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Monitoring tool wear using classifier fusion

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ABSTRACT

Real time monitoring of manufacturing processes using a single sensor often poses significant challenge. Sensor fusion has thus been extensively investigated in recent years for process monitoring with significant improvement in performance. This paper presents the results for a monitoring system based on the concept of classifier fusion, and class-weighted voting is investigated to further enhance the system performance. Classifier weights are based on the overall performances of individual classifiers, and majority voting is used in decision making. Acoustic emission monitoring of tool wear during the coroning process is used to illustrate the concept. A classification rate of 87.7% was obtained for classifier fusion with unity weighting. When weighting was based on overall performance of the respective classifiers, the classification rate improved to 95.6%. Further using state performance weighting resulted in a 98.5% classification. Finally, the classifier fusion performance further increased to 99.7% when a penalty vote was applied on the weighting factor.

1. Introduction

The difficulty associated with tool condition monitoring during machining is primarily due to the continuous nature of tool wear. Several techniques have thus been investigated for estimating the tool condition [1–6]. A variety of classifiers have also been used for this purpose, and these include artificial neural networks [4,7–11], hidden Markov model [12,13], k-nearest neighbor [14], maximum likelihood, and support vector machine [15].

Since individual classifiers perform differently, depending on the type of application, the use of multiple classifiers has been investigated in some fields for making monitoring systems more robust [16–22]. Conceptually, this is similar to sensor fusion which capitalizes on the advantages of individual sensors and reduces sensitivity to noise [8,23–29]. Classifier fusion, on the other hand, capitalizes on the advantages of individual classifiers.

In earlier work on classifier fusion [30], a technique was investigated that evaluates the performances of a number of classifiers and selects the best among them using the concept of "overproduce and choose". This is similar in concept to the Fisher criterion [31], which is based on ranking of candidate process features.

In an application based on the modified Bagging method, the best of several artificial neural networks was selected for predicting the state of tool wear during drilling [32]. Another method for monitoring drilling operations was based on a decision fusion center algorithm [33]. Monitoring of the end milling process has also been investigated using machine ensemble techniques such as majority voting and generalized stacking [34].

Multi-classifier algorithms have often made use of a voting system, for example, majority voting [35,36]. However, as

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pointed out by Petrakos et al. [37], the results obtained using classifier fusion will not differ from that of a single classifier if the classifiers agree on class decision. On the other hand, voting plays an important role if the individual classifiers have different decisions. Another major challenge associated with voting is the issue of 'tie votes'. This is often addressed using weighted voting [38,39] where the weights are normally constant. In situations where the classifier performances vary in the course of the process, such as may occur during tool degradation, then it becomes essential to account for such variation.

This paper extends the concept of decision fusion to classifiers, with a view to making tool condition monitoring systems more robust. This would enhance their performance by reducing classification errors that may result with individual classifiers. In addition, the state-performance weighting factor and penalty voting concepts are introduced to further improve classification rates.

Acoustic emission (AE) is used as the sensor signal, and the process investigated is the coroning process. Thus in Section 2, a brief background is provided on AE, the coroning process, and classifier fusion. This is followed in Section 3 by the experimental procedure. The results are presented and discussed in Section 4, and finally, the conclusions in Section 5.

2. Background

2.1. Acoustic emission (AE)

Acoustic emission refers to the elastic stress waves generated as a result of the rapid release of strain energy within a material due to a re-arrangement of its internal structure. Early applications of AE to machining can be traced to the work of Grabec and Leskovar [40], and Iwata and Moriwaki [41], who examined the fundamental characteristics of AE from machining. Subsequent work by Moriwaki [42] indicated that AE signals with large amplitude were associated with tool failures such as cracking, chipping, and fracture. Kannatey-Asibu and Dornfeld [43] later developed a relationship between AE and the cutting process. Good correlation was found between predicted and experimental results.

Emel and Kannatey-Asibu [44] monitored tool wear and breakage using pattern recognition analysis of AE signals generated during the process. In order to reduce cutting condition effects, an autoregressive analysis was used to model the acoustic emission signal sensed from the cutting process by Liang and Dornfeld [45]. Teti [46] presented experimental results for AE generation during machining of carbon steel using high speed steel tools under realistic cutting conditions. Blum and Inasaki [47] investigated both the force and AE signal generation during orthogonal cutting. A neural network consisting of two sequential learning stages, unsupervised Kohonen's feature map and input feature scaling was introduced by Leem et al. [4] for on-line monitoring of tool wear. High accuracy rates with robustness in the classifications of time and three levels of tool wear were achieved. In another application, AE was used to monitor both chatter and tool wear by Chiou and Liang [48].

A comprehensive summary of early work on AE monitoring of the machining process was presented in a review by Dornfeld [49] and Li [50]. Recent research in this field has focused more on micromachining operations [51–53]. Hung and Lu [53] modeled AE generation during micromilling, considering both the mechanics of the signal generation and propagation mechanisms. They accounted for the shear strain rate distribution on the shear plane and the dislocation density, considering a Gaussian probability density function for the distribution of AE source on the shear plane.

2.2. The coroning process

Coroning is a complex multi-dimensional metal removal process that is used for gear fabrication. Gears finished by polishing improve functional flank topology and reduce gear noise [54]. A coroning tool and system are shown in Fig. 1. It has a ring shape with teeth inside, which are coated with diamond. The tool is engaged with a gear and then rotates under pressure. In addition to the tool rotation, there is also simultaneous grinding action parallel to the rotation axis. Thus, the coroning process ensures final gear quality before its assembly in a transmission box. It has been used for transmission manufacturing, especially in volume production [54,55]. Such a mass production process requires a real-time monitoring system to ensure quality and productivity. However, tool condition monitoring (TCM) for the coroning process has not been reported in the literature.

2.3. Multi-classifier fusion

The fusion procedure for multiple classifiers [18,56,57] being considered here is illustrated schematically in Fig. 2, using the hidden Markov (HMM), Bayesian rule, Gaussian mixture (GMM), and K-means models [58,59].

We first define a matrix **B** consisting of the class pattern (decisions) determined by individual classifiers:

$$\mathbf{B} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & \cdots & b_{1,m} \\ b_{2,1} & b_{2,2} & b_{2,3} & \cdots & b_{2,m} \\ \vdots & & & & \vdots \\ b_{n,1} & b_{n,2} & b_{n,3} & \cdots & b_{n,m} \end{bmatrix}, \quad b_{i,j} \in \{1, 2, 3, \ldots, N\} \tag{1}$$