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Crater wear patterns analysis on multi-layer coated carbides using the wavelet transform

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ABSTRACT

The crater topography patterns on multi-layer coated tools after turning for a series of machining times have been measured using Confocal Laser Scanning Microscopy and Stylus Profilometry. These patterns have been collected to study the evolution of crater wear and explore a possibility of predicting the wear profile through the physics-based wear models. The raw crater patterns were processed using multi-resolution 1D and 2D wavelet analysis to eliminate the noise and spike/pits and then to decouple the large- and short-scale wear features. The wavelet method is proved to be a very powerful tool to filter noise/artifacts without losing the general crater pattern and to decouple roughness, waviness and form. Wavelet-decoupled roughness contained the scoring marks whose presence was monitored along the chip-flow direction and related to the preeminence between abrasion and dissolution based on the temperature distribution predicted by Finite Element Simulation.

1. Introduction

Tool wear is a major area of machining research which has received great attention since machining process appeared in literature over 100 years ago. Although many reported their findings in the past, the study of tool wear still remains to be a quite relevant problem today. The unique combination of high-temperature deformation, high strain rates, and complex work–tool interfacial phenomena makes of machining, and thus tool wear, a technically challenging problem to tackle. It is no surprise that a complete analysis of tool wear requires a multidisciplinary approach including materials science, physics-chemistry, heat transfer, mechanics of materials, dynamics, tribology and mathematical modeling.

To complicate the phenomenon further, the number of new and potential tool materials for which physics-chemistry and tribology properties are difficult to obtain or model is on the rise. So far, the analysis of tool wear has been limited to empirical or semi-empirical approaches which can only be applicable for a certain combination of work–tool materials. Thus, the knowledge gained from such studies cannot be directly applied to other combinations of tool and work materials and extensive experimentation is required to find a trade-off between cost and productivity. We will refer to the cases of machining Compacted Graphite Iron [1] for which the interfacial phenomenon seems to be the key, $AlMgB_{14}$-based tools [2] which enhances machining titanium alloys, or even multi-layer coated carbides which present a multi-phase wear front as time progresses [3].

To advance this particular area of machining research in a more fundamental fashion, the measurements of tool wear surface patterns and their temporal progresses in correlation to well-established wear mechanisms are of surmount importance. The two most common measurements of tool wear, crater depth and flank wear land, are incapable of capturing the important aspects of tool wear in order to elucidate the genesis and evolution of tool wear. Due to the complexity in measuring the surface topography of worn tools, only few advanced techniques enable us to measure the 3D surface of wear patterns with sufficient accuracy. With the 3D surface topography of worn cutting tools in hand, the next task is to distinguish the features in wear patterns (e.g., micro-features (roughness) and larger scale features (waviness and form)) to correlate wear geometrical features with other parameters involved in machining. For example, one correlation worth pursuing could be that of work material microstructure (e.g., lamellae sizes for carbon steels) with the width of grooving marks (micro-ridges) on worn tool to determine the inclusion responsible for abrasive wear. Also, the differences in roughness values may be used to discriminate among the possible wear mechanisms. For example, the high ("rough") roughness values are associated with abrasive grooving marks while the small ("smooth") roughness values are linked to the smooth wear pattern associated with dissolution wear phenomena.

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Several works [3–9] have been performed to obtain crater wear patterns using 3D measurement equipment. 3D Stereo Microscopy [4] has been applied to measure crater wear volumes. However, due to its inherent coarse resolution (~100 μm transversal and ~125 μm axial), surface micro-features were impossible to capture. To obtain the evolution of crater wear on single-layer coated carbides, curve-fitting rendering of the data coming from 3D stylus profilers [5] has been used. Again, a coarse mesh was inevitable, which does not allow observations in a meso-scale frame (1.6 mm × 1.6 mm) without any filtering detail such as *z*-thresholding and curve fitting. A recent assessment of crater topography [6] utilized phase-shift profilometry to obtain full-field 3D data sets of the crater on coated tools. The topographic data was filtered and the obtainable vertical accuracy (5–18 μm) impairs the analysis of micro-mechanisms on the surface. The crater wear of uncoated carbides has been also observed using interferometry [7] and analyzed through *z*-threshold algorithms to identify meso-scale features of the crater. In spite of its outstanding vertical resolution (0.1 nm), no information was obtained regarding short-wavelength features (roughness) which can be used for the analysis of wear mechanisms. The interferometry 3D data sets were compared with 3D CAD models of new tools to determine the wear of uncoated and ceramic-coated polycrystalline cubic boron nitride [8]. Nonetheless, as surface-fitting was used, the detailed features of the surface were lost.

Confocal Laser Scanning Microscopy (CLSM) has been successfully used in tool wear analysis to obtain the crater wear evolution in multi-layer coated carbides [3,9]. A transversal resolution of 5 μm and a 50 nm vertical accuracy was achieved without any sample preparation. However, due to the noise and artifacts (spikes and pits) in the topographical data, a custom-built running average filter [3,9] was necessary to truncate the spikes and pits. This paper uses the wavelet-filtered images through CLSM to observe the crater wear and its evolution in order to identify and understand the tool wear mechanisms of crater wear of the multi-layer coated tools together with the finite element simulation of turning process.

