Measuring the features sensitivity of Fusion sensor using neural network in Milling operation

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ABSTRACT

The main objective of this research is to monitor tool wear in end milling on line. In this paper, two approaches to monitoring tool wear in end milling are presented. The first approach adopts fusion sensors techniques to identify the tool wear conditions. The inputs to the neural network are the values of cutting forces and other known cutting parameters such as vibration, acoustic emission and sound. Also, the changes of condition of machining will be monitored using force and strain sensor. The other approach uses a regression model to estimate the sensitivity of the sensors to the tool wear. The regression model is established based on data obtained from experiments. It is confirmed experimentally that the tool wear can be well estimated by both approaches when cutting aluminum with a multi-tooth cutter and eliminate the used sensors with high monitoring performance.

KEYWORDS

Condition Monitoring, Machining operation, Signal processing, Sensor Fusion, Tool Wear.

INTRODUCTION

Milling processes are considered one of the most common manufacturing processes in industry. Milling is typically used to manufacture different and complex objects that are not axially symmetric and have many features. Parts that are fabricated completely through milling often include components that are used in limited quantities, perhaps for prototypes, such as custom designed fasteners or brackets. Milling is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that milling can offer, it is ideal for adding precision features to a part whose basic shape has already been formed (Metalwebnews, 2011). One of the main parameters that influence the milling process is tool wear, which is defined as the amount of volume loss of tool material on the contact surface due to the interactions between the tool and workpiece (Cho and Komvopoulos, 2001).

Tool wear has a large influence on the economics of the machining operations. Thus, knowledge of tool wear mechanisms and capability of predicting tool life are important and necessary in metal cutting. The functional elements that affect the wear of a cutting tool are as follows:

1. The workpiece material and its physical properties (mechanical and thermal properties, microstructure, hardness, etc), which determine cutting forces and energy for the applied cutting conditions.

2. The interface conditions: In 80% of the industrial cutting applications, coolants are used to decrease cutting temperatures and likely reduce tool wear.

3. The cutting tool: Tool parameters such as tool material, tool coatings, and tool geometric design. The optimal

performance of a cutting tool requires a correct combination of the above tool parameters and cutting conditions.

4. The dynamic characteristics of the machine tool, affected by the machine tool structure and all the components taking part in the cutting process, plays an important role for a successful cutting (Yung-Chang et al, 2004).

Automated Machine tool requires reliable on-line tool condition monitoring (TCM) techniques for manufacturing. TCM systems in cutting operations have been the topic of research for decades. Monitoring tool wear in order to prevent downtime due to tool failure is an important economic consideration. The cost of a tool failure can be significant compared to the price of the cutting tool (Ertunc and Loparo, 2001).

The ultimate objective of automated condition monitoring systems for machining operations is to enhance the quality of manufactured products using detection of process and machine faults. During any machining operation a multitude of various signals are emitted from the machine tool and the process. Although these signals can provide useful inputs to a machine and process condition monitoring and diagnostic system, they usually include a significant amount of noise. Consequently, the 'raw' unprocessed signals are unsuitable for monitoring purposes. In order to extract useful information from machine condition monitoring data, several stages of signal processing and data analysis are normally needed. The ultimate goal of signal processing and data analysis is to search for the machining signals for abnormal patterns. The capability of a condition monitoring system relies on two basic elements: first, the number and type of sensors used and secondly, the associated signal processing and simplification methods used to extract important information from signals. In addition to design of an effective fusion model and reduction in cost of machine and process monitoring systems with automation of the design process (Al-Habaibeh et al, 2002). The setup of a monitoring system in milling operation need to have all of the above aspects regarding design of the detecting system.This research focuses on the gradual tool wear monitoring, in the milling operation, using multi sensors model.

FUSION SENSOR APPROACH

The use of a single sensor signal in the development of a tool condition monitoring system fails to recognise the complex and diverse nature of the cutting process. Such models are often less robust, unreliable and generally not capable of total tool condition monitoring as reported by Dornfeld (1990). The information from a single sensor may simply not be good enough to make a reliable decision on tool condition monitoring. Chen and Jen (2000) have proposed many investigations to overcome the limitations of sensor methods, by using multisensors to create a stronger correlation between indirect signals and actual tool condition. These investigations demonstrate that multi-sensor systems could give additional signals for better prediction results.

