Vol. 3, No. 1, pp. 1-5, June 2004

INTERNATIONAL
JOURNAL OF SAFETY
www.kosos.or.kr

Characterization of Surface Quality in Orthogonal Cutting of Glass Fiber Reinforced Plastics

Gi Heung Choi

Department of Mechanical Systems Engineering, Hansung University, Seoul, 136-792, Korea

(Received October 10, 2003; Accepted May 12, 2004)

Abstract : This study discusses frequency analysis based on autoregressive (AR) time series model, and the characterization of surface quality in orthogonal cutting of a fiber-matrix composite materials. A sparsely distributed idealized composite material, namely a glass reinforced polyester (GFRP) was used as workpiece. Analysis method employs a force sensor and the signals from the sensor are processed using AR time series model. The experimental correlations between the fiber pull-out and AR model coefficients are then established.

Key words: GFRP, surface quality, AR model

1. Introduction

In recent years, composite materials such as fiber reinforced composites (FRC) have gained considerable attention in the aircraft and automobile industries due to their light weight, high modulus and specific strength. The reliability of machined FRC components in high strength applications and the safety in using these components are often critically dependent upon the quality of surface produced by machining since the surface layer may drastically affect the strength and chemical resistance of the material. In practice, control of chip formation appears to be the most serious problem since chip formation mechanism in composite machining has significant effects on the finished surface [1-5].

If the process of machining composite were to be the one of intelligent nature for insuring surface quality needed, the ability to sense the desired characteristics of the process and the properties of a product would be essential. Successful implementation of such an intelligent sensor typically requires a realistic model of composite machining process. Despite the necessary in-plant calibration, process modeling and characterization based on an empirical model would make practical implementation of an intelligent sensor possible. Among various sensor signals available nowadays, force (vibration) signals from various types of machining operations were found to contain very rich information about the process [6]. The fundamental understanding of the cutting force signals and frequency analysis, therefore, play an important role in the monitoring and control of machining processes.

Current study will discuss frequency analysis based on autoregressive (AR) time series model and the characterization of surface quality in orthogonal cutting of a fiber-matrix composite materials. A sparsely distributed idealized model composite material, namely a glass reinforced polyester (GFRP) was used as workpiece. Analysis method employs a force sensor and the signals from the sensor are processed using AR time series model. Effects of fiber orientation, cutting parameters and tool geometry on the cutting mechanisms and surface quality are discussed.

2. Orthogonal Cutting of GFRP

Machining of GFRP involves shearing and cracking of matrix material (polyester), brittle fracture across the fiber (glass), fiber pull-out and fiber-matrix debonding (by tensile fracture), and delamination prior to final fracture both in the chip and below the cutting plane depending on the fiber orientation. Damage of the machined surface was found to be highest when machining materials with roving oriented 45° towards the cutting edge or the fiber orientation angle (FOA) q=135° in Figure 1 [3, 7]. Three distinct mechanisms, i.e., cutting, shearing

*Corresponding author: gihchoi@hansung.ac.kr

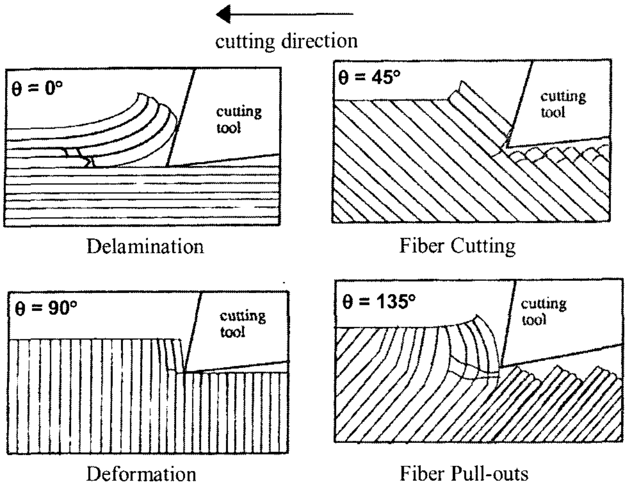

Fig. 1. Schematic of cutting mechanisms in orthogonal cutting of GFRP.

and fracture along the fiber-matrix interface were then identified. More specifically, depending on the fiber orientation, cutting mechanisms can be categorized into the following 4 types:

(1) Type I (0° fiber orientation): Cutting mechanism is characterized by Mode I loading and fracture along the fiber-matrix interface, Mode II loading through tool advancement, and fracture perpendicular to the fiber direction under bending load. Combined effect of these mechanisms can be manifested by the delamination of adjacent fiber layers along the machined surface (or fiber-matrix debonding).

