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A Novel Subpixel Edge Detection Based on the Zernike Moment

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Abstract: A novel sub-pixel edge detection and center localization algorithm for micro-parts is presented for improving the resolution and accuracy of micro-assembly systems. Firstly, the invariant moments are employed to descript the feature of the micro parts, then, we extracts the edge of micro parts at pixel level using canny operator. Secondly, Zernike orthogonal moments is used to relocate the edge of micro size part at sub-pixel level. Last, we apply least squares ellipse fitting to position the center. Experiment results show that the algorithm, we presented could achieve higher location accuracy and consume less time.

Key words: Sub-pixel edge detection, Zernike orthogonal moments, least squares fitting

INTRODUCTION

With the increased need for the higher precision, the traditional manipulation at the pixel level is not enough. To improve the precision of the micromanipulation system, there are many ways to deal with it such as improving arts of the image sensor and imaging system or increasing the magnification of the object in the imaging system. However, the higher precision of the system by improving the hardware is limited by the cost and realization. So, subpixel technique as a software method to improve the system performance becomes a hotspot of the current research in image processing.

Many mathematical methods have been applied in edge detection to localize the edge at sub-pixel accuracy. CaiHong and Jing (2008) presented an improved algorithm for sub-pixel edge detection is proposed for the disadvantages of traditional edge detections and sub-pixel edge detections, which is used in the measurement of spring length. Sumrain and Giakos (2006) presented explore subpixel detection of back scattered polarimeric signatures from targets in a variety of experimental scenarios utilizing high sensitivity polarimetric detection techniques. Tan *et al.* (2008) proposed a method for recovering the subpixel surface geometry by studying the relationship between the subpixel geometry and the reflectance properties of a surface. Donate *et al.* (2008) presented an efficient algorithm to achieve accurate subpixel matchings for calculating correspondences between stereo images based on a path-based matching algorithm. Compared to point-by-point stereo matching algorithms, path-based algorithms resolve local ambiguities by maximizing the cross correlation along a path, which can be implemented efficiently using dynamic programming.

As the moment is based on the integration computing, it is considered as the stability characteristics for the reason of not sensitive to noise and has been applied in image recognition and other fields. In this paper, we employ the Zernike moment edge detection method to position the edge at sub-pixel level accuracy.

In order to improve the resolution and accuracy for micro-assembly system, a novel sub-pixel edge detection and center localization algorithm for micro-parts is presented. Firstly, extracts the micro parts edge at pixel level using canny operator. Secondly, Zernike orthogonal moments is used to relocate the edge of micro size part at sub-pixel level. Last, we apply least squares ellipse fitting to position the center. Experiment results show that this algorithm could achieve higher location accuracy and consume less time. It can be concluded that this algorithm is efficient to implement subpixel-level edge detection and improve measuring accuracy in micromanipulation.

SUBPIXEL EDGE ALGORITHM

Subpixel technique for object location is often based on the feature detection. Firstly, the coarse location is got by the feature detection at pixel level; secondly, a local image pattern is adopted to refine the location at sub-pixel level.

For the image center to be located, the centroid method and the gray centroid method are often adopted.

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Compared with the gray centroid method, The centroid method is simple, but it is applied only for the binary image. In the edge location, we can consider two steps: one is the ideal edge extraction method and the other is the gray edge extraction. Generally, The coarse edge is extracted firstly by using the classical edge algorithm, which can calculates the local maximum gradient. And then the sub-pixel edge algorithm is used to refine the coarse edge.

The common subpixel edge algorithm can be classified to three classes: reconstruction techniques, interpolation techniques and moment-based techniques (Park *et al*., 2003; Broadwater and Chellappa, 2007; Dimitris *et al*., 2001; Kerekes and Baum, 2002; Wu *et al*., 2007):

- Moment-based techniques use information derived from the gradient to compute statistical measures such as the gray-level moments, spatial moments, centroid values, local energy values, expectation values, etc
- Reconstruction techniques is to reconstruct the continuous gradient profile from the discrete signal obtained from the coarse location. The main reconstruction kernel function is sinc function, Gaussian function and splines function
- For the interpolation techniques, we adopt often the interpolating gradient function. The main difference between the interpolation techniques and the reconstruction technique is that the interpolating function parameters are valid only for the neighborhood of the coarse and the reconstruction function can be used in the complete gradient profile

THE NOVEL SUBPIXEL EDGE LOCATION ALGORITHM

To identify the multi-micro parts, we must obtain the feature of the objects image. Therefore, the invariant moments is employed by us to descript the feature for the invariance of the translation, rotation and scale.