The utilisation of multisensor systems for TCM is intended to fuse the informational power of each unique sensor to provide complementary and redundant information about conditional changes in cutting tools. This is referred to as Sensor Fusion (Devillez and Dudzinski, 2007). In these multisensor systems, signal processing techniques extract sets of features that are sensitive to the tool condition as explained by Wang and Dornfeld (1992). In the last decade, various pattern classification methods have been applied in the field of multisensor TCM to ensure high level of accuracy in prediction or classification of results. Some researchers have emphasized that pattern recognition can be an effective sensor fusion strategy in TCM. However, the level of complexity and robustness of the TCM model has been rarely part of the design objectives (Sultan and Arzu, 2009).

Specifically, a multisensor platform consists of force sensor, accelerometer, acoustic emission, sound and power sensor (Loadcontrols, 2010). The major advantage of the indirect sensors related parameters to detect malfunctions in the cutting process is that the measurement apparatus does not disturb the machining (Teti et al, 2010).

REGRESSION APPROACH

In order to reduce cost and development time, the automated design method of condition monitoring systems will be used along with multisensors and features extraction to select the most appropriate sensor and its associated signal processing methods. A novel approach, termed automated sensor and signal processing selection (ASPS), is presented for rapid design of condition monitoring systems for machining operations using a new flexible approach for the selection of sensors and signal processing method (Al-Habaibeh, 2001). This paper builds on the ASPS approach to investigate further combination of techniques and parameters. Where the sensitivity "sensory characteristic features" is extracted for each sensory signal obtained. These features are related to cutter conditions using a wide range of signal analysis and simplification techniques. As illustrated in Figure 1, the tool condition monitoring system proposed in this study consists of five components: (1) multisensor data acquisition system, (2) signal processing, (3) feature extraction, (4) feature selection, and (5) determine which feature is more sensitive of the changes in the machining operation.

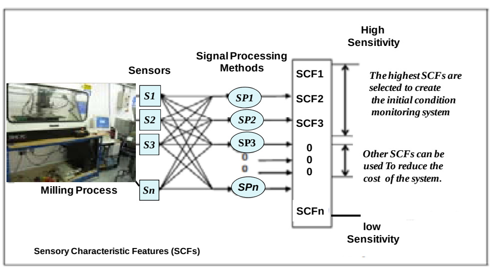


Figure: 1 Structure of sensors, signal processing methods and SCFs.

EXPERIMENTAL WORK

As shown in Figure 2, the experimental setup of the TCM system of this study has been carried out on a milling machine which are selected as a machining process conducted on a three-axis Computer Numerical Controlled (CNC) machining center type (DENFORD). Several sensory signals have been used including Acoustic Emission sensor (AE), strain, accelerometer, cutting forces (Fx, Fy, and Fz), and microphone for measuring sound. The AE sensor (Kistler 8152b111) is attached to the workpiece to monitor AE signals transmitted during machining and connected to AE coupler (Kistler 5125B). The accelerometer (B&K4366) is mounted on the moveable table of machine and connected to charge amplifier (Kistler 5001). The force signals are monitored using 3-component Dynamometer (Kistler 9257A) and the work piece is fixed on the dynamometer. The dynamic and quasistatic force signals are monitored using a strain sensor (Kistler 9232A). Both the force dynamometer and the strain sensor are connected to a 4-channel charge amplifier (Kistler 5070A).

Cutting operation sound data were also collected through a microphone (type – EM400) placed in the direct vicinity of the workpiece. All the wires and cables of the sensors are connected separately in National instrument connection box (SCB-100). The signals are monitored using data acquisition card NI PCI-6071E from National Instrument using special data acquisition software written using the National Instrument CVI programming package. The experimental work is performed on milling machine using Aluminium workpiece. The sampling rate is 40k sample/second per channel and the number of sample per channel is 5000 samples. The milling process is performed at the conditions as shown in the table 1.

Table: 1 the machining parameters of the milling process.

