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Neural Image Processing of the Wear of Cutting Tools Coated with Thin Films

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Small milling cutters are susceptible to very small changes in geometry on the surface of the cutting edge that are substantial when machining at the microscale. The purpose of this paper is to show how to design a neural image processing program to accurately determine the amount of wear accumulated on small milling cutters after successive machining operations. After determining the amount of wear on a small milling cutter, the program creates the appropriate amount of compensation to be used for a computer numerical control (CNC) machining program that will account for in-process tool wear.

Keywords machining, milling tools, neural networks, surfaces, tool coatings

1. Introduction

There have been many methods developed for the estimation of tool wear for conventional machining operations. These methods include vibration monitoring, acoustic emission monitoring, and force feedback systems, which indirectly determine the approximate tool wear that has accumulated. With these methods, much research has been put forth to decode and interpret the cutting force signals (Ref 1-4), tool vibrations (Ref 5, 6), sound (Ref 7), and acoustic emission (Ref 8, 9). All of these methods can be used to estimate the amount of tool wear during a machining operation. However, they are not of much use for wear compensation. When a tool wears, the cutting tool diameter decreases, causing a loss of machining accuracy. It has been proven by the authors that the most assured way of knowing how to compensate for the tool wear is to visually quantify the tool edge after a machining operation and reference the tool wear to an unworn tool. By referencing the worn tool to an unworn tool, the change in diameter is directly calculated, through the use of a neural image-processing program written by the authors. Once the amount of wear is determined, a text file is created, which is used for a computer numerical control (CNC) controller to compensate for the change in tool diameter, thus maintaining the appropriate level of accuracy for a larger number of parts than would otherwise be possible. In addition, the program could be used for extending the useful life of a tool, which contributes to a decrease in manufacturing costs.

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2. Experimental Procedures

2.1 Machining Experiments

The machining experiments consisted of machining tracks into an A-2 tool steel workpiece. Two sizes of tools were used for this experiment: 6.350 and 9.525 mm diameter, 4 flute, uncoated, high-speed steel (M-42) small milling cutters. The depth of cut for all of the machining tests was 0.508 mm. The feed rate for the experiments was 2.54 mm/s. Five experiments were performed for each size of the small milling cutter. The numbers of machining passes for the 6.350 mm small milling cutter were as follows: 0, 5, 10, 15, and 18. The spindle speeds for the 6.350 and 9.525 mm small milling cutters were 760 and 500 rpm, respectively. The 9.525 mm milling cutter machining experiments were set at 0, 5, 10, 20, and 30 passes.

2.2 Microscopic Imaging of Cutting Tools

Once the machining tests were completed, each of the small milling cutters was examined using an environmental scanning electron microscope (ESEM) to determine the corresponding wear that each small milling cutter had experienced (Fig. 1). The method used for this experiment was to examine the amount of abrasive wear resulting in the degradation of the leading edge of the small milling cutter flute. It was decided that this would be an appropriate method for categorizing the degree of wear of each tool. Thus, by extrapolating a line from the ideal leading edge (the edge from a new, unworn tool), and the average line of tool wear, the amount of wear can be determined.

2.3 Outline of Neural Image Processing Program

The neural image-processing program consists of four major parts: generation of training data for the neural network, training the neural network, an edge-trace program, and a comparison program. Each of these programs was written using MATLAB v.6.5 software (The MathWorks, Inc., Natick, MA).

2.4 Generation of Training Data and Image Processing

The generation of training data for the neural network was accomplished by the creation of a white circle on a black background, as shown in Fig. 2. After the circle is drawn, Gaussian

