ADAPTIVE RESONANCE NETWORK AND ITS APPLICATION IN MANUFACTURING FAULT DIAGNOSIS

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ABSTRACT Compared with BP network, ART network is characterized by self-organization, adaptation and fast run speed. So it is suitable for fault diagnosis tasks in manufacturing process. Structure and mechanism of ART network are introduced in this paper, and an intelligent tool condition monitoring system based on ART network is designed, and the successful detection of micro-diameter drill state in drilling has been carried out.

KEY WORDS neural network, pattern recognition, diagnosis, cutting tool

Fault diagnosis is an important measure of quality control in automatic manufacturing system. From the point of view of pattern recognition, nature of fault diagnosis is fault classification, it classifies fault patterns and finds the sources based on available knowledge and certain reasoning mechanism. Although many pattern recognition techniques such as decision—tree, cluster analysis technique and fuzzy logic have been commonly developed, they are unsatisfactory in the usage in manufacturing process which is characteristic of multi—feature and low signal—noise rate in various operational environments. There are many obstacles needed to be overcome [1] Compared with these traditional techniques, neural networks have advantages to handle complex multi—mode tasks and to associated memory, which is vital to intelligent dynamic modeling. The ability to see through noises and distortions to a pattern is useful for fault diagnosis.

So far, multi-layer and feed-forward networks (e.g. BP network) are usually adopted as classifier in pattern recognition because of its powerful nonliner mapping ability, where a complete training set is essential for its supervised training algorithm [2]. But precise measuring instruments needed in labeling process are expensive, and operations to measure some manufacturing parameters are very inconvenient or impossible sometimes. When condition changes, process of labeling and learning have to be repeated again. This kind of systems lacks "flexible", in addition, long training time and unstable learning also prevent it from being widely used in practice.

Adaptive resonance network (ART network) provides a new approach for classification. It utilizes unsupervised training strategy, and is able to generalize automatically as a result of its structure, not by using human intelligence which is commonly found in traditional classification competition mechanism. Overall, the appearance of ART theory brings vitality for the usage of neural network in manufacturing fault diagnosis.

1 STRUCTURE AND MECHANISM OF ART NETWORK

The structure of ART network is shown in figure 1 [3, 4]. It belongs to ART-2

type which can handles arbitrary sequence of input patterns. Layers F0 and F1 are input layer which receive and transfer input vectors, output layer F2 represents classification result. Nuclei activities within each layer are called short term memory (STM), and weights between layer F1 and layer F2 are long term memory (LTM).

The classifier consists of two functionally complementary subsystems: the attentional subsystem and the orienting subsystem. It is able to classify an input vector, either familiar or unfamiliar, into one of a number of categories depending upon which of those stored classes it most resembles. An input vector that matches one of the stored classes within a specified tolerance will be regarded as a familiar pattern. The attentional subsystem will adjust the stored class to make it more like the input pattern. If the input does not match any stored classes, a new category is created by storing a pattern that is like the input vector.

Generally, the dynamic of ART network can be divided into three major phases: the STM stabilization phase, the competition phase and the LTM update phase.

(1) The STM stabilization phase. Each input vector is presented to the F0 layer, and is

Attentional Orienting subsystem subsystem F2 cp R_{i} $|bf(Q_i)|$ Ual $f(X_i)$ XQp $bf_1(Qp_1)$ vp_i *Up*, F0 $f(Xp_i)$ aUp $\mathbf{X}p_{i}$ Wp_{i}

Fig. 1 Architecture of ART

transferred through layer F1 up to F2 layer. Feedforward loops of layer F0 and F1 not only normalize each input vector, but also have the advantage of buffering input from top—down influence. All STM activities in F1 layer stabilize before a bottom—up pattern can be transmitted to F2 layer, likewise, all STM activities in F0 layer stabilize before transmitting its output to F1 layer.

(2) The competition phase. The node of F2 layer to which a bottom—up input pattern belongs is determined by competition, and is sent, in guise of a top—down pattern, back to F1 layer. This is a resonant process.

According to competitive "Winner-take-all" principle, the most closely matched F2 node is selected if this node becomes maximally active, whether or not the choice is correct depends upon the matching degree between the top-down template and the original bottom-up pattern. A vigilance parameter is used to control the accuracy of matching.

If match has been made, the choice is correct, the classifier enters the LTM update phase. Or the choice is incorrect, the orienting subsystem is activated, the F2 layer is reset and another category within F2 layer will be selected, until either the input pat-

tern will be placed in an existing category or learned as the first example of a new category, i.e., a new node is created in F2 layer.

(3) The LTM update phase. An input pattern is stored in the network by updating the template of selected category more closely to the input pattern. This learning process ensures encoding an input pattern to the selected class to an even more precise representation.

Obviously, by contrast to BP algorithm, ART network is an unsupervised classifier and has performances of adaptation and self-organization, and it can learn and memory as one goes along. So ART network is hopeful to perform intelligent pattern recognition in manufacturing process.