2. Background

2.1. Confocal Laser Scanning Microscopy (CLSM)

The key advantage of CLSM is the so-called optical slicing capability provided by the confocal aperture, which brings along a drastic increase in image contrast and improvement in resolution [3]. An optical slice is the collection of pixel intensities detected at a specific focus (stage) position. A set of "*n*" contiguous optical slices covering the vertical range of interest and identified by $I_n = I_n(x,y,z_n)$, where "I_n" represents the light intensity detected by the photomultiplier known as the intensity matrix. From this matrix, the surface position at each pixel location is detected using the focus detection technique [3] where the actual position of the surface is equated to the vertical position with the maximum light intensity. The surface position detected (z) at each pixel location (x,y) constitutes the z-matrix, $z = z(x,y)$, which is conveniently stored as a Height Encoded Image (HEI) mapping grayscale levels to height positions. If the value of the maximum intensity detected at each pixel location is extracted from $I_n(x,y,z_n)$, the resulting matrix $I_{max} = I_{max}(x,y)$ is known as the Intensity Maxima matrix. The image rendering this matrix is known as the Maximum Brightness Image (MBI). MBIs are somewhat similar to the extended depth of field images and thus very useful for visual inspection. However, to investigate the crater wear topography, HEIs are required. The reader is referred to previous works [3,14] for in-depth information about CLSM.

2.2. Wavelets

The introduction of wavelets provided a breakthrough in the field of signal analysis in the 1990s. In several applications, wavelets analysis has proven to be more powerful than traditional filtering techniques such as Fourier analysis [10–13]. The key feature of wavelets resides in their ability to decompose a signal into an effective scale-time space representation allowing localization of events in time. In the case of surface analysis, the final product of a wavelet transform is the representation of a surface in a scale-position space which provides a mean to identify the surface changes locally, i.e., the surface is broken-down into its large-scale and small-scale features without loosing their localization in the surface. If the wavelet transform is subsequently applied to the surface topography data for an arbitrary number of times, a multi-scale representation of the surface is obtained, i.e., the surface is broken into a spectrum of scales. Similar to Fourier analysis, the wavelet transform represents the original surface in terms of wavelet coefficients. With the coefficients in hand and based on what is known about the surface, it is possible to separate multiple scale features of the surface and filter noise or artifacts.

The "kernel" of the wavelet analysis is the mother wavelet. The mother wavelet is a function that produces "resemblance" coefficients known as the wavelets coefficients when stretched, shifted and convoluted with the topography data, either 2D ($f(x)$) or 3D ($f(x,y)$). These coefficients represent how well the mother wavelet resembles the topography data at a particular location and scale. Mother wavelets are used to extract comparatively small details from the current data set. In order to keep track of the gross surface information, the scaling function, which is related to the mother wavelet via Fourier transform [15], is needed. When 2D topography data or profiles ($f(x)$) are analyzed, 1D wavelet analysis is used to produce two sets of wavelets coefficients: the approximation (cA) and details (cD) coefficients. These coefficients can be inverse-transformed separately to provide the surface approximation (A) and the surface details (D) which represent the original surface decoupled into large-scale and small-scale features, respectively (i.e., $f(x) = A + D$). As for 3D topography data or surfaces ($f(x,y)$), 2D wavelet analysis is used and 4 sets of coefficients are produced, namely approximation (cA), horizontal details (cH), vertical details (cV) and diagonal details (cD) coefficients. Analog to the 1D case, 2D wavelet analysis reconstructions via Inverse Wavelet Transform are needed to give the approximation and details, A, H, V and D (i.e., $f(x,y) = A + H + V + D$).

In the present work, the Wavelet multi-resolution analysis (MRA) approach was used. Roughly, this method consists on passing the topography data through high-pass and low-pass filters based on the mother wavelet chosen and the associated scaling function, respectively. Before going to the next level of wavelet decomposition, the data set is down-sampled, i.e., remove every other sample point from the data set. This process is repeated several times until the level of decomposition desired is achieved or the transversal resolution of the topography data set allows. In this scheme the original surface topography ($f(x)$ or $f(x,y)$) can be viewed as the approximation at level "0" or zeroth level (A_0). For a 2D topography data set ($f(x)$) the 1st level of MRA decomposition gives cA_1 and cD_1, the 2nd level cA_2 and cD_2, and the "jth" level cA_j and cD_j. MRA reconstruction (the equivalent to the inverse transform) starts at any level of decomposition to give the individually reconstructed features at the zeroth level, i.e., A_1,D_1, A_2,D_2, . . ., A_j,D_j. It is worth noting that individual reconstructions coming from any level to the zeroth level can be added arithmetically in any useful combination, e.g., $f(x) = A_1 + D_1 = FORM_1 + DETAILS_1$. In the 3D topography case ($f(x,y)$), the wavelet MRA coefficients are cA_1, cH_1, cV_1, cD_1, cA_2, cH_2, cV_2, cD_2, . . ., cA_j, cH_j, cV_j, cD_j for the 1st, 2nd, . . ., and "jth″ levels, respectively. Accordingly, the wavelet MRA recon-