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Incremental learning for online tool condition monitoring using Ellipsoid ARTMAP network model

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ABSTRACT

In this paper, an Ellipsoid ARTMAP (EAM) network model based on incremental learning algorithm is proposed to realize online learning and tool condition monitoring. The main characteristic of EAM model is that hyper-ellipsoid is used for geometric representation of categories which can depict the sample distribution robustly and accurately. Meanwhile, adaptive resonance based strategy can realize the update of the hyper-ellipsoid node locally and monotonically. Therefore, the model has strong incremental learning ability, which guarantees the constructed classifier can learn new knowledge without forgetting the original information. Based on incremental EAM model, a tool condition monitoring system is realized. In this system, features are firstly extracted from the force and vibration signals to depict dynamic features of tool wear process. Then, fast correlation based filter (FCBF) method is introduced to select the minimum redundant features adaptively so as to decrease the feature redundancy and improve classifier robustness. Based on the selected features, EAM based incremental classifier is constructed to realize recognition of the tool wear states. To show the effectiveness of the proposed method, multi-teeth milling experiments of Ti-6Al-4V alloy were carried out. Moreover, to estimate the generation error of the classifiers accurately, a five-fold cross validation method is utilized. By comparison with the commonly used Fuzzy ARTMAP (FAM) classifier, it can be shown that the averaging recognition rate of EAM initial classifier can reach 98.67%, which is higher than FAM. Moreover, the incremental learning ability of EAM is also analyzed and compared with FAM using the new data coming from different cutting passes and tool wear category. The results show that the updated EAM classifier can get higher classification accuracy on the original knowledge while realizing effective online learning of the new knowledge.

1. Introduction

Tool wear has negative effects on surface quality, dimensional precision of work-piece, and may even cause a harmful effect on safe operation of total machining system. According to the research, about 20% machine downtime is caused by the tool wear [1]. In addition, the cost of cutting tool and tool changing is about 3–12% of the total machining cost [2]. Therefore, it is necessary to build an online tool condition monitoring (TCM) system for machining industry to detect and recognize the variation of tool wear state fast and effectively.

Tool wear is a complex nonlinear process under combined action of the cutting tool, work-piece and machine tools. Therefore, different kinds of artificial intelligence based monitoring strategies, such as artificial neural networks (ANNs), support vector machine (SVM) and hidden Markov model (HMM) have been proposed in recent years. By using multi-layer perceptron (MLP) network and back-propagation (BP) training algorithm, Purushothaman and Srinivasa [3] realized a TCM system to judge whether the cutter was worn or not. To realize the classification of multi categories tool states, Dimla and Lister [4] developed a tool condition monitoring system based on multi-layer perceptron (MLP) neural networks. In this system, four kinds of tool states (sharp, part worn, worn and fractured tools) were monitored by adopting cutting force and vibration signal. The authors claimed that it was capable of accurate tool state classification in excess of 90% accuracy. To depict the complex relationship between features and tool wear states, Brezak et al. [5] used radius basis function (RBF) neural network to classify tool states under three wear levels during milling process. To avoid over fitting phenomenon and realize stable learning under small samples cases, SVM based classifiers have been proposed and widely used in recent years. Xu and Wang [6] used SVM model to realize the tool wear identification by using acoustic emission sensory information and wavelet package based feature extraction algorithm. The results show that its identification accuracy reaches as high as 93.3%. Sun et al. [7] introduced an improved SVM approach combining with one-versus-one learning strategies to carry out multi-classification of the tool states. The authors claimed that the percentage error of the classifier was about 4.8%. Wang et al. [8] presented a TCM system based on ν support vector machine (ν-SVM) to realize multi categories tool wear classification during milling process of Ti-6Al-4V alloy. The vibration signals corresponding to four kinds of tool wear states were collected and time-frequency domain features were extracted based on wavelet packet decomposition. The analysis shows that the classification accuracy of the system exceeds 92%. To depict the time dynamics of the selected features, Kassim et al. [9] used HMM to classify various states of the tool wear during end milling operation by taking the fractal features of machined surface as the input. The results show that the HMM based model can provide reliable tool condition classification. Boutros and Liang [10] proposed a discrete HMM for the

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recognition of tool wear states during milling process. The experiments under three different tool conditions were conducted and the corresponding acoustic emission data were collected. The results show that the success rate for the tool wear severity classification was greater than 95%. Cetin et al. [11] applied multi-rate coupled HMMs to characterize the stochastic processes of the tool wear during titanium alloy milling. The authors concluded that it can achieve an excellent classification performance.

