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On-machine tool prediction of flank wear from machined surface images using texture analyses and support vector regression

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ABSTRACT

In this paper, a method for on-machine tool condition monitoring by processing the turned surface images has been proposed. Progressive monitoring of cutting tool condition is inevitable to maintain product quality. Thus, image texture analyses using gray level co-occurrence matrix, Voronoi tessellation and discrete wavelet transform based methods have been applied on turned surface images for extracting eight useful features to describe progressive tool flank wear. Prediction of cutting tool flank wear has also been performed using these eight features as predictors by utilizing linear support vector machine based regression technique with a maximum 4.9% prediction error.

1. Introduction

Condition monitoring of cutting tool leads an important role in unmanned machining to maintain product quality. This technology saves human resources, production time and product cost with high product quality [1]. Direct and indirect tool condition monitoring (TCM) are performed by inspecting cutting tool visually and by measuring the process signals viz. force, acoustic emission (AE), power, surface finish, respectively. In direct TCM, on-machine tool inspection of tool flank wear is complex due to difficult accessibility of tool flank wear portion. On the other hand, degree of tool wear can be evaluated more easily using indirect TCM from process signals using several types of sensors. But progressive TCM for accurate product quality is inevitable and it is difficult to achieve using AE sensor, power sensor and force sensor [2]. On the other hand, stylus based surface profiler, which is more flexible and economic, is used to monitor tool flank wear by measuring machined surface roughness. But surface profiler is a tactile measuring instrument which may cause scratches on soft materials. Thus, a non-tactile, flexible and low-cost sensor is essential for on-machine tool prediction of progressive tool wear, which can be achieved by inspecting machined surfaces using machine vision system [3]. Machine vision system consists of an area scan camera, an illumination system, image processor and decision making tool. Area scan camera has an advantage to capture 2D information of machined surface image within lesser time than a contact type surface profiler. Since cutting tool creates an imprint on workpiece, machined surface image carries the information about the cutting tool condition as well as the machining condition. Thus, machined surface images carry the information about the cutting tool condition with progressive machining time. Dutta et al. [2] reviewed application of machine vision techniques applied for indirect TCM by evaluating machined surface images, over the decade. They noticed that mainly statistical and signal processing based texture analysis methods were applied on machined surface images for surface finish evaluation. Dhanasekar et al. [4] inspected speckle pattern of ground and milled surface using the autocorrelation technique. However, the system to create speckle pattern is costly and less useful for on-machine tool inspection of turned surfaces. Al-kindi and Zughaer [5] performed on-machine tool surface roughness evaluation of milled specimens using histogram based first order statistical texture analysis. However, the change of illumination is severely affecting the robustness of first order statistical texture analysis according to Elango and Karunamoorthy [6]. Thus, gray level co-occurrence matrix (GLCM)-based second order statistical texture analysis, where co-occurrence of gray levels of pixel pair is evaluated, was successfully utilized in TCM. Gadelmawla et al. [7] extracted texture features from GLCM of face turned

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surfaces and found a correlation of these extracted features with machining time. However, prediction of tool wear using texture features is missing in their study. Dutta et al. [8] found a correlation of GLCM features extracted from turned surface images with the corresponding tool flank wear. An accurate detection of progressive tool wear has also been performed by them using optimum pixel pair spacing parameter to build accurate GLCM. However, tool flank wear prediction has not been done by them. Dutta et al. [9] extracted GLCM and run length statistical texture features from end milled surface images to detect progressive tool flank wear. They found high correlation of GLCM features with tool flank wear. Datta et al. [10] inspected the minute details of change in feed marks on machined surfaces using Voronoi tessellation (VT)-based texture analysis which is a geometrical texture analysis technique. Here, Canny edge detection, in the image pre-processing phase, reduces the effect of intensity variation caused due to inhomogeneous illumination. However, in statistical and geometrical texture analysis, the frequency and phase information of an image cannot be evaluated, although this information is very important for evaluating a surface texture. Discrete wavelet transforms (DWT)-based texture analysis method is a multi-resolution analysis technique which was applied to extract information about space–frequency localization of surface texture images to predict surface roughness of machined surface. Chang and Ravathur [11] predicted surface roughness from the extracted energy feature of DWT image of shaped, polished and ground surfaces using response surface methodology model. They used *Daubechies* 4-tap wavelet as a mother wavelet which is an orthonormal wavelet. However, orthonormal wavelets are asymmetric about their midpoint and for this reason they may introduce phase distortion which can introduce error in surface roughness evaluation [12].

