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Development of Tool Condition Monitoring System Using Unsupervised Learning Capability of the ART2 Network

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Abstract

The feasibility of using an adaptive resonance network (ART2) with unsupervised learning capability for tool wear detection in turning operations is investigated. Specifically, acoustic emission (AE) and cutting force signals were measured during machining, the multichannel AR coefficients of the two signals were calculated and then presented to the network to make a decision on tool wear. If the presented features are significantly different from previously learned patterns associated with a fresh tool, the network will recognize the difference and form a new category as worn tool. The experimental results show that tool wear can be effectively detected with or without minimum prior training using the self-organization property of the ART2 network.

1 Introduction

One important task of human operator in conventional machining system is to monitor the machining process and to take a preventive action if any undesirable machining condition would happen. Thus, to achieve untended machining, the control system of the machine tool should have the pattern recognition and decision making capabilities which can be reinforced by learning as the empirical data is accumulated. Also, to take full advantage of modern adaptive controllers many different forms of feedback information from the machine tool is neccessary. Therefore, it is very important to develop and characterize sensor systems for machining processes (see [1]-[5]).

In machining operations, cutting tools are subject to an extremely harsh rubbing action both on the rake and flank faces close to the tool tip. The rubbing actions between the cutting tool and chip on the rake face of the tool and between the cutting tool and the machined surface of the work on the flank face create very high stress and temperature, resulting in tool wear. As the tool wears out, the performance of the cutting operation deteriorate seriously so that in time effective machining is impossible. Therefore, the cutting tool has to be changed as it wears out.

However, tool life is very difficult to predict and has very widely scattered distribution, because tool wear is very complex phenomenon. Since it is a result of various interacting effects like tool and workpiece material properties, cutting conditions, and other environmental effects, it is impossible to setup generally acceptable tool change policies.

In [18] an architecture for an on-line tool wear monitoring system which is based on an multilayered perceptron type neural network for integrating information from multiple sensors was developed and the performance of the system was experimentally evaluated.

Before actual application, neural networks have to be given the expertise of human problem solving through a learning process. In many cases, the objective of learning can be desribed as the problem of gradually building up an associative mapping between input and output patterns. This procedure of refining the internal structure of the network for correct associative mapping is associative learning. There are 2 different types of the associative learning depending on how learning occurs. In supervised learning the associative mapping can be built up into the learning system by presenting the system with input/output pattern pairs. With a given input pattern, the system computes an output pattern according to its current internal model. Then the computed output is compared with the target output pattern provided by an external teacher, so that the internal model can be adjusted in the direction of reducing the difference between the actual output and the taget output. Another class of associative learning is unsupervised learning. An unsupervised learning system is presented only with input patterns. For each input pattern, the system learns to respond to the input pattern so that the output pattern is optimal in some sense. The performance criterion is measured by an evaluative feedback from the external environment of the system. Since the feedback information in unsupervised learning is only evaluative and not informative as a target output pattern in supervised learning, unsupervised learning is usually more difficult than most supervised learning problems.

To learn the necessary input/output mapping for tool wear detection, the weights and thresholds of the multilayered perceptron type network in [19] were adjusted according to the back propagation method which is a supervised learning technique during off-line training.

In this study, the feasibility of using the ART2 network [20] with unsupervised learning capability for tool wear detection in turning operations is investigated. Specifically, AE and cutting force signals were measured during machining, and the autoregressive (AR) coefficients of the two signals were calculated through a signal processing block and then presented to the network to make a decision on tool wear. If the presented features are significantly different from previously learned patterns of fresh tool, the network will recognize the patterns are different and form a new category as worn tool.

2 Adaptive Resonance Theory

Clustering techniques are methods of automatically partitioning input data into several categories (clusters) according to the characteristics of the data so that each input is assigned a unique label corresponding to a cluster in such a way that a certain measure is optimized (see [10]-[14]). In this study, the adaptive resonance network based on Grossberg's adaptive resonance theory (ART2) [20] used for clustering of sensor outputs in turning operations for detection of tool wear.

ART2 network is an artificial neural network that can perform clustering of input patterns based on how human senses are scanned for patterns and categorized by mind into the objects of perception.

