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CONDITION MONITORING OF CUTTING TOOL WEAR AND PREDICTION OF SURFACE ROUGHNESS

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Abstract: *Metal cutting plays an important role in the present day manufacturing. Over the years, the manufacturing industry has matured by introducing new materials and processes. Superior manufacturing facilities, with the state of the art technology processes are now available, catering to the stringent product requirements, like form, fit and function. They generate surface finishes that produce the right texture enhancing the products aesthetic appeal or satisfying the designers functional requirements. The product quality has been built into the product, with every aspect of the process studied, monitored and excelled. With the advent of computer technology and its allied growth in the software industry, newer computing techniques and algorithms push the technology to its limits and application engineers are curious to study the impact of these in various situations that may interest them. As manufacturing brings to life the various abstract designs, there exists a huge potential to create newer and newer products by various processes. This moots the study of the implication of such algorithms and techniques on these processes with a goal to manufacture better products in a shorter time, keeping the cost aspects low and complying with the quality requirements. This also opens up another related domain called condition monitoring. Condition monitoring studies are carried out on processes, machines, tools and the like. It is the periodic or continuous measurement of various parameters that indicate the condition of the tool, stability of the process or condition of the machine. The focus is to avoid producing parts that are out of tolerance or those which are in non-conformance with the specified finish and to avoid surprise breakdown of the machine itself.*

Introduction:

Manufacture of products undergoes different processes before they are assembled to serve their intended function. Over the years, many new materials and processes have been introduced. Latest machines have better process capability and are competent of achieving the right fit between mating parts. Todays industries are equipped with the state of the art technology machines, with processes catering to the specific needs of the product requirements, like form, fit, function. Some products demand stricter tolerances and better surface quality. Designers demand specific surface finishes that produce the right texture enhancing the products aesthetic appeal or satisfying the manufacturers assembly requirements. So one can say that, in todays scenario, where manufacturing processes have matured and quality of products need to be built into them, every aspect of the process requires to be studied, monitored and be perfected. With the availability of computer technology and its allied growth in the software industry, newer computing techniques and algorithms push the technology to its limits and application engineers are curious to study the impact of them in various situations that may interest them. As manufacturing brings to life the various abstract designs, there exist a huge potential to create newer and newer products by various processes. This moots the study of the implication of new algorithms and techniques on these processes with a goal to manufacture better products in a shorter time, keeping the cost aspects low and complying with the quality requirements. This also opens up another related domain called condition monitoring. Condition monitoring studies are carried out on processes, machines, tools and the like.

Literature Survey:

Paper 1. WEAR AREA

Using ultrasound waves to correlate the reflected energy with the crater wear is studied to monitor the tool during the turning operation. The ultrasonic parameters, amplitude, pulse width and root mean square (RMS) of the signal are used to quantify the crater depth and width. The power spectrum analyses of received signals show the importance of frequency components in defining the tool wear. In the work presented by Dinakaran *et al.*, the normalizing of signals are carried out by insert hole, which is provided for clamping. This signal is not influenced by the wear but affected by other factors like tool material variation, improper coolant, temperature, *etc*. The response of the wear signal is normalized to the response of whole signal by mathematical division. A new approach adaptive neuro-fuzzy inference system (ANFIS) for monitoring of crater in carbide insert is presented. This improves the system accuracy and eliminates the limitation in statistical modelling [19].

Paper 2. VIBRATION

A review of the work carried out in the area of vibration analysis for tool condition monitoring was presented by many researchers [20-24]. There are number of techniques based on fast Fourier transform and pattern recognition are widely reported. To name a few, Artificial Neural Networks (ANN) [24-28], fuzzy [28], Neuro-fuzzy [29], FFT and Power spectral density [30]. It is important to note that there are numerous articles published in the area of tool condition monitoring using ANN. The main difference among them lies in the different configuration and network paradigms. To

