (Shown RMS values for F_x and peak-to-peak for F_y).

3.3. Acoustic emissions

Unlike mid-range frequencies (5kHz – 10kHz), both low (50Hz – 100 Hz) and high (15kHz – 22kHz) frequency ranges exhibited a strong response to tool wear. Filtered signal RMS extraction yielded data such as those in Figures 5 (a, b) show RMS signals plotted for fly cutter tools of varying wear condition.

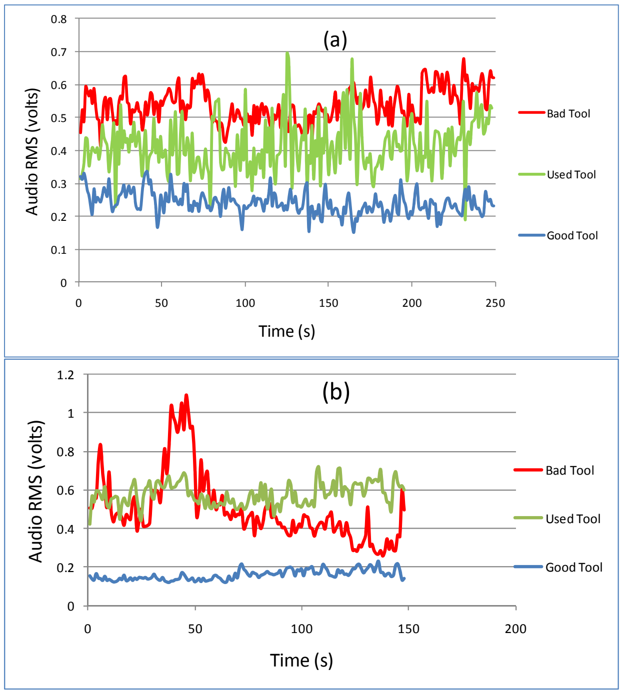

Figure 5 (a, b). RMS current signal for (a) 50Hz-100Hz and (b) 15kHz-22kHz over the duration of the cut (test case A1).

3.4. Current

Figure 6 illustrates the effect of tool wear on the main spindle current signal (shown over two cycles; test case A1).

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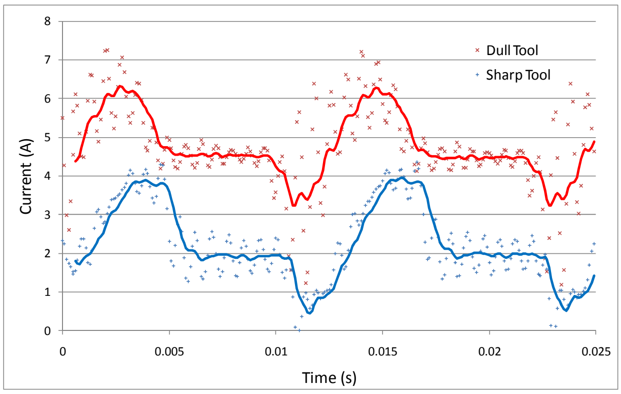

Figure 6. Effect of tool wear on the main spindle current signal (shown over two cycles; test case A1).

Extracted current RMS signal features for the main spindle motor and the x- and y- drive motors are plotted against total machining time collected on the tool in Figure 7. The plot shows considerable sensitivity to tool wear for all measurements over time.

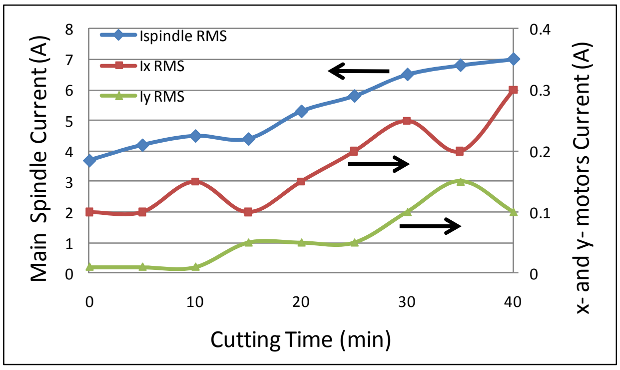

Figure 7. Increase over total cutting time in RMS current for the main spindle and x-, y- drive motors.

4. TOOL CONDITION PREDICTIONS

A neural network emulates a biological neural system in the sense that in a sort of feedback mechanism or learning, optimizes its neural connections, or weights to attain a specified target output. Figure 8 [9] is a schematic of the process.