(2) Type II (15° - 75° fiber orientation): In this positive fiber orientation, cutting mechanism is composed of fracture from compression induced shear across the fiber axis and interfacial shearing along the fiber direction which eventually causes fiber-matrix debonding.

(3) Type III (75° - 90° fiber orientation): Cutting mechanism is characterized by compression induced fracture perpendicular to the fibers and inter-laminar shear fracture along the fiber/matrix interface.

(4) Type IV (beyond 90° fiber orientation): Cutting mechanism in this type is basically similar to Type III. However, intermittent fracture across the fiber axis is visible, which in turn contributes to the burst type force signal.

3. Spectral Analysis

3.1. Autoregressive (AR) Time Series Model

A time series model that approximates many discrete time deterministic and stochastic processes in engineering problems represents the stationary time correlation of the process. An AR process of order r, in particular, is given by

$$x(n) = \sum_{i=1}^{r} a_i x(n-i) + \sigma u(n) \tag{1}$$

where $x(n)$ is the output sequence of the filter that models the observed data. σ is a filter gain, $u(n)$ is a zero mean, unit variance Gaussian input driving noise sequence and $a_0=1$. Model parameter a_i comprises a pattern vector A=$\{a_0, a_1, \ldots, a_r\}$. In the present case, $x(n)$ is the measured discrete force signal sequence. Let

$$G(z) = 1 + \sum_{i=1}^{r} a_i z^{-i}, \quad z = e^{2\pi j \Delta T w} \tag{2}$$

in z-domain where ΔT is sampling time interval. Then, $x(n)$ is obtained from $u(n)$ by the spectral components through a linear filter whose characteristic function is s/G(z) [8]. The continuous power spectrum, as a function of frequency w, corresponding to the a_i is given (within a constant factor) by

$$P(w) = \frac{1}{\left|1 + \sum_{i=1}^{r} a_i e^{-2\pi j w \Delta T i}\right|} \tag{3}$$

The AR coefficients of a random process can be found exactly only if the exact autocorrelation function of the process is available. However, the autocorrelation is not available in practice and only an estimate of the AR parameters can be found based on the available data. In this study, the blockwise processing method was used due to its superior ability to estimate the AR coefficients. The sequential methods are, however, more suitable for real time applications due to their ability to constantly adapt the coefficients as each sample becomes available.

3.2 Discrimination Information (Cross Entropy) Analysis

Let $x(n)$ be a state of some process that has a set $\boldsymbol{C}$ of possible states. Let Ψ be the set of all possible probability densities q on $\boldsymbol{C}$ such that $q(x \in C) \geq 0$ and

$$\int_c q(x)dx = 1 \tag{4}$$

The entropy of a process with the probability density q is represented as:

$$E[q] = -\int_C q(x)\log q(x)dx \quad (5)$$

The entropy is a measure of the amount of information produced by a random process $x(n)$, or a measure of uncertainty in a random process. The larger value of entropy corresponds to more information (uncertainty) in the process. The discrimination information (or cross entropy) is a generalization of entropy when the *prior* density p of $x(n)$ is available, and given by:

$$H[q,p] = \int_C q(x)\log\left(\frac{q(x)}{p(x)}\right)dx \quad (6)$$

Eq(6) states that the total amount of information produced by a process $x(n)$ equals the sum of the amount of information gained by the *posterior* (current) density q and the information already acquired by p. The priors must be strictly positive, i.e.,

