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Paper:

Aiding of Micro End-Milling Condition Decision Using Data-Mining from Tool Catalog Data

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When the minor diameter of an end-mill is 1.0 mm or less, handling of tools becomes difficult because of the influence of the characteristic size effect and bending of the cutting edge. Furthermore, it is hard for engineers to derive the cutting conditions that can serve as indexes in the early stage of micro end-milling. In this study, a system that can make instantaneous decisions was developed, on the basis of workpiece material-characteristics and tool shape parameters, by applying data mining techniques together with non-hierarchical and hierarchical clustering methods on micro end-mill catalog data. Slotting experiments using cemented carbide square micro end-mill were carried out to investigate the practicability of derived mining conditions under slotting of A7075 (JIS). We found that catalog mining can be used to derive the guidelines for deciding the micro end-milling conditions.

Keywords: micro end-mill, tool catalog data, data-mining, slotting, cutting condition

1. Introduction

Requirements placed on the parts that have microscopic contours have been increasing as a result of miniaturization of the optical apparatus, medical equipment, and electronics. In processing such as microscopic contours, micro end-mills with outside diameters of 1.0 mm or less are promising low-cost and quick-delivery technologies for machining metal. The micro end-mills have unique processing characteristics such as the size effect [1] that other general purpose end-mills do not have. Not only is the tool feed rate comparatively small relative to the nominal size of the edge blade but also the tool stiffness and hardness are rather low, and this causes the size effect. In many cases, high velocity revolutions used as a method to control the load of the tool are influenced by the circumference of the radial run out of the tool. Therefore, engineers have trouble finding the suitable cutting conditions that can serve as indexes of the optimal conditions.

While there has been extensive research on micro end-mill processing from the viewpoint of tool wear [2–4], surface roughness [5–7], and cutting force [8–10], not much research has gone into the development of micro end-milling condition decision support systems. In this work, we have studied the advanced cutting condition decision support systems that can make decisions on the cutting conditions of ball end-mills and square end-mills for rough processing [11–13]. In this paper, we present a cutting condition decision support system (hereinafter a catalog-mining system [11–13]) that uses significant features extracted from the catalogs of the tool makers who have proven track records in manufacturing high-quality micro end-milling.

2. Catalog Mining System

Data mining is the process of finding valid, novel, potentially useful, and ultimately understandable data patterns; it is used for predicting large amount of data in which there are no predetermined notions about what will constitute an interesting outcome [14–16]. As shown in **Fig. 1**, the first method in the catalog-mining process is data selection. In this process, data on cemented carbide micro end-mills tools with outside diameters of 1.0 mm or less were obtained from the 2015–2016 versions of the catalogs from cutting-tool makers A, B, and C in Japan (4177 pieces of micro end-mill data in total). The end-milling condition decision equations consist of the end-mill shape parameters and material characteristics of workpieces in the catalog as the predictor variables and the end-milling conditions recommended by the cutting tool makers as the criterion variables. **Table 1** lists the ranges of predictor and criterion variables of the makers A, B, and C. For the micro end-milling conditions, the micro end-mill catalogs were mined and the extracted data were used to define the cutting speed V, feed rate f, axial depth of cut Ad, and radius depth of cut Rd for side-milling. These conditions are defined as criterion variables. We selected carbon steel, alloy steel, quenched steel, aluminum alloy, copper alloy, titanium alloy, super-heat resisting alloy, and austenitic stainless steel as the workpieces. Next process was of attribute extraction, in which target data were grouped for making

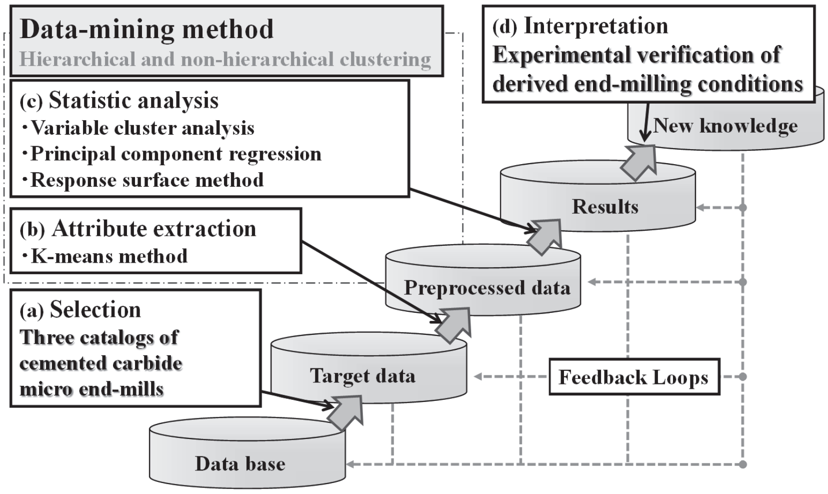

Fig. 1. Catalog mining process for micro end-mill.

