Autoregressive Modeling in Orthogonal Cutting of Glass Fiber Reinforced Composites

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2차원 GFRC절삭에서 AR모델링에 관한 연구

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Abstract : This study discusses frequency analysis based on autoregressive (AR) time series model, and process characterization 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 resulting pattern vectors of AR coefficients are then passed to the feature extraction block. Inside the feature extraction block, only those features that are most sensitive to different types of cutting mechanisms are selected. The experimental correlations between the different chip formation mechanisms and AR model coefficients are established.

초 록 : 본 연구에서는 복합소재인 GFRP(Glass Fiber Reinforced Polyester)의 2차원 절삭공정에서 절삭 메커니즘과 소재의 신뢰도 및 안전성과 밀접한 관련이 있는 표면정도를 중심으로 한 공정의 특성화를 시도하고, 주파수 분석에 관하여도 논의한다. 구체적으로는, 공정중 발생하는 절삭력 신호를 AR(Autoregressive) 모델링하여 해석에 사용한다. 특히, 특징추출과정을 통해 AR계수로 이루어진 패턴벡터 중 다양한 절삭 메카니즘에 민감한 계수만 선택할 수 있다. 이들 계수와 절삭 메커니즘과의 실험적 관계를 설정함으로써 섬유경사각(Fiber orientation angle), 절삭 변수 그리고 공구형상이 절삭 메커니즘에 미치는 영향을 평가하였다.
Key Words : glass reinforced polyester, orthogonal cutting, cutting mechanism, autoregressive modeling

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 a empirical model would enable practical implementation of an intelligent sensor possible. Among

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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 is 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 process characterization 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. The resulting pattern vectors of AR model coefficients are then utilized to the feature extraction block. Inside the feature extraction block, only those features that are most sensitive to different types of cutting mechanisms are selected. Selected features are then used to characterize the chip formation process in orthogonal cutting of GFRP. Specifically, the experimental correlation between the different chip formation mechanisms and model coefficients are established. Effects of fiber orientation, cutting parameters and tool geometry on the cutting mechanisms and surface quality are also 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) θ =135° in Fig. 1[3,7]. Three distinct mechanisms, i.e., cutting, shearing 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:

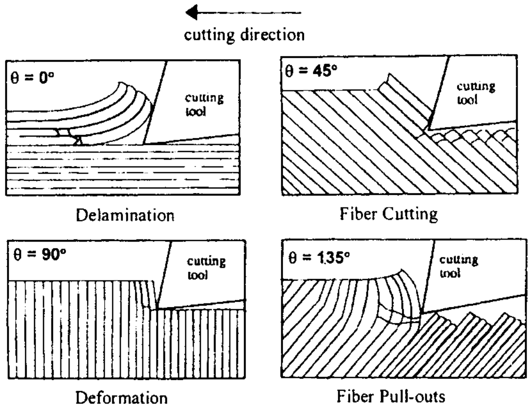

Fig. 1. Schematic of cutting mechanisms in orthogonal cutting of GFRP

(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 interlaminar 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. Autoregressive Modeling

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 p, in particular, is given by

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

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

4. Feature Selection

Using high dimensional AR coefficients for a process characterization requires a large number of data samples and a higher order model without necessarily improving its ability to discriminate the cutting mechanisms. Only those coefficients that are sensitive enough to cutting mechanisms and do not show sensitivity to changes in cutting parameters and environmental noise are selected. A cluster of pattern vectors resulting from characterization of sampled signals can be represented by a single centroid in many applications. For example, M pattern vectors $A(k)$; $k=1,...,M$ resulting from M measurements under different combinations of cutting parameters and tool geometry may be represented by a centroid $\hat{A}$. When the distortion measure is Euclidean distance, $\hat{A}$ is determined to minimize the average distance D_c ($\hat{A}$), i.e.,

$$\hat{A}=\min[D_c(\hat{A})]=\min\left[\frac{1}{M}\sum_{k=1}^{M}D[A^{(k)},\hat{A}]\right] \quad (2)$$

where $D_c[A(k),\hat{A}]$ is the Euclidean distance between $A(k)$ and $\hat{A}$. The minimum of $D_c(\hat{A})$ is achieved simply by the components of $A(k)$ each being the arithmetic mean of the components of $A(k)$[8]. For any cutting mechanism specified by a subscript "1", an i-th parameter mean can be defined for the i-th model coefficient as

$$[a_{i,1}]_{mean}=\frac{1}{M}\sum_{k=1}^{M}a_{i,1}^{k} \quad (3)$$

where M is the number of sample data. One natural way of evaluating two different cutting mechanisms specified by subscripts "1" and "2" is through the observation of its between-class variation $Q_i^{1,2)}$ defined as[9]

$$Q_1[1,2]=\|[a_{i,1}]_{mean}-[a_{i,2}]_{mean}\| \quad (4)$$

To formulate a better index for selecting features (model coefficients) that give maximum separation between classes, a within-class variation for any particular cutting mechanism l is also defined as

$$S_{i,l}=\left[\frac{1}{M}\sum_{k=1}^{M}(a_{il}^{k}-[a_{il}]_{mean})^2\right]^{1/2} \quad l=1,2,3,... \quad (5)$$

