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## An Investigation on a Low-cost Machine Vision Measuring System for Precision Improvement

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In this paper, we describe the investigation on a machine vision size measuring system to improve its precision on the basis of the inexpensive devices from the viewpoint of industrial applications. The uniformity and stability of the system were analyzed. The results showed the maximum gray value standard deviation of the edge as 2.6 pixels, and the maximum error of edge detection results was approximately 9 pixels (0.279 mm). The traditional noise reduction algorithms were applied to reduce random noise and dark current noise, and a novel uniform-background algorithm was proposed to improve the uniformity of image background. In addition, a calibration method based on the average gray value of the specified areas was developed to correct gray value errors of the left and right edges. A large number of experiments were carried out using the combined methods, the results showed that the measuring speed was approximately 1 piece per second, and the maximum error of lengths measured by the proposed method was within 1  $\mu\text{m}$ , whereas the maximum error of uncalibrated results was about 0.25 mm. The measuring precision and speed of the proposed methods can meet the requirement of industrial applications.

**Keywords:** Error correction, Size measurement, Uniform-background algorithm

### Introduction

As the thin or crisp objects to be measured can be easily crooked or broken in manual inspections, various machine vision applications are utilized in industrial measurements.<sup>1</sup> In comparison to artificial measurements, measurements based on machine vision have features of fast, high precision and good reproducibility. Much research has been conducted on measuring different objects with machine vision system using a variety of methods.<sup>2-4</sup> These researches developed various algorithms or schemes to obtain the precise measurement results, which were mainly based on high performance but expensive equipments. However, a great deal of measuring work is still achieved by traditional manual or semi automatic measurements in many factories, primarily because the equipment cost is much higher than labour cost, and equipping such a measurement system for each production line is costly and inefficient. In this paper, we investigated the influencing factors of the machine vision, size measuring system consisting of the inexpensive

devices, proposed the software-based method to calibrate pixel gray values of images, and implemented the algorithms to improve the precision of measuring results.

### Experimental equipment and performance analysis

#### Experimental equipment

The low-cost machine vision measuring system used in the experiments mainly included CMOS area scan camera, lens, and LED illumination devices. The CMOS camera was acA2500-14 gm (Basler Inc.) whose resolution was  $2594 \times 1944$ . The lens was M3514-MP (Computar Inc.) with the focal length of 35 mm. The LED illumination device was CV-FL-100  $\times$  100R (MORITEX Inc.), and its optical surface dimension was 100 mm  $\times$  100 mm. The camera and illumination device were powered by the AC power supply (output accuracy within 1%) to reduce voltage fluctuations. A light guide panel was placed on the LED illumination device to expand the illumination area. The dimensions of ceramic substrates which are used as insulating materials in circuits industry were measured, and the length and width were approximately 70 mm and 60 mm respectively.

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### Uniformity analysis

Errors would be introduced by these low-cost devices in image acquisitions, and the pixel gray values would be affected by the uniformity and stability performance of the system. The uniformity was analyzed first. An image of a ceramic substrate was acquired, and the ceramic substrate edges were extracted using the edge detection algorithm based on the Sobel operator. An image sequence  $I$  consisting of 50 images without ceramic substrate was acquired in the same illumination condition, and the average image  $\bar{I}$  was generated. For each edge pixel  $(i, j)$ , the sequence  $S(i, j)$  in the image  $\bar{I}$  consisting of 11 pixels perpendicular to edge coordinates was obtained, and the gray value standard deviations of each  $S(i, j)$  were calculated:

$$\sigma(i, j) = \sqrt{\frac{1}{p} \sum_{m=1}^p (S_m(i, j) - \bar{S}(i, j))^2} \quad \dots (1)$$

where  $S_m(i, j)$  is the gray value of the  $m$ -th pixel of  $S(i, j)$ ,  $p$  is the number of pixels in  $S(i, j)$ , and  $\bar{S}(i, j)$  is the average gray value of all pixels in sequence  $S(i, j)$ .

### Stability analysis

In the stability analysis, an image sequence of 25 ceramic substrate images was acquired, and the edges of all images were extracted.