Table 1. Ranges of target data.

Predictor variables			
End-mill shape parameter		Workpiece mechanical properties	
Out side diameter D mm	0.1 ∼ 1.0	Vickers hardness Hv	19 ∼ 740
Shank diameter Ds mm	3.0, 4.0	Thermal conductivity λ W/m・K	7.54 ∼ 237
Overall lenghth L mm	35 ∼ 70	Tensile strength σ_B N/mm^2	70 ∼ 2280
Length of cut l mm	0.08 ∼ 5.0	Proof stress $\sigma_{0.2}$ N/mm^2	30 ∼ 1815
Number of flutes z	2, 3, 4	Young's modulus E GPa	68 ∼ 210
Helix angle θ degree	0 ∼ 45	Machinability index MI	15 ∼ 160
Criterion variables (Cutting Conditions)		The kind of tool coating	
Cutting speed V m/min	8 ∼ 157	(Al, Ti)N, (Al, Ti, Cr)N, (Al, Ti, Si)N, DLC, Non-coating	
Feed rate f mm/tooth	0.00015 ∼ 0.045		
Axial depth of cut Ad mm	0.001 ∼ 5.0		
Radial depth of cut Rd mm	0.001 ∼ 0.5		

the characteristic clusters using the K-means method, a non-hierarchical clustering method. In the third step, variable cluster analysis (a hierarchical clustering method) was used as a statistical analysis to create a hierarchical structure of the target data that can be visualized as a tree diagram. Principal component regression was used to quantify the correlation between predictor and criterion variables. The response surface method was then used to create micro end-milling condition decision equations for each cluster. The detailed calculation algorithm of this method has been reported in the literature [11–13].

3. Mining Result and Consideration

3.1. Attribute Extraction Using K-Means Method

Figure 2 shows a diagram of an end-mill, the distribution map for each cluster obtained with the K-means method for each material and the representative shape of each cluster. In this step, data were grouped using the K-means method, a non-hierarchical clustering method. The aim of this process was to classify the whole catalog data into five clusters from the viewpoint of the tool shape parameters. We set three variables (L/l, l/De, and Ds/De) and visualized the shape of the micro end-mill. As 3–5 cluster degree is the limit for human beings [17], we classified the capacity of interpretation by a person on the basis of the number of clusters of that level. **Fig. 2** shows the relationship between L/l, l/De, and Ds/De. In the same manner as in the previous studies [11, 13], an equivalent De was calculated as the diameter from the weight at the flute in order to consider the changes in shape because of the number of flutes. By fixing the values of these three variables, we determined the external form of the square end-mill. The clusters in **Fig. 2** had the characteristic tool shapes, usages, and patterns mentioned below.

– Cluster 1: Micro end-mills with longer edges that have a lower Ds/De and higher l/De (1329 pieces of data).

– Cluster 2: Micro end-mills with long neck or length of cut dedicated to deep groove processing (584 pieces of data).

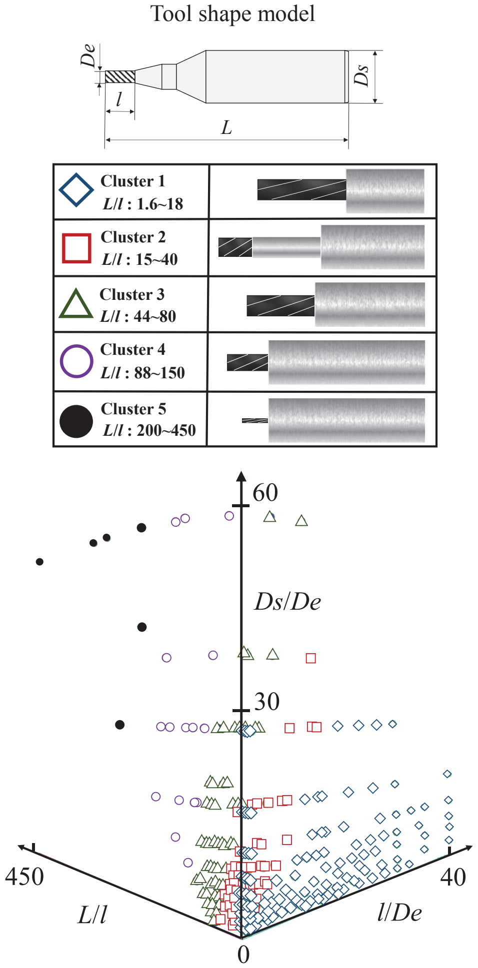

Fig. 2. Distribution map and tool shape ratio of each of the extracted clusters.

