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Detection Of Tool Breakage In Milling Operations Using Neural Networks (ART 2)

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Abstract

Unsupervised neural network system was used to detect tool breakage in face milling operations. An unsupervised neural network was prepared based on the adaptive resonance theory (ART 2). The ART 2 networks are suitable for processing analog, or gray-scale pattern vector components as well as binary components. The ART2 was initially trained on simulated data and then used to monitor the experimental data. The ART2 neural networks are a very good when many different cutting conditions are encountered during cutting operations. The ART-2 network was then used to monitor tool breakage while continuously updating learned recognition codes and establishing new categories as needed. The ART2 network correctly categorized 97% of the presented experimental data sets after initial learning on simulated cases. The accuracy of ART2 network on tool breakage detection and proper vigilance factor selection for minimum node assignment issues are discussed.

key words: Neural network, milling operations, adaptive resonance theory and simulation.

1.INTRODUCTION

The recent trend in manufacturing is to achieve integrated and self-adjusting machining systems, which are capable of machining varying parts without the supervision of operators. The absence of human supervision requires on-line monitoring of machining operation, ensuring safe and efficient metal removal rate and taking corrective actions in the event of failures and disturbances [1]. One of the most important monitoring requirements is a system capable of detecting tool breakages on-line. Unless recognized in time, tool breakage can lead to irreparable damage to the workpiece and possibly to the machine tool itself. The cutting force variation characteristics of normal and broken tools are different. With the normal and broken tool cutting force variation signals is possible to train neural networks. The milling operations can be monitored with the neural network, after training. The use of adaptive resonance theory (ART2) type neural network was evaluated for detections of tool breakage, in this study [2]. Also simulation-based training is proposed to reduce the cost of preparing the systems that monitor the real cutting signals.

Neural networks with parallel processing capability and robust performances provide a new approach to adaptive pattern recognition. Adaptive Resonance Theory (ART2) architectures are neural networks that carry out stable self-organization of recognition codes for arbitrary sequence of input patterns. Artificial neural networks refer to a group of architectures of the brain [3]. Neural networks are also classified as supervised and unsupervised according to their learning characteristics. In unsupervised learning, the neural network classifies the signals by itself.

In this paper, ART2 type unsupervised neural network paradigm was used for detection of tool breakage. ART2 paradigm was used for the following reasons.

(a) The training of paradigm is much faster than the back-propagation technique;
(b) The back-propagation technique generalizes the given information in order to store it inside the initially selected hidden layers. The back propagation technique cannot give reliable decisions on the sufficiency of previous training; and
(c) ART2 has very important advantage since it can be trained in the field and continuously updates previous experience.

The unsupervised ART2 neural networks can monitor the signal based on previous experience and can update itself automatically while it is monitoring the signals [4]. When as ART2 network receives an input pattern, this bottom-up pattern is compared to the top-down, or already known patterns. If the input pattern is matched with known pattern in memory, the weights of the model are changed to update the category. If the new pattern cannot be classified in a known category, it is coded and classified as a new category.

Another important issue is the training of the neural network. It is extremely expensive and time consuming to collect cutting force data at different cutting conditions with normal and broken tools. To overcome this problem, simulation-based training of neural networks was introduced. Simulated data was used to select the best vigilance of the ART2 type neural network and to evaluate the performance of paradigm. The theoretical background of ART2 type neural network, the proposed data monitoring system and their performance is presented in the paper.

2. UNSUPERVISED ADAPTIVE RESONANCE THEORY (ART2) NEURAL NETWORKS

The theory of adaptive resonance networks was first introduces by Carpenter and Grossberg,(1987b). Adaptive resonance occurs when the input to a network and the feed back expectancies match. The ART2 neural networks developed by Carpenter and Grossberg self –organize recognition codes in real time [4].

