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Imaging and Wear Analysis of Micro-tools Using Machine Vision

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Abstract

Tool positioning and tool wear or breakage is an integral part of the development of a micromachining center. The nature of worn tools, producing deficiencies in good surface finish and dimension control, is a major concern in machining operations. Current techniques in place for tool location depend on the encoder feedback of the CNC system, with the assumption of accurate tool radius compensation. Additionally, in order to maintain machining quality and to prevent damage to the work-piece, accurate monitoring or early prediction of tool condition is important. These techniques however are insufficient for micro-machining where the tool itself is usually invisible to the human eye. Because the diameter is so small, accuracy is inherently compromised. Furthermore, due to the micron scales of micro-machining, detection as well as determination of tool wear or breakage is quite challenging. This paper reports on the results of an ongoing research project to investigate and develop machine vision applications for micro machining tool location and tool wear monitoring. The determination of an optimal optical setup is reported together with some algorithms for image processing and feature classification. The optical setup utilizes a 3 mega pixel CMOS capturing device mounted on 12X ultra zoom lens. Lighting is achieved by direct, indirect and backlighting. Initial image analysis, utilizing basic Gaussian filters and histogram equalization indicates that lighting is a critical factor in this application. Wear determination is performed by a comparison of the image of an unused tool with that of a used tool using exclusive operators. Although the results seem promising, there is need for finer enhancements on images prior to the application of classification algorithms.

Introduction

Tool wear monitoring continues to be a major area of concern in machining. Several techniques have been researched including machine vision, mathematical models based on direct measurements of certain machining parameters such as cutting forces [1], or megnetoristriction [2]; and models based on indirect measurements of parameters such as acoustic emission [3]. The effectiveness of these models often requires that large amounts of accurate data be gathered under varying machining conditions and/or the use of expensive instrumentation. Coupled with this is the fact that the measurements also tend to be stochastic and non-stationary, and thus difficult to model accurately. At the macro-machining level, other issues need to be addressed especially in high speed machining and machining of difficult-to-machine materials. For micromachining applications, size effects on the material properties present challenging problems in the measurement of the parameters traditionally used for wear detection such as those discussed above [4].

The use of machine vision in the determination of tool wear is fairly wide spread in the manufacturing literature, and dates back thirty years. Comprehensive literature reviews have been published by Kerr et al [5], Dimla [6] and Kurada and Bradley [7]. The majority of previous research efforts utilize simple image processing techniques that are prone to error especially under varying illumination conditions. Consequently, they do not perform well and tend to be unreliable and inflexible since they rely on ideal workplace conditions. Additionally, any variations in position, surface texture, etc. cause severe degradation in performance. Most of the methods involve segmenting the image to extract regions corresponding to tool wear, from which further measurements (e.g., shape descriptors) are made. However, this methodology is inevitably problematic since performing good segmentation, is in general extremely difficult.

Recently, optical scattering techniques have been proposed as an improved approach to tool condition monitoring, utilizing direct sensing of flank or crater wear [8]. Sortino [9] reports on the application of a series of filters; a statistical filter to detect edges, and a high pass filter to reduce low values and a final filter to reconstruct the wear land and measure the amount of wear. Although a fair amount of success is reported, this method, like all the others discussed above, requires a fair amount of off-line processing and is not suitable for on-line monitoring. Existing literature also shows that few of these methods have successfully been implemented in practical industrial applications [5 – 7, 10].