name a few paradigms, Multi-layer perceptron (MLP) [31-33], Radial Basis Function (RBF) [34], Adaptive Resonance Theory (ART) [35-37] *etc.* These are used in indirect methods during the measurement of vibration signals. They contain one or more peizo-electric crystal elements, either made of natural quartz or man-made ceramics. These crystals produce voltage when stressed in tension, compression or shear called as peizo-electric effect, which is proportional to the force applied. There are many types of transducers available to measure acceleration like capacitance type, strain gauge type, piezo-electric type *etc.* The piezo-electric accelerometer has wide frequency and dynamic range, good linearity throughout the ranges as it has no moving parts which may get worn out due to friction. It is the widely used transducer for vibration measurements. Piezoelectric materials such as quartz, Rochelle salt, barium titrate, lead zirconate *etc*., generate electric charge when subjected to mechanical strain. Amongst them, barium titrate is poly crystalline in nature and can be formed into a variety of shapes. It has to be polarized before it can exhibit the piezoelectric effect.
Piezoelectric accelerometers rely on the self-generating, piezoelectric effect of either quartz crystals or ceramic materials to produce an electrical output signal proportional to the acceleration. The piezoelectric effect is that which causes a realignment and accumulation of positively and negatively charged electrical particles, or ions, on the opposed surfaces of a crystal lattice, when that lattice undergoes stress. The number of ions that accumulate is directly proportional to the amplitude of the applied stress or force.

Paper 3. ACOUSTIC EMISSION
Acoustic emission (AE) is the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from a localized source or sources within a material, or the transient elastic wave(s) so generated (ANSI/ASTM E 610-77). An AE is a sound wave or rather, a stress wave that proliferate through a material as the result of some sudden release of strain energy. AE instruments and systems are used for the monitoring and non-destructive testing of the structural integrity and general quality of a variety of materials, manufacturing processes, and some important devices. AE is an effective technique for in-process wear monitoring and wear mechanism identification of multilayer ceramic-coated tools. AE occurs during metal cutting processes when there is a (i) plastic deformation during the cutting process in the workpiece; (ii) plastic deformation in the chip; (iii) frictional contact between the tool flank face and the workpiece resulting in flank wear; (iv) frictional contact between the tool rank face and the chip resulting in crater wear; (v) collisions between chip and tool; (vi) chip breakage; (vii) tool fracture[38].
Many quantifiable characteristics of AE can be displayed as follows [39]:
Ring down count: the number of times the signal amplitude exceeds the present reference threshold;

AE event: a micro-structural displacement that produces elastic waves in a material under load or stress;

Rise time: the time taken to reach peak amplitude from the first present threshold voltage crossing of the signal;

Peak amplitude: this can be related to the intensity of the source in the material producing an AE signal;
RMS voltage: a measure of signal intensity.

Paper 4. ULTRASONIC EMISSION (UE)
An ultrasound online monitoring of crater wear of the uncoated carbide insert during the turning operation is presented by Dinakaran *et al.* [19]. The method relies on inducing ultrasound waves in the tool, which are reflected by side flank surface. The amount of reflected energy is correlated with crater wear depth. Various ultrasonic parameters are considered for defining the crater wear and individual contribution of each parameter is analyzed. The ultrasonic parameters, amplitude, pulse width and root mean square (RMS) of the signal are used to quantify the crater depth and width.
The power spectrum analysis of received signals shows the importance of frequency components in defining the tool wear. Nayfeh [40-41] showed that a linear correlation exists between the level of the reflected ultrasonic energy and the wear land height. Colgan [42] used both vibration and ultrasonic emission to predict the tool breakage since only UE signals alone may not be enough to predict accurately. The boundaries between what constitutes mechanical vibrations, AE and UE are not clearly defined, with the result that many studies in this area overlap [18]. The differences in sonic emissions that are audible, high frequency acoustic waves that travel over the surface of the cutter and machine tool structure, and ultrasonic emissions require better and stricter definition to assist in classification of experimental methods and results from research in these similar, but distinct, areas of investigation.

Algorithms

Decision tree algorithm C4.5 performs both feature selection and the classification simultaneously. The feature selection results have already been presented; classification results are presented in Table 6.1. Observing Table 6.1, C4.5 algorithm takes a little less time for building a model for DWT-entropy features and the classification accuracy is also high. The error percentages are considerably low for DWT-entropy features compared to DWT-energy features. The study reveals the superiority of the DWT-entropy features over DWT-energy features when C4.5 algorithm is used.