### Image processing

Software-based methods were proposed to correct the gray value errors and improve the measuring precision. The stability is affected by various causes, among them, the random noise and dark current noise are the predominant factors<sup>5,6</sup>, and the uniformity is mainly related to the camera, illumination and the light guide panel in the system.

### Random noise and dark current noise reduction

Random noise is usually reduced using algorithms based on multiple images in size measurements, as the images acquired at the constant condition can improve the pixel reliability. The method of averaging images was applied to reduce random noise in the experiments.

The dark current noise is a signal-independent noise which is heavily related to the temperature of the working camera<sup>7</sup>, so the calibration was performed after the system was stable. The aperture of the camera was closed during calibrations, and 50 images were captured with an interval of 10 seconds.

No light was received by the CMOS sensors due to the closing of the aperture, the pixel gray values were only affected by random noise and dark current noise. The random noise was reduced using the averaging method and the dark current noise of the pixel  $(i, j)$  was calculated by:

$$\bar{G}_{dark}(i, j) = \sum_{m=1}^n (f_m(i, j) + n_m(i, j))/n \quad \dots (2)$$

Where,  $n$  is the number of images,  $f_m(i, j)$  is the random noise gray value at the pixel  $(i, j)$  of the  $m$ -th image, and  $n_m(i, j)$  is the dark current noise at the pixel  $(i, j)$  of the  $m$ -th image.

### Uniformity calibration

The uniform background can reduce the algorithm complexity and improve the accuracy of edge detection results. As the light guide panel placed on the top of the illumination device couldn't make the illumination uniform enough, the maximum light intensity was received in the centre area of the CMOS sensor, and it was reduced from the centre to boundary. The uniform-background algorithm based on the edge gray values was proposed to calibrate the pixel gray values of background, in which all pixels of the image was calibrated by the calibration matrix.

An image sequence (50 images of a ceramic substrate) was acquired, the ceramic substrate edges of all images were exacted, and  $G_{edge}$  as the average gray value of all edge pixels was calculated. An image sequence (50 images without ceramic substrate) was acquired, and  $\bar{G}$ , the average gray value of pixels at the same coordinate  $(i, j)$  in all images were calculated for reducing the influence of random noise. The  $G_{edge}$  was divided by the gray value of each pixel in  $\bar{G}$  to obtain the calibration matrix  $C$ . All pixels of the image to be measured were multiplied by the corresponding pixels in matrix  $C$ , and the calibrated image was:

$$f_{calibrated}(i, j) = C(i, j) \times f(i, j) \quad \dots (3)$$

Before measurements, an image sequence consisting of 50 images of a standard ceramic substrate was acquired, then two rectangles ( $R_1$  and  $R_2$ ) on left and right parts of the ceramic substrate were marked, the lengths of the rectangles were decided by the short edge lengths, which equalled to 1500 pixels, and the width of the rectangles was 300 pixels. The average gray values ( $G_{r\_ref}$ ) of all pixels in the rectangle  $R_1$  and  $R_2$  were calculated. After the implement of the uniform-background algorithm, the

average gray value ( $G_t$ ) of the  $R_1$  and  $R_2$  of the image to be measured was computed, and the gray values of all pixels of the image were multiplied by the ratio  $G_{r\_ref}/G_t$ .

**Results and Discussion**

**Uniformity analysis**

All the gray value standard deviations  $\sigma(i, j)$  were divided into bins whose width was 1 pixel according to the gray value of the edge pixel  $(i, j)$ . The results are shown in Fig. 1(a), and the average gray values of edge areas are from 199 to 240 and the maximum standard deviation is 2.6 pixels when the gray value is 236.

**Stability analysis**

The gray values of edge pixels with the same coordinate in all images were analyzed, and the results are shown in Fig. 1(b) and (c). The gray value standard deviations and maximum errors are increasing with average gray values, and the maximum error is up to 9 pixels (0.279 mm) when the average gray value is around 230. The analyses demonstrate that the stability and uniformity performance of the system is poor for high precision measurements.