2 A EXAMPLE OF ITS APPLICATION IN MANUFACTURING FAULT DIAGNOSIS

Tool state monitoring in cutting process is one of the focal issues of quality control tasks in automatic manufacturing system ^[5] A new type of monitoring system built on ART classifier is designed, and is tested in micro-diameter drill state identification in drilling process. Tests are carried out on an emco FIP-CNC mill. Diameters of drills are from Φ 1 mm to Φ 4 mm. Workpieces are carbon steel plates. Block diagram of the

ART – based cutting tool state monitoring system is illustrated in figure 2. A transducer picks up acoustic emission(AE) signal from drilling process. Via certain pre—treatment by filter, amplifier and pulse analyzer, AE counting rate signal and enveloping signal are obtained. Parameters of mean square root, pulse peak and pulse width of the two AE signals are extracted by signal analysis technique. After normalized to eliminate the influence of operational conditions, these parameters are feeded into ART classifier as input pattern.

A drill drills holes one by one until breakdown, and its states are diagnosed separately by BP classifier and ART classifier. BP network consists of an input layer (6 nodes), a hidden layer (10 nodes) and an output layer (3 nodes). The first output node of BP classifier denotes sharp drill state, the second node worn drill and the third node drill failure (such as chip blocking or drill breakdown). ART classifier has the same input vectors with BP classifier, but its output nodes are created by itself in the monitoring process.

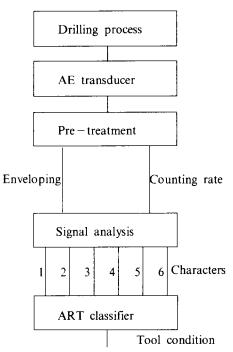


Fig. 2 Diagram of cutting tool condition monitoring system

The drilling process is stable while the drill is sharp. Cutting sound becomes apparently in the process of hole 32. The chisel worn can be seen obviously now. It sounds more and more loud afterwards, and the cutting state becomes worse and worse.

The tool holder can not stand up the big torque force arising from worn tool and comes loose in the drilling process of hole 37. Cutting process continues after the drill is held tightly again. The drill is hold—up by chip at hole 42, and breaks down at hole 43.

Table 1 Diagnosis of BP classifier and ART classifier (n = 1500 r/m, f = 0.08 mm/r, d = 2 mm)

Hole No	Normalized input pattern						Re	Results	
	11	12	13	14	15	16	BP	ART	
8	0.216	0.283	0.140	0.017	0.133	0.200	1	1	
11	0.232	0.281	0.272	0.042	0.047	0.200	1	1	
13	0.216	0.289	0.252	0.045	0.262	0.206	1	1	
14	0.232	0.289	0.252	0.064	0.188	0.200	1	1	
20	0.240	0.251	0.200	0.059	0.119	0.200	1	1	
22	0.216	0.296	0.244	0.058	0.133	0.038	1	1	
28	0.240	0.270	0.220	0.068	0.110	0.200	1	1	
32	0.240	0.279	0.256	0.100	0.164	0.058	2	2	
34	0.256	0.270	0.004	0.126	0.154	0.200	2	2	
37	0.332	0.330	0.436	0.546	0.472	0.442	3	3	
42	0.404	0.516	0.512	0.823	0.679	0.544	3	3	
43	0.368	0.406	0.894	0.850	0.800	0.600	3	3	

The classification shown in the column "BP results" in Tab. 1 is the biggest output node in output layer of BP classifier, it also indicates the category of tool state in each test, while signs in "ART results" read out the selected F2 node of ART classifier, which correspond to the ART classification. Both BP and ART classifiers arrive at the same diagnosis which coincides with actual tool states too.

The cutting tool state monitoring tests prove that ART network is powerful for signal pattern recognition tasks. This self-organized clustering technique can find the distribution regularity of a given tasks in pattern space by learning automatically, even if none of target result is known. And it runs speedily in on-line form. The intelligent classifier can meet the need of real-time monitoring in manufacturing process.

3 CONCLUSIONS

- (1) The powerful capability of signal pattern recognition provides for ART network the property to be widely used in manufacturing fault diagnosis as an intering fault diagnosis as an intelligent classifier.
- (2) ART network is characterized by self-organization and adaptation. No labeled training set is needed in its learning process. But interpretation of classification result remains a problem.
- (3) ART network units its working and learning process in a stage, it runs speedily. So it can meet the need of real-time monitoring in manufacturing process.
- (4) In order to arrive at a precise, reliable and stable diagnosis result, network parameters should be selected carefully.

REFERENCE

- 1 Yang Z K, Tan Z, Chen L. Pattern Recognition and Neural Network, Beijing: Mechanical Engineering Press, 1992
- 2 Lua K T. Pattern Recognition, 1992, 25(8): 877
- 3 Gail A Carpenter, Stephen Grassberg. APPLIED OPTICS, 1987, 26(23): 4919
- 4 Carpenter G, Grossberg S. Computer Vision, Graphics and Image Understanding, 1987(37): 54
- 5 Rangwala S, Dornfeld D A. Proc Symposium on Integrated and Intelligent Manufacturing Analysis and Synthesis. New York: ASME, 1987: 109

ART 网络及其在故障诊断中的应用

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摘要 与 BP 网络相比, ART 网络具有自组织、自适应以及运行程度快等特点,因而在机械制造过程的故障诊断领域具有很大的应用前景。本文介绍了 ART 网络的工作机理,并设计了一种智能型的刀具状态监测系统,该系统已被成功在用于小直径钻头钻削状态识别。

关键词 神经网络,模式识别,诊断,刀具