While computer vision techniques have been utilized with some significant success [11], they lack the necessary feature extraction techniques that can accurately characterize tool condition. Moreover, most vision techniques rely on offline processing and cannot be integrated into a partial real-time monitoring system. Although some researchers have developed pseudo-automated systems [12], fully automated offline capability is yet to be realized with machine vision. While these pose as major research issues in tool wear at macro level, the problem is compounded at the micro-level. To resolve an image of a micro-tool adequately, one would require a microscope. This is practical for use on a micro-machining center, especially for automated tool monitoring. The utilization of an ordinary camera on the other hand poses a real challenge. The camera will require a zoom lens, which in turn may distort the image due to difficulty in determining an optimal combination of focal length, field of view and amount of zoom that minimizes the distortion of the image. Secondly, given that, the tool will have a shiny surface, it is difficult to select appropriate lighting that will provide a suitable contrast and good image. This paper report presents results of an ongoing research aimed at developing a practical tool wear monitoring system based on standard CCD or CMOS camera, with on-line capabilities. In this project, an appropriate optical setup has been determined; together with a dome lighting source, for use in capturing of micro-tool images. The tools studied were two-fluted micro end mills of diameters 0.04, 0.025 and 0.01 inches (01.0, 0.625 and 0.25 mm respectively) produced by Performance Micro Tools company (www.pmtnow.com). Some preprocessing techniques including use of selected filters and analysis algorithms are also reported in this paper.

Experimental Setup

a) Camera and Lens

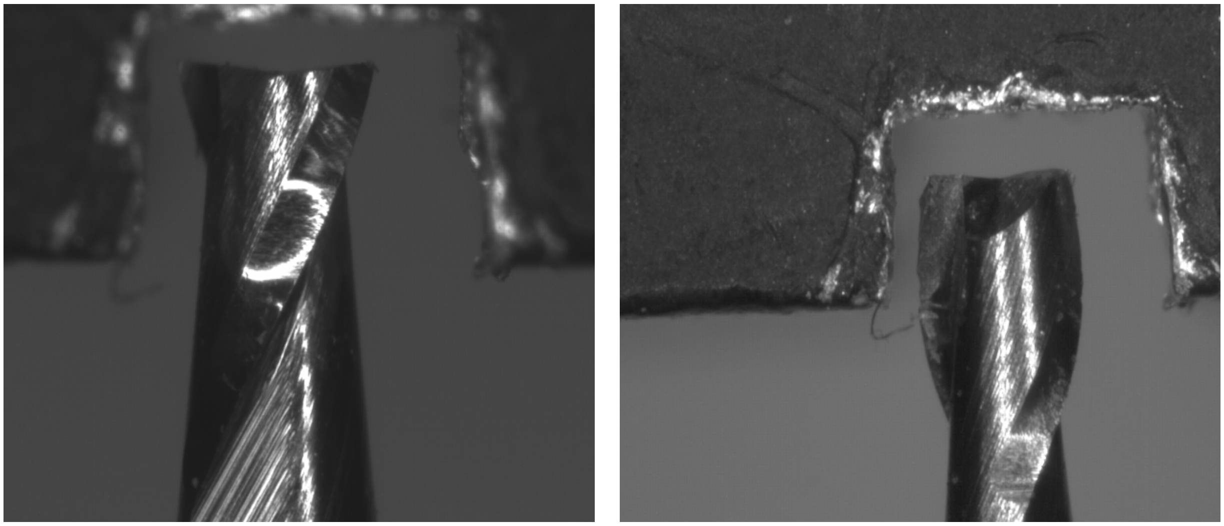
Various types of cameras and lenses were tested with different tool sizes. Major problems encountered included vibrations, and obtaining correct zoom for the given field of view. Given the weight of the zoom lenses tested, a rigid support was necessary, as any slight movement around the camera setup caused distortions in the images. It was also necessary to develop an experimental system that would allow the image to be captured consistently at the same position and orientation during each capture. Thirty images of five different size micro-tools were captured with different cameras, using different lens combinations with a back-lighting setup. Initial trials showed the backlighting provided the least amount of reflection and best possible contrast for every lens and camera combination. After visual observation of the images, an optimal optical set up for the project was determined, the details of which are provided in table 1 below.