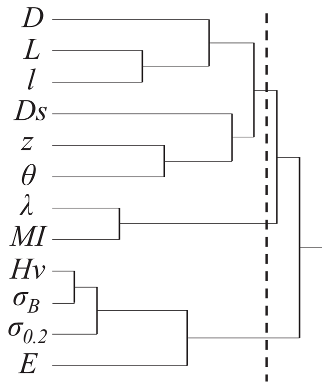

Fig. 3. Tree diagram of Cluster 2 under slotting condition.

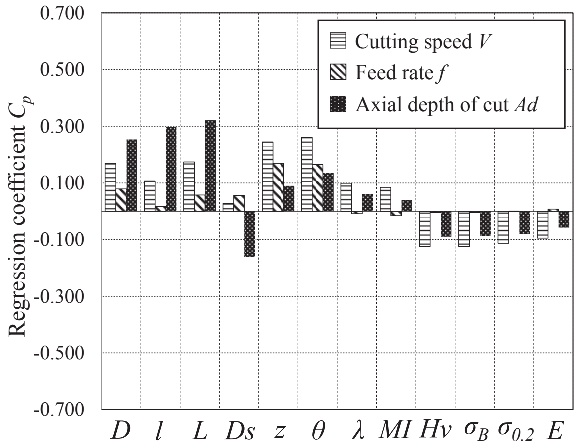

Fig. 4. C_p values of Cluster 2 under slotting condition.

– Cluster 3: General-purpose micro end-mills used mostly for high-speed milling (1876 pieces of data).

– Cluster 4: Micro end-mills with outside diameters of 0.5 mm or less (292 pieces of data).

– Cluster 5: Micro end-mills with outside diameters of 0.2 mm or less (91 pieces of data).

The K-means method was used to make clusters (attribute extraction) expressing the tool-shaped feature.

3.2. Structural Visualization of Predictor Variables

The methods on how to choose significant predictor variables to estimate end-milling conditions have been reported in previous studies [11–13]. The catalog-recommended end-milling conditions were divided into two main processing methods, namely, side-milling and slotting. Therefore, each cluster was divided into two attributes on the basis of the processing method. In this study, since we focused on the slotting process of micro end-milling, we mainly focused on the analysis results of slotting. In our previous paper [18], analysis results of other clusters with side-milling and slotting were discussed. **Fig. 3** shows the tree diagrams of Cluster 2 which are the results of the variable cluster analyses. Ward's method [19] was used to calculate the distance after the clusters were combined to form cluster pairs. We can interpret the correlations for each variable by focusing on the groups to the left of the vertical dashed-dotted line (cutting line) in **Fig. 3**. The closer to the left the groups combine, the higher is the correlation between the two variables. Form of the tree diagram that expresses the configuration of the data is fundamentally the same in each cluster. The variables, including tool shape parameters D, L, l, Ds, z, θ, and workpiece characteristic parameters λ, MI, and Hv, σ_B, $\sigma_{0.2}$, E for Cluster 2 under slotting conditions are divisible into three groups. The correlation of λ and MI, which are material characteristics of the workpiece, is closer to the correlation of the tool shape parameters than those of other material characteristics.

3.3. Quantification of Correlation Between Predictor and Criterion Variables

Vertical axis in **Fig. 4** shows the regression coefficients (C_p) of Cluster 2 under the slotting condition that quantifies the correlation between the predictor and criterion variables using principal component regression. Visual

Table 2. Correlation between predictor and criterion variables of Cluster 2.