So far, multilayered perceptrons trained with the back propagation algorithm have been most widely used, and have led to considerable success in many applications (see [15]-[19]). However, the back propagation technique lacks the self- organizing capability through unsupervised learning. On the contrary, adaptive resonance architectures are neural networks with unsupervised learning capabilities which self- organize stable recognition codes in real time in response to arbitrary sequences of input patterns. Furthermore, the adaptive resonance networks are more heavily based on the operating principles of biological neural networks than those using back propagation. Adaptive resonance theory was proposed by Grossberg [20] to quantitatively explain how human senses are scanned for patterns and then categorized by the mind into the objects of perception as an extension of competitive learning.

Although competitive learning models proved effective for a certain class of problems the learning becomes unstable in response to a variety of input environments. The inherent instability of a competitive learning system led to research on the design of a learning system that remains stable in response to irrelevent events while maintaining plasticity (ability to encode knowledge for all time) in response to significant new events. An effort to design an adaptive pattern recognizer that could self-stabilize its learning in response to arbitrary input environments led to the introduction of the adaptive resonance theory by Grossberg. Grossberg showed that a certain type of top-down learned feedback and matching mechanism could significantly overcome the instability problem.

In the ART2 network the output represents the category for the input pattern determined by the network itself by generating a clustering of the input data according to similarities between samples. The ART2 network consists of two sets of nodes. The first set, F1 (feature representation field), is connected to input vector and gives the short term memory (STM) activation vector which is a modified form of the current input vector at its output. The second set, F2 (category representation field), generates an output activation vector giving the recalled category from long term memory (LTM) for the current input vector through the winner-takes-all type competition. The ART2 network encodes new input patterns, in part, by adaptively changing the bottom-up weights which connect F1 to F2. Such a combination of adaptive filtering and competition is common to many models of adaptive clustering techniques. What distinguishes the ART2 network is the feedback connections (top-down weights) and the mechanism (orienting subsystem) that resets the winning category in the case of mismatch between the input vector and the recalled memory. In addition to the bottom-up mechanism of a competitive learning system, an ART2 system has a top-down mechanism for matching bottom-up input patterns with top-down expectations; and for releasing orienting subsystem in a mismatch situation. Using these mechanisms, an ART2 network can generate recognition codes adaptively, and without a teacher, in response to a series of environmental inputs. As learning goes on, interactions between the inputs and the system generate new steady states. The steady states are formed as the system discovers and learns critical feature patterns that represent invariants of the set of all experienced input patterns. These learned codes are stabilized against noises contaminated irrelevant inputs. ART has been used for data analysis in speech perception, word recognition, visual perception and olfactory coding, and demonstrated its effectiveness.

Fig. 1 shows the detailed structure of the ART 2 network as proposed by Grossberg. Initially, the nodes in F1 are activated by the input feature vector. This pattern activates all of the nodes in F2 simultaneously via bottom-up weights from F1 to F2. These activations compete until F2 becomes active with a candidate category with the strongest activation of a pattern stored in LTM. The STM in F1 then receives the recalled LTM pattern via top-down weights from F2 to F1. The expected activation vector is compared against the vigilance threshold to determine closeness of fit by the orientation subsystem. If the new category matches the input pattern, the system resonates for some interval such that learning occurs and the LTM pattern is reinforced by the new input pattern. If the recalled pattern is not sufficiently close to the input pattern, a strong inhibit signal is sent to F2 by the orientation subsystem. This suppresses the previous winning category and another category is selected, and tested until either an adequate match is found or a new category is established.

The STM activation V_i of the ith element at any node of the first stage, F1 is based on the membrane equation:

$$\epsilon\frac{d}{dt}V_i = -AV_i + (1 - BV_i)J_i^+ - (C + DV_i)J_i^- \qquad (1)$$