Item	**Description**
Infinity 3 MG pixel camera	CMOS image capturing system with a variable resolution up to a total of 3 megapixels
Zoom lens	12x, 12:1 Ultrazoom lens with 3mm fine focus, detents (1, 2, 3, 4, 5, 6, 7x) on zoom ring and aperture
Objective lenses	5X, 10X and 20X objective lenses for ultra zooming
Stage	Optical Stand 11 x 13 x 1/2 inch base with a 16 inch x 20mm post together with a focusing block

Table 1. Details of the image capturing system

b) Lighting

One of the main components of a machine vision system is a good source of consistent light. Unsteady illumination may cause pixel distortions and a lack of consistent images, causing an erroneous wear detection system. In micro-tool imaging, this problem is compounded with the need for high magnification lenses. Various lighting systems were tested. These systems included front lighting with guides, backlighting, combinations of backlighting, LED strobes and dome lighting. When used without combination, both back and top lighting created multiple reflections that distorted the image. A sample of the images on 0.04 inch diameter tool is shown in figure 1 below. After several trials, the best combination was found to be a Boreal dome light with low intensity backlighting. The system is shown in figure 2 below, together with a sample image of a 0.025 inch diameter tool. The new image shows minimized amounts of reflection from the shiny tool surface, and an improved background and contrast.



Backlighting Toplighting

Figure 1. Samples of images with various light setting

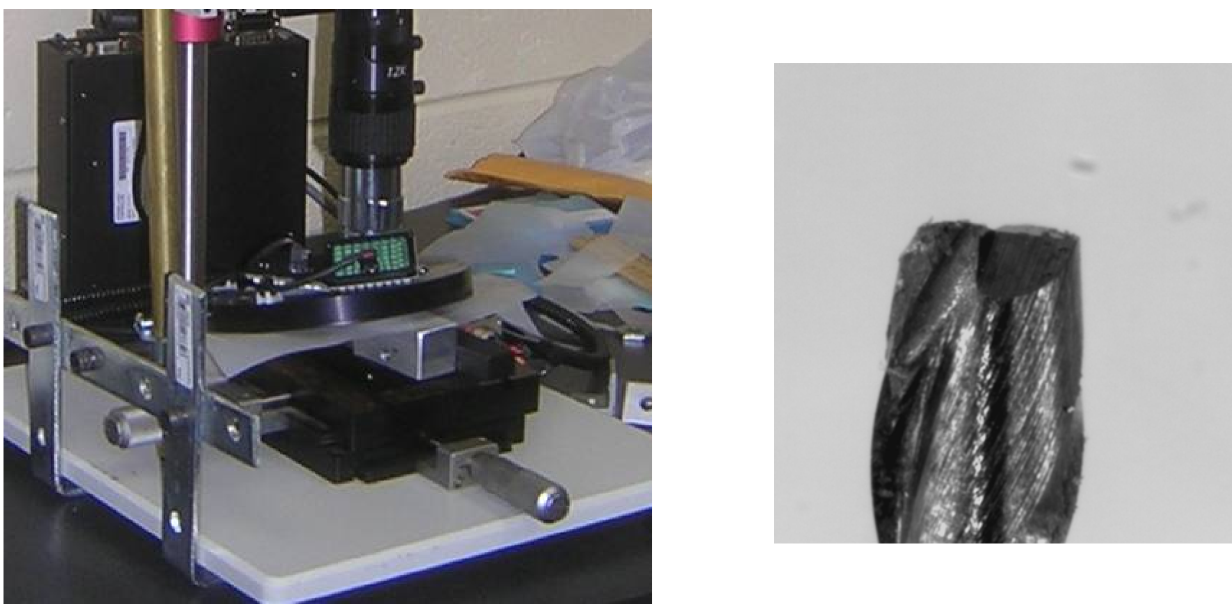


Figure 2. Setup of the lighting showing its position with relation to the zoom lens objective and a sample image of a 0.025 inch diameter tool

c) Fixturing

Because the tool being used is a two flute end mill, analysis of the tool wear and position has to be carried out with the tool in multiple orientations. In addition, the tool should be placed in the same position every time an image is captured. To achieve this, a fixture was made out of 1 inch

X 1 inch X 4 inch aluminum. A 0.125 inch diameter hole was drilled 0.750 inches deep. Since the micro tools used were 1.500 inches long, over half of it is exposed.