↑ : *Cp* 0 ~ 1.9 ↓ : *Cp* 0 ~ -1.9
↑↑ : *Cp* 2.0 or more ↓↓ : *Cp* -2.0 or less

	Group 1						Group 2		Group 3			
	D	L	l	Ds	z	θ	λ	MI	Hv	σ_B	$\sigma_{0.2}$	E
V	↑	↑	↑	↑	↑↑	↑↑	↑	↑	↓	↓	↓	↓
f	↑	↑	↑	↑	↑↑	↑↑	↓	↓	↓	↓	↑	↑
Ad	↑↑	↑↑	↑↑	↓	↑	↑	↑	↑	↓	↓	↓	↓

tool shape parameters, such as D, l, and L indicate almost the same tendency for each cutting condition. The larger the tool shape parameter, the higher is the tendency for the cutting condition. Specially for Ad of Cluster 2, l and L are highly positive correlations. As for L, nominal size of pump changes with the amount of over hang in the state that chucking of the end-mill was carried out to the holder. Therefore, in this study, it is desirable to be able to determine Ad based on the value of l. The material characteristic parameters (Hv, σ_B, $\sigma_{0.2}$, and E) show negative correlation to the cutting conditions except for the feed rate. In general, the larger the values of Hv, σ_B, $\sigma_{0.2}$, and E become, the more the machining characteristics approach those of difficult-to-cut materials. Therefore, in many cases, the cutting conditions should be set to account for the decrease in these values in order to extend the tool life. However, for more difficult-to-cut materials, the tool catalogs recommend a higher feed rate. While λ and MI are material characteristics, the tree diagram suggests that the tool shape parameters are strongly correlated to them. This tendency is also reflected in the degree of influence of the criterion variable.

3.4. Significant Predictor Variables Selection

Table 2 shows the correlation between the predictor variables and criterion variables obtained from **Figs. 3** and **4** with the help of the arrow shape. From the results of the variable cluster analysis and principal component regression, we divided the explanatory variables into three groups that have a high correlation according to the cutting line of the tree diagram and compared the regression coefficients of the criterion variables to the order of predictor variables with high correlation in the same group. We used highly correlated predictor variables and discarded the weakly correlated variables. The significant variables for Cluster 2 used in each equation are l, z, θ, λ, MI, and Hv.

3.5. Derivation of Micro End-Milling Condition Decision Equations

We compared the relationship between the predictor variables and criterion variables for Cluster 2, which mainly comprises of micro end-mills with long necks and length of cut dedicated to deep groove processing. We developed equations for determining the end-milling conditions using the response surface method, which uses the significant variables. For example, the ones under slotting for Cluster 2 are shown below. To evaluate the accuracy of the end-milling condition decision equations, we compared the residual per unit freedom. In general, adjusted R-squared (R^2_{ad}) is used for judging accuracy [20].

$$\begin{aligned} Ad(R^2_{ad}0.53) = {} & -0.06l - 0.002\lambda - 0.0001HV \\ & +0.02l^2 + 5.6\times10^{-6}\lambda^2 + 0.001l\lambda \\ & +2.7\times10^{-5}lHV + 3.8\times10^{-6}\lambda HV \\ & +0.08 \end{aligned} \quad (1)$$

$$\begin{aligned} V(R^2_{ad}0.21) = {} & 53.3\theta + 0.7\lambda + 0.5HV \\ & -0.7\theta^2 + 0.0008\lambda^2 - 6.8\times10^{-5}HV^2 \\ & -0.02\theta\lambda - 0.01\theta HV - 987.6 \end{aligned} \quad (2)$$

$$\begin{aligned} f(R^2_{ad}0.05) = {} & -8.4\times10^{-5}MI - 0.0005E \\ & +1.1\times10^{-5}zMI + 4.5\times10^{-6}zE \\ & +6.9\times10^{-7}MI^2 + 1.9\times10^{-6}E^2 \\ & +0.03 \end{aligned} \quad (3)$$

Figure 5 shows the cutting conditions as estimated by catalog mining on the horizontal axis and the catalog-recommended values on the vertical axis for Cluster 2. For deciding Ad, l is dominant and has a higher positive correlation with Ad than λ or HV. Thus, the influence that other tool shape parameters and material property values have on deciding Ad is smaller than that of l. The R-squared values of V and f are less than 0.5 demonstrating that the deriving value is not significant. However, from the results of slotting in **Fig. 5**, the estimated values of V are mostly lower than the catalog values. In most cases, the catalog-recommended values require very fast spindle rotations or table feed for use by machining centers in small and medium-sized enterprises. Therefore, if the estimated value is low, suitable cutting conditions for practical use can be derived from the resulting equation.