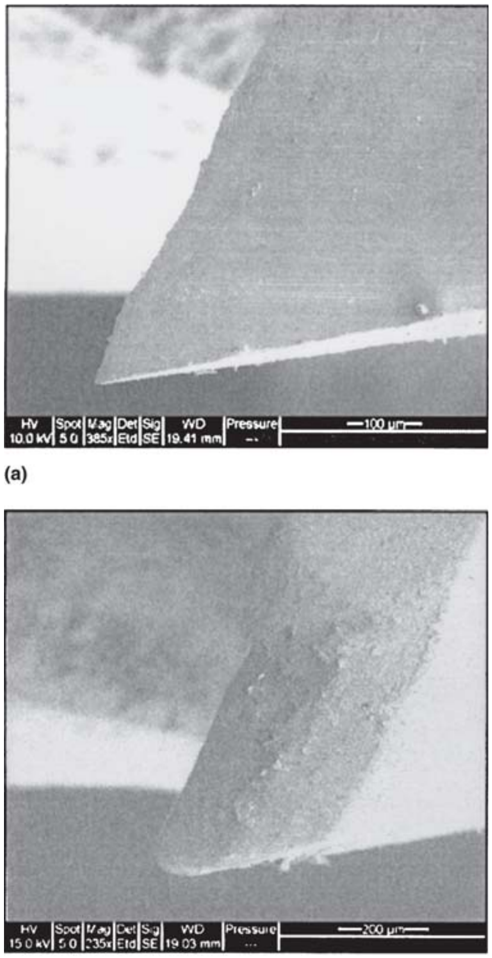

Fig. 1 Examination of a 9.525 mm small milling cutter during machining experiments after (a) zero passes and (b) 30 passes

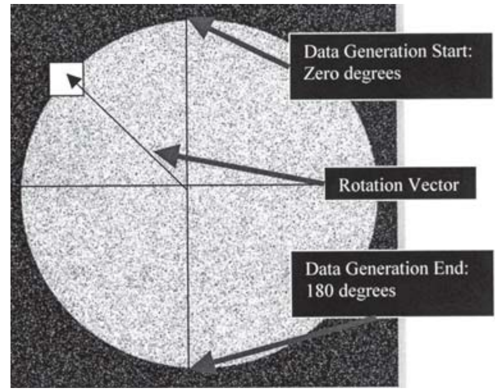

Fig. 2 White circle on a black background

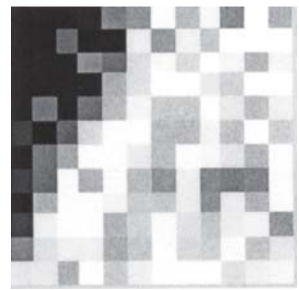

Fig. 3 Extracted subimage

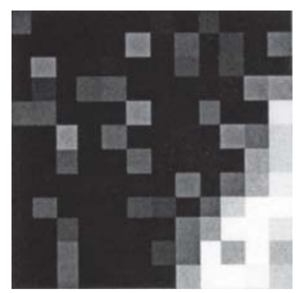

Fig. 4 Shifted subimage

noise is added to enable the data to mimic an actual image. The next step in data generation is to extract a 12 × 12 subimage. Once an image is extracted (Fig. 3), it is saved along with its appropriate target values, which teaches the network how to extract the next subimage from the large image of a tool. The target displacement values are the appropriate amounts to center the dividing line between the white and black pixels on the subimage. These targets are used to direct the network for the next subimage extraction. To enable the network to handle data that is not centered in the subimage, the subimage is shifted along the normal vector, which defines the rotational degree of the image. An example of a shifted image is shown in Fig. 4.

After each data set is stored, the rotation vector is incremented by 0.01°. This yields approximately 30,000 data sets to be used for training and validation for the neural network, which was thought to be enough data to represent the tool edge at any orientation. In addition, after each 180° of generation data, the shade of the white image was decreased, thus generating gray images on a black background.

3. Neural Network Parameters

Once the training data was generated, it was saved into a data file for the neural network. The training data was divided in half, such that one half could be used for validation of the network to achieve the best generalization. All of the data was prescaled between –1 and 1 because "tansig" functions were to be used as the network transfer functions. A feed-forward back-propagation neural network was used to classify the wear images. It was chosen because it works well at performing a nonlinear mapping from an image to a vector output.

The network consists of four layers: a 144 input layer, two hidden layers, which consisted of 12 neurons in one layer and two neurons in the second. The output layer is composed of two "purelin" neurons. The hidden layer transfer functions used for the network are tansig functions. The equation for the tansig function is as follows:

$$X = \frac{2}{1 + \exp(-2*n) - 1} \qquad \text{(Eq 1)}$$

where n is the independent variable, and X is the dependent

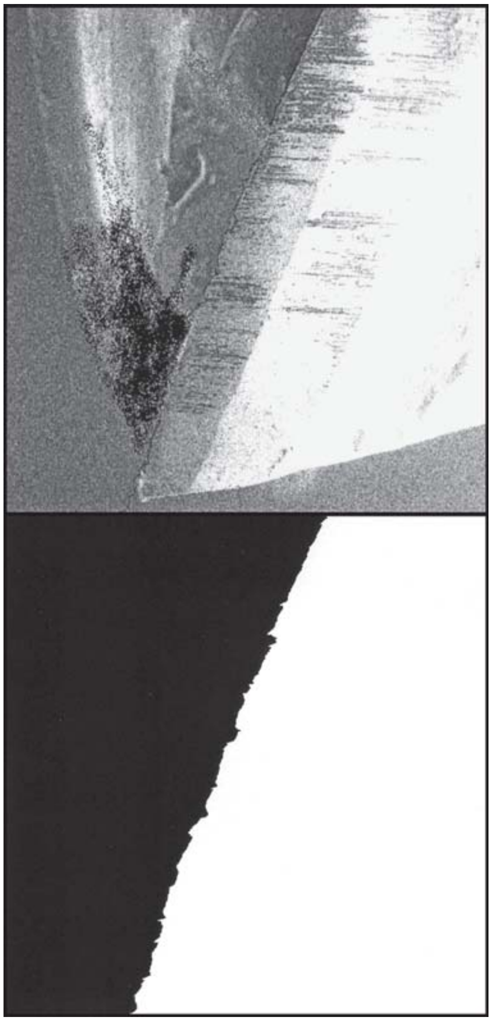

Fig. 5 Unworn 6.350 mm small milling cutter: ESEM micrograph and neural network image

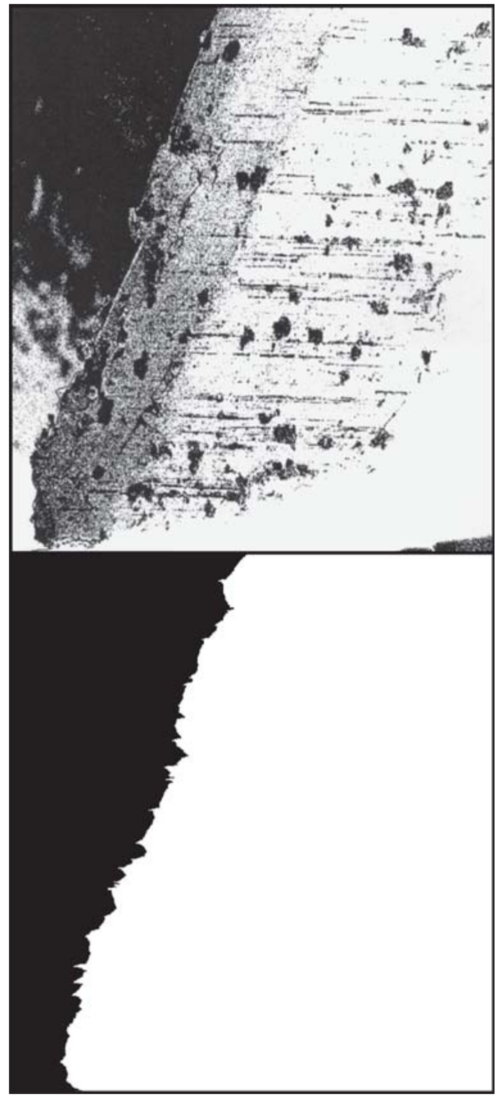

Fig. 6 Worn 6.350 mm small milling cutter after 5 machining passes

variable. The neural net performed exceptionally well when learning the nonlinear mapping for the images. The net had a validation stop after it achieved a mean square error of approximately 0.030 after 150 epochs. Once training had ended, the net was saved, such that it could be used for the edge-tracing program.

3.1 Edge-Trace Program

The first part of the edge trace program reads-in a 950 × 1024 image that was taken from the ESEM. Once the image is read-in, the starting point of the line is determined. This point is at the top of the image where the tool edge is defined. Then, a 12 × 12 image is collected from the large image. This small image is sent to the network for determining the appropriate amount to move down and across for the next image. The change in the horizontal and vertical displacement defines the line to be drawn on the image. After the line is drawn, a black and white bitmap image is generated that corresponds to the line drawn on the real image. This process is repeated until the lines are drawn to the bottom of the real image. Once the edge defining line is complete and the black and white image is finished, the new edge-defining image is saved to a data file for the comparison program. Because some of the images having charging effects from the ESEM, which creates unwanted white areas that interfere with the logic used for the neural network, a few of the images had to be altered. Figures 5-12 illustrate how the neural network defines the edge of a tool, and generates a black and white image corresponding to the line created by the net.

Figure 5 illustrates an image taken from an unworn 6.350 mm small milling cutter; due to the charging effects of the ESEM, the image had to be slightly modified along the base of the small milling cutter. Future revisions to the edge-tracing program will filter the charging effects from the image, creating an ideal image for the neural network. This image will be used as a reference for the worn 6.350 mm small milling cutters.

It can be seen from Fig. 6 how the neural net follows the contour of the worn small milling cutter. There are some slight discrepancies, which are caused by the built-up edge on the tool; however, it approximates reasonably well.

Figure 7 illustrates a nearly perfect trace of the cutting edge of the small milling cutter. The image has a well-defined transition between the flute edge and the background, thus an adequate representation was achieved.

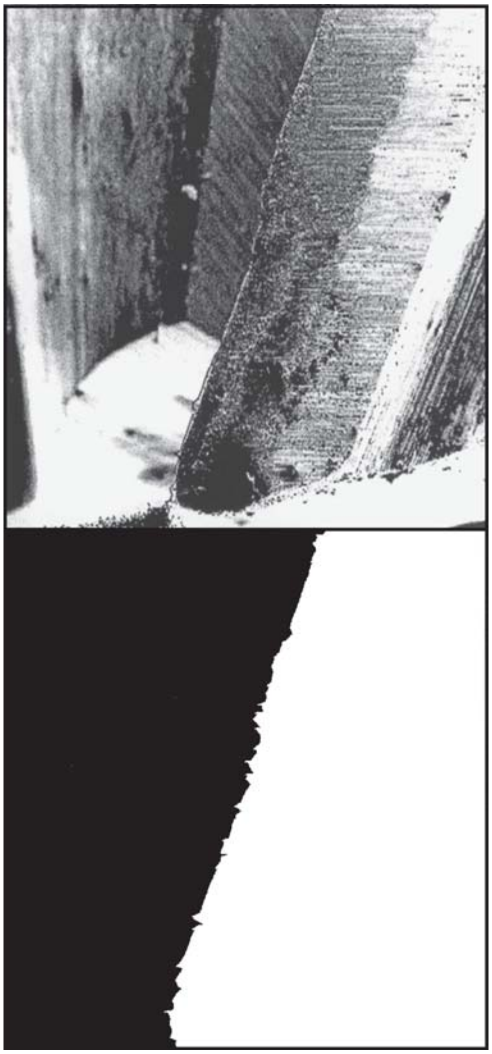

Fig. 7 Worn 6.350 mm small milling cutter after 10 machining passes

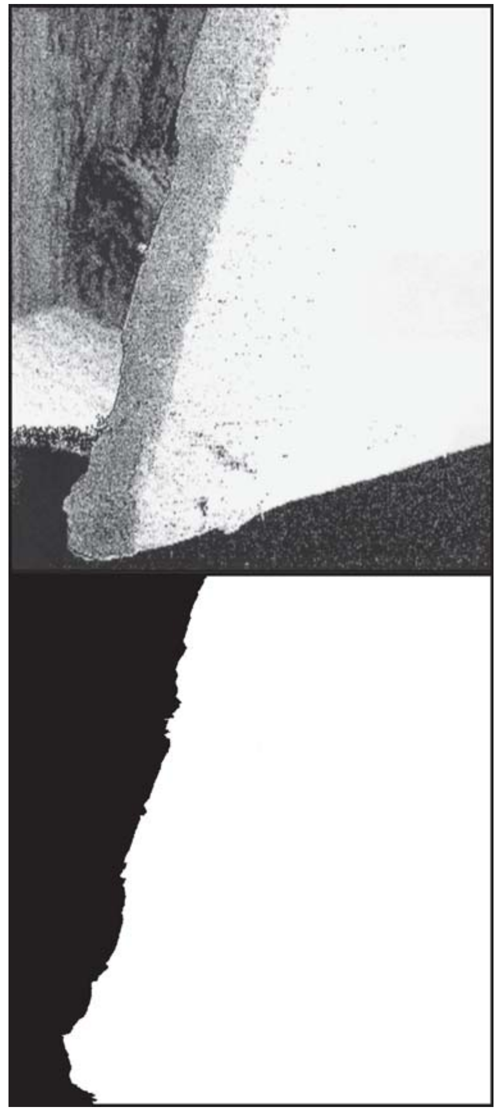

Fig. 8 Worn 6.350 mm small milling cutter after 15 machining passes

Figure 8 illustrates a large amount of wear on the leading edge. Because the image has a well-defined transition on the cutting edge, adequate representation was achieved. When a small milling cutter achieves wear to this magnitude, it is usually discarded because of its inability to attain sufficient machining tolerances; however, once the degree of wear is accounted for, the life of the tool may be extended.

Figure 9 is an image taken from an unworn 9.525 mm small milling cutter. This image is used as a reference for the worn 9.525 mm small milling cutters. The progression of wear of the 9.525 mm milling cutters is shown in Fig. 10-12. Here, the neural network program tracks the progression of wear as the small milling cutters machines tracks in A-2 air-hardening tool steels.

Figure 10 and 11 illustrate how the cutting edge becomes rounded off, and the built-up edge influences the logic of the neural network. This is not of utmost concern, as the network was able to generalize the approximate location of the leading edge. The amount of error is tolerable because the built-up edge is in approximately the same location as the leading edge.

Figure 12 demonstrates how the network performed exceptionally well, in recognizing the difference between the built-up edge and the leading edge. Again, a small milling cutter experiencing wear of this magnitude would dramatically reduce the tolerances to be held when machining.

3.2 Comparison Program

The first step to the comparison program is to read-in a tool reference image (unworn image corresponding to the tool size). The reference image consists of a black and white bitmap image of an unworn tool that was drawn from the edge-trace program. The next step is to read-in the black and white image for the worn tool that is to be examined. Once both of the images are read-in, the difference between the locations of the edge of the small milling cutter must be determined. This is performed by finding the location at the top of the image where the transition between black and white occurs. The difference between the reference image and the worn tool image determines the amount of shift for the worn image. Once the two images are coincident, the amount of material wear is determined by subtracting the two matrices that comprise the two bitmap images. The difference between the two

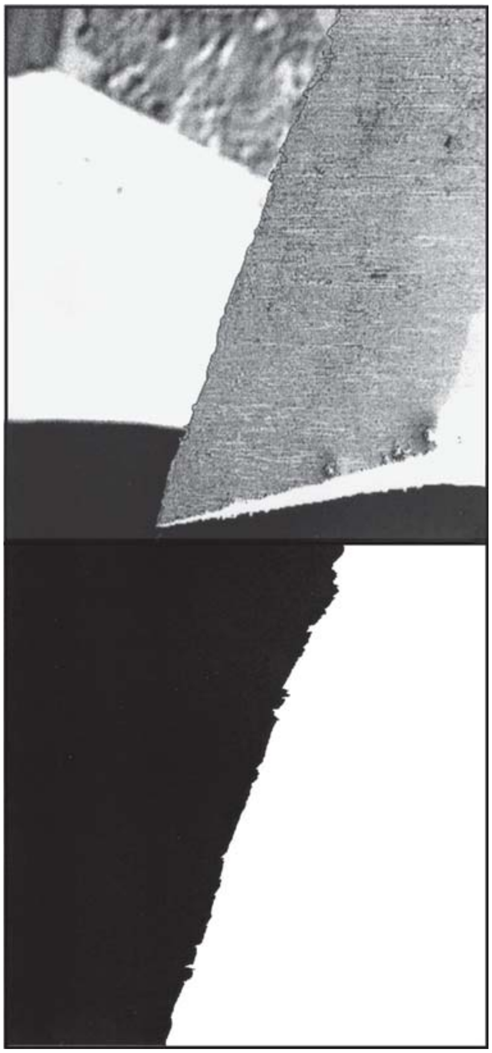

Fig. 9 Unworn 9.525 mm small milling cutter

bitmap images is displayed to the screen for the user to analyze. Once the worn material data is stored, it is then used to calculate the actual material worn. The appropriate amount of wear is then output to the screen as the average and the maximum amount of wear imparted to the worn tool. Figures 13-18 illustrate how the comparison program uses the bitmap images created using the neural network to determine the amount of wear.

4. Experimental Results

Figures 13 and 14 illustrate the successive wear that occurs during machining operations. The wear profile remains relatively the same shape as the initial leading edge. However, the cutting diameter is reduced. Once the wear has been accounted for, an appropriate amount of compensation may be used.

Figure 15 illustrates a large amount of wear experienced by the small milling cutter. The maximum amount of wear on this small milling cutter was 0.09 mm, which corresponds to a loss of approximately 0.178 mm on the diameter. This would result in a machined part that would not meet any but the loosest of

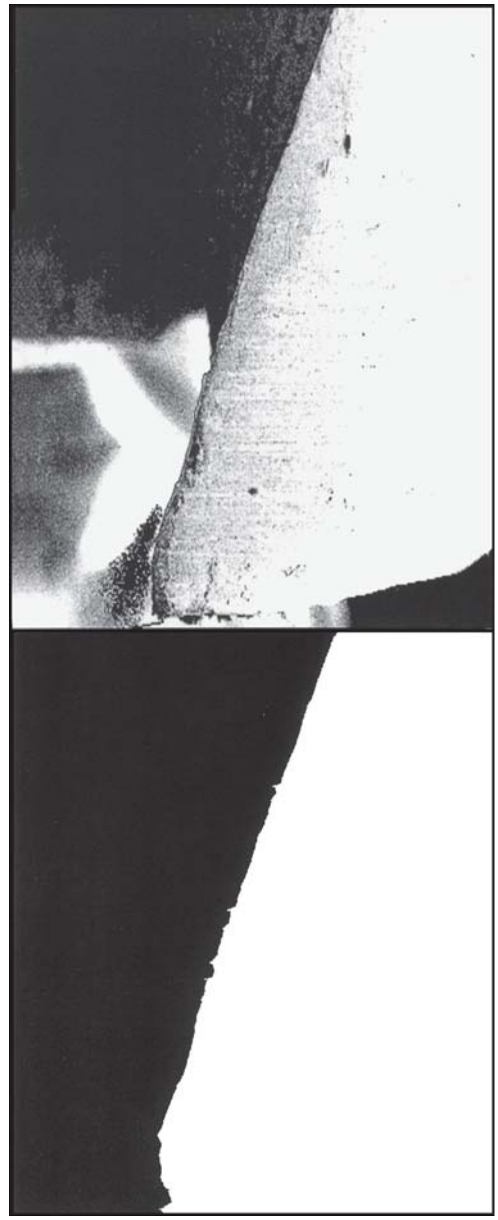

Fig. 10 Worn 9.525 mm small milling cutter after 5 machining passes

tolerances. Again, this wear is accounted for, thus the tolerances of the part could still be met.

Figure 16 illustrates an insignificant degree of wear, thus the CNC machine would not require any compensation.

Figures 17 and 18 illustrate the successive wear that occurs on a small milling cutter. The amount of wear for the tools at this stage would be detrimental to the required workpiece tolerances; however, because the wear is known, the appropriate compensation can be used.

5. Conclusions

The results of the program are very promising in that the program accurately calculates the amount of wear of a tool. In addition, because the program was written for a very general case, it may be useful for a variety of manufacturing opera-