**Random noise and dark current noise reduction**

To guarantee the measuring speed of this online measuring system, the number of averaging images in one measurement was verified, and the result is shown in Table 1. The maximum error of y-coordinate is within 1.406 pixels (about 0.0436 mm) when the number of averaged images is 4, which could meet the demands of industrial applications. Moreover, the gray values of its surrounding pixels were averaged to improve precision during calculations.

The calibration matrix  $\bar{G}_{dark}$  was subtracted from the image to be processed to reduce dark current noise. From the histogram shown in Fig. 2, the

numbers of pixels with gray values greater than 1 are less than before, especially the numbers of pixels with gray values greater than 5 are halved. As a result, the number of pixels whose gray value equal to 0 is increased, and 85.2% dark current noise pixels with gray value greater than 1 were removed.

**Uniformity calibration**

The efforts of uniform illumination are shown in Fig. 3, the background of the calibrated image is more uniform than the original image, and the gray value gradient of the background pixels is decreased.

In addition, the illumination surface of the LED illumination device is square, while the ceramic substrate is a rectangular slice, thus the light received in the long edge areas was less than the short edge

Table1 — The statistics of measured y-coordinates of different averaged images

The number of averaged images	Maximum error (pixel)	Standard deviation (pixel)
2	2.634	0.62057
3	1.791	0.40322
4	1.406	0.35999

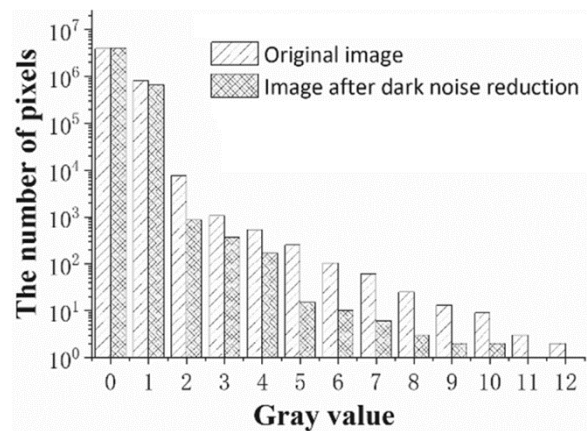


Fig. 2 — The histogram of the original image and the image after dark current noise reduction

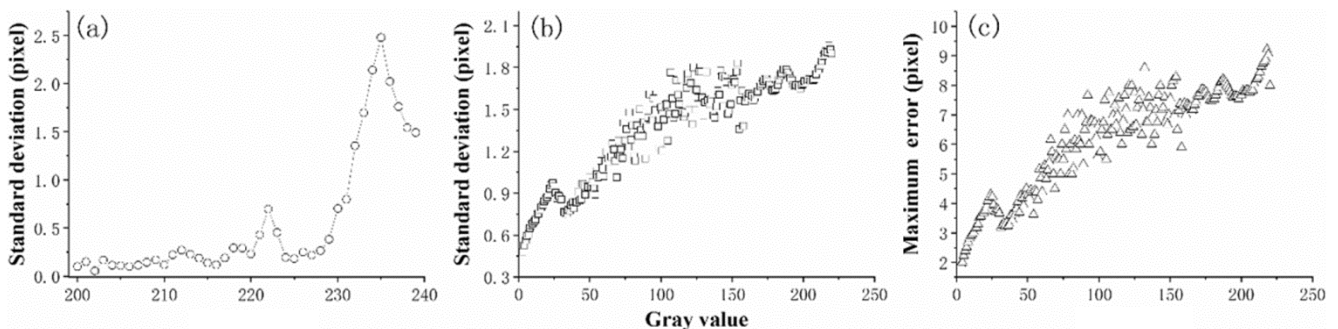


Fig. 1 — (a) The relationship of standard deviations to the gray values in edge areas, (b) the relationship of standard deviations of average gray value to edge pixel gray values, (c) the relationship of maximum errors to edge pixel gray values

