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CNC internal data based incremental cost-sensitive support vector machine method for tool breakage monitoring in end milling

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ABSTRACT

A tool breakage monitoring (TBM) system needs to detect tool breakage promptly in an unattended automation workshop. Traditional TBM systems that employ external sensors to acquire diagnostic signals such as spindle power for making judgments are inconvenient since extra sensors should be installed. Moreover, the signals from the external sensors are independent of the computer numerical control (CNC) system, and it is difficult to label them with the corresponding machining task information so that the target data can be segmented automatically. This paper proposes an incremental cost-sensitive support vector machine (ICSSVM) tool breakage monitoring method based on CNC internal data, which is inherently machining-task labeled and can be accessed directly from the CNC system without extra sensors. To satisfy the dataset's integrity at the initial stage of model training, a simulation method that is based on the actual tool breakage characteristics is applied to generate simulated tool breakage data. The ICSSVM method combines cost-sensitive SVM (CSSVM) and modified incremental SVM (ISVM) to solve the imbalanced classification problem, which increases the misclassification probability of the minority class, train the model incrementally from the absence of samples, and guarantee high algorithm efficiency as the size of the dataset increases. It is proved that the ICSSVM algorithm has better algorithmic efficiency compared to the batch cost-sensitive SVM (BCSSVM). It is also proved that the ICSSVM algorithm has better imbalanced classification performance than batch SVM (BSVM), as assessed by the receiver operator characteristic (ROC) curves. The industrial practicability of the proposed method is verified by actual machining with a CNC system integrated with the TBM module.

1. Introduction

Tool breakage in an unattended machine tool will cause breakage of the tools that are used for the subsequent processes, thereby scrapping the workpiece in a modern automation workshop. This reduces the production yield and increases the production cost of the enterprise, which seriously restricts the progress of workshop automation. The TBM system can find the tool breakage promptly and minimize adverse effects, thereby promoting workshop automation.

For end milling, tool breakage is divided into two types: shank breakage and flute breakage (Li, 2001). Shank breakage, in which the tool is completely broken along a cross-section, is one of the most severe forms of tool failure. Flute breakage is the breakage of a cutter edge. This paper will study an end mill shank breakage monitoring method in mass production.

The generic methodology of tool condition monitoring is presented in Fig. 1. This paper focuses on the raw data, preprocessing, and decision-making parts.

In general, the raw data are acquired with external sensors in real time. The cutting force (Cho et al., 2005; Huang et al., 2015; Zhou et al., 2009), the vibration signal (Wang et al., 2014a, b), the acoustic emission signal (Cao et al., 2008; Vetrichelvan et al., 2015), the acoustic signal (Ai et al., 2012), the feed axis motor current (Bassiuny and Li, 2007; Li et al., 2008) and the spindle power (Abbass and Al-Habaibeh, 2015; Reñones et al., 2010) are used in TBM systems. Adding sensors increases the installation complexity and cost. Moreover, the signals from the external sensors are independent of the CNC system, and it is difficult to label the external signals with the corresponding machining task information so that the target data can be segmented automatically. This is the main obstacle in the industrial applications.

Segmentation is a key step in raw data preprocessing. Signal information should be extracted when the tool is actually removing metal in a steady state, since only this portion of the signal contains information about process or tool conditions (Teti et al., 2010). In commercial TBM systems and most laboratory systems, useful signal segmentations are

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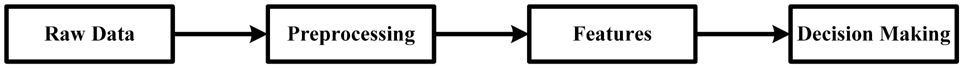

Fig. 1. Generic methodology of tool condition monitoring.

selected by the system user, which is difficult, inconvenient, and prone to random changes of cutting conditions and human errors (Bombiński et al., 2016). The threshold (Bhattacharyya et al., 2007; Ghosh et al., 2007) and time windows (Heinemann and Hinduja, 2012) are always used to automatically segment the data. However, the threshold value and length of time windows are rigid. Thus, they cannot adapt to the changes in machining operations.

The tool state decision-making methods always adopt the artificial intelligence (AI) methods (Kaya et al., 2012; Lenz et al., 2016; Painuli et al., 2014; Tobon-Mejia et al., 2012) since they can dynamically change the classification criteria based on the distribution of the dataset. However, AI methods that are used in industry exist three problems which are as follows:

First, in supervised learning, no abnormal samples are used at the initial stage of incremental model training, since only normal samples are available. This causes misclassification when the first abnormal sample is encountered. The abnormal samples are always obtained by machining experiments (Kaya et al., 2012) before model training, which is costly and time-consuming in industry.