The dimensionless parameter, ϵ is the ratio between the STM relaxation time and the LTM relaxation time which is $0 < \epsilon \ll 1$. For $B = C = 0$, the equation for STM activation reduces to

$$V_i = \frac{J_i^+}{A + DJ_i^-} \qquad (2)$$

where J_i^+ is the total excitory input to the ith element, and J_i^- is the total inhibitory input. According to the Grossberg's design, the STM activations, p_i, q_i, u_i, v_i, w_i and x_i in Fig. 2 can be written

$$p_i = u_i + \sum_j g(y_i)z_{ji} \qquad (3)$$

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

$$u_i = \frac{v_i}{e + \| v \|} \qquad (5)$$

$$v_i = f(x_i) + br_i \qquad (6)$$

$$w_i = I_i + au_i \qquad (7)$$

$$x_i = \frac{w_i}{e + \| w \|} \qquad (8)$$

where $\| p \|$, $\| v \|$, and $\| w \|$ denote the L_2-norm of vectors, p_i, v_i, and w_i, respectively, and where I_i is the input vector to the network, y_j is the STM activation of the jth F2 node, and z_{ji} is the top-down weight from the jth node in F2 to the ith node in F1.

The functioning of the feature representation field, F1 can be summarized as normalizing the input pattern, suppressing noise and renormalizing to find a modified form of the input pattern. In order to suppress the noise, Grossberg and Carpenter suggested the following squashing function:

$$f(x) = \begin{cases} x & \text{if } x > \theta \\ 0 & \text{if } x < \theta \end{cases} \qquad (9)$$

where θ is a threshold level.

The primary functions of F2 are contrast enhancement of the filtered input pattern from F1, and reset of active F2 node when a pattern mismatch at F1 is large enough to activate the orienting subsystem. Initially, F2 is inactive. As input patterns are presented to F1, F2 is activated with an input signal from F1 via p_i which is an adapted form of the input pattern. Actually, the activations of all categories in LTM are computed according to

$$y_j = \sum_i p_i z_{ij} \qquad (10)$$

The nodes at the category representation fields receive the inner product of the bottom-up weight vector with the processed input vector from the feature representation field. The winning node is selected according to the winner-take-all type competition among all the nodes in the category representation field as in competitive learning. Then F2 makes a choice by passing the activation of the maximally active node through a gated dipole threshold function given by

$$g(y_J) = \begin{cases} d & \text{if } y_J = max(y_j \mid \text{the } j\text{th F2 node has not been reset on the current trial}) \\ 0 & \text{otherwise} \end{cases} \qquad (11)$$

and inhibiting all other nodes. This signal is then passed back to F1 via the top-down weights, z_{ji} modifying the F1 activity, p_i as

$$p_i = \begin{cases} u_i & \text{if F2 is inactive} \\ u_i + dz_{Ji} & \text{if the } J\text{th F2 node is active} \end{cases} \qquad (12)$$

As mentioned previously, the major difference between the ART2 and the competitive learning is that the competitive learning systems merely update the weight vector of the winning node regarding the winning node as the representative category of the current input pattern, while the ART 2 tests whether the winnng node sufficiently matches the input pattern. How closely tne STM pattern at F1 matches an active LTM pattern is determined by the activation, r_i, which is given by

$$r_i = \frac{u_i + cq_i}{e + \| u \| + \| cq \|} \qquad (13)$$

The sum of the square difference, r, will be 1 if the patterns match perfectly, and will be less than 1 in proportion to the dissimilarlity between STM and LTM patterns. The degree that patterns are allowed to be dissimilar before resetting the network can be controlled by adjusting the vigilance parameter that controls activation of the orienting subsystem. Lower vigilance tolerates larger mismatch at F1, which causes coarser categories while higher vigilance imposes a stricter matching criterion and lead to finer categories. The orienting subsystem will reset F2 if the following condition is satisfied:

$$\frac{\rho}{e + \| r \|} > 1 \qquad (14)$$

where ρ is the vigilance parameter. When this condition is not satisfied, the network will begin to resonate such that learning takes place and the LTM pattern is reinforced by the new input pattern. On the other hand, if the condition is met, the reset causes the winning node in F2 to be suppressed and then another pattern to be recalled from F2 and presented to F1.