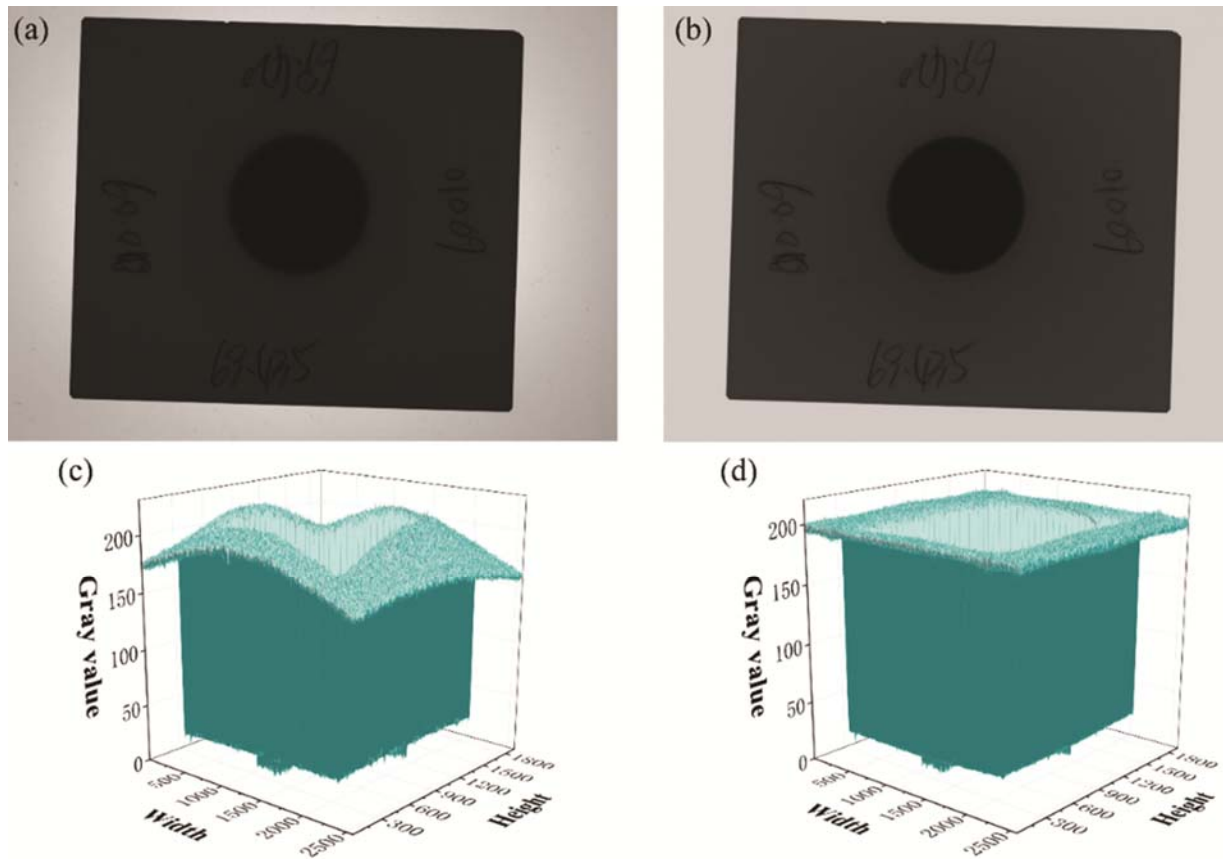


Fig. 3 — The result of the uniform-background algorithm. (a) the original image, (b) the image after calibration, (c) 3D gray value plot of the original image, (d) 3D gray value plot of the image after calibration

Table 2 — The statistics of measured results

Edge	The proposed method					The original method				
	Average (mm)	Min (mm)	Max (mm)	Max error ( $\mu\text{m}$ )	Standard deviation	Average (mm)	Min (mm)	Max (mm)	Max error ( $\mu\text{m}$ )	Standard deviation
Top edge	69.36146	69.3610	69.3618	0.8	1.628E-4	69.495	69.253	69.475	221	2.314E-3
Bottom edge	69.19892	69.1985	69.1992	0.77	1.637E-4	69.301	69.187	69.301	114	8.724E-4
Left edge	59.3315	59.3307	59.3312	0.96	3.238E-4	59.530	59.225	59.472	247	3.627E-3
Right edge	59.29998	59.2996	59.3003	0.66	2.027E-4	59.213	59.156	59.386	230	3.834E-3

areas, i.e., the pixel gray value of the short edge areas was greater. In order to correct the different gray values of the left and right edge areas, an extra calibration was applied after the uniform-background algorithm.