Invariant moments theory: In the pattern recognition field, the shape feature of image is an important feature target for extraction. Some basic two-dimensional shape features have a direct relationship with the moment. Because the invariant moments have many advantages such as translation, reduction and rotation invariance, Therefore, we employ the invariant moments to describe the feature attributes of image.

Image (p+q) order moments: We presume that f(i, j) represents the two-dimensional continuous function. Then, it's (p+q) order moments can be written as Eq. 1:

$$M_{pq} = \int\int i^p j^q f(i,j)\,di\,dj \tag{1}$$

In terms of image computation, we use generally the sum formula of (p+q) order moments shown as Eq. 2:

$$M_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) i^p j^q \quad (p,q = 0,1,2...) \tag{2}$$

where, p and q can choose all of the non-negative integer value, they create infinite sets of the moment. According to papulisi's theorem, the infinite sets can determine completely two-dimensional image. For the binary image, if its background value is 0 and the region value is 1, zero-order moment can represent area of the shape region. So, we can obtain the result from image moment divided by zero-order moment, it has the invariance of the shape scale changes.

Image (p+q) order center moment: In order to ensure location invariance of the shape feature, we must compute the image (p+q) order center moment. That is, calculates the invariant moments using the center of object as the origin of the image. The center of object (i', j') can obtain from zero-order moment and first-order moment. The center-moment formula can be shown as Eq. 3:

$$M_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)(i-i')^p (j-j')^q \quad (p,q = 0,1,2...) \tag{3}$$

If we use the area of the shape to normalize the center moment, namely, use M_{pq}/M'_{00} to replace M_{pq}, then the invariant moments obtained can meet the independence of the scale changes of the shape.

At present, most studies about the two-dimensional invariant moments focus on extracting the moment from the full image. This should increase the computation amount and can impact on the real-time of system. Therefore, we propose the invariant moments method based on edge extraction, which gets firstly the edge image and then achieve the invariant moments feature attribute. Obviously, it keeps the region feature of moment using the propose method. In addition, being the role of edge detection, the data that participate calculation have made a sharp decline, reducing greatly the computation amount.

The invariant moments is the function of the seven moments, meeting the invariance of the translation, rotation and scale. The calculation formula is shown in Eq. 4:

$$
\begin{aligned}
&\Phi_1 = m_{20} + m_{02}\\
&\Phi_2 = (m_{20} - m_{02})^2 + 4m_{11}\\
&\Phi_3 = (m_{30} - 3m_{12})^2 + (3m_{21} - m_{03})^2\\
&\Phi_4 = (m_{30} + m_{12})^2 + (m_{21} + m_{03})^2\\
&\Phi_5 = (m_{30} - 3m_{12})^2(m_{30} + m_{12})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2]\\
&+(3m_{21} - m_{03})(m_{21} - m_{03})[3(m_{30} + m_{12})^2 - (m_{21} + m_{03})^2]\\
&\Phi_6 = (m_{20} - m_{02})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2] +\\
&4m_{11}(m_{30} + m_{12})(m_{21} + m_{03})\\
&\Phi_7 = (3m_{12} - m_{30})^2(m_{30} + m_{12})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2]\\
&-(m_{03} - 3m_{21})[3(m_{30} + m_{12})^2 - (m_{21} + m_{03})^2]
\end{aligned}
\tag{4}
$$

After feature extraction, the micro parts have been identified. In order to manipulate the micro object, we must obtain the edge and center of object. Two steps processing is adopt to extract the edge. One is the edge location at pixel-level, the other is the edge extraction and center location at subpixel-level using the method that we presented.

