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Generation of Effective Cutting Conditions for Machining Safety in a Manufacturing Industry

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Abstract : As part of an effort to systematize the operation planning for cutting processes, the neural network method has been applied to model the process of selecting cutting conditions and subsequently to arrive at effective and safe cutting conditions through learning during training of the model. New cutting conditions that are more effective and safer for the given circumstance are obtained. The proposed algorithm deletes the old information previously learned, and then makes the network make at improvement by learning. As a result, the new algorithm provides useful cutting conditions for safer manufacturing environments. A variety of simulation cases illustrate the performance of the proposed methodology. The simulation results are provided and discussed.

Key words : cutting conditions, machining safety, neural network, process planning

1. Introduction

In manufacturing systems, CAPP(Computer-aided Process Planning) is driven to design [1] links design to manufacturing. It determines a set of instructions and machining parameters required to manufacture a part. There are generally two approaches to CAPP systems, namely variant one and generative one. The variant approach is basically a computerized database retrieval approach. The variant or retrieval approach is based on group technology methods of classifying and coding parts for the purpose of segregating these parts into family groups. The second approach to CAPP is the generative type. Systems of this type synthesize the process plan for a new part [2].

The generative approach provides fast advice to designers early in the stage of design process and is closely coupled with the product-modeling activities. Once the manufacturing technology and the type of equipment or process have been chosen, further detailed planning is carried out as usual [3]. In the first stage of process planning, the machining processes, machines and tooling capable of performing these processes, and the machining groups are established. In the second stage of process planning called operation planning, partial operations are selected, cutting parameters are determined, and time and cost are calculated to convert a piece part from its initial form to a predetermined shape as per the engineering drawing [4].

The problem of the past works that the retrieved data should be modified according to the actual operation conditions because only a few - i.e. material type, tool type - among many factors affecting the operation are considered for selecting cutting parameters.

Related to machining safety in metal cutting, there are a representative and habitual mistake that operators perform without considering carefully the characteristic of machine or workpiece for a reduction of working hours. That is operators tend to determine excessively cutting parameters such as depth and width of cut, feed, velocity, etc. for finishing the work more quickly. It causes many potential risks. These are: a broken tool and a splitted insert can harm the operator's eyes, skin and body; hot metal and flying particles can cause skin burns and damage the eyes; and the spindle vibration of an over-loaded machine tool can make operators tense and can induce operator's secondary mistakes.

In this study, for efficient and safe enhancements of cutting conditions, ESCC(Enhancement System of Cutting Conditions for machining safety) for milling operations has been developed. In the system, the methodology of the fuzzy ARTMAP neural network, including the

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newly suggested algorithm, is applied to model the process of learning and enhancing cutting conditions. This research has several efficiencies such as reducing processing time and cost as well as satisfaction of machining safety in the manufacturing situations. A variety of simulations illustrate the performance of the ESCC, and then the simulation results are provided and discussed.

2. New Algorithm for the Enhancement of Cutting Conditions

When new cutting conditions that are more effective are obtained through real machining experiments, etc., the new algorithm proposed here deletes the old information learned through the fuzzy ARTMAP, and then makes the network learn the better ones.

A fuzzy ARTMAP is selected for incremental learning of the obtained cutting conditions. Compared with other popular neural networks, it showed the most efficient and robust learning performance. In addition, it has the unique property of incremental supervised learning, and overcomes the problems of long training and catastrophic forgetting, associated with many popular networks. Further details of this network can be found in [5].

This algorithm is two procedures such as: deletion and creation. By the deletion procedure, the previously learned category J and K link of the fuzzy ARTMAP is removed, and then new category J and $K^{(new)}$ link for more effective learning patterns is generated by the creation procedure. This new algorithm can be briefly described as follows:

The Deletion Procedure

- Perform complement coding of input pattern $\mathbf{a}^{(i)}$ on layer $\mathbf{F}_0^a$ for ART_a, and then present the complement coded input pattern $\mathbf{I}_a = (\mathbf{a}^{(i)}, \mathbf{a}^{c(i)})$ to layer $\mathbf{F}_1^a$.
- Determine a winner neuron J at layer $\mathbf{F}_2^a$ by a choice function $\mathbf{T}_j(\mathrm{I}_a)$, and then perform the vigilance test.
- Search weight $\mathbf{w}_{jk}^{ab}$ that has a value of one, and category $k = K$ using category $j = J$
- Set the previously found weight $\mathbf{w}_{JK}^{ab}$ to zero.