Second, AI methods in the laboratory are always regardless of the dataset imbalance. Bustillo and Rodriguez (2014) pointed out that real datasets are extremely imbalanced because breakage occurs in very few cases compared with normal operation of the cutting process. Since the minority class occurs infrequently, classification rules that predict the minority class tend to be rare, undiscovered or ignored; consequently, test samples that belong to the minority class are misclassified more often than those that belong to the majority class (Sun et al., 2009). Das et al. (2018) have also pointed out the data irregularities and discussed the notable and recent approaches handling the problems.

Imbalanced learning can handle imbalanced industrial datasets. Imbalanced learning approaches can be divided into four categories (He and Garcia, 2009; Sun et al., 2009): data-level approaches, algorithm-level approaches, cost-sensitive learning methods, and boosting approaches. In data-level approaches, the minority class is oversampled, and the majority class is subsampled. Algorithm-level approaches employ a reasonable strategy for correcting the algorithm's bias. Cost-sensitive learning methods adjust the model parameters by establishing a cost matrix and using different cost strategies for different samples. Boosting approaches include ensemble learning and cost-sensitive boosting.

For SVM, there are three ways to deal with the imbalance problem (Masnadi-Shirazi et al., 2012): (a) decrease the imbalance degree of the dataset distribution by oversampling the minority class and undersampling the majority class; (b) kernel function modification; and (c) modify the SVM algorithm to achieve cost sensitivity, which is done in one of four ways. The first is a naïve method that is known as boundary movement SVM (BMSVM), which shifts the decision boundary by simply adjusting the threshold of the standard SVM. The second is the bias penalty SVM (BPSVM) method, which introduces different penalty factors, namely C_+ and C_-, for the positive and negative SVM slack variables during training. The third is combining the first and the second methods. Datta and Das (2015) proposed the near-Bayesian SVM by combining the philosophies of decision boundary shift and unequal regularization costs. The fourth is CSSVM, which extends the SVM hinge loss and is derived as the minimizer of the associated risk.

Third, the training and construction of AI models usually depend on the offline learning strategy (Hsueh and Yang, 2009; Liu and Jolley, 2015; Tobon-Mejia et al., 2012), in which the classifier is trained before the model is applied. Many training samples, including normal and abnormal sample, should be provided so that the model achieves good performance. However, acquiring such training samples is costly and time-consuming. Especially for TBM, the samples are generated from absence over time, which is not suitable for offline learning. Incremental learning is a good choice for solving these problems. According to Geng and Smith-Miles (2009), incremental learning is a new machine learning paradigm for incrementally adjusting the learned model parameters according to new samples. Incremental learning can be used in the following situations: (a) When the initial sample acquisition costs are high, incremental training is used to incrementally train and generalize from the absence of samples. (b) When it is difficult to meet the computational and storage requirements of batch learning, incremental learning can be used to break down the calculation and storage. (c) Only new samples are incrementally learned, rather than relearning the whole dataset by batch learning, which can save time and computation resources.

For SVM, Poggio and Cauwenberghs (2001) proposed a single-sample incremental and decremental SVM algorithm. Subsequently, a batch-sample incremental SVM algorithm (Diehl and Cauwenberghs, 2003) was proposed based on the single-sample incremental SVM algorithm. Mathematic proofs of the convergence and feasibility of ISVM methods were presented by Laskov et al. (2006) and Gu et al. (2013).

The purpose of this paper is to develop a CNC internal data based TBM system using the ICSSVM algorithm. First, the CNC internal data are used instead of signals from the external sensors. The internal data include the electronic data, which are the spindle power data, and the control data, which are the G code instruction line numbers. The electronic data are inherently mapped with the control data. Second, automatic data segmentation is achieved by using the mapping relationship between the electronic data and the control data. The control data can be used to obtain the target electronic data that correspond to the specific machining task. Third, the tool breakage data simulation algorithm is proposed for solving the problem of lack of abnormal samples at the initial stage of incremental model training. Finally, the ICSSVM algorithm that combines CSSVM and the modified ISVM is proposed for solving the dataset problems, which are imbalanced distribution and lack of a representative dataset for offline training. The ICSSVM algorithm is an accurate and applicable algorithm for TBM systems. It is also an efficient algorithm whose computation time is stable as the number of samples increases, which is verified in the experiment.

The rest of this paper is organized as follows: Section 2 reviews the theoretical preliminaries of the characteristics of shank breakage, the standard SVM, and the assessment metrics for imbalanced learning. Section 3 introduces the ICSSVM-based tool breakage monitoring method, including the overall procedure of the method, the spindle power segmentation method, the tool breakage data simulation and the ICSSVM algorithm. Section 4 verifies the algorithmic efficiency and accuracy of ICSSVM, and the practicability of the TBM system. Section 5 discusses the ICSSVM algorithm and the TBM framework. Section 6 presents some conclusions and discusses prospects for future work.

2. Preliminaries

2.1. Tool shank breakage

The process of shank breakage consists of the moment of breaking and air cutting after breaking, as shown in Fig. 2. The characteristics of the spindle power that correspond to the two processes are obvious. A short-term sudden increase in spindle power appears when the tool is breaking. The phenomenon can be described by an impulse function