Edge location at pixel level: The aim of the edge location operator at pixel-level is to find all the possible edge points in the image. Before detection, it is necessary to do the filter process for image to eliminate the noise points in the pixel-level using mid-value filter algorithm. Then, we use the canny operator to extract the edge of micro parts at pixel level. Figure 1a and b is the original image of operation targets and manipulator in microscopic environment. Figure 2a and b show the edge image of operation targets and manipulator in microscopic environment using canny operator.

Sub-pixel edge detection using Zernike orthogonal moments combined with least squares ellipse fitting. The kernel of Zernike moments is the set of orthogonal.

Zernike polynomials defined over the polar coordinate space inside a unit circle (Haddadnia *et al*., 2003; Arvacheh and Tizhoosh, 2005). The two dimensional Zernike moments of an image intensity function are defined as:

$$\xi_{nm} = \frac{n+1}{\pi}\iint_{x^2+y^2\le 1} f(x,y) * \overline{V}_{nm}(x,y)dxdy \tag{5}$$

where, $V_{nm}(x,y)dxdy = \overline{V}nm(\rho,\theta) = R_{nm}(\rho)e^{-jm\theta}$ is the Zernike polynomials.

The real valued radial polynomials:

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} \frac{(-1)^s(n-s)!}{s!(\frac{1}{2}(n+|m|)-s)!(\frac{1}{2}(n-|m|)-s)!}\rho^{n-2s} \tag{6}$$

Zernike moments are rotation-invariant: the image rotation in spatial domain simply implies a phase shift to the Zernike moments.

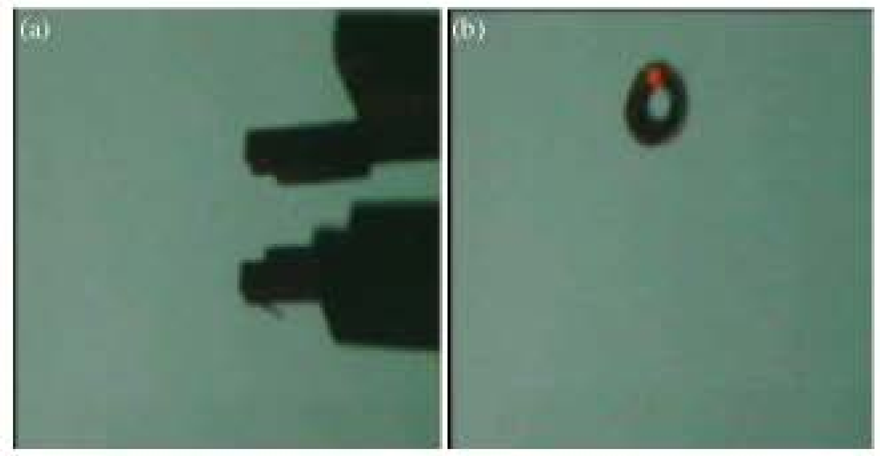

Fig. 1: The original image of operation targets and manipulator in microscopic environment; (a) micro gripper and (b) cylindrical metal part

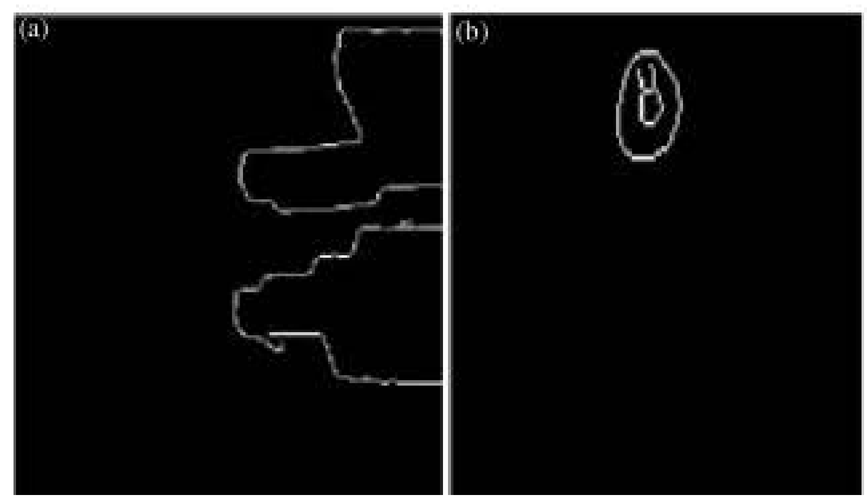

Fig. 2: The edge image of operation targets and manipulator in microscopic environment using canny operator; (a) micro gripper and (b) cylindrical metal part