Creation Procedure

- Perform complement coding of input pattern $\mathbf{b}^{(i)(new)}$.
- Using $\mathbf{I}_a$ and $\mathbf{I}_b = (\mathrm{b}^{(i)(new)}, \mathrm{b}^{c(i)(new)})$, call the Fuzzy ARTMAP learning procedure.

3. Procedure for the Enhancement of Cutting Conditions

ESCC consists of two fuzzy ARTMAP networks with the suggested algorithm and other auxiliary sub-modules. The first fuzzy ARTMAP (Model-V) is for learning and enhancing cutting speed V, and the second fuzzy ARTMAP (Model-f) is for learning and enhancement of feed f. Table 1 and 2 show input parameters defined for the fuzzy ARTMAP networks, real values, and encoded input values which range from 0 to 1 for ART_a, ART_{bV}, and ART_{bf}. For the Model-V, input parameters described in Table 1 and Table 2 (a) are used, and for the Model-f, input parameters described in Table 1

Table 1. Input parameters for ART_a.

Input parameters	Real values		Input values of ART_a
Workpiece material	Medium carbon leaded (ANSI : 10L45, 10L50)		0.9000
	:		:
Hardness (BHN)	50~400	225	0.5000
		:	:
Cutter type	Face mill		0.8750
	:		:
Cutter material	Carbide-Uncoated (ISO : P20, P30, P40)		0.8000
	:		:
Depth of cut (mm)	0.01 ~ 13.0 (15.0)	10	0.6664
:	:		:
Tool life (min)	0.01~60	60	0.9999
		:	:
Nose radius (mm)	0.1~3.2	2.4	0.7419
		:	:

Table 2. Input parameters for ART_b.

(a) ART_{bV}

Input parameters	Real values		Input values of ART_b
Cutting speed, *V (m/min)*	18~160	80	0.4366
		:	:

(b) ART_b

Input parameters	Real values		Input values of ART_b
Feed, *f (mm/tooth)*	0.01~0.5	0.415	0.8265
		:	:

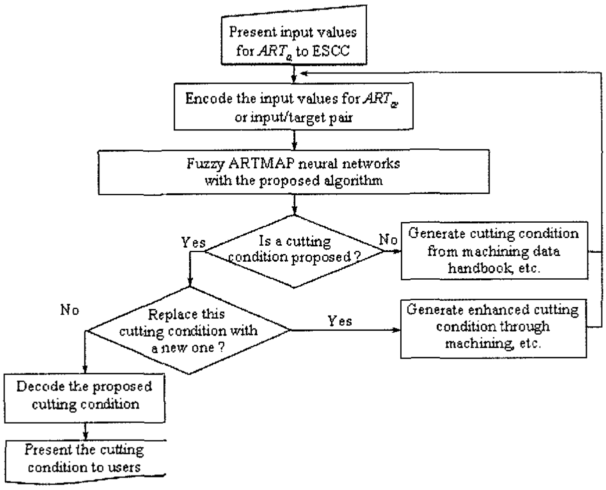

Fig. 1. Enhancement procedure in ESCC.

and Table 2 (b) are used.

The flowchart in Fig. 1 summarizes the overall procedure in ESCC. Real values of input parameters for ART_a sent to ESCC is encoded to the input form for ART_a, and then checked. If a cutting condition is not proposed, or in other words, the pattern is previously unlearned in the networks, the cutting condition generated from machining data handbook is sent to the previous encoding module, and then learned by the fuzzy ARTMAP networks. Otherwise, The new algorithm performs the step to confirm whether the proposed cutting condition is enhanced through the suggested algorithm or not. If the cutting condition has to be enhanced, the better one generated through machining experiments, etc. is sent to the encoding module, and enhanced by the suggested algorithm. Otherwise, the cutting condition is presented to the user through the decoding module.

:	:	:	:	:	:	:	:
4	0.9000	0.5000	0.8750	...	0.7500	0.4366	0.8265
15	0.9000	0.5000	0.7500	...	0.7500	0.0423	0.0571
18	0.9000	0.5000	0.7500	...	0.7500	0.0141	0.0306
26	0.9000	0.5000	0.7500	...	0.7500	0.0423	0.0306
29	0.9000	0.5000	0.7500	...	0.7500	0.0141	0.0061
:	:	:	:	:	:	:	:
4'	0.9000	0.5000	0.8750	...	0.7500	0.5856	0.8265
15'	0.9000	0.5000	0.7500	...	0.7500	0.1741	0.7714
18'	0.9000	0.5000	0.7500	...	0.7500	0.2075	0.4857
26'	0.9000	0.5000	0.7500	...	0.7500	0.3187	0.4163
29'	0.9000	0.5000	0.7500	...	0.7500	0.2607	0.3449

Fig. 2. Examples of learning patterns.

