Intelligent tool wear identification based on optical scattering image and hybrid artificial intelligence techniques

X Q Li, Y S Wong and **A Y C Nee***
Mechanical and Production Engineering Department, National University of Singapore

Abstract: Tool wear monitoring is crucial for an automated machining system to maintain consistent quality of machined parts and prevent damage to the parts during the machining operation. A vision-based approach is presented for tool wear identification in finish turning using an adaptive resonance theory (ART2) neural network embedded with fuzzy classifiers. The proposed approach is established upon the fact that the optical scattering image of a turned surface is related to the wear of the cutting tool. By applying the technique of the ART2 neural network embedded with fuzzy classifiers, the state of wear of the turning tool is determined from captured images obtained by laser scattering from the machined surfaces of the workpiece. This approach is not unlike the visual inspection of the surface of a machined workpiece to determine the state of wear of a cutting tool by an expert machinist. However, experimental results indicate that the conventional technique of measuring surface finish does not give values that correlate well with tool wear. On the other hand, the laser scattering image provides a good indication of the tool wear as it is not readily affected by buildup edge or cold-welded material, scratches and other disruptive defects on the turned surface as the tool wears. In this paper, the theory on the laser scattering image and the principle of tool wear identification are described. Based on the scattering images, the proposed approach can correctly identify the condition of 'significant wear' prior to the rapid tool wear stage for the cutting tool.

Keywords: tool wear, optical scattering, fuzzy recognition, neural network

1 INTRODUCTION

In finish machining, existing indirect measurement techniques, such as those based on cutting force, vibration or acoustic emission, are not sensitive enough to detect tool wear [**1**]. The magnitude of the signal is relatively not as significant against the background noise, due primarily to the smaller depth of cut and lower feed rate. Direct techniques, involving measurement of the workpiece dimension or its surface roughness to sense tool wear, are not suitable for on-line use. In finish machining, the major cause of tool change is due to the inability of worn tools to maintain good finish and dimension control. The normal and severe wear stages are typically not distinct. Nevertheless, a criterion for the early recognition of tool wear is required, which is usually different from that in rough machining. In order to maintain machining quality and to prevent damage to the part, the need for tool change should be predicted or identified early enough to prevent the cutting tool from approaching its rapid wear stage. In addition, due to a great diversity of individual tool life, a strategy for tool replacement based on some fixed period, e.g. according to the Taylor equation, is insufficient for a reliable and cost efficient automated machining environment.

Optical methods (e.g. see references [**2**] to [**7**]) have been shown to provide non-contact means for real-time assessment of engineering surfaces, and are thereby applicable to tool wear detection as the machined surface can be considered to be a 'fingerprint' of the machining condition [**8**, **9**]. Of these, the optical scattering technique has been found to be useful for on-line monitoring of conventional machined surfaces that are not necessarily very smooth. However, in the presence

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**Corresponding author: Mechanical and Production Engineering Department, National University of Singapore, 10 Kent Ridge Crescent, Singapore 119260.*

of notable surface waviness or buildup edges, the machined surface roughness does not correlate well with the intensity of its optical scattering pattern, rendering it not so ready for use in tool wear detection [**10**, **11**].

Thus far, the performance of an automatic tool wear monitoring system is rarely better than a skilled operator who can make appropriate identification of tool wear primarily based on visual inspection of the machined surface, such as its shine and texture, etc. A more reliable and flexible approach for tool wear recognition is yet to be available in practice for automated machining systems, though intelligent tool condition monitoring methods employing expert systems [**12**], fuzzy classification [**13–15**] and neural networks [**14–19**] appear to have great potential.

In this paper, the optical scattering technique with laser illumination is used to characterize the topography of turned surfaces. Based on captured images of the optical scattering patterns from the turned surfaces, an adaptive resonance theory (ART2) based neural network embedded with fuzzy classifiers is employed for tool wear identification in finish turning.