Machining condition	specifications
Feed rate	215 mm / min
Depth of cut	0.36 mm
Coolant type	No coolant (Dry)
Spindle speed	4000 RPM
Diameter of tool	3 mm
Material of tool	High Speed Steel (HSS End mill cutting
Type of tool	End mill Tool

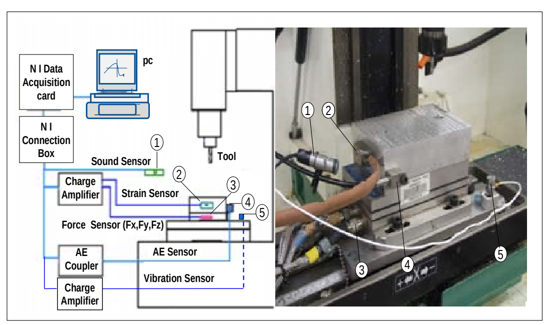


Figure: 2 Schematic diagram of experimental setup for the monitoring system on milling machine.

RESULTS AND DISCUSSION

The tests started with a fresh tool and finished with completely worn tool. The raw signals for the tool are collected from the sensors as illustrated in Figure 3. Because milling process has complex machining signals, it has been found difficult to predict the most sensitive signals and signal processing methods to tool wear directly from raw data. Therefore, signal processing and analysis is needed to extract the important information from the signals (i.e. Sensory Characteristic Features (SCFs)).

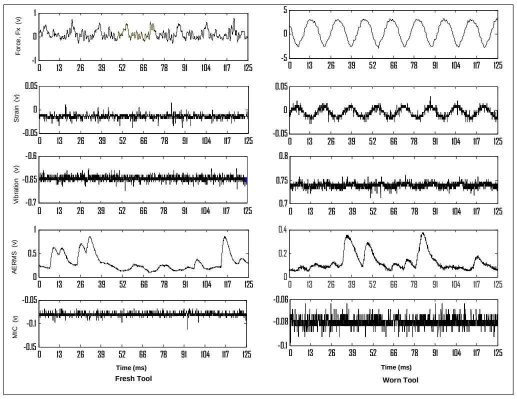
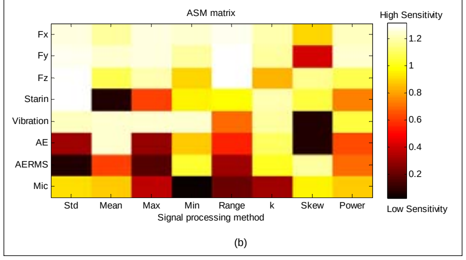


Figure: 3 Example of the raw signals of the machining process.

The machining test is used to investigate the process characteristic and to select the sensitive Sensory Characteristic Features (SCFs). The raw signals are processed using several time domain signal processing methods to extract 8 SCFs form every sensory signal. The signal processing methods used are standard deviations (*std*); the average (μ); maximum (max); minimum (min) ; the range; kurtosis value (*K*); skew value and power; The 8 signal processing methods are used to process the 8 sensory signals establishing an Association Matrix ASM of (8×8) which allows the investigation of 64 sensory characteristic features (SCFs) for the design of the monitoring system. The SCFs are arranged according to their sensitivities to tool wear based on the absolute slope of the linear regression method. The SCFs are visually inspected and it has been found that SCFs with high absolute slope show higher sensitivity to the fault. Figure 4 presents the Association Matrix (ASM) which includes the sensitivity of a few SCFs implemented in this monitoring system.

	Signal processing methods							
Sensors	Std	Mean	Max	Min	Range	Kurtosis	Skewness	Power
Fx	1.268	1.182	1.264	1.251	1.284	1.199	0.905	1.223
Fy	1.279	1.247	1.265	1.099	1.129	1.178	0.420	1.248
Fz	1.296	1.082	1.211	1.188	1.312	0.833	1.164	1.072
Strain	1.297	0.076	0.614	0.966	0.983	1.197	1.054	0.741
Vibration	1.226	1.248	1.248	1.249	0.698	1.178	0.074	1.095
AE	0.313	1.251	1.293	0.873	0.560	1.093	0.083	0.630
AERMS	0.080	0.623	0.175	1.042	0.313	1.265	1.180	0.696
Mic	0.913	0.805	0.382	0.025	0.218	0.309	0.965	0.878

(a)



(b)

Figure: 4 The Associated matrix of the system (a) and a graphical presentation of the sensitivity (b).

From Figure 4, it can been concluded that the force and the vibration sensors were the most sensitive sensors to monitor tool wear in the current case. Consequently, in industrial environment, the use of vibration and force sensors might be sufficient to monitor the faults in this case. Figure 5 presents examples of high, medium and low-sensitivity features to tool wear and explains that the vibration sensor is more sensitive for the tool damage.