The basic ART2 architectures consists of two types of nodes, the short term memory(STM) nodes, which are temporary and flexible, and the long term memory (LTM) nodes; which are permanent and stable. The input pattern (i) is received by the STM, where it is normalized, matched, learned, and stored in the LTM (z_{ji}) [5]. The STM is divided into two sets of nodes, F1 and F2. The STM F1 nodes are used for normalization, control, gain and learning procedures. The F1 field in Art2 includes a combination of normalization and noise suppression, in addition to the comparison of the bottom-up and top-down signals needed for the reset mechanism. To accomplish this, F1 uses the following equations to calculate the nodes[6]:

$$u_i = \frac{v_i}{e + \|v\|} \qquad - \qquad (1)$$

$$w_i = S_i + au_i \qquad (2)$$

$$p_i = u_i + \sum q(y_i) z_{ji} \qquad - \qquad (3)$$

$$q_i = \frac{p_i}{e + \|p\|} \qquad - \qquad (4)$$

$$v_i = f(x_i) + bf(q_i) \qquad - \qquad (5)$$

$$x_i = \frac{w_i}{e + \|w\|} \qquad - \qquad (6)$$

Here $\|p\|$, $\|v\|$ and $\|w\|$ denote the norms of the vectors p,v and w, and s_i is the input. The non-linear signal function in equation (5) is used for noise suppression . the activation function (f) is given by the equation.

$$f(x) = \begin{cases} x & \text{if } x \geq \theta \\ 0 & \text{if } 0 \leq x < \theta \end{cases} \qquad - (7)$$

Where θ is an appropriate constant. The function f, filters the noise from the signal. θ can be set to zero for the case where filtering is not desired. The constants a, b, and e are selected based on the particular application. The STM F2 nodes are used for the matching procedure. F2 equations select, or active, a nodes in the LTM. When F2 chooses a node, all other nodes in the LTM are inhibited, and only one is allowed to interact with the STM. The node that gives the largest sum with the F1 F2 input pattern (bottom-up) is the key property that is used for node selection.Bottom-up inputs are calculated as in ART2 [5]

$$T_j = \sum_i p_i z_{ji} \quad - \quad (8)$$

The j^{th} node is selected if equation (9) is satisfied.

$$T_j = \max \{ T_j: 1,2 \ldots N \} \quad - \quad (9)$$

Competition on F_2 results in contrast enhancement where a single winning node is chosen each time. The output function of F_2 is given by

$$g(y_i) = \begin{cases} d & \text{if } T_j = \max \{ T_j : J=1,2, \ldots N) \\ 0 & \text{otherwise} \end{cases} \quad - \quad (10)$$

Equation (3) takes the following form:

$$p_i = \begin{cases} u_i & \text{if F2 is inactive} \quad - \quad (11) \\ u_i + dz_{ij} & \text{if the Jth node on } F_2 \text{ is active} \end{cases}$$

The bottom-up and top-down LTM equations are

bottom-up ($F_1 \rightarrow F_2$) :

$$\frac{d}{dt} z_{ij} = g(y_j) [p_i - z_{ij}] \quad - \quad (12)$$

top – bottom ($F_2 \rightarrow F_1$) :

$$\frac{d}{dt} z_{ji} = g(y_i) [p_i - z_{ji}] \quad - \quad (13)$$

When F_2 is active, then equations (12) and (13) are modified from equation (10) to:

$$\frac{d}{dt} z_{ij} = d (p_i - z_{ij}) \quad - \quad (14)$$

$$\frac{d}{dt} z_{ji} = d (p_i - z_{ji}) \quad - \quad (15)$$

Where d is a constant (0 < d < 1). An orienting ART2 sub system is used to decide, if a new pattern can be matched to a known pattern by comparing with a given vigilance parameter, ρ:

$$r_i = \frac{u_i + cp_i}{e + \|u\| + \|cp\|} \quad - \quad (16)$$

If $\|r\| < \rho - e$, then F_2 resets another node. If $\|r\| \geq \rho - e$, a match has been found and the new pattern is learned by the system. The LTM node weights are recalculated and the pattern is learned by the system. If no match has been found after all nodes have been activated, a new node is created, and the new pattern is stored.