2 THEORY AND MEASUREMENT OF OPTICAL SCATTERING IMAGE

When a rough surface (with irregularities not much smaller than the wavelength of incident light) is illuminated by a parallel light beam at a certain incident angle, the reflected light is scattered into various directions to form an optical scattering pattern on a suitably positioned observation screen. Consider a point on the rough surface $\boldsymbol{r} = x\boldsymbol{x}_0 + y\boldsymbol{y}_0 + z(x, y)\boldsymbol{z}_0$, where $\boldsymbol{r}$ is the position vector of the point, $\boldsymbol{x}_0$, $\boldsymbol{y}_0$, $\boldsymbol{z}_0$ are unit vectors and $z(x, y)$ is a surface roughness function. The optical scattering field is given by the Kirchhoff solution in scalar form [**20**]:

$$I = \frac{\left|\int_{-w}^{w}\int_{-l}^{l}(a\,\partial z/\partial x + c\,\partial z/\partial y - b)\mathrm{e}^{\mathrm{i}v\cdot r}\,\mathrm{d}x\,\mathrm{d}y\right|}{4lw\cos\theta_1}I_0 \qquad (1)$$

with

$$v = \frac{2\pi}{\lambda}[(\sin\theta_1 - \sin\theta_2\cos\theta_3)\boldsymbol{x}_0 - \sin\theta_2\sin\theta_3\,\boldsymbol{y}_0 - (\cos\theta_1 + \cos\theta_2)\boldsymbol{z}_0] \qquad (2)$$

$$a = (1 - R)\sin\theta_1 + (1 + R)\sin\theta_2\cos\theta_3 \qquad (3)$$

$$b = (1 + R)\cos\theta_2 - (1 - R)\cos\theta_1 \qquad (4)$$

$$c = (1 + R)\sin\theta_2\sin\theta_3 \qquad (5)$$

where

λ = wavelength of incident light
i = imaginary unit
θ_1 = incident angle
θ_2 = scattering angle
θ_3 = inclination of the scattering plane
l = half of illumination length
w = half of illumination width

I_0 and R are scalar values of the reflected field and the reflection coefficient respectively of an ideal smooth plane that will reflect the incident wave specularly in the single direction ($\theta_2 = \theta_1$, $\theta_3 = 0$). The mean level of the surface is the plane $z = 0$. Equation (1) indicates that the intensity of the scattered light in its field varies with the topography of the measured surface and is closely related to the condition of tool wear. Therefore the corresponding optical image is formed on the observation plane.

Figure 1 illustrates the optical scattering image measurement set-up. A parallel beam of monochromatic light (0.63 μm wavelength) from a 5 mW He–Ne laser is directed at the turned surface at an incident angle of 30. Its scattered light is projected on an appropriately placed observation screen made of ground glass to form a two-dimensional optical scattering image. The image is captured and processed by a PC microcomputer with a Matrox IP-8 frame grabber card connected to a charge coupled device (CCD) camera mounted at a distance 50 mm away. An optical reflector is also used to serve as a reference smooth surface [to define I_0 later in equation (6)].

