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Progressive cutting tool wear detection from machined surface images using Voronoi tessellation method

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ABSTRACT

Tool condition monitoring by machine vision approach has been gaining popularity day by day since it is a low cost and flexible method. In this paper, a tool condition monitoring technique by analysing turned surface images has been presented. The aim of this work is to apply an image texture analysis technique on turned surface images for quantitative assessment of cutting tool flank wear, progressively. A novel method by the concept of Voronoi tessellation has been applied in this study to analyse the surface texture of machined surface after the creation of Voronoi diagram. Two texture features, namely, number of polygons with zero cross moment and total void area of Voronoi diagram of machined surface images have been extracted. A correlation study between measured flank wear and extracted texture features has been done for depicting the tool flank wear. It has been found that number of polygons with zero cross moment has better linear relationship with tool flank wear than that of total void area.

1. Introduction

Product quality and productivity improvement have been achieved by modification of tool condition monitoring (TCM) system in automated and flexible manufacturing. TCM system can incorporate unmanned machining which in turn reduce production cost and production time. Quality of machined part gets deteriorated with the increase in tool wear, which is an obvious phenomenon in machining. Surface roughness of machined part, cutting force, vibration, chatter increase with increase in cutting tool wear. Direct and indirect TCM techniques are employed for monitoring and control of the predominant factors of machining. Different types of tool wears viz. flank wear, crater wear and nose wear are directly measured using optical microscope, optoelectronic method and by processing the tool wear images captured by using digital camera in direct TCM (Byrne et al., 1995; Dutta et al., 2013). However, a tool disengagement has been performed in direct TCM which in turn affect the tool-workpiece alignment. Change in tool-workpiece alignment deteriorates the accuracy of machining. On the other hand, a degree of tool wear is evaluated in indirect TCM by analysing cutting force signals, spindle power signal, current signal, vibration signal, acoustic emission (AE) signal and surface roughness information obtained by using dynamometer, power and current sensors, accelerometer, AE sensor and surface profiler, respectively. Though the classification of sharp and severely worn tool can be accomplished very well from the above mentioned signals, but detection of progressive tool wear is difficult by incorporating most of the above mentioned sensors. Whereas, positional placement of AE sensor and accelerometer are also a challenging task in this field. Also, the flexibility of power and current sensors and dynamometer are very less. Although stylus based surface profiler can monitor progressive tool wear, surface profiler may damage soft material due to its invasive nature. Thus a requirement of low-cost, flexible and non-invasive TCM technique necessitates the use of machine vision for progressive monitoring of tool wear. In this machine vision approach, images of machined surface are captured by an area scan camera with homogeneous illumination and those images are analysed using image texture analysis techniques to extract surface finish features. This is a type of indirect tool condition monitoring.

Surface texture (a macroscopic region of surface where primitives are situated repeatedly) of machined surface image contains the information about the machining conditions (i.e. feed rate, depth of cut, machining speed), alignment of work piece and cutting tool, vibration and chatter, interaction between cutting tool and work piece. Machined surface image is also carrying the information about condition of cutting tool by tool imprint on workpiece (Al-Kindi and Zughaer, 2012). The light, reflected and diffused from the machined surface, gives the information about the changes of surface texture with machining time and machining conditions. With the increase of cutting tool wear, surface quality of

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the machined surface deteriorates, which can be depicted from machined surface images. Also, machine vision approach is non-invasive, low-cost and flexible in nature (Kassim et al., 2007). Thus, machine vision approach is a growing research field over the years in the field of TCM.

1.1. Literature survey

Research on TCM by applying texture analysis on machined surface images has been developing over the years (Dutta et al., 2013). The standard techniques for texture analysis can be classified into statistical, geometrical, model based and signal processing based techniques (Tuceryan and Jain, 1998).

1.1.1. Statistical texture analysis

Statistical based methods involve the computation of histogram-based features, co-occurrence based features, run length statistical features from the images. A correlation of first and second order statistical measures extracted from the machined surface image histogram with measured surface roughness has been demonstrated in various researches (Bradley and Wong, 2001; Gupta and Raman, 2001; Al-Kindi and Zughaer, 2012). However, any correlation study of extracted image texture features with tool wear has not been performed in their work. A second order statistical texture analysis technique called grey level co-occurrence technique has been applied on turned surface images by Datta et al. (2012) and Dutta et al. (2012) for progressive tool wear detection. However, any study about the variation of texture features with different machining conditions has not been presented in their research. In order to calculate higher order statistical relationship between the grey level intensity of image pixels, Ramana and Ramamoorthy (1996), Mannan et al. (2000) and Kassim et al. (2007) applied run length statistical technique on machined surface images. However, any quantitative correlation study of extracted features with tool wear at various machining conditions has been missing in these researches.