All the algorithms were developed and implemented in Visual Studio 2012 (Windows 7, 64-bit) on a laptop with Intel Core i5-4200M CPU, and the experiments were performed in a room without other light sources. In the experiments, the dimensions of ceramic substrates were measured by a micrometre first, then the ceramic substrate was placed on the measuring platform and measured using the proposed algorithms.

The 50 measurement results of the proposed method and the original method are shown in Table 2. The maximum errors of short edges and the long edges are within  $1 \mu\text{m}$  and  $0.8 \mu\text{m}$  respectively, and the standard deviations are within  $3.238\text{E-}4 \text{ mm}$ . The maximum errors of results measured by the proposed method are less than the uncalibrated results whose maximum error of one edge is approximately  $0.25 \text{ mm}$ . Two previous researches<sup>8,9</sup> have reported the dimension measurements of ceramic substrates, their accuracies were  $0.01 \text{ mm}$  and  $0.0066 \text{ mm}$  respectively, which are greater than the results in the present work. The standard deviations of the left edge are greater than the right edge, it mainly results from

the lens distortion on the left side which cannot be calibrated completely.

The measuring time of one ceramic substrate was defined as the average time of 50 measurements. The processing time of the proposed method and the original methods were 0.973 seconds and 0.648 seconds respectively. In practical measurements, ceramic substrates are placed and removed by manipulators, and the process takes about one second per piece, which indicate that the measuring time of the proposed method is in an acceptable range.

### Conclusions

This study has investigated a low-cost machine vision system, analyzed the influencing factor during image acquisitions and processing, and proposed the software-based methods to improve its precision. The system performance of stability and uniformity was tested. The random noise and dark current noise were reduced, and the uniform-background algorithms were proposed to calibrate the pixel gray values of background and the left and right edge parts. A mass of measurements of ceramic substrates (10 sets, 1000 measurements in each set) was performed to validate the proposed algorithms, and the results showed the maximum error of measured sizes was within 1  $\mu\text{m}$  and the processing time of measuring one ceramic substrate was approximately one second, which could meet the required precision and speed of the practical

application. This proposed method also can be applied in other similar low-cost machine vision measuring system.

### References

- 1 Shirmohammadi S & Ferrero A, Camera as the instrument: the rising trend of vision based measurement, *IEEE Instrum Meas Mag*, **17** (2014) 41–47.
- 2 Korobiichuk I, Podchashinskiy Y, Shapovalova O, Shadura V, Nowicki M & Szweczyk R, Precision increase in automated digital image measurement systems of geometric values, *Adv Mechatronics Sol*, (2016) 335–340.
- 3 Lin C S, Wu J M, Ho C W, Lee C, & Yeh M, Automatic inspection system for measurement of lens field curvature by means of computer vision, *Indian J Pure Appl Phys*, **47** (2009) 708–714.
- 4 Karn A, Ellis C, Arndt R & Hong J, An integrative image measurement technique for dense bubbly flows with a wide size distribution, *Chem Eng Sci*, **122** (2015) 240–249.
- 5 Faraji H & MacLean W J, CCD noise removal in digital images, *IEEE Trans image process*, **15** (2006) 2676–2685.
- 6 Golebiewska U P & Yanagisawa C, How to calibrate your CCD in the dark? a precise CCD calibration method, *Biophys J*, **112** (2017) 296a,
- 7 Abdallah M B, Malek J, Azar A T, Belmabrouk H, Monreal J E & Krissian K, Adaptive noise-reducing anisotropic diffusion filter, *Neural Comput Appl*, **27** (2016) 1273–1300.
- 8 Jiao Liang, Research of software and experiment of high precision measurement and automatic assembly system of precise parts based on machine vision, Master's degree thesis of South China University of Technology, 2016.
- 9 Wang Y Y, Li Y Z, & Han J W, "Digital Image Processing in Auto-sorter of Ceramic Substrate", *Mech Eng Autom* **5** (2009) 002.