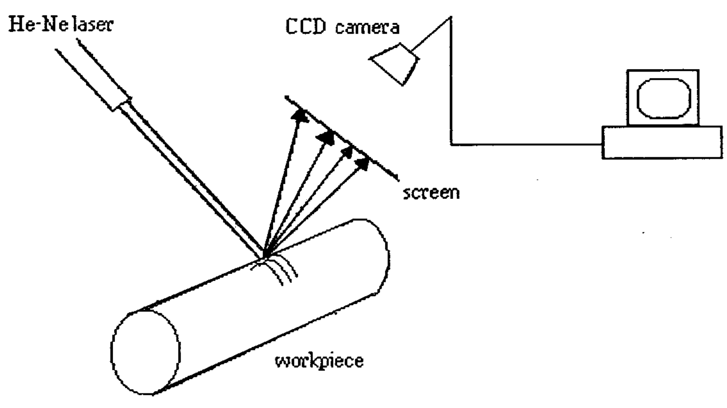

Fig. 1 Vision-based flank wear measurement system

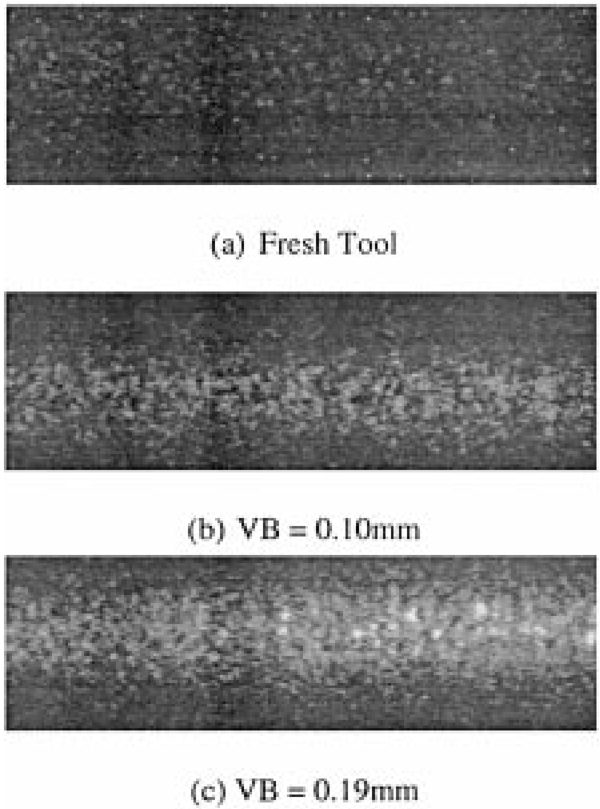

Fig. 2 Laser scattering images of turned surfaces

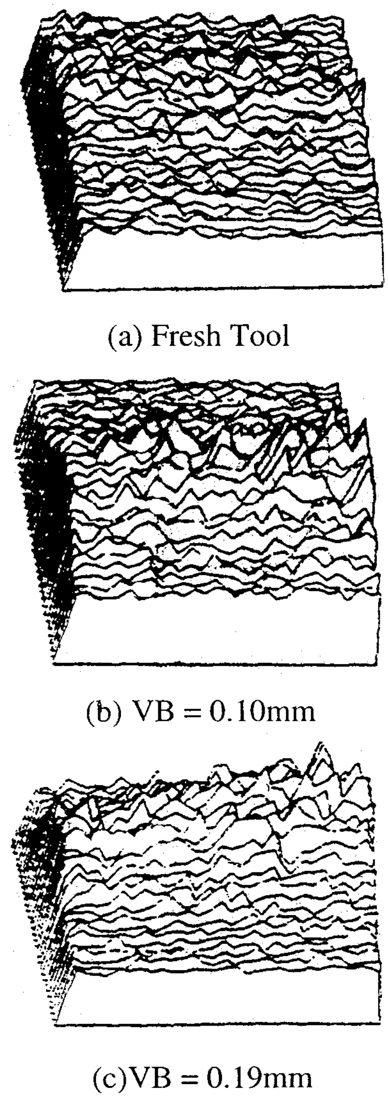

Fig. 3 Intensity of laser scattering images

Figures 2a to c show three captured scattering images of a near-finish turned surface produced at three corresponding stages of tool wear: fresh, some wear at $VB \approx 0.10$ mm and significant wear (i.e. severe enough to affect finish condition and dimensional accuracy) at $VB \approx 0.19$ mm, as would be predicted by a skilled operator. The respective intensity plots of the scattered light field are shown in Figs 3a to c. It can be seen that besides fluctuation in the intensity distribution, the scattering image changes with the wear of the tool due to the phenomenon that the intensity of the light scattered from the turned surface varies according to the surface topography. This has been observed for the turned surfaces obtained in this study.