When the network resonates the top-down and bottom-up LTM weights are modified, respectively, by the following two differential equations to encode the new information from the input pattern:

$$\frac{d}{dt}z_{Ji} = d(p_i - z_{Ji}) \qquad (15)$$

$$\frac{d}{dt}z_{iJ} = d(p_i - z_{iJ}) \qquad (16)$$

3 Discussion of Experimental Results

The experimental setup for the tool wear detection consists of a Tree 1000 lathe, an SAIC Delta Neurocomputer workstation, electronic interface hardware for the communication between the Neurocomputer and the lathe, and a multiple sensor system composed of an AE sensor, a force sensor, and a current sensor. A series of metal cutting experiments was conducted on the Tree 1000 lathe, for evaluation of the tool wear detection system. In the experiments, 4 inch diameter AISI 4340 cylindrical bars were machined with fresh and worn Kennametal TPGF-322 K68 cutting tools. The size of the wear land on the frank face of the cutting tools used as worn tools was about 0.04 in., and the machining conditions were varied from 0.005-0.08 in. depth of cut, 0.01-0.07 in/rev feed rate, and 250-350 ft/min cutting speed.

During the machining process, the AE and the cutting force were measured by an AET 375 AE sensor attatched to the cutting tool and a Kistler 9257A dynamometer mounted on the tool fixture, respectively. These signals were sampled by the PC through 12-bit A/D convertor (DACA board) and saved as an ASCII file before further processing. The sampled sensor data were later used for off-line evaluation of the tool wear detection scheme. In the evaluation the data were fed to the signal processing program and the resulting AR coefficients were normalized, since the ART 2 networks are designed to work with normalized input vectors. However, in identification of tool wear, the magnitude of the cutting force, spindle motor current or the RMS AE level are all known as good indicators of tool wear. Thus, important information may be lost by using normalized input vector. One way of using this information may be to increase the number of input features by using the scale variable $\sum x_i^{2/m}$ along with the normalized input vector to incorporate the magnitude of the input vector as proposed by Burke [21]. The resulting normaized input vector was then fed to the adaptive resonance network. For the neural network simulation a special software was written in C and run on the Delta Neurocomputer workstation.

An example of the changes in the bottom-up weights, z_{ij} and the top-down weights, z_{ji}, with time during training of the network is shown in Fig. 2. When a new input vector is presented to the network, the changes in the bottom-up weights ($\sum_i \sum_j \mid z_{ij} \mid$) and the top-down weights ($\sum_i \sum_j \mid z_{ji} \mid$) suddenly increase and then decay as the network goes through encording the new information from the current input vector.

To test the effectiveness of the ART2 network in classifying the fresh and worn tool data the network was presented with 8 fresh tool data sets followed by another 8 worn tool data sets, and the output category from the network was observed.

Table 1 shows typical output categories from the network when the vigilance parameter of the orientation subsystem was varied. The network effectively distinguishes the worn tool from the fresh tool under wide range of vigilance parameter (0.7-0.99). However, the network becomes too sensitive to small differences in input vector with the vigilance parameter of 0.995 or higher as evidenced in Table 1 with classification of the input vectors into more than 2 output categories. On the other hand, with a low vigilance parameter the sensitivity of classification will be decreased. Thus, too high or low vigilance parameters should be avoided. The effect of change in the dimension of input vector to the network in the performance of classification is shown in Fig. 3. According to the figure, there is an optimum number for the input dimension, and the performance of the classification gets worse if smaller or larger numbers are used for input dimension. In our particular case 4-6 was the optimum number for the input dimension. It seems that with just 2 AR parameters too little information on the state of the tool is provided. On the other hand, the network is presented with some irrelevent information as too many AR coefficient are used as the input vector to the network resulting in poor performance. In contrast to the size of input vector, the size of output category has little influence on the performance of the network as shown in Fig. 3. The network correctly classified the data into 2 groups irrespective of the size of output category. So, any number larger than 2 can be used as the dimension of output category. However, too small or large number should also be avoided, because the changes in characteristics of sensor signal can be caused not only by tool wear but also by other factors and reservation for those changes should be made with reasonably large output dimension, and because too large a number is undesirable from the view point of computational efficiency.

Performance of the system under various cutting conditions is shown in Tables 2 and 3. We expected that the system would perform better under harsher cutting conditions, because the sensor signals from fresh and worn tools showed more dissimilarities when operated under harsher cutting conditions. Actually, the classification proved to be more reliable under harsher cutting conditions. When the depth of cut or feed rate is small the network easily misclassifys the sensor data, but as these parameters become larger the network establishes the 2 classes correctly.