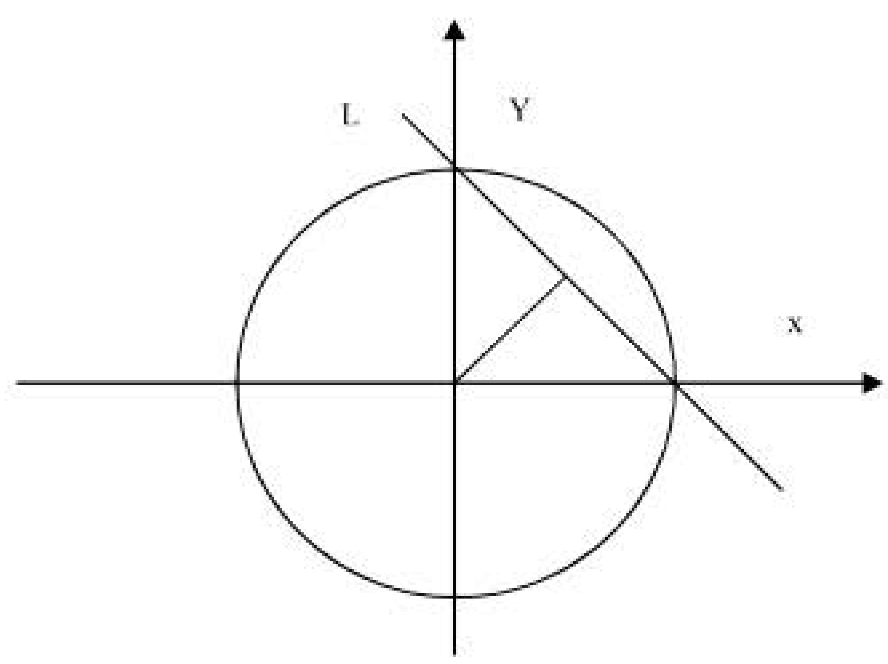

Fig. 3: The sub-pixel step edge model

Zernike moment is the integral form operator, so it cannot be sensitive to noise. The ideal step edge model is shown as Fig. 3, where h is the step height; L is the straight line of edge, d is the vertical distance from the disk center to the edge, d∈[-1, 1]; θ is the angle of edge with the x-axis.

The Zernike moments z^r_{nm} of rotated image $f^r(x, y)$ and the Zernike moments z_{nm} of original image f (x, y) have the following relationship:

$$z'_{00} = z_{00}$$
$$z'_{11} = z_{11}e^{j\theta}$$
$$z'_{20} = z_{20}$$

According to this relationship and definition of Zernike moments, the edge parameters such as d, h and b, which b is the gray background of circle, can be worked out. And the relationship is defined as follows:

$$d = \frac{\xi_{20}}{\xi_{11}} e^{-j\theta} \tag{7}$$

$$h = \frac{3\xi'_{11}}{2(1-d^2)^{3/2}} = \frac{3\xi_{11}}{2(1-d^2)^{3/2}} e^{-j\theta} \tag{8}$$

$$b = \frac{\xi_{00} - h\pi/2 + h\arcsin d + hd\sqrt{1-d^2}}{\pi} \tag{9}$$

Zernike moments can be computed using the template. We can obtain the template by sampling the shaded area as shown in Fig. 4. Through the convolution operation of the three templates and images, we can also obtain the edge parameter of each pixels, then we do the threshold operation to l and k and obtain the accuracy of the location of the micro-part edge.