The above-mentioned methods can reflect the relationship between the tool wear states and the selected features accurately and effectively. Nevertheless, the construction of these classifiers depends on the predefined training samples. When new data appears, the whole classifier should be re-trained because the parameters of network cannot be adjusted locally and incrementally. In such case, the previously acquired knowledge is easier to be forgotten when the re-trained classifier is constructed. However, for the tool condition monitoring of small batch manufacturing process, the types of the cutter and work-piece materials vary frequently. Moreover, the morphology and position of the tool wear are so complicated that it is not realistic to collect all the data corresponding to different tool states only by finite cutting experiments. Therefore, it is necessary to update an existing classifier in an incremental fashion so as to memorize new training data without sacrificing the classification performance on the original knowledge [12].

In recent years, incremental learning based classifiers, such as ARTMAP based classifiers, nearest generalized exemplar (NGE) [13], generalized fuzzy min–max neural networks (GFMMNN) [14], growing neural gas (GNG) [15] and function decomposition (FD) [16] are proposed to memorize new knowledge without catastrophic forgetting the previously knowledge. Among these algorithms, ARTMAP based classifiers, due to its superior local representation and discrete distribution ability, have been studied by many researchers to realize supervised learning and classification tasks [17–19]. Within the ARTMAP family, fuzzy ARTMAP (FAM) is one of the commonly used typical structure in which the training data is coded and represented using hyper rectangle shape node. Up to now, it has been used in some applications ranging from data clustering [20,21], incremental learning [22,23] and tool condition monitoring [24–26]. However, FAM processes two potential weaknesses. First, the hyper-rectangle used in FAM is more suitable for uniformly distributed data [27,28]. However, it is not an ideal shape to represent complex sample distribution in real application [29]. Second, FAM use hard competitive learning to form their categories and lack of smoothing operation algorithm, which make it easier to over-fitting and sensitive to noise.

Therefore, in this study, Ellipsoid ARTMAP (EAM) network in which the node is represented by hyper ellipsoid is presented. In comparison with FAM, hyper-ellipsoid shape retains virtually all of the excellent characteristics of hyper rectangle, such as batch and incremental learning with fast learning ability, and overcome some of its drawbacks at the same time [30]. The major characteristic of EAM can be summarized as follows. The first is that EAM learn associative mappings based on adaptive resonance theory, which means it can undergo both batch and incremental learning. The second is that training process of the EAM classifier can converge to a stable state rapidly due to its fast learning ability. In fact, these two characteristics are also owned by FAM. What makes the EAM more suitable for classification lies in the third feature. That is, instead of hyper-rectangle, EAM describes the distribution of the sample data by hyper-ellipsoid shape. Therefore, the nonlinear decision boundary can be described by EAM, which gives a more accurate and smooth boundary description. In real application, the sample data is usually uniformly distributed and the sample data near the boundary is sparse. Therefore, the noisy data near the boundary has a great influence on the shape of the decision boundary. In this case, EAM based nonlinear boundary description strategy can effectively eliminate the influence of the noisy data. Xu et al. [31] utilized EAM to cluster tissues by analysis of the gene expression data generated by DNA microarray experiments. Anagnostopoulos and Georgiopoulos [32,33] studied the EAM using artificial classification example named the circle-in-a-square problem and compared it with FAM classifier. The authors declared that EAM showed better ability in clustering and classification tasks. However, the incremental learning and online classification ability of EAM is seldom investigated especially in the field of tool condition monitoring. Therefore, in this study, EAM based classifier is constructed to realize online incremental learning of complex machining process and recognition of the tool wear states. Within the EAM model, offline training is used to construct the initial classifier using batch mode and incremental learning is adopted to update the classifier without access to previous training data. The combination of batch and incremental learning can improve the generalization performance of the classifier. To characterize the dynamic tool wear process accurately [34], both the force and vibration signal in three different directions were collected. Moreover, 138 different features in the time, frequency and time–frequency domain are extracted from the collected signals. Fast correlation based filter (FCBF) algorithm is then employed to search for a minimum redundant feature subset adaptively. Finally, the EAM classifier is constructed to realize the tool state classification and incremental learning. To show the effectiveness of the proposed system, milling experiments of Titanium alloy were carried out. Both FAM and EAM classifier are constructed to compare the performance based on five-fold cross validation method. The results show that the accuracy of the EAM is about 98.7%, which outperforms the FAM model for the recognition of the tool wear state. In addition, the incremental learning ability of EAM is also discussed by taking the new data as the online learning samples. It can be concluded that EAM can realize effective incremental learning without forgetting the original knowledge.