However, by using GLCM based texture analysis, only spatial correlation information of pixels can be obtained, which may extract the waviness information of machined surface texture. Although VT-based texture analysis is independent of inhomogeneous illumination problem, the change of feed mark information due to tool wear can only be extracted using this method. Minute details of surface roughness information can be obtained from DWT-based texture analysis due to its space–frequency localization property in multi-scale. Since, change of tool wear is affecting the surface texture (i.e. waviness and roughness) as well as feed marks of machined surface, the effect of tool imprint due to the change of tool shape on the machined surface may be obtained by utilizing the useful texture features extracted by applying GLCM, VT and DWT-based texture analyses, simultaneously, on machined surface images, which is proposed in this work.

In decision making phase of a TCM system, classification of tool condition or prediction of tool wear is usually performed using pattern recognition models. Kassim et al. [13,14] utilized hidden Markov model (HMM) on fractal dimension, and also artificial neural network (ANN) model on Hough transform based texture features extracted from machined surface images for classification and prediction of tool condition, respectively. However, HMM and ANN are based on empirical risk minimization (ERM) principle which is less robust in terms of generalization capability [15,16]. On the other hand, support vector machine (SVM) utilizes structural risk minimization (SRM) principle. In SRM principle, learning machines are less dependent on the volume of training set and therefore it is computationally efficient. Thus, a better generalization can be achieved through SVM than that through ANN or HMM [17].

In this work, firstly, three features from the GLCM, two features from the VT and three features from the DWT of turned surface images are extracted. Finally, these extracted eight features are utilized as predictors and measured tool flank wear ($VB_{average}$) values are utilized as target variable to predict progressive tool flank wear using support vector machine based regression (SVR) technique for enhancing the robustness of TCM system.

2. Methodology

Machined surface gets rougher with an increase in tool wear. Smoother surface, resulting from a fresh tool, is more prone to follow Snell's law of reflection than that of a rougher surface resulting from a worn tool [8]. So, rougher surface becomes brighter than smoother surface due to scattering of light (Fig. 1a and b). As turned surfaces are carrying a set of attributes of a repetitive pattern (feed marks), three texture analyses methods, explained in the following sub-sections, are applied on turned surface images, in this work. Before texture analysis, a contrast limited adaptive histogram equalization (CLAHE) technique has been applied as image pre-processing to all the images for correcting the problem of inhomogeneous illumination [18] as shown in Fig. 1.

2.1. GLCM based analysis

GLCM is a matrix whose elements are the probability of co-occurrence of pixel pairs with a particular pixel pair spacing (s) oriented in a particular direction (0°, 90°, 45° or 135°) [19]. This second order statistical texture analysis is applied here for its suitability to micro-texture classification [3]. Fig. 2b shows the GLCM of a typical image fragment (Fig. 2a). Pixel value 35 is occurring two times with another 35 pixel for $s = 1$ oriented in $\theta = 0°$, as shown in Fig. 2a with square blocks. This phenomenon is represented in its GLCM (Fig. 2b) at third row and third column.

Thus, GLCM of an image is defined as

$$\mathrm{GLCM}(i,j)_{s,\theta} = \left| \left\{ (a,b) \,\middle|\, I(a)=i, I(b)=j \right\} \right| \tag{1}$$

where $(a, b) \in M \times N$ and $M \times N$ is the image size, pixel a is at a distance of s from its pair b, oriented in θ direction. $I(a)$ and $I(b)$ are gray level intensities of a and b, respectively. GLCM of machined surface produced by a fresh tool is more prone to diagonal distribution than that of the machined surface produced by a worn tool [8]. On this basis, contrast (Con), dissimilarity (Dis) and second diagonal moment (SDM) are extracted from the GLCMs of machined surface images, in this work. Con, which is a measure of diagonal distribution of GLCM or scatterings of an image texture, is expressed in the following equation [20]:

$$\mathrm{Con} = \sum_i \sum_j (i-j)^2 p(i,j) \tag{2}$$

where $p(i, j)$ is the normalized GLCM elements for expressing probability of co-occurrence of pixels. There should be an increasing trend of Con with increase in tool flank wear [8]. Dis is depending on the diagonal distribution of the GLCM or local spatial variability of an image, which is expressed in the following equation [20]:

$$\mathrm{Dis} = \sum_i \sum_j \left| i-j \right| p(i,j) \tag{3}$$

Second moment of differences for diagonal distribution of GLCM can be measured by SDM as expressed in the following equation [20]:

$$\mathrm{SDM} = \sum_j j \sum_i \frac{\left| i-j \right| p(i,j)}{2} \tag{4}$$

Thus, Con, Dis and SDM should have an increasing trend with the increase in tool flank wear. There should be an optimized s for periodic distribution of feed marks of turned surface images [21]. Thus, a periodic variation of features with s value has been observed in Ref. [8]. Position of the peak of power spectral density

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