Consider the mask, the pixel-level edge points (x, y) can be modified to sub-pixel level points (x_s, y_s) according to Eq. 7-9.

$$\begin{bmatrix} x_s \\ y_s \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + N/2 * d \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix} \tag{10}$$

Now, we employ least squares ellipse fitting to locate the micro-part center. We presume that the edge coordinate of cylindrical metal part at pixel level is (i, j). Its 8-neighborhood is been shown in Fig. 5. We obtain the image information of its gradient direction at 8-neighborhood and then can obtain the center location of cylindrical metal part at sub-pixel level by employed the least squares curve fitting.

After feature identification of elliptic and obtaining the edge data, we employ least squares optimization algorithm to do the ellipse fitting for sub-pixel center positioning of elliptic. We presume that the data of edge coordinate of elliptic is shown as Eq. 11:

$$G = (x_1, y_1), (x_2, y_2), (x_3, y_3), ..., (x_n, y_n) \tag{11}$$

The objective function of mean square error is shown as:

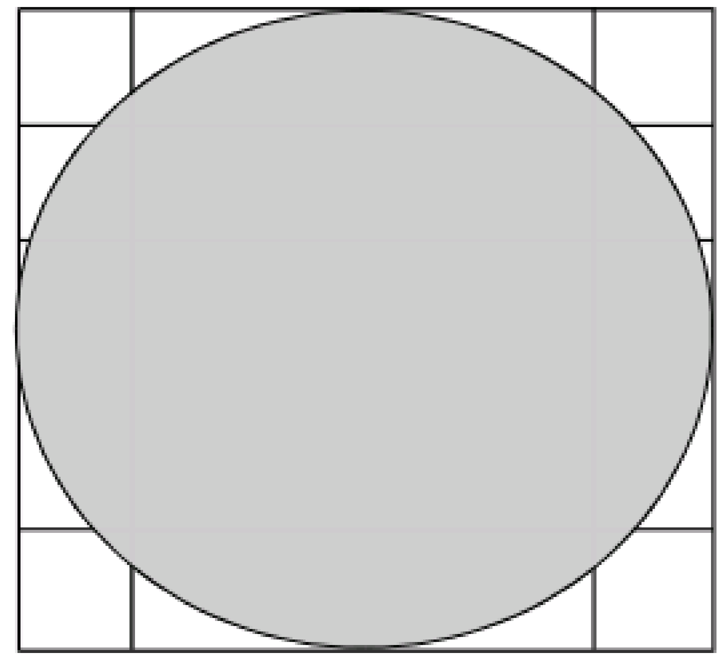

Fig. 4: The image sampling window of 5 H 5 pixels

(I-1,j-1)	(i-1,j)	(i-1,j+1)
(i,j-1)	(i,j)	(i,j+1)
(i+1,j-1)	(i+1,j)	(I+1,j+1)

Fig. 5: The 8- neighborhood of cylindrical metal part at sub-pixel level

$$\delta^2 = \sum_{i=1}^{n} [\frac{(x_i - x')^2}{a^2} + \frac{(y_i - y')^2}{b^2} - 1]^2 \tag{12}$$

Now, we set the initial value of computation:

$$x' = \frac{Max(x_i) + Min(x_i)}{2}$$
$$y' = \frac{Max(y_i) + Min(y_i)}{2}$$
$$a = \frac{Max(x_i) - Min(x_i)}{2}$$
$$b = \frac{Max(y_i) - Min(y_i)}{2} \tag{13}$$

We apply the nonlinear optimization method that reported by Levenberg-Marquardt to do the non-linear recursive search for the objective function shown in Eq. 11 and then it can be obtained the ellipse center.

We set the δ^2 in Eq. 12 where is the minimum, it can be obtained center coordinates of elliptic, which achieve cylindrical metal part centers positioning at sub-pixel level.

EXPERIMENTS

Micromanipulation robotic system includes 3D micro-move platform, micro-gripper driven by piezoelectricity, micro-adsorption hand driven by vacuum, microscope vision and so on. Micro-vision platform uses a two-way orthogonal optical vision, which includes the horizonal microscopes vision and the vertical microscopes vision. The system construction of experiment is shown in Fig. 6.

