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Image edge detection based tool condition monitoring with morphological component analysis

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ABSTRACT

The measurement and monitoring of tool condition are keys to the product precision in the automated manufacturing. To meet the need, this study proposes a novel tool wear monitoring approach based on the monitored image edge detection. Image edge detection has been a fundamental tool to obtain features of images. This approach extracts the tool edge with morphological component analysis. Through the decomposition of original tool wear image, the approach reduces the influence of texture and noise for edge measurement. Based on the target image sparse representation and edge detection, the approach could accurately extract the tool wear edge with continuous and complete contour, and is convenient in charactering tool conditions. Compared to the celebrated algorithms developed in the literature, this approach improves the integrity and connectivity of edges, and the results have shown that it achieves better geometry accuracy and lower error rate in the estimation of tool conditions.

1. Introduction

In modern manufacturing, an effective tool condition monitoring system has a major influence in manufacturing economics, which can improve productivity, enhance product quality and ensure safety of running machines. Previous works have investigated various tool condition monitoring methods, either from direct measurement or indirect estimation from measurement features. Among them, force has been one of the most important signals in the monitoring due to its close correlation to the tool conditions. Researchers have reported that forces contain reliable information on cutting conditions and the most effective for tool condition monitoring [1]. Reference [2] proposed an approach based on stochastic process modeling of cutting forces and tool conditions; it achieved good tool wear monitoring results by considering denoising and discriminant force feature extractions. Vibration has also been one of the most widely studied signals for monitoring due to its convenient implementation [3,4]. The acoustic emission signal and its frequency spectrum characteristics could monitor the tool conditions and meet different application aspects [5,6]. For concise and robust representations of these measurements, feature extractions are generally applied in the condition monitoring. A weighted multi-scale morphological gradient filter was presented in [7], which could depress the noise at large scale and preserve the impulsive shape details at small scale, for bearing fault detection. Others features such as wavelet based statistical features [8], and higher order spectra [9] methods were also studied for feature extraction in condition monitoring. With these features extracted, artificial intelligence methods were often applied to realize the final state classification. Among them, neural network models [10] and its combination with other methods such as fuzzy methods [11], support vector machine [12] were most widely studied. Bayesian networks for fault detection was studied in [13], combined with kernel density estimation to enhance its capabilities in handing non-Gaussian variables. Compared to the performance of principal component analysis (PCA) and independent component analysis (ICA), it was validated to be superior in utilizing process knowledge and enabling more intelligent dimension reduction and easier interpretation of results.

The indirect estimation approaches above generally suffer from small amplitude (force, vibration), low signal-noise rate (force, vibration), wide band and high sampling frequency in the precision machining monitoring. In order to overcome the above shortcomings, direct monitoring approaches based on image acquisition

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and processing were applied to monitor machining condition. A direct tool condition monitoring system was implemented in [14] using two fiber optic lighting and CCD cameras to obtain the tool flank wear images. It put applied a cascade median filter to reduce the image noise and utilized image segmentation method to extract tool wear area from its background. The error rate was not satisfactory as reported however. Other researches also tried image analysis approaches such as surface defect detection [15], successive image analysis [16] and the threshold independent method with sub-pixel accuracy [17] etc. These studies achieved a lot of success, while they had difficulties in establishing a noise robust correlation of the extracted features and tool wear states under varying working conditions. At this point, edge detection method provides a possible solution. The edge detection is an image processing technique applied to find points at which the image brightness changes sharply [18]. It could markedly reduce data volume and eliminate the irrelevant information in image processing, so as to provide a foundation for image segmentation or classification. Laplacian operators and wavelet transform had also been studied to realize image edge detection in [19] and [20]. It was formulated in [21] with three features (brightness, color, and texture) associated with natural boundaries to construct a methodology for benchmarking boundary detection algorithms. Others image edge detection methods included multi scale analysis [22], energy function [23] and second derivatives [24]. Based on these methods, researchers expected to find a detection approach that has strong noise robustness, accurate localization and low detection error. To detect too flank wear, an edge detection scheme was developed by statistical filtering of color images, while the accuracy of this wear measuring system is limited with wear width at 10 mm [25]. The wear edge were also studied to monitor tool conditions based on the contour signature [26], Hough transform [27] and spatial moments [28]. An automatic flank wear measurement scheme was studied using vision system to extract the boundary with edge points and wear area [29]. The method was prone to be affected by noise. A vision approach was investigated with a high-speed CCD camera to capture images for drilling tool condition monitoring [30]. The system reached satisfactory results based on a Canny edge detector to extract tool image features. However, the approach could hardly be generalized to the detection of different shaped tools.