3 PRINCIPLE OF TOOL WEAR IDENTIFICATION

3.1 Fuzzy clustering

Tool wear in finish machining generally progresses gradually, with hardly distinct changes in the state of the workpiece or machining condition. A suitable technique needs to be developed that can effectively identify the progressive transition in the state of the tool from normal wear to significant wear. Fuzzy set theory is employed for this purpose as it has been known to be an effective tool for solving highly non-linear, uncertain or ill-defined complex problems that are not amenable to precise mathematical expression or modelling.

Four fuzzy linguistic terms or fuzzy clusters are defined to describe the tool wear ($\boldsymbol{W}$) in finish turning: 'negligible wear (w_1) (starting from fresh state)', 'some wear (w_2)', 'more wear (w_3)' and 'significant wear (w_4) (affecting finish and accuracy, and possibly close to the rapid wear stage)'. The defined clusters are not unlike the main types of tool conditions qualitatively evaluated by an expert machinist on the tool conditions according to visual inspection of the shine and texture of the machined surface of the workpiece. A fuzzy relation between the condition of the machined surface and the state of tool wear is established through the optical scattering images via a set of membership functions. Figure 4 shows the membership functions used in the study, which are measured between zero and one for cases 'completely not belonging to' and those

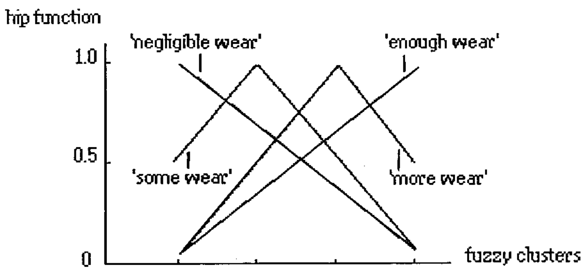

Fig. 4 Membership function for fuzzy classifiers

'completely belonging to' a cluster. The criterion for fuzzy clustering and judgement is based on the maximum value of the membership function.

3.2 Signal processing through the neural network

Average relative grey levels of the image pixels are used to characterize the pattern features of the captured optical scattering images. Each optical scattering image consists of 49×98 pixels. Let the grey level of a pixel be I_k and its relative value be

$$I_k^{(\mathrm{r})} = \frac{I_k}{I_0} \tag{6}$$

where I_0 is the value with respect to a smooth plane as described in equation (1) and serves as the reference value which is obtained from the optical reflector (Fig. 1). Supposing that the range between 0 and 1 is divided into ten bands B_i ($i = 1, 2, \ldots, 10$); i.e. $0 \leqslant B_1 < 0.1$, $0.1 \leqslant B_2 < 0.2$, $0.2 \leqslant B_3 < 0.3$, $0.3 \leqslant B_4 < 0.4$, $0.4 \leqslant B_5 < 0.5$, $0.5 \leqslant B_6 < 0.6$, $0.6 \leqslant B_7 < 0.7$, $0.7 \leqslant B_8 < 0.8$, $0.8 \leqslant B_9 < 0.9$, $0.9 \leqslant B_{10} < 1.0$. Then the average relative grey level for N_i pixels with $I_k^{(\mathrm{r})}$ values that lie in band B_i is

$$\bar{I}_i^{(\mathrm{r})} = \frac{1}{N_i}\left(\sum_{k=1}^{N_i} I_k^{(\mathrm{r})}\right) \qquad (i = 1, 2, \ldots, 10) \tag{7}$$

If no pixel has $I_k^{(\mathrm{r})}$ value in a particular band, say B_j, $\bar{I}_j^{(\mathrm{r})}$ for that band is zero. The set of $\bar{I}_i^{(\mathrm{r})}$ is presented to an ART2 neural network in the form of a feature vector $\boldsymbol{S}$:

$$\boldsymbol{S} = (\bar{I}_1^{(\mathrm{r})}, \bar{I}_2^{(\mathrm{r})}, \ldots, \bar{I}_i^{(\mathrm{r})}, \ldots, \bar{I}_{10}^{(\mathrm{r})}) \tag{8}$$