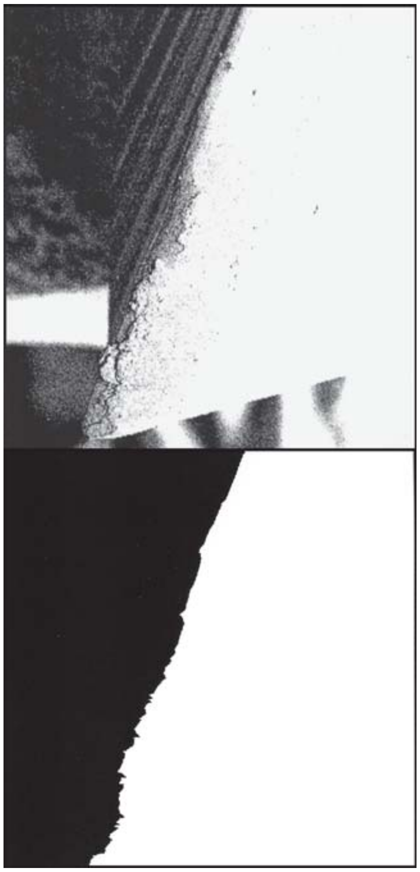

Fig. 11 Worn 9.525 mm small milling cutter after 10 machining passes

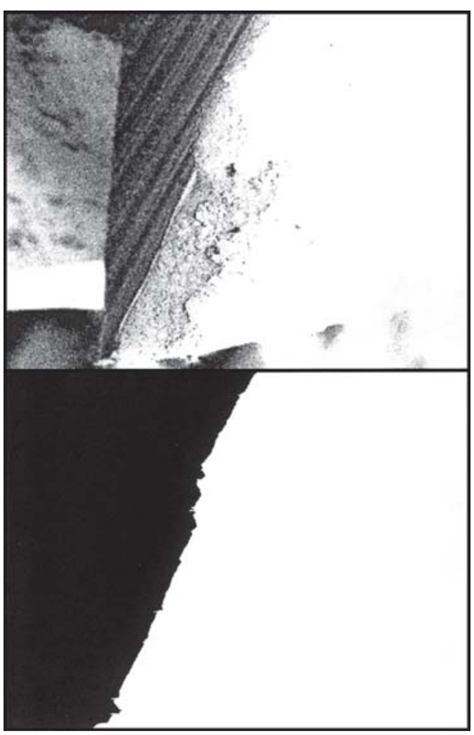

Fig. 12 Worn 9.525 mm small milling cutter after 30 machining passes

Fig. 13 Worn 6.350 mm small milling cutter after 5 machining passes. Average wear, 1.5×10^{-2} mm; maximum wear, 2.54×10^{-2} mm

Fig. 14 Worn 6.350 mm small milling cutter after 10 machining passes. Average wear, 2.45×10^{-2} mm; maximum wear, 4.83×10^{-2} mm

Fig. 15 Worn 6.350 mm small milling cutter after 15 machining passes. Average wear, 3.30×10^{-2} mm; maximum wear, 9.14×10^{-2} mm

Fig. 16 Worn 9.525 mm small milling cutter after 5 machining passes. Average wear, 0.50×10^{-2} mm; maximum wear, 1.39×10^{-2} mm

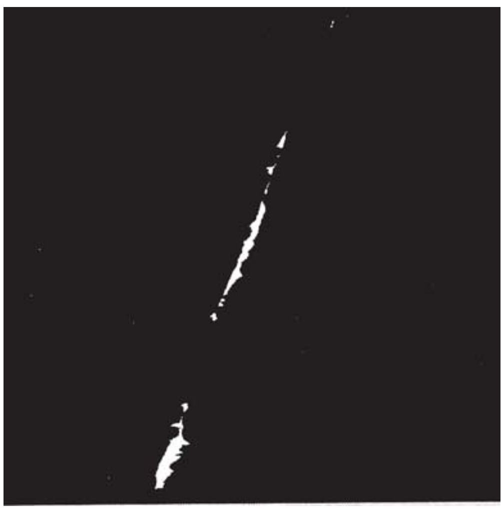

Fig. 17 Worn 9.525 mm small milling cutter after 10 machining passes. Average wear, 0.52×10^{-2} mm; maximum wear, 3.56×10^{-2} mm

tions, where the wear is defined by a change in geometry. Thus the program could be used to accurately output an appropriate amount of compensation for any change in geometry, whether it is a displacement, change in voltage/current, etc. The next step to this project is to interface the program directly with a digital camera, so that it can be directly linked to a machine that could benefit from real-time wear compensation.

Fig. 18 Worn 9.525 mm small milling cutter after 30 machining passes. Average wear, 3.30×10^{-2} mm; maximum wear, 6.10×10^{-2} mm

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