A tool wear detection system should be sufficiently insensitive to the changes in cutting parameters or other environmental factors, while maintaining a high sensitivity only to tool wear. In the next set of experiments, the network was presented with 8 input vectors from fresh tool followed by another 8 input vectors also from fresh tool but for a different cutting condition from the first 8 in order to test the sensitivity of the network to changes in cutting conditions. Typical results are shown in Tables 4 and 5. In Table 4, the output category from the network when operated with various vigilance parameters is recorded. Unfortunately, the network is more or less sensitive to changes in cutting condition (depth of cut). The sensitivity is slightly higher with higher vigilance parameter. Table 6 (a) and (b) show the output category when the depth of cut changes from 0.02 in. to 0.04 in. and from 0.01 in. to 0.04 in., respectively. For the larger change in cutting condition (depth of cut) the network is apparently more sensitive.

4 Conclusions

The feasibility of using unsupervised learning capability for tool wear detection in turning operations was investigated in this study. The following are the conclusions drawn:

1. By applying the AR series model and the artificial neural network structure with unsupervised learning capability (ART2) for learning characteristics of the signals from multiple sensors depending on the state of cutting tool, tool wear can be detected.
2. The ART2 is better suited for tool condition monitoring purposes than more popular multi-layerd perceptrons trained with the back propagation in the sense that it has the self-organizing capability which makes time-consuming off-line training unneccesary, and that it can accomodate gradual changes in the characteristics of the machine and environmental conditions.
3. The various parameters of the neural network have significant effect on the performance and efficiency of the tool wear detection system. So, the parameters should be carefully chosen.
4. The tool wear detection scheme showed some sensitivity to changes in cutting conditions as well as changes in cutting tool states. Furthermore, the scheme showed better classification performance under harsher cutting conditions, and the rate of misclassification became high under light cutting conditions. So, the tool wear detection scheme is better suited for harsh cutting operations which do not involve changes in cutting conditions in the middle of the run.
5. The ART2 seems more suitable for classification of sensor signals which have sudden drastic changes in the characteristics of the signal rather than gradual changes, because the adaptive resonance network can accomodate gradual changes due to its adaptation capability. So, one possible extension of this study may be detection of tool breakage in metal cutting operations.

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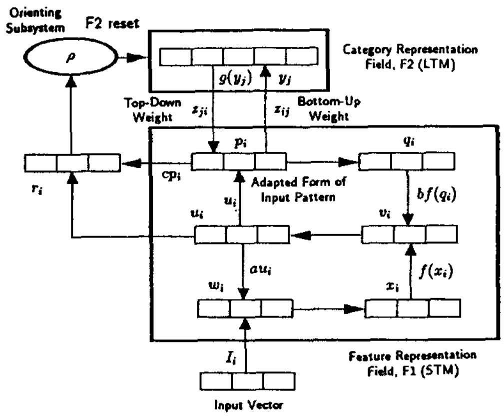

Fig. 1 Architecture of the ART 2 network.

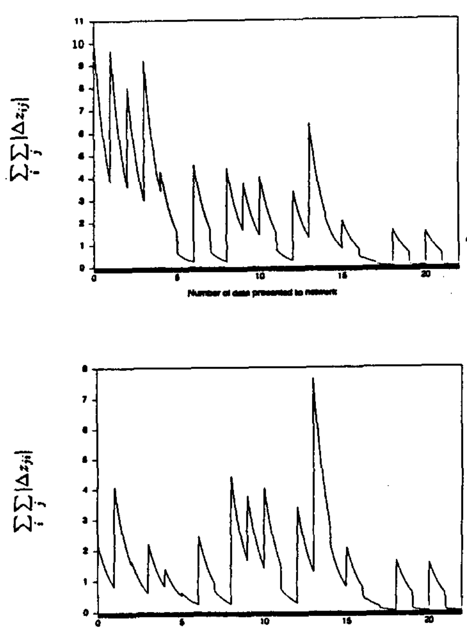

Fig. 2 Convergence of the bottom-up weights, zji, and the top-down weights, zij.