As shown in Fig. 5, the adaptive resonance theory (ART2) based neural network is made up of two successive layers of cells: an input feature representation layer F1 and an encoded category representation layer F2, which are linked by feedforward and feedback weighted connections. Each F1 cell consists of three sublayers with six nodes and performs feature enhancement in a synchronous manner on the input $\bar{I}_i^{(\mathrm{r})}$ ($i = 1, 2, \ldots, 10$) and the feedback weight (W_{ji}) ($j = 1, 2, 3, 4$) connections. Each F2 cell responds to a specified pattern while receiving signals through the forward weight (W_{ij}) connections. Once an input pattern matches one of the stored exemplars, only the corresponding F2 cell will resonate with the input; i.e. it will output the maximum value close to 1, with the others remaining at 0. The matching operation between an input pattern and a sample pattern is adjusted through a vigilance parameter (ρ). The detailed ART2 algorithm can be found in reference [**21**].

3.3 Learning and classification

The output of the ART2 neural network is characterized by a fuzzy feature vector $\boldsymbol{W}$ for the depiction of tool wear, as shown in Fig. 5:

$$\boldsymbol{W} = (w_1, w_2, w_3, w_4) \tag{9}$$

For a given sample input $\boldsymbol{S} = (\bar{I}_1^{(\mathrm{r})}, \bar{I}_2^{(\mathrm{r})}, \ldots, \bar{I}_i^{(\mathrm{r})}, \ldots, \bar{I}_{10}^{(\mathrm{r})})$ corresponding to a state of tool wear, the ART2 network will be trained to obtain a designated output vector $\boldsymbol{W}$ for the four F2 cells. In other words, each of the four fuzzy stages of tool wear is represented by the corresponding four values of its membership function, among which an F2 cell with the maximum value of 1

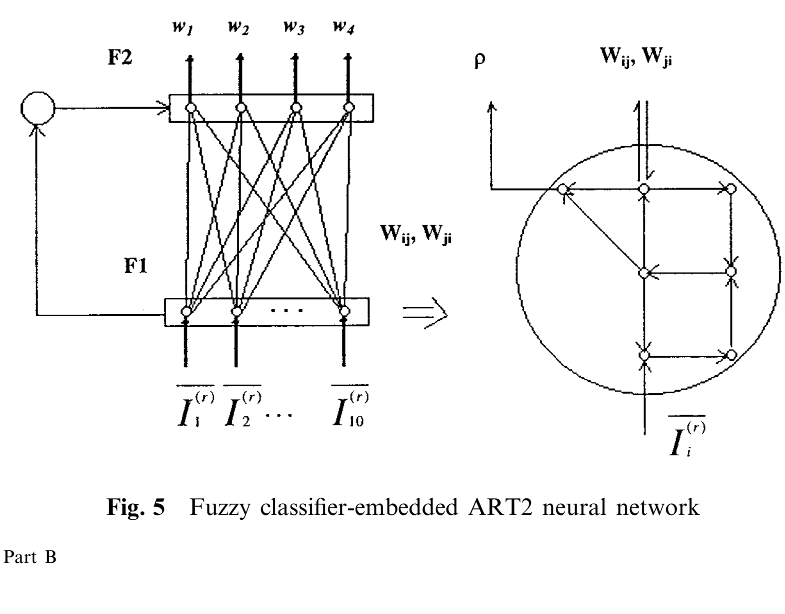

Fig. 5 Fuzzy classifier-embedded ART2 neural network

Table 1 Summarized results

Cutting tool (carbide)	Workpiece materials	Cutting speed (m/min)	Depth of cut (mm)	Feedrate (mm/rev)	ART2 network outputs at 'significant wear' condition w_1	w_2	w_3	w_4	Metrology and microscopic observation: Tool wear (mm)	Workpiece texture: Roughness R_a	Waviness	Imperfections
Tool A	Steel AISI 1045	130	1.0	0.050	0.16	0.24	0.72	0.94	VB = 0.15	No change	Less discernible	Pressed layers
Tool B		254	1.0	0.050	0.19	0.36	0.58	0.91	VB = 0.13	Decrease (5 times)	Less discernible	Pressed layers
Tool C	Aluminium alloy	90	0.5	0.026	0.24	0.35	0.63	0.96	VB = 0.16	Increase (1.2 times)	Less discernible	Tiny scratches
Tool D		110	0.5	0.026	0.28	0.42	0.77	0.95	VB = 0.19	Decrease (0.8 times)	Less discernible	Tiny scratches