4. Experimental Verification of Catalog-Mining Recommended End-Milling Conditions

4.1. Experimental Set-Up

To validate the end-milling conditions derived from the equations, we conducted micro end-milling slotting ex-

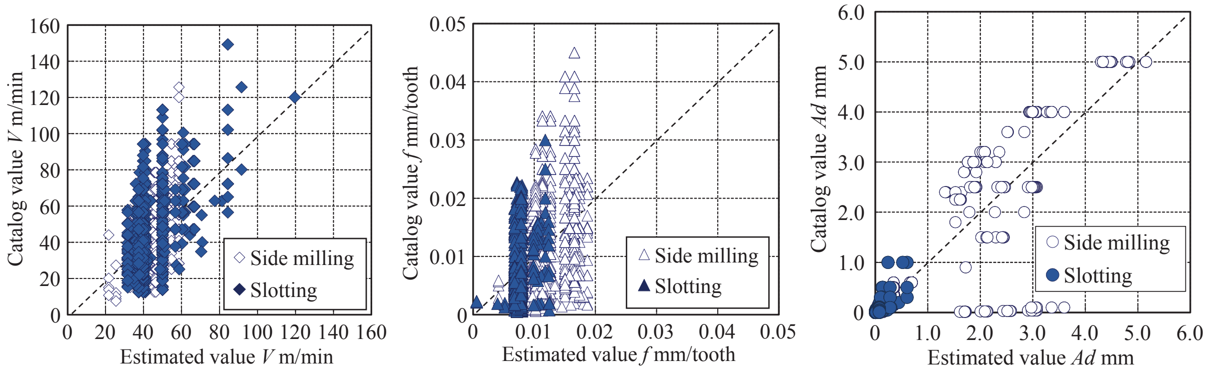

Fig. 5. Relationship between estimated and catalog recommended values.

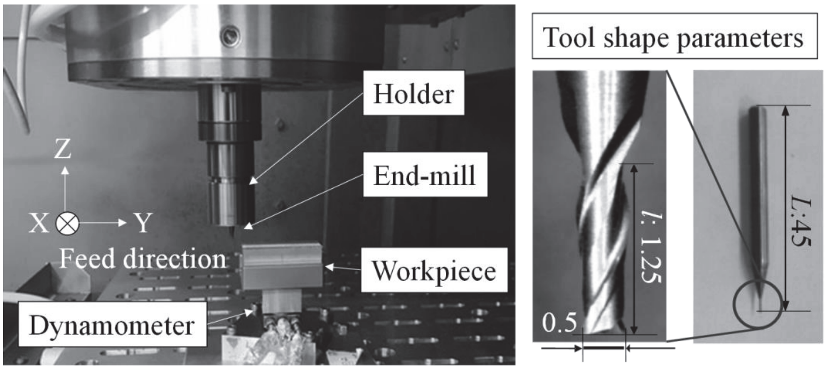

Fig. 6. Experimental set-up and tool shape parameter used in experiments.

Table 3. End-milling conditions.

Cutting condition	V m/min	f mm/tooth	Ad mm	MRR mm^3/min
Test 1 (Catalog condition)	79	0.0010	0.15	8
Test 2 (Mined condition)	52	0.0060	0.70	139
Test 3	31	0.0060	0.70	83 - 195
			0.42	
	52	0.0036	0.70	
			0.42	
	73	0.0060	0.70	
			0.42	
Test 4	52	0.0060	0.15	30
Test 5	73			42
Test 6	52	0.0084		

periments (**Fig. 6**) under conditions derived from data mining (mined conditions) and also catalog recommended conditions for general-purpose aluminum alloy. We performed slotting commuting a net cutting time of 15 min into the cutting distance. The workpiece was $50 \times 50 \times 50$ mm^3 of aluminum alloy (A7075 (JIS), HV: 170, λ: 130 W/(m/K), E: 72 GPa, MI: 120). We used TiAlN-coated φ0.5 square end-mills with long cutting length suitable for deep slotting which belongs to Cluster 2. The material removal rate (MRR, mm^3/min) is defined as $MRR = F \cdot Ad \cdot D$ where, F is the table feed. The machine tool was UVM-450C (TOSHIBA MACHINE Co., Ltd.). The tool extension was 12 mm. In the experiment, we measured the bottom surface roughness using 3D optical surface profiler NewView 7300 (Zygo Co., Ltd.) and cutting force by using piezoelectric dynamometer (Kistler Co., Ltd.). **Table 3** lists the mined conditions obtained by substituting the tool parameters and workpiece material property into Eqs. (1)–(3) and the mined conditions used in the experiments. The slotting experiments were conducted under a total of eight conditions: catalog condition (Test 1), mined mining condition (Test 2), and other conditions which made up 60% to 140% of each mined condition for V, f, and Ad (Test 3).