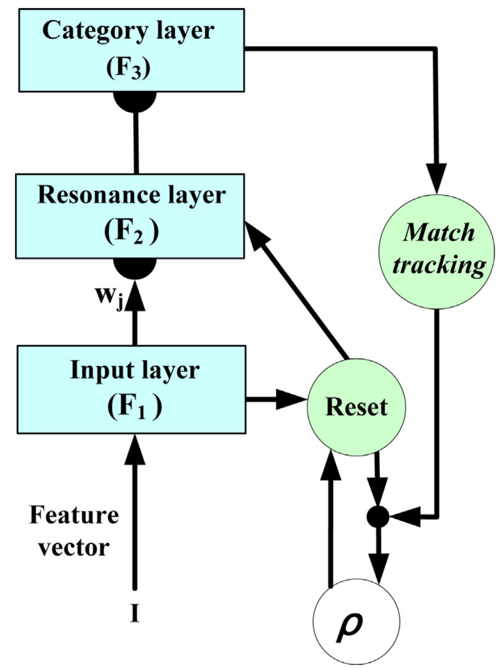

Fig. 1. Structure of Ellipsoid-ARTMAP classifier.

The remainder of the paper is organized as follows: in Section 2, the principle of EAM incremental learning and classification is presented. Section 3 outlines the architecture of the proposed method. The principle of data acquisition, feature extraction and features selection are given in details. In Section 4, a multi-teeth milling experiment of Ti-6Al-4V alloy was carried out and 138 features are extracted from the force and vibration in three directions. In addition, FCBF algorithm is utilized to select the minimum redundant features and the corresponding dataset are built. In Section 5, FAM is adopted simultaneously to make comparison with EAM classifier. Moreover, incremental learning ability of EAM classifier is testified using the dataset from different cutting passes and tool wear category. The results show the EAM model outperforms the FAM model for the recognition of the tool wear state. Besides, EAM can realize effective incremental learning without forgetting the original knowledge. Some useful conclusions are drawn in Section 6.

2. Principle of EAM network

2.1. Structure of EAM

The structure of EAM based classifier is illustrated in Fig. 1. It is mainly composed of three layers: input layer F_1, resonance layer F_2 and category layer F_3. F_1 and F_2 layer are linked by weight vector $\mathbf{w}_j$, which is also called template vector. The weight vector $\mathbf{w}_j$ is used to encode the input vector into jth node in F_2 layer. The nodes which pass the vigilance test (VT) are called committed nodes. The commitment test (CT) is then carried out for these nodes and the winner node is mapped into the category layer so as to get the classification results. During the training process, match tracking (MT) process need to be invoked if the result of F_3 is incorrect. The function of MT is to search for an appropriate node that can correctly classify a presented training sample in the case that the category of this sample was originally mismatched.

The representation of a two-dimensional EAM node in F_2 is shown in Fig. 2(b). Different from the rectangle type node (as shown in Fig. 2(a)), the node in EAM is a hyper ellipsoid type which is described by a template vector $\mathbf{w}_j = [\mathbf{m}_j, \mathbf{d}_j, R_j]$, where $\mathbf{m}_j$ is the center of hyper-ellipsoid. $\mathbf{d}_j$ is direction vector of the node, which coincides with the direction of the hyper-ellipsoid's major axis. R_j is called radius, which equals to half length of the major axis.