Superscript k stands for a particular sample coefficient ai within class l. A discrimination index $J_i^{1,2)}$ between two cutting mechanisms "1" and "2" based on i-th coefficient can then be obtained by normalizing $Q_i^{1,2)}$ with $S_{i,1}$ and $S_{i,2}$. That is

$$J_i[1,2]=\frac{Q_i[1,2]}{[S_{i1}S_{i,2}]^{1/2}} \quad (6)$$

The greater discrimination index implies that difference in this specific model coefficient for two cutting mechanisms is more pronounced, and that the coefficient varies less within either of the cutting mechanisms. The most important coefficient is the one that maximizes the discrimination index. Features are selected based on the their discrimination indices.

5. Experiment

A series of orthogonal cutting experiments were conducted for both CuFRP and GFRP composite materials. The GFRP plate were 4.0mm thick with glass yarns of 0.4mm diameter arranged approximately

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	120C for 2 hours

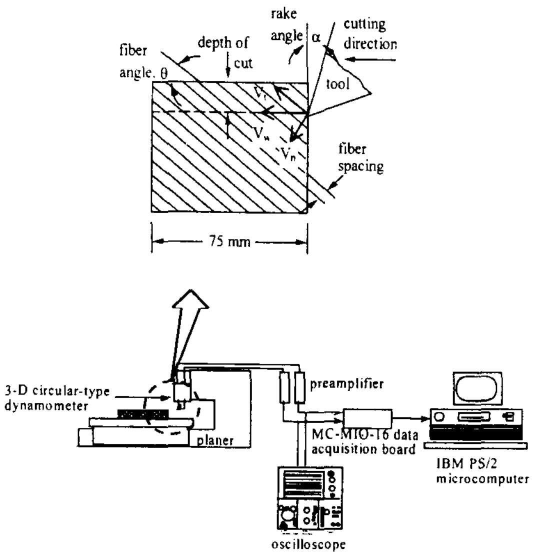

Fig. 2. Designation of angles and schematic diagram of experimental setup

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 25mm 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 Fig. 2. Schematic of the workpieces and relative angles between the cutting direction and fiber orientation is also shown in Fig. 2.

The force signals were obtained using a three-dimensional circular-type strain gage dynamometer that was 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[1~3].

6. Results and Discussion

In general, the power spectra of force signals in composite machining are dominated by the frequency component that corresponds to the frequency of mechanical shock coming from the abrupt engagements of tool in fiber cutting. The cutting force signal is, therefore, periodic in nature with a fundamental frequency determined by the number of fibers in unit length, the fiber orientation angle and the cutting speed.

The sensitivity of AR coefficients to the fiber orientation-dependent cutting mechanisms was examined. Table 2 summarizes the experimental conditions and trends observed in orthogonal cutting of GFRP. AR coefficients for 3 different classes, i.e., “CLASS 1”, “CLASS 3” and “CLASS 5” (or types of cutting mech-