4.2. Process for Determining an Appropriate Value of *Ad*

It is not clear if we can conduct stable milling by using maker-recommended end-milling conditions (catalog condition). Such conditions are absolute criteria for maximizing *MRR*, so engineers typically have to adjust them in accordance with machine tool functionality and stiffness used in milling, workpiece shape, clamping method, milling cost, delivery date, and chip emission treatability. Therefore, appropriate end-milling conditions have a wide range of use [21]. In slotting, when a micro end-mill with a long, effective cutting length is used, the stiffness of the cutting part decreases in inverse proportion to the third power of the nominal size of the pump of the cutting force added to cutting flutes. In the case of *Ad* being enlarged, since the cutting force of the cutting part increases, the choice of *Ad* should be highlighted as a factor that determines the stability of machining. Test 1 conducted 15 minutes of stable machining without a large amount of tool wear. However, in the other seven conditions, the tools broke at the moment of contact with the workpiece. Next, the values of V, f, and Ad were verified in terms of whether they provided stable machining. Focusing on the value of Ad, an experiment was first conducted under conditions in which the *Ad* value was 30% lower than that in Test 2 (contained in the **Table 3**); the conditions were set to 0.15 mm Ad, which is equivalent to the catalog value (Test 4). Although the tool broke with an *Ad* of 30% (0.21 mm) of the mined conditions, 15 minutes of stable machining was performed under conditions (Test 4) that set *Ad* to 0.15 mm, as in Test 1. Therefore, when *Ad* was lowered to a value near to 0.15 mm, stable machining became possible. The process of determining *Ad*, which became clear after running tests, needs to be fed back into the process of creating a support system for determining indicative cutting conditions for micro slotting.

4.3. Derivation of Optimal Cutting Conditions based on Mined Conditions

Figure 7 shows the range of conditions in which stable machining was possible and the wear state of the tool tip. Test 1 was compared with the conditions in Test 4. As shown in **Table 3**, the *MRR* of Test 4 was approximately four times the *MRR* of Test 1. In terms of the total amount of material removed after 15 minutes, the result for Test 1 was 150 mm^3 and the result for Test 4 was 450 mm^3. In addition, the machining efficiency in Test 4 was higher than that in Test 1. The bottom-slot surface roughness of Test 1 was *Ra*: 0.183 μm, and *Rz*: 1.59 μm while the bottom-slot surface roughness of Test 4 was *Ra*: 0.216 μm, *Rz*: 1.95 μm and was therefore rougher. Fx (the principal force) of Test 4, as shown in **Fig. 8**, was approximately four times that of the Test 1, and Fy (the feed force) was about three times that of the Test 1. As a result, the final surface quality of Test 4 did not decrease noticeably. The *MRR* of Tests 5 and 6 were approximately 5.5 times the *MRR* of Test 1. The total amount of material removed after 15 minutes was 638 mm^3 in Tests 5 and 6, and the machining efficiency was even higher than that of Test 4. However, in Test 5, since the irregularity in alignment with the cutter mark of the tool bottom occurred on the bottom-slot, the accuracy of finishing deteriorated more than that in Test 1. Moreover, in Test 6, Fx and Fy were approximately four times larger than in Test 1, and the finished surface roughness after processing was also high compared to that in other conditions. It turned out that the Test 4 possessed the optimal cutting conditions. This set the *Ad* to 0.15 mm, the value derived from Test 2 with the data-mining method. Mi-

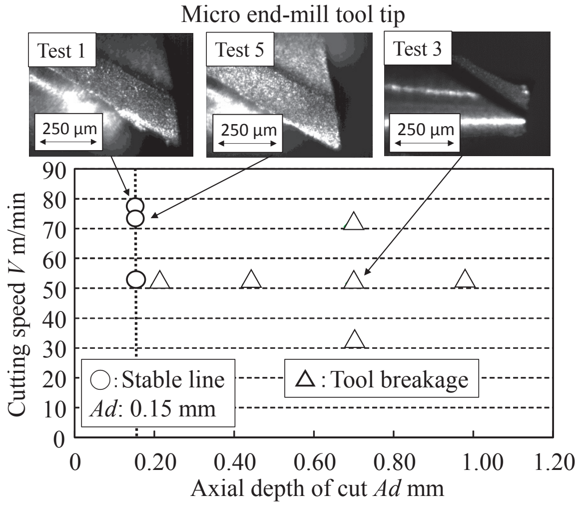

Fig. 7. Ranges of cutting conditions and wear state of tool.