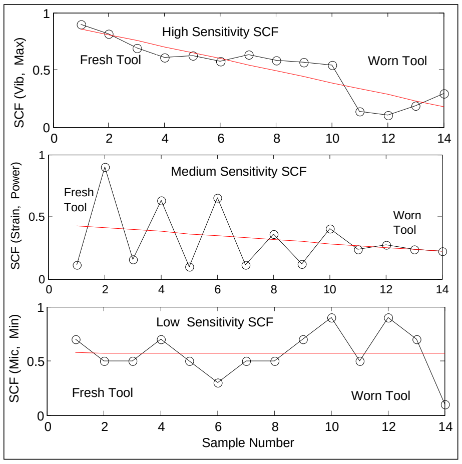


Figure: 5 Example of low, medium and high sensitivity SCF.

CONCLUSION

The implementation of automated monitoring systems in machining operations is becoming essential to increase production quality, and to decrease production costs and faults. The multi-sensors system developed and employed in this paper combines force, vibration, acoustic emission, strain and sound sensors for the monitoring of milling operations. Multi-sensory systems eliminate the disadvantage of single sensor systems, since loss of sensitivity in one sensor can be compensated by information from other sensor within the system. The applied approach helps in designing a condition monitoring system from experiment using a simple automated algorithm to determine the sensory characteristic features (SCFs), which are most sensitive to process tool wear. In this paper, force and vibration sensors are found the most useful to detect tool wear while the microphone is found to be the least sensitive to tool conditions.

REFERENCES

Al-Habaibeh, A. and N. Gindy, 2001. Self-Learning Algorithm for Automated Design of Condition Monitoring Systems for Milling Operations. *International Journal of Advanced Manufacturing Technology*, 18(6), pp.448-459.

Al-Habaibeh, A., Zorriassatine, F., and Gindy, N. 2002. Comprehensive experimental evaluation of a systematic approach for cost effective and rapid design of condition monitoring systems using Taguchi's method. *Journal of Materials Processing Technology,* 124(3), pp.372-383.

Chen, S.L. and Jen, Y.W., 2000. Data Fusion Neural Network for Tool Condition Monitoring in CNC Milling Machining. *International Journal of Machine Tools and Manufacture*, 40(1), pp.381-400.

Cho, S. S. and Komvopoulos, K., 2001. Cutting force variation due to wear of multi-layer ceramic coated tools. *ASME J Tribology*, 120, pp.75–81.

doi:10.1115/1.2834193.

Devillez, A. and Dudzinski, D., 2007. Tool vibration detection with eddy current sensors in machining process and computation of stability lobes using fuzzy classifiers. *Mechanical Systems and Signal Processing,* 21(1), pp.441-456.

Dornfeld, D., 1990. Neural Network Sensor Fusion for Tool Condition Monitoring. *Annals CIRP*, 39(1), pp.101-105.

Ertunc, H. M. and Loparo, K. A., 2001*: A decision fusion algorithm for tool wear condition monitoring in drilling, Manufacture.* pp.1347-1362.

Load controls incorporated, 2011. *Power Sensors and Load Controls,* File Format - PDF/Adobe Acrobat(accessed on line) www.loadcontrols.com/downloads/power_sensors.pdf.

Metalwebnews, 2011. *Milling operations Types of Milling Machines*,[online] PDF/Adobe Acrobat. Available at: www.metalwebnews.com/machine-tools/ch8.pdf.

Sultan, B. S. C. and Arzu, O., 2009. *Machine ensemble approach for simultaneous detection of transient and gradual abnormalities in end milling using multisensor fusion Technology*, Volume 7, pp.4728-4738.

Teti, R. , Jemielniak, K., O'Donnell, G. and Dornfeld, D., 2010. Advanced monitoring of machining operations, *CIRP Annals - Manufacturing Technology,* 59 (2), 2010, pp.717-739.

Wang, Z. and Dornfeld, D. A. 1992. *In-Process Tool Wear Monitoring Using Neural Networks*, Japan/USA Symposium on Flexible Automation Part 1 (of 2), San Francisco, pp.263-270.

Yung-Chang, Y., Jörg S., Blaine L. and Taylan A., 2004. Estimation of tool wear in orthogonal cutting using the finite element analysis. *Journal of Materials Processing Technology,* 146 (1), pp.82-91.