Image Processing and Algorithm Development

To characterize tool wear, it is essential to be able to extract or determine important features and parameters that pertain to the wear. The method proposed in this research is to utilize a bank of images of unused tools and compare them with used ones. The first stage therefore is to enhance the images by removing noise. The next stage is to apply algorithms that expose the pertinent features, and finally compare these features (used vs. unused). The following steps describe the image processing procedures used in this work.

a) Image reduction.

The raw images are obtained in 24 bit RGB from the camera. The first step is to convert image to 8 bit grayscale. The main descriptor for wear or breakage will be changes in the profile of the tool edges. Since only a reliable edge is needed, RGB is not necessary. Also, it is important to reduce the size to make the algorithms for edge detection and feature extraction computationally less intensive.

b) Filtering

The raw images will require filtering to remove noise or any unwanted features. Due to the poor contrast and background illumination, it is essential to perform histogram equalization. Figure 3 below shows a raw image after conversion to grayscale with a plot of the histogram distribution. In figure 4, the image is clearer after histogram equalization.

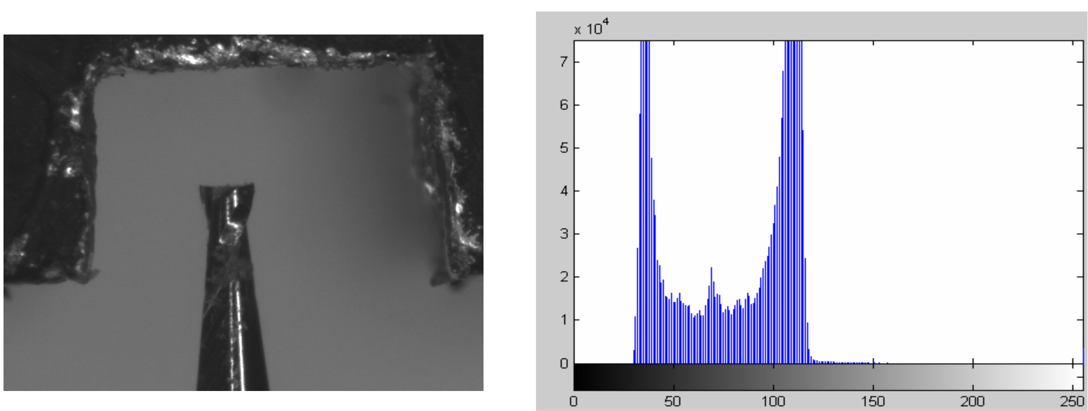


Figure 3. Original Image with Histogram

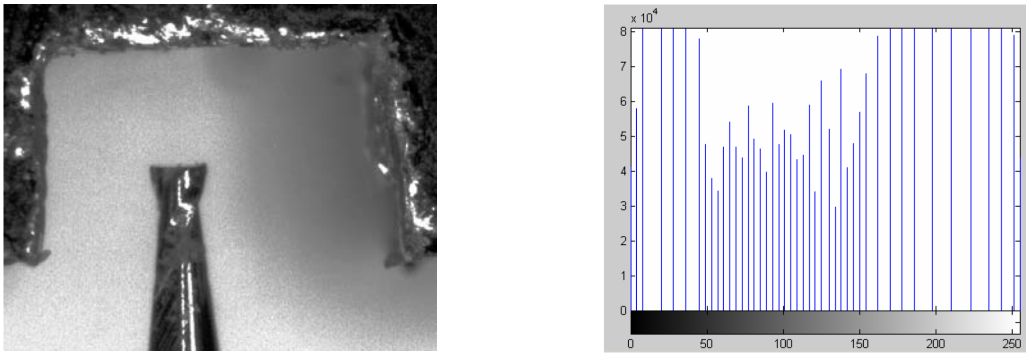


Figure 4. Image after Histogram equalization

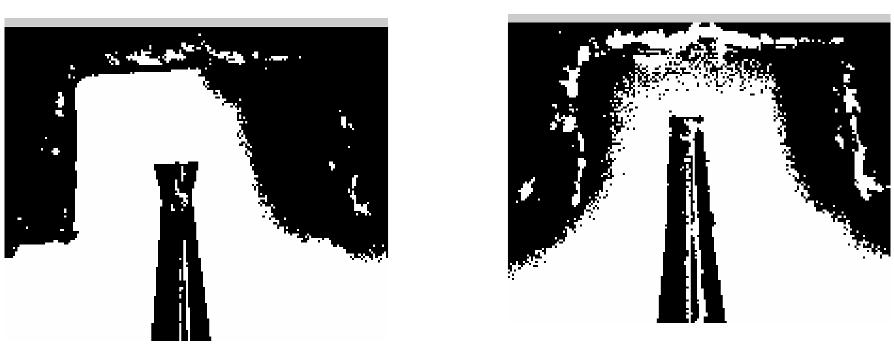
The histogram equalization is followed by a filtering process. Several filtering algorithms were tested and the best for this application was found to be a Gaussian (3X3).

c) Algorithm for wear determination

The main theme in micro-tool imaging is to keep track of pixel distribution and how they are different for a worn tool. One algorithm tested was an exclusive OR (XOR) operator on a master image of an unworn tool and that of a broken tool. In order to perform this XOR, the image had to be thresholded to binary. The XOR operator performs a pixel-to-pixel comparison and will return a zero if the pixels are identical or a 1 if they are not identical. Mathematically this is expressed as:

$$\begin{aligned}
&\text{If } F(i,j) = XOR(A(i,j), B(i,j)): \\
&\qquad \text{then } F(i,j) = 0 \\
&\qquad\qquad \text{if } A(i,j) = B(i,j) \\
&\qquad \text{or } \quad F(i,j) = 1 \\
&\qquad\qquad \text{if } A(i,j) \neq B(i,j)
\end{aligned}$$

The next step then would be to compare the original master with the operated image and set some limits as to what constitutes reasonable wear. This stage has not been reached yet. Figure 5 below shows thresholded images of an unused and used tools and figure 6 shows the image after an XOR operation.



Unused　　　　Used

Figure 5. Thresholded images of unused and used tool

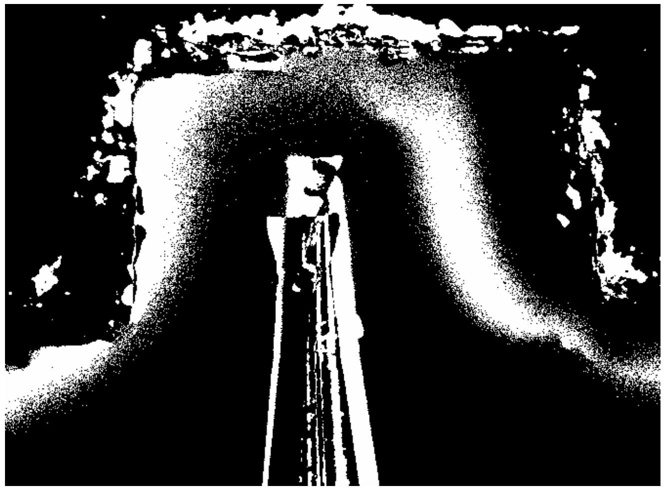


Figure 6. Image after an XOR operator

Conclusions and Future Work.

Image processing techniques have been developed for determining tool wear. At this stage, the research has determined that image reduction is necessary, followed by histogram equalization and filtering. An XOR algorithm has been tested and preliminary findings show good results. However, there is still further work to be done. Because of the inconsistency of tool images, it is essential to develop more advanced algorithms for edge detection and feature classification with the aid of neural networks and fuzzy logic. The research group has started building a library of consistent images that will be used to train the fuzzy classifiers. Also, it is essential to be able to take images of the tools at several angles of rotation. The image with the flutes vertical will definitely be different from that with the flutes horizontal. To solve this problem, an indexing system that will utilize a stepper to rotate the object is being developed. Multiple images of the tools will be reconstructed into a master. Ultimately, the project also plans to automate the capturing and processing of the image and this is currently under development.

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