indicates to which category it belongs. With reference to Fig. 4, for example, the tool wear condition 'significant wear' is expressed by $\boldsymbol{W} = (0.1, 0.34, 0.67, 1.0)$. Through the adjustment of the vigilance parameter ρ, the four patterns of tool wear can be established on the ART2 network, i.e. four fuzzy classifiers are embedded in the net connections.

When an input pattern for a cutting tool matches one of the four exemplars of tool wear—'negligible wear', 'some wear', 'more wear' and 'significant wear'—which are stored in the trained ART2 network, the four F2 cells will resonate with it in a corresponding form of membership function. The consistent record of each group in their outputs can help to trace the progress in the tool wear. Once an output pattern (w_1, w_2, w_3, w_4) of the network is matchable to the designated set $(0.1, 0.34, 0.67, 1.0)$ such that w_4 has the maximum value close to 1, the tool is diagnosed to have reached its condition of 'significant wear' and needs to be replaced.

4 RESULTS

Turning experiments were conducted on steel and aluminium workpieces under different cutting conditions. After each turning run, the degree of tool wear and the condition of workpiece surface were determined and checked with a microscope. The surface roughness R_a of the workpiece was measured by the Talysurf stylus contact method. The R_a of the workpiece obtained at the 'significant wear' stage of the tool was compared with that at the fresh or 'negligible wear' stage.

Table 1 lists a summary of the experimental conditions and results. It also shows the successful identification of the 'significant wear' by the outputs of the ART2 neural network embedded with fuzzy classifiers. The outputs (w_1, w_2, w_3, w_4) corresponding to tools A, B, C and D at the 'significant wear' stage range between 0.9 and 1.0 respectively. The values of flank wear width (VB) for these tools also indicate that the tool is at the replacement stage. On the other hand, the ART2 outputs also show that there is no definite relationship between tool wear and surface roughness of a workpiece. An $R_a \approx 1-2$ μm was obtained at the initial or 'negligible wear' stage. At the 'significant wear' stage, the R_a of the turned surface could be 1.2 times higher (for tool C), or up to 5 times lower (for tools B and D), or even with hardly any change (for tool A). In addition, it was found from microscopic observation of the workpiece surfaces that the feedmarks were less discernible at the 'significant wear' condition, due largely to burnishing, rather than cutting, of the workpiece by the worn tool tip and/or the rubbing of the worn tool against the workpiece. Other imperfections, such as intermittent cold-welded materials or buildup edges (with tools A and B) and tiny scratches (with tools C and D) were also observed on the turned surfaces. These results suggest that features of the machined surface topography can be affected by these imperfections, with corresponding effects on the measured surface roughness [**11**], but, as the above results indicate, not on the ART2 neural network with fuzzy classifier.

5 CONCLUSIONS

The approach adopted in this study is established upon the fact that the optical scattering image is related to the topography of the turned surface which, in turn, changes with the progressive wear of the tool. The laser-based optical scattering pattern recognition method is not susceptible to the ambient light and background noises. In spite of imperfections on the turned surfaces affecting the relation between the finish condition and the state of wear of the tool, it is sufficiently robust to successfully classify the 'significant wear' stage using the ART2 neural network embedded with fuzzy classifiers. Nevertheless, the influence of the change in tool wear with the topographic features of the turned surface and the corresponding effect on the optical scattering pattern needs to be further investigated and understood to ensure robust and efficient tool wear identification over a broad range of turning or machining conditions.

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