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

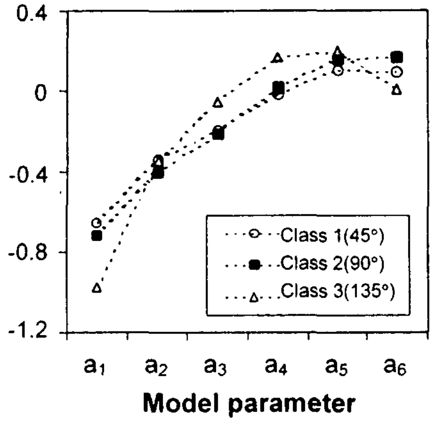

Fig. 3. Model coefficients for CLASS 1, 3 and 5

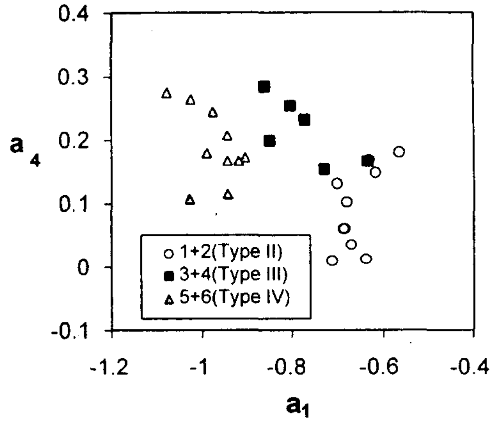

Fig. 4. Feature spaces for discriminating types of cutting mechanism

anisms, i.e., TYPE II, TYPE III and TYPE IV) were, for example, plotted on the feature spaces in Fig. 3. The order of AR model was set to 6 for all cases. The figure clearly indicates that there are overlaps among model coefficients. Since the boundaries of a_2 and a_5 are not clearly distinguished, examining all AR coefficients does not necessarily provide the discriminatory information on the cutting mechanisms. The discrimination indices for different combinations of cutting mechanisms and cutting parameters summarized in Table 3 were then calculated for each model coefficient. The results of this test show that the separation attributed to changes in cutting parameters (J[1,2], J[3,4] and J[5,6]) is low, whereas the separation resulting from different cutting mechanisms (J[1,3], J[1,5] and J[3,5]) is comparatively high.

Table 3. Discrimination index J for different combinations of cutting mechanisms and experimental conditions

	Characteristics to be correlated	a_1	a_2	a_3	a_4	a_5	a_6
J[1+2, 3+4]	Cutting Mechanism(CM)	2.4	0.642	0.544	1.655	2.584	0.163
J[1+2, 5+6]	CM	7.781	0.76	2.604	2.289	1.937	2.792
J[3+4, 5+6]	CM	3.775	0.001	2.705	0.528	0.586	1.924
J[1+2, 7+8]	Cutting Parameters(CP)	2.417	0.333	0.498	0.535	0.222	0.788
J[3+4, 9+10]	CP	3.63	2.323	2.514	1.429	2.33	1.84
J[7,8]	CP	0.562	0.691	0.002	1.034	0.382	0.294
J[9,10]	CP	0.395	0.608	0.343	0.086	0.565	0.233

Next, all data under condition 1 and 2 (3 and 4, 5 and 6) were combined into a single class, i.e., "CLASS 1+2"("CLASS 3+4" and "CLASS 5+6"), and the discrimination indices were calculated. Results summarized in Table 4 show lower discrimination indices compared to the cases where classes for varying cutting parameters are not combined (i.e., J[1,3], J[1,5] and J[3,5]). This is expected from the fact that the combined class has a higher within-class variation.

Based on the discrimination indices, a_1 and a_4 were selected to be the most important features in terms of characterizing the cutting mechanisms while maintaining insensitivity to changes in cutting parameters. Shown in Fig. 4 is the feature space for combinations of model coefficients that are selected to maximize the discrimination index. It is observed that three classes were reasonably separated in the feature space so that correlation with the cutting mechanism can be established by quantitatively analyzing the AR coefficients of force model.

The figure also indicates that a1 has wide variation for the range of cutting parameters used. On the other hand, a_4 is distributed over the relatively narrow range so that CLASS 3+4 and CLASS 5+6 are not clearly separated in the selected feature space. Referring to Table 4, one can notice that J[3+4,5+6] is lower than J[1+2,3+4] or J[1+2,5+6]. This experimental observation indicates that high frequency components (higher order model coefficient, i.e., a_4) arising from fracture along and across the fiber are not distinguishable for both

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case, whereas low frequency components (low order model coefficient, a_1) show enough sensitivity to cutting mechanisms. The similarity of fiber cutting mechanism in cutting GFRP with fiber orientations between 90° and 135°, therefore, appear to be reflected in AR coefficients. Examination of discrimination index J[1+2,7+8], J[3+4,9+10], J[7,8] and J[9,10] indicates that cutting mechanism with positive rake angle exhibits different characteristics from what is observed with negative rake angle (or zero rake angle). However, no noticeable change in cutting mechanism is seen for either negative or zero rake angle. The sensitivity of AR coefficients to the effective fiber orientation angle in Table 4 indicates that it is indeed an effective measure of distinguishing cutting mechanisms.

7. Summary and 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 cutting mechanisms were also found. By implementing feature selection technique, only those model coefficients that are sensitive to cutting mechanisms but insensitive to changes in cutting parameters were found. Model coefficients under single cutting condition are then sufficient to represent the coefficient under other conditions, which will enable the calibration of model coefficients under realistic cutting situation. Combinations of model coefficients that maximize discrimination index seem to depend strongly on the characteristics of cutting process to look at. Both the fiber orientation angle and tool rake angle have significant effects on the cutting mechanism. The effects of tool rake angle and fiber orientation angle on the frequency characteristics of force signal are, however, mutually contradictory.

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