The main task of classification is to identify and classify the manipulator (micro gripper, vacuum suction) and operation targets (cylindrical metal part, glass ball), which can provide convenience for follow-up visual servo task. In order to obtain the center coordinate of micro cylindrical metal part for the follow micro assembly tasks, we extract the edge of micro gripper and micro cylindrical metal part in the first step using the robert edge operator and the canny operator at pixel level. The second step is that employs the proposed method to locate the center of micro cylindrical metal part at subpixel level. Figure 7a and b show the original image of operation targets and manipulator in microscopic environment. Figure 8a-c and 9a-c show the image after center localization of operation targets and manipulator in microscopic environment in horizontal view fields and in vertical view fields using the robert edge operator and canny edge operator and the proposed method.

We can see from the Fig. 7 and 9 that the canny operator is better than the robert operator in refinement and testing accuracy, which can be benefit from the canny operator's good noise detection, with the ratio of signal to noise can obtain optimization. Compared with the robert operator and canny operator, it can be seen that the proposed method can obtain higher precision in edge extraction, with the refine edge at sub-pixel level. We obtain the center location of cylindrical metal part by micro-scale (X-axis direction) is 32.457, with pixel unit. We presume 32.457 is the ideal setting for the purpose of its location.

Table 1 shows the result of edge detection using three methods. It can be seen from Table 1 that the smallest standard deviation can be obtain using the method we proposed, which shows that it has the highest measurement accuracy.

Fig. 6: The system construction of three hands cooperation micromanipulation

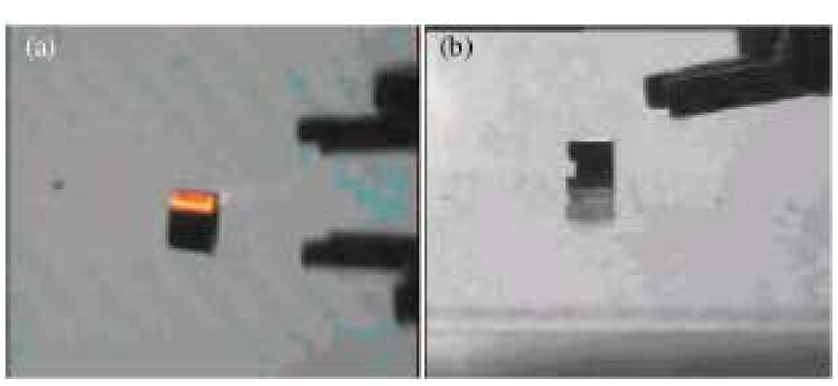

Fig. 7: The original microscopic image of object and the end effector in vertical; (a) Vertical view field of microscopic images and (b) Horizontal view field of microscopic images view field