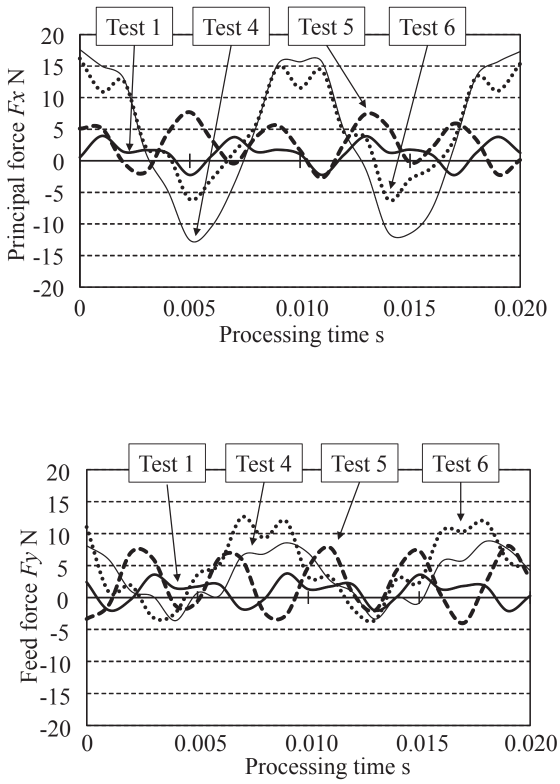

Fig. 8. Cutting force of each of the end-milling conditions.

cro end-milling condition decision determinants derived from data-mining process are important indicators for adjusting end-milling conditions on the basis of end-milling efficiency and tool-life, at the beginning of the manufacturing stage.

5. Conclusion

We developed a process that uses both hierarchical and non-hierarchical clustering methods to mine data in micro end-mill catalogs. We derived micro end-milling conditions using end-milling condition decision equations derived from the catalog mining system. Slotting experiment was conducted in order to evaluate the usefulness of data-mining support system for determining micro end-mill cutting conditions. The following results were obtained for how the three elements (cutting speed V, feed rate f and axial depth of cut Ad) influence the cutting force at the time of processing, the finished surface roughness after processing, and the amount of tool wear. Setting the amount of Ad affects the tool wear during microscopic slotting using micro end-mills enormously. If the value of Ad is determined, even if the value of V increases, the tool can be used without breaking. However, the irregularity resulting from the trajectory of a cutter being deeply transferred by the bottom of a slot occurs. Although stable machining is possible even if f is increased, the cutting force increases. Moreover, the quality of the finished surface worsens. We found that catalog mining can be used to derive the guideline cutting conditions for unskilled engineers and to extract the end-milling condition decision tendency.

References:

[1] G. Bissacco, H. N. Hansen, and L. De Chiffre, "Size Effects on Surface Generation in Micro Milling of Hardened Tool Steel," Annals of the CIRP, Vol.55, No.1, pp. 593-596, 2006.

[2] K. Hamaguchi, H. Kodama, and K. Okuda, "Tool Wear and Surface Roughness in Milling of Die Steel Using Binderless CBN End Mill," Int. J. of Automation Technology, Vol.11, No.1, pp. 84-89, 2017.

[3] S. Wang, L. Li, N. He, R. Bian, Z. Zhan, and J. Liu, "Research on Tool Wear of PCD Micro End Mill in Machining of ZrO_2 Ceramics," Materials Science Forum, Vol.800-801, p. 2025, 2014.

[4] K. Nagamura and M. Mori, "High Precise Milling Process by cBN End Mills," Int. J. of Automation Technology, Vol.6, No.4, pp. 542-545, 2012.

[5] K. Hamaguchi, Y. Kagata, H. Shizuka, and K. Okuda, "Effect of Tool Tilting Angle on Tool Wear and Surface Roughness in Micro Ball End Milling," Advanced Materials Research, Vol.325, pp. 606-611, 2011.