Based on the above analysis, the above edge detection approaches are not applicable for precision machining process with which high precision complex components are manufactured under varying working conditions and heavy noisy environment. The detected edges are usually discontinuous and incomplete due to heavy noise, the blurred boundary, and unevenly distributed brightness. In this study, an edge detection algorithm based on morphological component analysis for tool wear region is developed to meet the needs. The proposed method can eliminate the influence of the background and noise on the tool wear region effectively, and the extracted wear edge possesses continuous and complete outline, which is convenient for tool state estimation.

2. Edge detection based on morphological component analysis

How to solve the influence of the background and noise in the tool wear region is key to apply the edge detection algorithm successfully. The classical image edge detection algorithm includes gradient operators, Marr-Hildreth edge detector and Canny edge detector [31]. But the classical edge detection algorithm is applied to tool wear image directly, which cannot obtain good results because of the noise and background in original image. In recent years, the morphological component analysis (MCA) [32], has attracted attention for image representation. The MCA and improved MCA were often used to image denoising and classification. Reference [33] proposed a remote sensing image denoising method based on generalized morphological component analysis (GMCA), which adopted an iterative thresholding strategy to extract the most significant features in the image, and then progressively incorporated smaller features for finer tuning. In [34], a multiple morphological component analysis (MMCA) was presented to exploit multiple textural features of remote sensing images. The merit of this method was the possibility to retrieve detailed image texture information, rather than using a single spatial characteristic of the texture. In addition, the MCA was also applied to texture enhancement. With adaption, the MCA allowed texture to be separated into multiple morphological components corresponding to different visual characteristics [35].

Basically, the idea of MCA is to use the morphological differences of image's components, different signal component can use a different dictionary sparse representation [36], and manage to separate them according to their corresponding dictionaries. The decomposed components have physical meaning. It can effectively decompose original image into target object image, texture (background) and noise. This study applies the idea to tool monitoring in micro-milling, which has been the most versatile and most widely applied process in high precision metallic component manufacturing. In micro milling, the wear image background generally has similar textures, while the target tool image is locally heterogeneous. In this aspect, the MCA method can be adapted to decompose original tool images into various components. In this paper, by utilizing the properties of the MCA algorithm and traditional edge detection methods, a novel approach is proposed to detect the wear edge of micro milling tool image. Through the MCA analysis on the original tool wear image, this approach eliminates the texture and noise, and based on the sparse representation of the extracted target image, it finally extracts the tool wear edge. Fig. 1 shows such a scheme.

2.1. *Morphological component analysis model of the micro milling tool images*

The morphological component analysis (MCA) was developed in [32] to separate components contained in an image when they present different morphological properties. The idea of MCA is based on the observation that many complex signals may not be sparsely represented using only one over-complete dictionary, but by combination of several dictionaries. It assumes that a dictionary can be built by combining several sub-dictionaries such that the representation of the separated component is sparse in its corresponding sub-dictionary but not in others. Thus the dictionary plays the role of a component discrimination, and when the dictionaries are learned, pursuit algorithms that search for the sparsest representation would lead to the desired separation.

For a signal S composed of linear combination of mixed morphological component S_k, it can be represented by an over-complete dictionary:

$$S = \sum_{k=1}^{n} S_k = \sum_{k=1}^{n} \mathbf{D}_k \alpha_k,\ k = 1, \ldots, n \tag{1}$$

For each component S_k there is a corresponding $\mathbf{D}_k$ dictionary that represents it sparsely with coefficients α_k. The Eq. (1) is ill-conditioned as the number of unknown parameters is generally greater than that of equations. While constraining the coefficients α to be sparse, it is solvable with the idea of MCA: