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].

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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

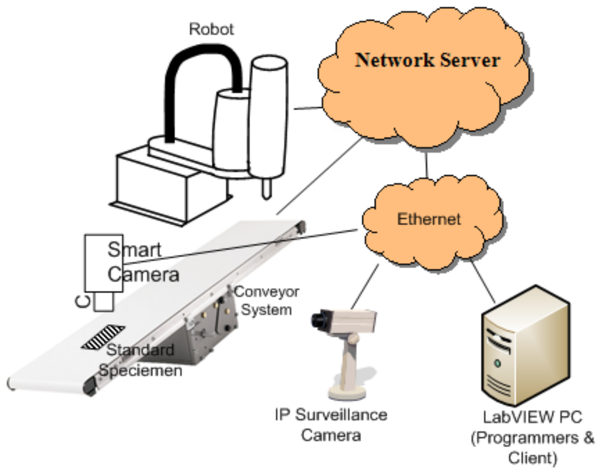

Figure 1. System configuration

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

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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.

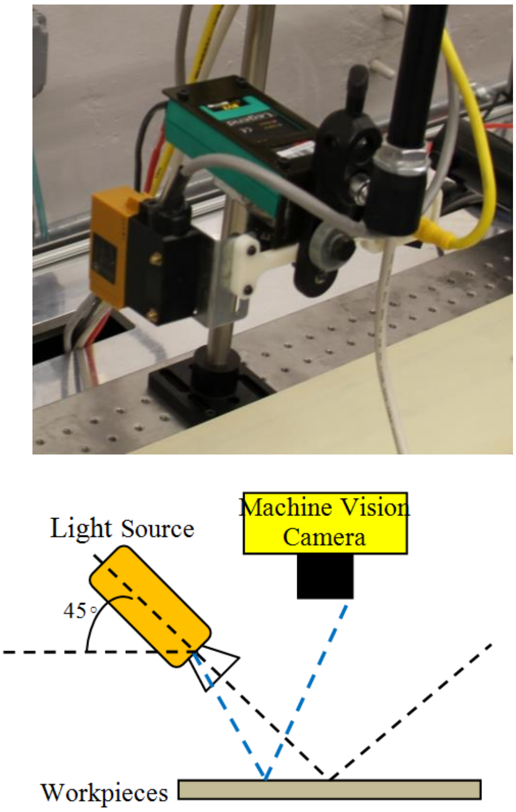

Figure 2. Illumination environment for machine vision camera

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.

Figure 3. CNC mill and machined parts for quality inspection

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 numerical value from 0 to 255 to demonstrate the gray intensity level.

For the machine vision camera, the built-in Softsensors are usually applied for pattern recognition and item positioning. To correlate the surface roughness parameters using optical methods, the front script Softsensors need to be further implemented. After the region of interest is determined by Intensity Softsensors, an algorithm is applied into the front script sensor program. The algorithm to determine the average surface roughness can be summarized with the following equation. According to the definition of surface roughness standard, the average surface roughness R_a expressed as Equation (1). It is one dimensional profile data and it articulates the surface profile with digitizing method.

$$R_a = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \bar{y}\right| \tag{1}$$

where n = Number of sampling data, y_i = Height of roughness irregularities, and $\bar{y}$ = Mean height of profile elements.

To correlate R_a with the optical characteristics, the intensity level is widely used in the image processing method. Because the physical surface height can be expressed in terms of intensity level, the mean intensity level is calculated based on Equation (2). Differing from $\bar{y}$, X is the average intensity of a two dimensional image. With this method, an image can be analyzed in a very short cycle time instead of traditional one dimensional profiling method. The total number of pixels N in the distribution can be computed through Equation (3),

$$X = \frac{1}{N}\sum_{i=0}^{255} F_i X_i \tag{2}$$

$$N = \sum_{i=0}^{255} F_i \tag{3}$$

where F_i = Number of pixels at a certain intensity level X_i, and X_i = Grey intensity level coordinate (i = 0, 1,…, 255).

To express the characteristics of a surface, the standard deviation computation is also included in the experiment. The variance of a surface can be derived from the histogram of an image. To calculate the standard deviation of the grey level distribution, Equation (4) shows the method to determine the value of the standard deviation of the distribution (σ).

$$\sigma = \left(\frac{1}{N-1}\sum_{i=0}^{255} F_i\left(X_i - X\right)^2\right)^{1/2} \tag{4}$$

In addition to standard deviation, the root mean square value is derived based on the height of the grey-level distribution. The mathematical formula of the root mean square (RMS) height of the distribution is expressed in Equation (5).

$$RMS = \left(\frac{1}{N}\sum_{i=0}^{255} F_i^2\right)^{1/2} \tag{5}$$

In this project, the correlation of surface roughness R_a with image processing parameters is analyzed and discussed.

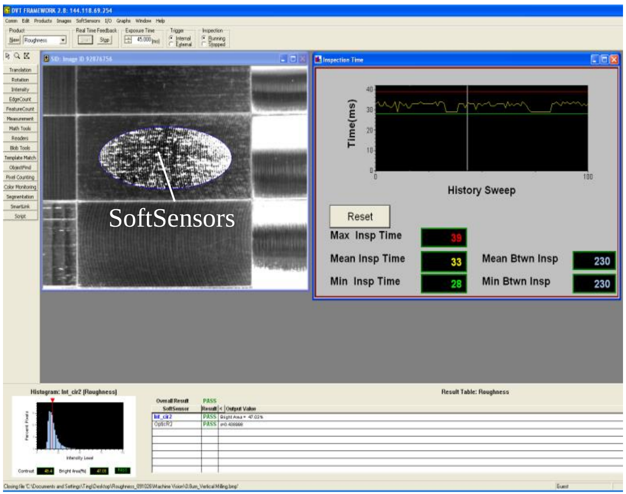

Figure 4. Monitoring of the history data

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 I. Experimental Results

Surface Roughness (um)	Mean Intensity	Standard Deviation	Root Mean Square
R_a	X	σ	RMS
0.05	27	8.80	6.77
0.1	23	5.76	7.67
0.2	36	27.46	5.89
0.4	78	71.71	5.01
0.8	131	72.39	7.03
1.6	171	61.07	9.52

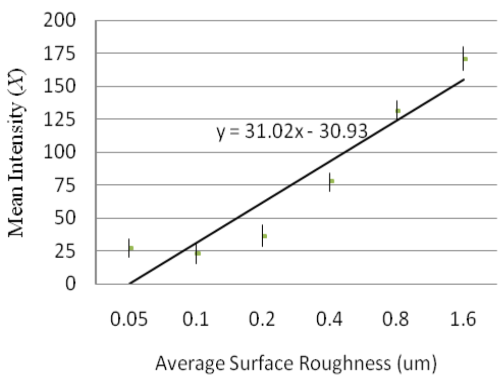

Figure 5. Mean intensity versus surface roughness

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.

$$X = 31.02\,R_a - 30.93 \qquad (6)$$

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 II. CATEGORIZATION OF SAMPLE PARTS

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

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 *um*. 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.

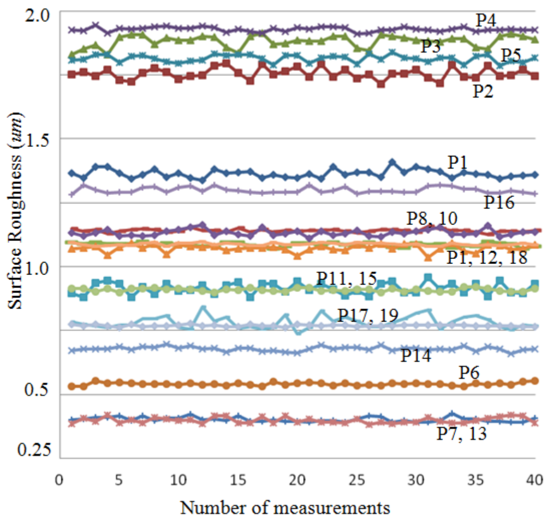

Figure. 6. Repeatability of the surface roughness data

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.

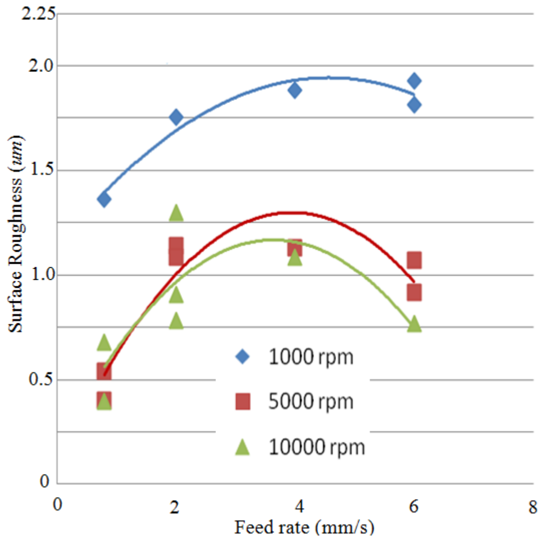

Figure. 7. Surface roughness versus feed rate

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.

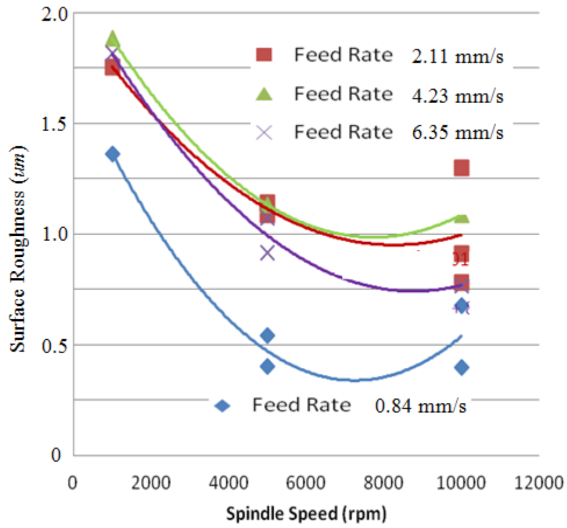

Figure. 8. Surface roughness versus spindle speed

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.

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