$$p(x \in C) > 0 \quad (7)$$

The principle of minimum discrimination information provides a method of inference about a *true* unknown probability density $q^+ \in C$ when there exist a prior estimate of q^+ and new information about q^+ in the form of constraints on the expected values. $I=(q^+ \in \Phi)$ stands for the newly acquired information and is referred as a *constraint*, and Φ is a *constraint set*. New information I can take the form of equality and inequality constraints such that:

$$\int_C q^+(x)c_k(x)dx = 0 \quad (8)$$

$$\int_C q^+(x)c_k^*(x)dx \geq 0 \quad (9)$$

for known sets of bounded constraint functions $c_k(x)$ and $c_k^*(x)$. Let $p \in \Psi$ be an arbitrary prior estimate of density q^+ prior to learning I. $H[q, p]$ is the information-theoretic distortion between densities p and q. It can also be interpreted as the amount of information-theoretic distortion provided by I that is not inherent in p.

3.3. Spectral Distortion

One way of quantifying the distortion between a random signal $x(n)$ and a predefined pattern vector A is to use the discrimination information defined in terms of Itakura-Saito distortion measure [8]. Suppose q and p signify the probability densities associated with processes $x(n)$ and A, respectively. The discrimination information functional for Itakura-Saito distortion measure is given by:

$$H[q,p] = \frac{1}{\sigma^2}\left\{r_x(0)r_a(0) + 2\sum_{s=1}^{s} r_x(s)r_a(s)\right\} + \log(\sigma^2) \quad (10)$$

where

$$r_a(s) = \begin{cases} \sum_{i=0}^{S-s} a_i a_{i+s}, & s \leq S \\ 0, & otherwise \end{cases} \quad (11)$$

$r_x(s)$'s are the autocorrelation functions of $x(n)$ for lags $s=0,1,...,S$. The signal distortion measure in the form of discrimination information in Eq(10) and Eq(11) are known to be particularly useful in real-time application due to their simplicity in computation.

4. Experiment

A series of orthogonal cutting experiments were conducted for GFRP composite materials. The GFRP plate were 4.0 mm thick with glass yarns of 0.4 mm diameter arranged approximately 0.8mm apart. The reinforcement was arranged in the middle of the plate. Constituents of GFRP are given in Table 1. The workpieces were mounted on a Rockfort Shaper-Planer equipped with modified hydraulic system to provide a steady cutting motion. About 25 mm of the material was exposed for machining each time. Multi-purpose C2 grade carbide inserts were used in dry cutting of GFRP. Schematic diagram of data acquisition and experimental setup is given in Figure 2. Schematic of the workpieces and relative angles between the cutting direction and fiber orientation is also shown in Figure 2.

The force signals were obtained using a three-dimensional circular-type strain gage dynamometer that was

Table 1. Constituents of GFRP used in this study

	GFRP
Resin	Unsaturated polyester polymal 6304, 6320F at a ratio of 1:1
Reinforcement	ECG-75-11/2 3.3 S NA glass yarn of 0.4mm diameter
Reinforcement Volume Fraction (%)	0.85%
Post Curing	120 degrees Celcius for 2 hours

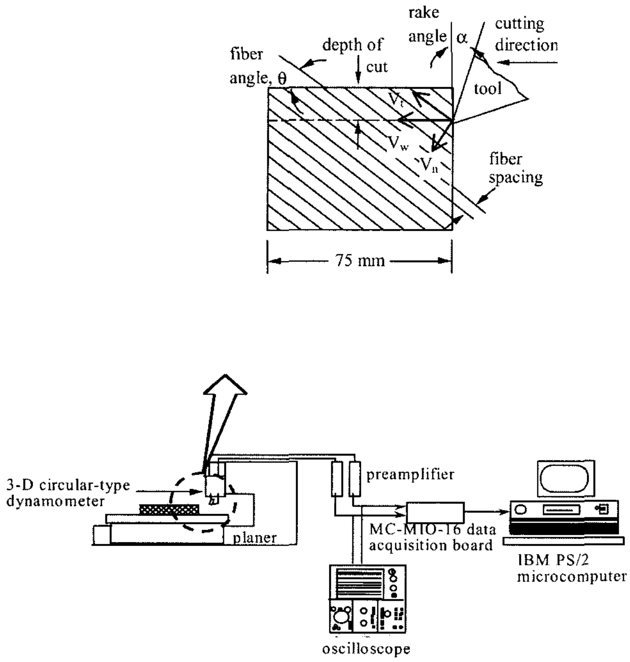

Fig. 2. Designation of angles and schematic diagram of experimental setup.