Table Classification results of C4.5 algorithm

Test Parameter	DWT-energy features	DWT-entropy features
Test mode	10-fold cross-validation	10-fold cross-validation
Time taken to build model	0.08 seconds	0.05 seconds
Total Number of Instances	720	720
Correctly Classified Instances	570 (79.17%)	693 (96.25%)
Incorrectly Classified Instances	150 (20.83%)	27(3.75%)
Mean absolute error	0.1322	0.0211
Root mean squared error	0.2887	0.133

Problem Statement

The problem consists of two phases of study; a tool status classification problem using supervised learning method and a surface roughness prediction problem using vibrations signals, flank wear and cutting parameters. The tool status classification study focuses on bringing out the best feature classifier combination of the vibration signals acquired during turning operation under different tool conditions that give the maximum classification accuracy. The second phase consists of prediction of surface roughness using cutting parameters, flank wear and the statistical features obtained from vibration signals acquired during the turning process. The study sets out to determine the predictability of surface roughness using three regression techniques viz. Multiple linear regression (MLR), support vector regression (SVR) and radial basis network (RBF). The influence of statistical parameterlearnings extracted from the vibration signals in predicting the surface roughness is determined. The effect of coating on surface roughness is compared by using carbide tipped tool and coated carbide tipped tool.

Future Scope:

- During the experimental study, in order to create the different tool wear conditions, it was decided to have 0.3 mm as tool blunt low and 0.6 mm as tool blunt high. The intention was to create two representative classes. This study can be extended to continuous monitoring of the progressive wear of the tool.
- The study has been carried out using C 4.5 algorithm for dimensionality reduction and feature selection. However, there are many other ways like PCA, Linear discriminant analysis, factor analysis, fisher’s linear discriminant analysis, feature subset selection, Minimum Description Length Method, Probability of Error and Average Correlation Coefficient method, Koller and Sahami’s method etc., that can be tried out.

Conclusion:

Here, different sets of features were extracted from the time-domain signal obtained during the experiment. The experiment consisted of collecting the vibration signals for different tool wear states and classifying them. The four classes were, Good, Tool Blunt low (TB1), Tool Blunt high (TB2) and Tool tip loose (TTL). C4.5 algorithm was used as it is simple and good in feature selection. The various kinds of features that were considered for study are

- Statistical Features
- Histogram Features
- Discrete Wavelet Transform Features
- The comparative study between ID3 algorithm and PCA on feature reduction using statistical features showed that ID3 is better than PCA in feature reduction.
- From the results and discussion in section 5.2 we find that among the 11 statistical features that were considered, only two features , namely,. Standard Deviation and Kurtosis contribute towards enhancement of classification accuracy while keeping the computational effort low.
- Similarly, among the twenty histogram features that were defined, only four features namely, h9, h10, h13 and h14 were found to be contributing to the classification accuracy. (refer section 5.2).

References:

1. Black, J.T., Flow stress model in metal cutting. Journal of Engineering for Industry, 1979. 101 (4): p. 403-415.
2. Thomas, T.R., Rough Surfaces. 2nd ed ed. 1999, London Imperial College Press.
3. Sick, B., On-Line and Indirect Tool Wear Monitoring in Turning with Artificial Neural Networks: A Review of More Than a Decade of Research. Mechanical Systems and Signal Processing, 2002. 16(4): p. 487-546.
4. Mitsui, K., In-proces sensors for surface roughness and their applications. Precision Engineering, 1986. 8(4): p. 212-220.
5. Shin, Y.C., Oh, S. J., & Coker, S. A, Surface roughness measurement by ultrasonic sensing for in-process monitoring. Journal of Engineering for Industry, 1995. 117: p. 439-447.
6. Cook, N.H., Prediction of tool life and optimal machining conditions. Wear, 1980. 62(1): p. 223-231.
7. Koren, Y., Adaptive control systems for machining. Manufacturing Review, 1989. 2(1): p. 6-15.
8. Kannatey-Asibu Jr, E. and D.A. Dornfeld, A study of tool wear using statistical analysis of metal-cutting acoustic emission. Wear, 1982. 76(2): p. 247-261.
9. Szecsi, T., Automatic cutting-tool condition monitoring on CNC lathes. Journal of Materials Processing Technology, 1998. 77(1-3): p. 64-69.
10. Shao, H., H.L. Wang, and X.M. Zhao, A cutting power model for tool wear monitoring in milling. International Journal of Machine Tools and Manufacture, 2004. 44(14): p. 1503-1509.