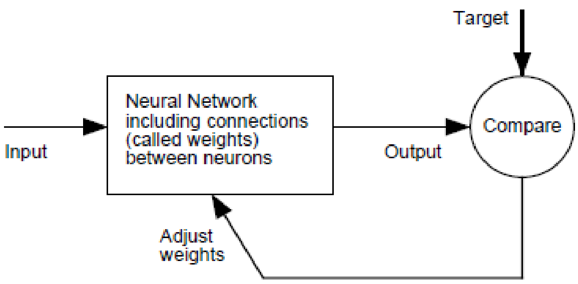

Figure 8. Neural Network feedback and weighing functions [9].

Figure 9 illustrates how the neural network is envisioned to work in this paper where the multiple sensor data is integrated into the ANN software (using Matlab). Specifically, inputs to the ANN network are:

1. Cutting parameters: speed, depth of cut
2. Cutting distance
3. Direct measurements of tool wear
4. Current (RMS and the other extracted parameters according to Table 2) for the
   a. Main spindle motor
   b. x- drive motor
   c. y- drive motor
   d. z-drive motor (not collected)
5. Measured x, y, and z forces (RMS and the other extracted parameters according to Table 2)
6. Acoustic emissions (RMS)

The only output is the tool flank wear. As advanced above, based on quantitative measurements, three 'gross' descriptions of the state of the tool are: sharp (or good), partially worn (or used), or dull.

In this method, some form of learning or pattern recognition tool is primarily used, in which the machine or program 'learns' how to classify the output given the input from the signal by comparison with predefined signal inputs and targets. After which, the software is capable of automatic classification of cutting tools undergoing new cutting conditions as 'good', 'used', or 'dull'.

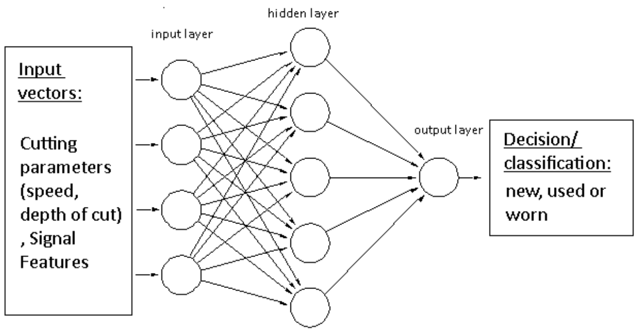

Figure 9. Illustration of how the neural network is envisioned to work in this paper

Using cutting parameters and sensor features listed in Table 2 as the input vector

$$p = (Depth\ of\ cut, speed, wear_{measures}, F_x, F_y, F_z, I_{spindle}, I_x, I_y, I_z, AE_{Low-freq}, AE_{High-freq2}, \ldots)$$

(2)

and a multiple-layer-perceptron network (MLP) with one hidden layer and an output layer, the network was trained to output the current state (or condition) of the tool .

Implemented and tested in this work is an MLP with 20 neurons in the hidden layer and the 3 class output (good', 'used', 'dull') according to the criteria in (1). This network uses scaled conjugate gradient back-propagation as its learning algorithm. After training this network with 240 data samples, the network was given 15 sample inputs and outputs compared to the required target class. Figure 10 shows the confusion matrix of this validation run.

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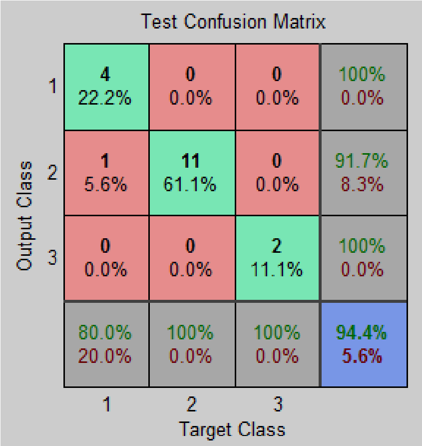

Figure 10. Confusion matrix for a validation run of 15 samples.

Except for a misclassification where the network classified an acceptable used tool as a bad/worn tool, Figure 10 shows mostly promising results for the network. More data would only strengthen the network and reduce classification errors.

5. SUMMARY

Artificial neural network, ANN, is implemented in order to predict the instantaneous tool condition of fly cutters in surfacing of Alumec. Several sensors were utilized to collect data indirectly related to wear: current from the spindle and two (x, y) drive motors, three (*x, y, z*) components of cutting force, and acoustic emission. Furthermore, direct wear measurements were collected using image capturing and dimensional measurements of the worn location. Utilizing this multiple-sensor data, the ANN yielded reasonable predictions of ‘good’, ‘used’, and ‘worn’ tools.

6. ACKNOWLEDGMENTS

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