3.RESULTS AND DISCUSSION

The experimental data was collected with a four flute end mill of 12.07 mm diameter at various cutting conditions. The ART2 neural network monitored the profile of the resultant force in different tests. In the three tests, experiments were done at different feed rates with the good and broken tool. The spindle speed, feed rate, and depth of cut of these different conditions are out lined in tables 1-4. The neural network did not have any prior information at the beginning of each test. In each one , the neural network inspected the resultant force profile and placed it into a category or initiated a new category if it was found to be different. The vigilance of the ART2 selected either 0.96 or 0.98 in all the tests. The ART2 assigned 2, 2, 3, 1 and 3 different categories for the good tool. For the broken tool 2, 1, 1, 1 and 3 different categories were selected. In all the tests, the neural network classified the good and broken tools in different categories. As seen in tables 1-4, the neural network generated only one category in the 2^{nd} (table 2) , 3^{rd} (table 3) and 4^{th} (table 4) tests for the broken tools. On the otherhand, the neural network assigned more nodes to the signal of a good tool with offset. It indicates that the broken tool signals are more similar to each other at different cutting conditions compared to the force patterns of normal tools.

Table1. Classification of experimental data with the ART2. Vigilance of the neural network was 0.96. The ART2 used four categories to classify all of the data.

Spindle speed (rpm)	Depth of cut (mm)	Feed rate mm/ min	Tool condi tion	Cate gory
500	1.016	50.8	G	1
500	1.016	50.8	B	2
500	1.016	101.6	G	1
500	1.016	101.6	B	3
500	1.016	203.2	G	1
500	1.016	203.2	B	3
500	1.016	254	G	4
500	1.016	254	B	5

Table2. Classification of experimental data with the ART2. Vigilance of the neural network was 0.96. The ART2 used three categories to classify all of the data.

Spindle speed (rpm)	Depth of cut (mm)	Feed rate mm/ min	Tool condi tion	Cate gory
500	1.524	50.8	G	1
500	1.524	50.8	B	2
500	1.524	101.6	G	3
500	1.524	101.6	B	2
500	1.524	203.2	G	1
500	1.524	203.2	B	2
500	1.524	254	G	3
500	1.524	254	B	2

Table3. Classification of experimental data with the ART2. Vigilance of the neural network was 0.98. The ART2 used four categories to classify all of the data.

Spindle speed (rpm)	Depth of cut (mm)	Feed rate mm/ min	Tool condi tion	Cate gory
700	1.016	50.8	G	1
700	1.016	50.8	B	2
700	1.016	101.6	G	3
700	1.016	101.6	B	2
700	1.016	203.2	G	4
700	1.016	203.2	B	2
700	1.016	254	G	4
700	1.016	254	B	2

Table4. Classification of experimental data with the ART2. Vigilance of the neural network was 0.96. The ART2 used two categories to classify all of the data.

Spindle speed (rpm)	Depth of cut (mm)	Feed rate mm/ min	Tool condi tion	Catego ry
700	1.524	50.8	G	1
700	1.524	50.8	B	2
700	1.524	101.6	G	1
700	1.524	101.6	B	2
700	1.524	203.2	G	1
700	1.524	203.2	B	2
700	1.524	254	G	1
700	1.524	254	B	2

The ART2 gained first experience on the simulation data and later, the neural network inspected the incoming signals and continued to assign new categories when different types of signals were encountered. After simulation training, the neural network started to monitor the experimental data collected at different conditions. The studies focused on selection of the best vigilance, which requires a minimum number of nodes and has acceptable error rate. When the vigilance of 0.98 is used, the network classified the perfect too input data into seven different categories and classified the broken tool input data into four different categories.

4.CONCLUSIONS

The effectiveness of the proposed encoding and selected paradigms was tested on simulated and experimentally collected data. ART2 type neural networks to detect tool breakage monitored the resultant cutting force of milling operations.

ART2 neural networks had only one category, which was assigned to the broken tool signals in small training sets. The results indicate that the proposed encoding approach selected very distinctive characteristics of the good and broken tool cutting force signals for the network. The effects of the cutting force profile variations related to the depth of cut and feedrate by compensating.

The continuous learning capability of the ART2 allows the neural network to be particularly off-line on the simulated or very limited experimental data. Later, the neural network could continuously update previous experiences on-line when new cutting conditions are presented during operation.

ART2 neural networks are a very good candidate when many different cutting conditions are encountered during cutting operations. Since the ART2 may start to monitor operations with very limited training and continue to further improve its experience while it is evaluating the sensory data.

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