[6] T. Matsumura and Y. Ueki, "Milling of Micro Grooves on Glass Cylinder Surface," Int. J. of Automation Technology, Vol.5, No.1, pp. 11-20, 2011.

[7] W. Chen, D. Huo, X. Teng, and Y. Sun, "Surface generation for Micro End Milling Considering the Minimum Chip Thickness and Tool Runout," Procedia CIRP, Vol.58, pp. 364-369, 2017.

[8] K. Haruki et al., "Basic Study on Micro End-milling – Cutting Phenomena of Side Cutting –," J. of SME-Japan, Vol.3, pp. 6-10, 2014.

[9] A. Mamedov, S. E. Layegh K, and I. Lazoglu, "Machining Forces and Tool Deflection in Micro Milling," Procedia CIRP, Vol.8, pp. 147-151, 2013.

[10] X. Zhang, K. F. Ehmann, T. Yu, and W. Wang, "Cutting forces in micro-milling processes," Int. J. of Machine Tools and Manufacture, Vol.107, pp. 21-40, 2016.

[11] H. Kodama, M. Shindou, T. Hirogaki, E. Aoyama, and K. Ogawa, "An End-milling Condition Decision Support System Using Data-mining for Difficult-to-cut Materials," Advanced Materials Research, Vol.565, pp. 472-477, 2012.

[12] H. Kodama, T. Hirogaki, E. Aoyama, K. Ogawa, and H. Hukasawa, "Proposal of Ball-endmilling Condition Decision Methodology Using Data-mining from Tool Catalog Data," Key Engineering Materials, Vol.523-524, pp. 386-391, 2012.

[13] H. Kodama, T. Hirogaki, E. Aoyama, and K. Ogawa, "Investigation of End-milling Condition Decision Methodology Based on Data Mining for Tool Catalog Database," Int. J. of Automation Trchnology, Vol.6, No.1, pp. 61-74, 2012.

[14] U. Fayyad, G. P. Shapiro, and P. Smyth, "From Data Mining to Knowledge Discovery in Databases," AI Magazine, Vol.17, No.3, pp. 37-54, 1996.

[15] J. Hosking, E. Pednault, and M. Sudan, "A Statistical Perspective on Data Mining," Future Generation Computer Systems, Vol.13, No.2-3, pp. 117-134, 1997.

[16] C. Glymour, D. Madigan, D. Pregibon, and P. Smyth, "Statistical Inference and Data Mining," Communication of the ACM, Vol.39, No.11, pp. 35-41, 1996.

[17] M. Tsukamoto, K. Kamei, and K. Inoue, "Concept Formation Model Using Heuristics," Trans. of Imformation Processing Society of Japan, Vol.37, No.2, pp. 1377-1378, 1988.

[18] H. Kodama, K. Okuda, and T. Tsujimoto, "Using Catalog Data Mining in Support of Determining Micro End-milling Conditions," Proc. of ISFA, 2016.

[19] F. Murtagh and P. Legendre, "Ward's Hierarchical Clustering Method: Clustering Criterion and Agglomerative Algorithm," J. of Classification, Vol.31, No.3, pp. 274-295, 2014.

[20] R. H. Myers and D. C. Montgomery, "Response Surface Method," John Miley & Sons, Inc., 1995.

[21] H. Kodama, T. Hirogaki, E. Aoyama, and K. Ogawa, "Knowledge discovery from end-milling conditions decision methodology using data-mining – Proposal of data-mining method using non-trivial cutting tool parameters –," J. of the Japan Society for Abrasive Technology, Vol.56, No.3, pp. 173-178, 2012.

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• "Experimental Research on Small-diameter Deep-hole Drilling of Austenite Stainless Steel," Mater. Sci. Forum., Vol.874, pp. 481-486, 2016.

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Main Works:
- "A Study on Straightness of Deep Hole in Small-Diameter Drilling of Stainless Steel," Advanced Materials Research, Vol.1017, pp. 344-349, 2014.
- "A Study on Tool Damage of Threading Tap in Screw Cutting of Stainless Steel 15-5PH," Key Engineering Materials, Vols.656-657, pp. 164-167, 2015.
- "Study on Surface Finish of Carbon Steel by Ultraprecision Diamond Cutting," J. of the Japan Society for Abrasive Technology, Vol.59, No.10, pp. 582-587, 2015 (in Japanese).

Membership in Academic Societies:
- Japan Society of Mechanical Engineers (JSME)
- Japan Society for Precision Engineering (JSPE)
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