time	state	ρ			
		0.9	0.95	0.99	0.995
1		2	5	2	5
2		2	5	2	5
3		2	5	2	5
4	fresh	2	5	2	5
5		2	5	2	5
6		2	5	2	5
7		2	5	2	5
8		2	5	2	5
9		4	2	5	3
10		4	2	5	3
11		4	2	5	4
12	worn	4	2	5	4
13		4	2	5	4
14		4	2	5	4
15		4	2	5	3
16		4	2	5	3

Table 1 A typical output category from the ART2 network with various vigilance level when the network was presented with 8 fresh tool data followed by 8 worn tool data. Cutting conditions: cutting speed, 350 fpm; depth of cut, 0.04 in.; feed rate, 0.007 ipr.

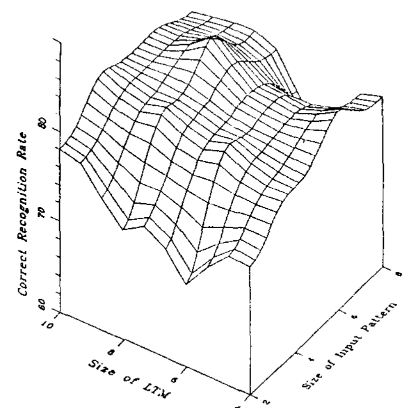

Fig. 3 Performance of ART2 network under various sizes of input pattern and LTM

time	state	d=.04in	d=.02in	d=.01in
1		5	2	4
2		5	2	4
3		5	2	4
4	fresh	5	2	4
5		5	2	4
6		5	2	4
7		5	2	4
8		5	2	4
9		2	4	4
10		2	4	4
11		2	4	4
12	worn	2	4	4
13		2	4	4
14		2	4	4
15		2	4	4
16		2	4	4

Table 2 A typical output category from the ART2 network with various vigilance level when the network was presented with 8 fresh tool data followed by 8 worn tool data under various depth of cut. Vigilance, 0.95. Cutting conditions: cutting speed, 350 fpm; feed rate, 0.007 ipr.

time	state	f=.01in/r	f=.007in/r	f=.004in/r
1	fresh	1	3	5
2		1	3	5
3		1	3	5
4		1	3	5
5		1	3	5
6		1	3	5
7		1	3	5
8		1	3	5
9	worn	5	3	2
10		5	3	2
11		5	4	2
12		5	4	2
13		5	4	5
14		5	4	5
15		5	3	2
16		5	3	5

Table 3 A typical output category from the ART2 network with various vigilance level when the network was presented with 8 fresh tool data followed by 8 worn tool data under various feed rate. Vigilance, 0.95. Cutting conditions: cutting speed, 350 fpm; depth of cut, 0.04 in.

time	d(in)	ρ			
		0.99	0.95	0.90	0.85
1	0.01	4	3	4	5
2		2	3	5	5
3		2	3	5	5
4		4	3	5	5
5		4	3	5	5
6		4	3	5	5
7		4	3	5	5
8		4	3	5	5
9	0.04	2	2	3	4
10		4	3	5	5
11		4	3	5	5
12		2	2	3	4
13		4	3	3	4
14		2	2	5	5
15		2	2	5	5
16		2	3	5	5

Table 4 A typical output category from the ART2 network with various vigilance level when the depth of cut changes suddenly from 0.01 in. to 0.04 in. Vigilance, 0.95. Cutting conditions: cutting speed, 350 fpm; feed rate, 0.007 ipr.

time	d(in)	d=.02 to .04in	f(in/r)	d=.01 to .04in
1	0.02	2	0.01	1
2		2		5
3		2		5
4		2		5
5		2		5
6		2		5
7		2		3
8		2		5
9	0.04	2	0.04	2
10		2		2
11		2		2
12		2		2
13		3		2
14		2		5
15		2		5
16		2		1

Table 5 A typical output category from the ART2 network when the depth of cut changes suddenly from 0.02 in. tp 0.04 in. and from 0.01 in. to 0.04 in. Vigilance, 0.95. Cutting conditions: cutting speed, 350 fpm; feed rate, 0.007 ipr.