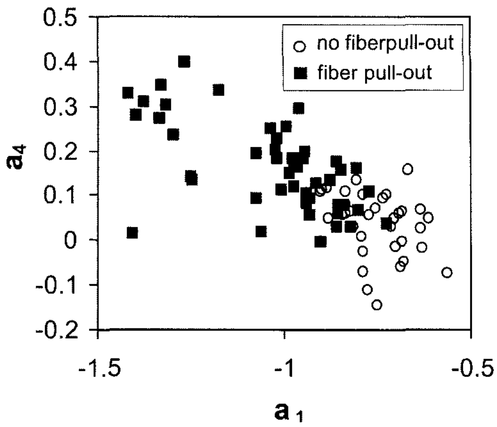

Fig. 3. Sensitivity of AR coefficients to fiber pull-out.

attached to the tool post. Signals were passed through a pre-amplifier and sampled using a National Instrument MC-MIO-16 data acquisition board. Sampling rate was 5000Hz. The sampled signals were stored in a IBM PS/2 computer for further analysis. AR coefficients were obtained using MATLab software. The machined surfaces were examined by projecting back light on to the side of the machined workpiece to observe and quantify the machining damage. Detailed description of the experimental procedures is given elsewhere [1, 2, 3].

5. Results and Discussion

The cutting stress distribution in the machining zone of material dictates not only the type of chip produced and but also the quality of the surface finish. Fiber pull-out from the matrix material by fiber-matrix debonding and matrix stripping significantly affect the surface quality in cutting GFRP. Specifically, poor surface results from the fiber pull-out. Depth of fiber pull-out as a function of fiber orientation angle, tool rake angle and cutting parameters has been previously observed experimentally [3]. Depth of fiber pull-out observed in our experiments ranged approximately from 0.1 mm to 0.5 mm for fiber orientation from 60° to 150°, rake angle from -20° to 20°, and 0.051 mm depth of cut. For the rest of fiber orientation, pull-out depth was minimal.

The sensitivity of AR coefficients to fiber pull-out was evaluated and shown in Figure 3. Two classes to be discriminated in this case are "Pull-out" class ("CLASS 3+4+5+6+9+10+11+12") with pull-out depth larger than 0.1 mm and "No pull-out" class ("CLASS 1+2+7+8") otherwise. Feature set was selected for maximum separation. As the fiber orientation angle increases, shift of cutting energy to the region slightly above the funda-

Table 2. Experimental conditions for machining GFRP. Depth of cut is 0.051 mm.

Class	Fiber Orientation Angle (FOA) (degrees)	Cutting Mechanism (Type)	Fiber Pull-out	Cutting Parameters	
				Cutting Speed (m/min)	Rake Angle (degrees)
1	45	II	N	3	20
2	45	II	N	6	20
3	90	III	Y	3	20
4	90	III	Y	6	20
5	135	IV	Y	3	20
6	135	IV	Y	6	20
7	45	II	N	3, 6	0
8	45	III	Y	3, 6	-20
9	90	IV	Y	3, 6	0
10	90	IV	Y	3, 6	-20

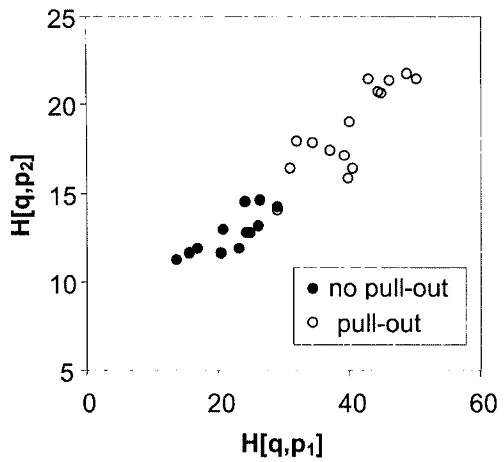

Fig. 4. Two dimensional plot of $H[q, p]$ for fiber "Pull-out" and "No fiber pull-out" cases.

mental frequency (particularly in 135° fiber orientation case) is noted. It may be reasoned that small scaled high frequency burst signal due to fiber pull-out causes such energy shift. The spectral peak in this region is, therefore, a good indication of the onset of fiber pull-out.