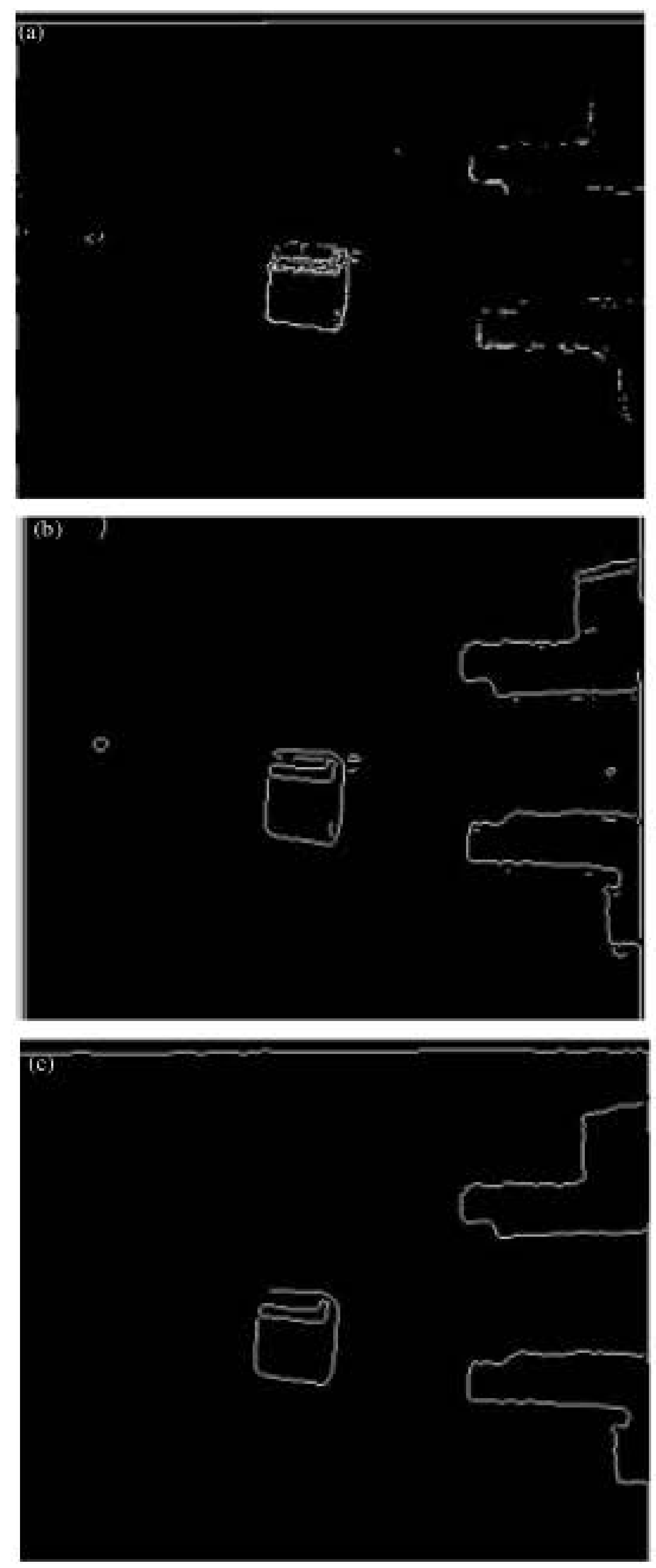

Fig. 8: The object center image and the end center of the end effector after center localization in vertical view fields; (a) Robert operator edge extraction, (b) Canny operator edge extraction and (c) The proposed edge extraction