4. Test and Results

The fuzzy ARTMAP neural network is capable of online and off-line learning in response to arbitrary sequences of analogue and binary input/target patterns. The performance of the fuzzy ARTMAP and the proposed algorithm is simulated through two classes of experiments on a personal computer. These experiments are (1) off-line learning performance of the fuzzy ARTMAP neural network in relation to back-propagation system, and (2) on-line learning performance of the fuzzy ARTMAP neural network. Fig. 2 shows encoded learning patterns collected to perform these experiments. The 36 learning patterns are composed of 31 machining data presented in the handbook [6] and five effective cutting conditions obtained from the reference [7]. The first column in Fig. 2 presents pattern number, and the rest of the columns are mapped with input parameters in Table 3. The following show procedures and results of experiments performed when the value of choice parameter α, learning rate β, and vigilance parameter in map field ρ_{ab} are 0.001, 0.999, and 1.0 respectively.

Table 3. Comparison with target values and calculated values proposed from fuzzy ARTMAP neural network, in case ρ_a and ρ_b are 0.99 and 0.99 respectively.

Type of Model	Pattern no.	Encoded values				Decoded values			
		V_T	V_C	f_T	f_C	V_T (m/min)	V_C (m/min)	f_T (mm/tooth)	f_C (mm/tooth)
	:	:	:	:	:	:	:	:	:
Model-V	7	0.4366	0.4338	-	-	80.00	79.60	-	-
	:	:	:	:	:	:	:	:	:
	:	:	:	:	:	:	:	:	:
Model-f	7	-	-	0.4898	0.4878	-	-	0.2500	0.2490
	:	:	:	:	:	:	:	:	:

V_T : Target V, V_C : Calculated V, f_T : Target f, f_C : Calculated f

Table 4. On-line learning results of the fuzzy ARTMAP neural network

Type of Model	Value of vigilance parameters, ρ_a, ρ_b	# of category		Mean test errors (%)		Max. test errors (%)	
		ART_a	ART_b	V *(m/min)*	f *(mm/tooth)*	V *(m/min)*	f *(mm/tooth)*
Model-V	ρ_a= 0.99, ρ_b= 0.99	31	10	0.02	-	0.64	-
Model-f		31	14	-	0.01	-	0.41

Case 1 Off-line Learning Performance of the Fuzzy ARTMAP Neural Network

First, the experiments for deciding the values of the network parameters providing the best learning performance were carried out with the given 31 learning patterns in off-line learning mode. The network showed the best performance when the values of vigilance parameters ρ_a and ρ_b were both 0.99. In this case, mean test errors (%) were 0.02 and 0.01, and maximum test errors (%) were 0.64 and 0.41 for V and f respectively. Target values were compared with decoded values that were proposed by the fuzzy ARTMAP in Table 3. In the case of the seventh pattern, the decoded values of V_T and V_C in the Model-V were 80.0 and 79.6, and the decoded values of f_T and f_C were 0.250 and 0.249 respectively in the Model-f.

The results tested with same learning patterns in the back-propagation system showed that mean test errors (%) were 7.6 and 9.1, and maximum test errors (%) were 46.7 and 146.1.

Case 2 On-line Learning Performance of the Fuzzy ARTMAP Neural Network

For the test of on-line learning ability of fuzzy ARTMAP neural network, 31 learning patterns were presented one by one to the network in an arbitrary order. Table 4 shows on-line learning results of the network. As shown in this table, compared with off-line learning results, the performance of on-line learning does not fall behind that of off-line learning.

The results of the on-line and off-line learning of the fuzzy ARTMAP neural network show that mean or max. test errors (%) are in acceptable error boundaries for V and f respectively, and by the proposed algorithm, the previously learned information - weights, categories, etc. - of the network on the cutting conditions is replaced to the new ones.

5. Conclusion

In this paper, a new methodology that enables the model to generate enhanced cutting conditions while the system is in continual use is proposed; the new algorithm for milling processes is developed and integrated into an operation planning system. Through experiments and testing runs, it is verified that the necessary part of the model can be replaced and improved during its use without the time consuming re-training of the back-propagation neural network.

Although this methodology has been applied only to milling operations in the current work, it also can be applied to turning operations with a little modification on the fuzzy ARTMAP input parameters. Furthermore, the proposed methodology can be adopted in other software systems that make decisions based on knowledge represented by numerical or literal values. In conclusion, the new algorithm provides many benefits such as safe operation, reduced time and reduced cost in the manufacturing operations.

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