The spectral distortion based on Itakura-Saito distortion measure weights the local maxima more heavily than the local minima. Define the log spectrum of inverse filter output normalized by a filter gain, i.e.,

$$V(G) = \log\left|\frac{x(e^{j\theta})}{\sigma/G(e^{j\theta})}\right|^2 \tag{12}$$

When $V(G)<0$, relatively large distortion is generated due to non-linearity of logarithmic function in Eq(12). On the contrary, small distortion is made when $V(G)>0$. If the energy spectrum is constrained to match the energy of the other by normalization as in our example, smaller error contribution can not be introduced by arbitrarily placing one spectrum far below the other [8].

What is most important for recognition of physical phenomena such as fiber pull-out are frequencies, not the missing frequencies. It is a fundamental tenet of signal detection that, in a noisy back ground, a frequency is easier to detect than a missing frequency. The distortion measure in Eq(12) is plotted for fiber "Pull-out" case and "No pull-out" case in Figure 4. Since the spectral distortion defined in terms of Itakura-Saito distortion measure tends to track more accurately the spectral peaks than the spectral valley, good sensitivity is seen when fiber pull-out is present. Moreover, different level of fiber pull-out may be attributed to the chip formation mechanism (cutting mechanism). The decision on the quality of surface can then be made by quantitatively analyzing the AR coefficients of cutting force model for both cutting mechanism and depth of fiber pull-out.

6. Conclusions

Frequency analysis based on autoregressive (AR) time series model of measured force signal in orthogonal cutting of GFRP has been discussed. A strong correlation between AR coefficients and the surface quality was also found. Since the spectral distortion based on Itakura-Saito distortion measure weights the local maxima more heavily than the local minima, good sensitivity between the fiber pull-out and the AR coefficient was obtained.

Acknowledgement

This Research was financially supported by Hansung University in the year of 2004.

References

[1] C.W. Wern and M. Ramulu, "Influence of Fiber on the Cutting Stress State in Machining Idealized Glass Fiber Composite", J. Starin Analysis, Vol. 32, No.1, pp.19-27, 1997.

[2] C.W. Wern, M. Ramulu and A. Shukla, "Preliminary Investigation of Stresses in the Orthogonal Cutting of Fiber Reinforced Plastics", Experimental Mechanics, Vol. 36, No.1, 1996, pp.33-41.

[3] C.W. Wern, "Fiber and Fiber-Matrix Interface Effects on the orthogonal Cutting of Fiber Reinforced Plastics", PhD Dissertation, Department of Mechanical Engineering, University of Washington, 1996.

[4] W. Konig, Ch. Wulf, P. Grab and H. Willerscheid, "Machining of Fiber Reinforced Plastics", Annals of CIRP, Vol.34, No.2, pp.537-547, 1985.

[5] R. Komanduri, "Machining Fiber Reinforced Composite", Mech. Engng., Vol.115, No.4, pp.58-64, 1993.

[6] G.C. Andrews and J. Tlusty, "A Critical Review of Sensors for Unmanned Machining", Annals of CIRP, Vol.32, No.2, pp.563-572, 1983.

[7] D. Arola and M. Ramulu, "Orthogonal Cutting of Fiber Reinforced Composites: A Finite element Analysis", Int. J. Mechanical Science, Vol.39, No.5, pp.597-613, 1997.

[8] J.E. Shore and R.M. Gray, "Minimum Cross-Entropy Pattern Classification and Cluster Analysis", IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. PAMI-4, No.1, pp.11-1103, Jan., 1982.