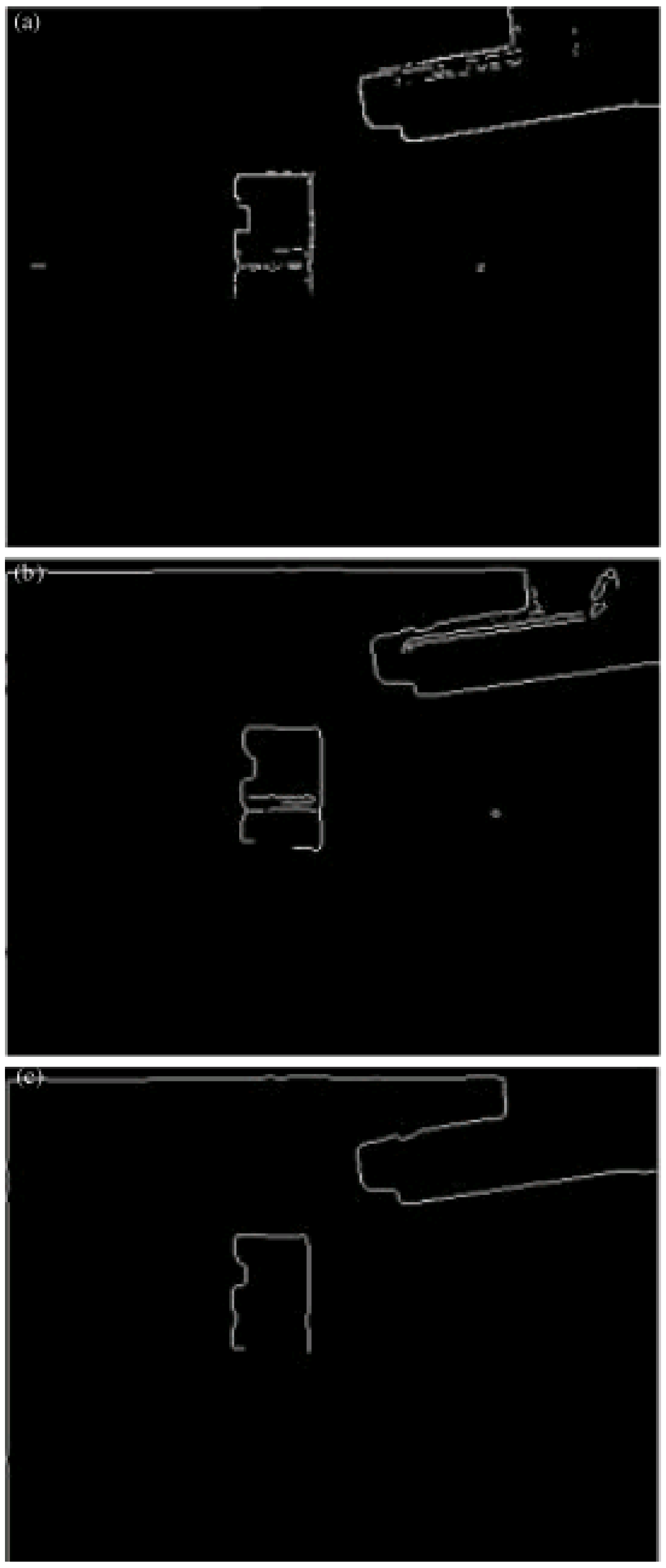

Fig. 9: The object center image and the end center of the end effector after center localization in horizontal view fields. (a) Robert operator edge extraction (b) Canny operator edge extraction and (c) The proposed edge extraction

Table 1: The result of edge detection using three methods (Unit: Pixels)

Algorithm	Times 1	2	3	4	5	Detection precision
Robert	32.398	32.44	32.41	32.435	32.312	δ = 2.01
Canny	32.448	32.455	32.457	32.45	32.446	δ = 1.43
Proposed	32.457	32.457	32.458	32.455	32.456	δ = 0.171

Next, we have adopted the proposed method to obtain the center coordinates of cylindrical metal part and calculated the average value of center coordinates. At last, we calculated the location deviation of 13 images of the center coordinates and the average. Table 2 shows the standard deviation of the center coordinates.

Table 2: The standard deviation of center coordinates (x', y') of elliptic (unit: pixels)

No.	ε_x	ε_y
1	0.0210	0.0201
2	0.0212	0.0196
3	0.0212	0.0204
4	0.0214	0.0214
5	0.0220	0.0201
6	0.0211	0.0199
7	0.0221	0.0202
8	0.0215	0.0211
9	0.0214	0.0206
10	0.0212	0.0199
11	0.0225	0.0212
12	0.0209	0.0199
13	0.0213	0.0200

It can be seen from the Table 2 that the proposed method has a good repeatability positioning accuracy within 0.06 pixels for the coordinates of elliptic center image. we can see also that the method has good adaptability and robustness for the small changes in brighten.

Now, we give the comparison of detection speed of the canny operator and robert operator and the proposed algorithm. Presumed the image size is 440×320, the canny operator time consuming is 2.58 sec and the robert operator time consuming is 1.32 sec and the proposed method time-consuming is 0.42 sec. Therefore, we can draw the conclusion that the proposed algorithm can meet the high precision goal of real time image processing and measurement.

CONCLUSION

A novel sub-pixel edge detection and center localization algorithm for micro-parts is presented for improving the resolution and accuracy of micro-assembly systems. Firstly, the invariant moments is employed to descript the feature of the micro parts, then, we extracts the edge of micro parts at pixel level using canny operator. Secondly, Zernike orthogonal moments is used to relocate the edge of micro size part at sub-pixel level. Last, we apply least squares ellipse fitting to position the center. Experiment results show that the algorithm we presented could achieve higher location accuracy and consume less time.

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