Experimental Study of High Speed CNC Machining Quality by Noncontact Surface Roughness Monitoring

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Abstract—This paper is aligned with a current trend for manufacturing industry, which includes remote monitoring/ control/ diagnosis, product miniaturization, high precision, zero-defect manufacturing and information-integrated distributed production systems. The use of modern sensors and data acquisition instrumentation for manufacturing processes is implemented into Computer Numerical Control (CNC) laboratory for Web-based measurement, inspection, diagnostic system, and quality control. The network hardware and software components are integrated with quality methodologies to achieve maximum effectiveness in Web-based quality concepts. An experimental study of surface roughness effect on light scattering from textured surfaces is described. The results and the system are useful in implementing light scattering instruments for on-line monitoring of machining processes which produce surface roughness patterns.

Index Terms—high speed CNC, machining quality, computer vision, surface roughness, remote noncontact, network based

I. INTRODUCTION

This project builds the fundamental work for a non-contact surface roughness measurement system through the use of Internet-based machine vision system. It allows users to remotely inspect the manufactured part’s surface quality via the Internet. Roughness is a measure of the texture of a surface. The surface roughness inspection is traditionally performed through the use of stylus-type profilometer which correlates the motion of a diamond-tipped stylus to the roughness of the surface under examination. The main disadvantage of such system is the risk of surface scratching and low throughput [1]-[3]. This paper presents the non-contact based roughness measurement techniques developed from the project so that it permits rapid surface roughness measurements with accepted accuracy for use in a web-enabled production environment [4]-[6].

This paper demonstrates the feasibility of using a machine vision system to compute non-contact, optical parameters for the characterization of surface roughness of machined surfaces. Statistical analysis of data collected through experimentation reveals that the vision parameters can discriminate different surface roughness heights and are insensitive to changes in ambient light during measurement. The results of the experimental analysis are used to conclude the feasibility of machine vision for the quality evaluation of surfaces [7]-[9].

II. EXPERIMENTAL SET-UP

Fig. 1 describes the architecture of the remote surface roughness measurement system. The system is composed of a conveyor belt, a machine vision smart camera, an IP Surveillance camera, and a PC-based remote inspection system. The machine vision camera has a built-in processor which allows it to perform real-time algorithms, along with live-time monitoring. The process is designed to be Ethernet based using TCP-IP communication. After a successful TCP handshake, images and extracted measurements can be sent back and forth remotely between the servers and clients. The machine vision camera is properly programmed with necessary
algorithms to calculate the various surface roughness parameters. In the LabVIEW-based Graphic User Interface (GUI), statistical quality algorithms for remote measurement are calculated. The controller communicates with the robot to instruct it to perform the required operations. In addition, the Internet-based vision system is integrated through the IP surveillance camera, displaying the products that are being analyzed. The most significant part of this automation system is the vision module.

As shown in Fig. 2, machine vision packages for the Cognex DVT 540 computer vision system are configured as a set of tools for inspections and measurements [10], [11]. SoftSensors are the working class inside Smart Image Sensors. Every type of SoftSensors serves a specific purpose, and the combination of the SoftSensor results represents the overall result of the inspection. The main groups of SoftSensors include 1. Presence/Absence SoftSensors, 2. Positioning SoftSensors, and 3. Specific Inspection SoftSensors. The SoftSensors help locate the parts to be inspected. In most applications, the type of positioning SoftSensors becomes the key to a successful setup because they locate the part to be inspected and pass an internal reference to the remaining SoftSensors indicating the location of the part. The SoftSensors perform basic checks for detection of features and edges or analyze the intensity level of the pixels in a certain area or linear path. All the SoftSensors perform many tasks from very specific inspections to a user defined task (programmable). The SoftSensors include: Measurement, Math Tools, Readers, Blob Tools, Template Match, ObjectFind, Pixel Counting, Segmentation, SmartLink, Script, and Spectrograph. The script sensor is a programmable tool that can access other SoftSensors for data gathering. DataLink is a built-in tool used to send data out of the system and receive any terminal commands.

Fig. 3 illustrates a high speed 4-axis CNC machine used for the project. The Haas OM-1 office mill features a maximum spindle speed of 30,000 RPM. The table in the CNC machine moving in the X and Y directions is connected to the individual lead screws that provide them with the required motions as programmed in the controller. A series of end milling experiments were conducted with 6061 aluminum alloy at different feed rates and spindle speeds on the CNC milling machine. An axial depth-of-cut of 1.0 mm was kept constant for all the cutting experiments. A three-flute end mill with a radius of 4.76 mm was used for the study of machining surface quality.

III. SYSTEM DEVELOPMENT

The machine vision camera is initially trained to learn the surface profiles and make measurements on the object being tested through teaching software. Each inspection and measurement task is defined through several soft-sensors. A simple view of soft-sensors is to consider them as a specific task defined in software to extract some information from the acquired image. Image acquisition is a crucial step for the non-contact roughness analysis. Several factors can influence the quality of the images. The most important factor is building an environment with adequate illumination. An extremely bright or dim environment will result in ineffective and impracticable data. The images in the system are captured via a smart machine vision camera. It has the function of digitizing the images and processing them in a real-time manner. The acquired image has the dimensions of 640 by 480 pixels and is in grayscale mode. Every pixel provides a
In this project, the correlation of surface roughness $R_a$ with image processing parameters is analyzed and discussed.

Figure 4. Monitoring of the history data

As shown in Fig. 4, the output history data from the machine vision camera can be processed by its teaching software. In addition, the output data, such as mean intensity, standard deviation, and root mean square, are transmitted to GUIs (graphic user interfaces) for quality inspection through the Internet at remote locations.

IV. EXPERIMENTAL RESULTS

Table I shows the experimental results of mean intensity, standard deviation, and root mean square.

<table>
<thead>
<tr>
<th>Surface Roughness (um)</th>
<th>Mean Intensity</th>
<th>Standard Deviation</th>
<th>Root Mean Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>5927</td>
<td>5.28</td>
<td>6.77</td>
</tr>
<tr>
<td>0.1</td>
<td>2373</td>
<td>5.76</td>
<td>7.67</td>
</tr>
<tr>
<td>0.2</td>
<td>3617</td>
<td>7.46</td>
<td>5.89</td>
</tr>
<tr>
<td>0.4</td>
<td>7817</td>
<td>71.71</td>
<td>5.01</td>
</tr>
<tr>
<td>0.8</td>
<td>1315</td>
<td>73.39</td>
<td>7.03</td>
</tr>
<tr>
<td>1.6</td>
<td>1715</td>
<td>161.07</td>
<td>9.52</td>
</tr>
</tbody>
</table>

Figure 5. Mean intensity versus surface roughness

The mean intensity result in the table is plotted in Fig. 5. Equation (6) show a correlation of mean intensity and surface roughness obtained from the figure.

\[ y = 31.02x - 30.93 \]
\[ X = 31.02 \, R_a - 30.93 \] \hspace{1cm} (6)

In a quality inspection system, the upper and lower control limits corresponding to the mean value of \( R_a \) can be determined from the equation. It allows the system to perform decision making for quality inspection with the control limits set up with this equation.

The test samples machined by high speed CNC with different cutting conditions were placed on the loading pallet. A total of nineteen (19) parts were loaded and automatically measured in sequence. To confirm the accuracy, each part was measured forty (40) times. As shown in Table II, the parts are categorized with different spindle speeds and feed rates. For example, sample parts 6 and 7 were machined with the cutting condition of federate 0.84 mm/s and spindle speed is 5,000 rpm.

<table>
<thead>
<tr>
<th>Cutting Conditions</th>
<th>0.84 mm/s</th>
<th>2.11 mm/s</th>
<th>4.23 mm/s</th>
<th>6.35 mm/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,000 rpm</td>
<td>P1</td>
<td>P2</td>
<td>P3</td>
<td>P4, P5</td>
</tr>
<tr>
<td>5,000 rpm</td>
<td>P6, P7</td>
<td>P8, P9</td>
<td>P10</td>
<td>P11, P12</td>
</tr>
<tr>
<td>10,000 rpm</td>
<td>P13, P14</td>
<td>P15, P16, P17</td>
<td>P18</td>
<td>P19</td>
</tr>
</tbody>
</table>

The overall experimental data of the nineteen parts are plotted in Fig. 6 and the standard deviations of all the data distributions are less than 0.2 \( \mu m \). As shown in the Figure, all the results verify the repeatability of the overall experimental data. The comparisons among these data show that the mean intensities and the standard deviations are consistent to the variations of roughness surface for the majority of the tests carried out. It supports the reliability of the developed measurement system.

![Figure 6. Repeatability of the surface roughness data](image1)

Fig. 7 shows the effect of feed at different spindle speeds on surface roughness. According to the collected data, the effect of the feed rate on surface roughness can be observed in the Figure. The trend lines are approximated to be polynomial types according to the plotted data. It can be found that both feed rate and spindle are significant factors in surface roughness. The measured surface roughness is better at low feed rate and high spindle speed. It has been observed that with the increase of feed rate the surface roughness starts to increase and attains the maximum value at a feed rate of 4.0 mm/s and then its goes down.

![Figure 7. Surface roughness versus feed rate](image2)

The graphs of surface finish versus spindle speed with four series of feed rates are plotted in Fig. 8. Among the four feed rates, it only provides good surface finish when the feed rate is 0.84 mm/s. In Fig. 8, the result of the trend lines demonstrates that better surface finish can be produced at higher cutting speeds. If the part is cut with a high spindle speed above 5,000 rpm and a low feed rate less than 2.11 mm/s, the differences between the surface finishes are comparatively low. It can be concluded that the spindle speed plays an important role on surface finish while the low feed rate has a significant effect on surface finish in high speed CNC milling.

![Figure 8. Surface roughness versus spindle speed](image3)

V. CONCLUSION

With the highly repeatable results for the measurement, it shows the robust development of the on-line surface
roughness automation quality control system. The present study considers the detailed examination of surface textures with image data arrays using a machine vision system. Progress has been made towards establishing a model of surface texture based on vision data for real-time remote quality inspection. In the paper, the automated inspection of standard specimen surfaces using computer vision integrated with LabVIEW-based real-time graphic user interface (GUI) has demonstrated the feasibility for online quality control. From the experimental results, the algorithms for statistical process inspection are in good agreement with basic vision-based roughness characterization results. It is noteworthy that it produces better surface finish at higher spindle speeds.

REFERENCES


Dr. Richard Y. Chiou has research background in mechanical engineering with an emphasis on mechatronics. Dr. Chiou’s tremendous experience in sensor monitoring and control includes environmentally conscious manufacturing, Internet-based mechatronics, and web-based quality control. His areas of research emphasis include manufacturing materials, robotics, mechatronics, automation, and sustainable and green manufacturing.

Dr. Yongjin (James) Kwon has many years of engineering experience in industrial and academic settings. He has extensive experience and practical knowledge in current design, manufacturing and quality control. His work has been cited a number of times in high profile journals. He is currently a professor in the Department of Industrial Engineering at Ajou University. Prior to joining Ajou, he was on the faculty of Drexel University, Philadelphia, USA.

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