1.1.2. Model-based texture analysis

Model based approach of texture analysis deals with the preparation of an image model and extracting textural features from that image model. Kassim et al. (2006) applied fractal model on machined surface images to determine the fractal dimension and used hidden Markov method to classify four stages of tool wears based on fractal dimension. Kang et al. (2005) utilised the fractal dimension for progressive detection of tool wear in end milling. However, the computational time for determining the fractal dimension is high which is less suitable for online tool condition monitoring.

1.1.3. Signal processing-based texture analysis

Frequency domain based texture analysis techniques were also applied on machined surface images by Tsai et al. (1998). However, any progressive tool wear monitoring was not present in their research. Bradley and Wong (2001) studied the correlations between the surface topography of machined surface and maximum flank wear indicated by VB_{max}. They employed three texture analysis techniques, based on image histogram analysis, frequency domain based texture analysis and texture segmentation method on magnified images of machined surface. They used these techniques for progressive wear monitoring of milling operation for a typical machining condition. However, the experimental space was limited in their method. Also, detailed micro-texture analysis is not possible by the methods of texture analyses used by them. Also the image histogram based analysis technique shown by them is not an illumination invariant technique.

1.1.4. Geometrical texture analysis

Geometrical methods of texture analysis include structure-based procedures for examination of surface texture, which requires extraction of the textural primitives (or elements) and determining the placement of these primitives according to certain placement rules. Analysis of surface texture using structural methods was done using connectivity oriented fast Hough transform method (Kassim et al., 2004).

1.1.5. Texture analysis based on Voronoi tessellation

However, the detailed variation of machined surface image is required to extract for more accurate quantification of surface finish. But most of the methods used to quantify the surface finish have not been able to extract the detailed variations of surface. Thus, a potentially powerful technique based on the use of Voronoi tessellation of the machined surface images has been used in this work to quantify the detailed variations of machined surfaces, especially useful for micro-texture detection. Also very few literatures are available on the detection of progressive tool wear monitoring using machined surface texture features for varying machining conditions. Thus, a detailed study has been presented in this work for varying machining condition to see the effect of feed rate and depth of cut on the extracted texture features for detecting progressive tool wear. Method of Voronoi tessellation of a set of points has been a popular topic in the field of computational geometry. The Voronoi diagram of an image provides a 2D description of point pattern. The polygons obtained from a Voronoi diagram give a description of the neighbourhoods for each of the constituting points. The geometric features of the Voronoi polygons depend on the arrangement or the distribution of points, and hence can be used to detect any underlying structural pattern in an image (Ahuja, 1982). Ahuja and Tuceryan (1989) have proposed a method to extract basic perceptual structure in dot patterns with the help of Voronoi tessellation methods. They had addressed a problem of grouping in dot patterns based on their relative locations. Tuceryan and Jain (1990) proposed a method to extract texture tokens by applying Voronoi tessellation on a given image. Also a guideline for extracting features from a Voronoi diagram of an image was provided by them (Tuceryan and Jain, 1998). Crain (1978) suggested that number of sides, lengths of sides, perimeter and area of polygon could be used as the features for describing a polygonal tessellation. Ahuja (1982) had proposed that area, perimeter, completeness, elongatedness, direction of principal axis, variance of side lengths and eccentricity can be extracted as the features from Voronoi diagram.

In this work, an attempt has been made to analyse the texture of machined surface images resulting from turning operations with the help of Voronoi tessellation method as explained by Ahuja (1982). The goal of this work is to successfully extract some features from the Voronoi diagram and to examine the correlation with measured flank wear of the cutting tool. Based on this goal, some properties of the Voronoi polygons have been put forward in this work, which could highlight the minute details of the machined surface images obtained at progressive machining time. Since, our aim is to effectively detect the degree of tool wear with time, a correlation of extracted features with tool wear values has been quantified using linear regression technique.

2. Experimental setup

In this work, a C-50 steel workpiece with 400 mm length has been turned using uncoated carbide insert in dry machining condition at nine combinations of cutting speed, feed rate and depth of cut. A charged coupled device (CCD) camera interfaced with a computer equipped with image acquisition capability was used to capture images of the machined surface. After machining, the