New method for subpixel image matching with rotation invariance by combining the parametric template method and the ring projection transform process

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Abstract. The need for accurate and efficient computation of template matching prevails in many applications. However, a challenge in template matching is to obtain high accuracy that involves acceptable computation complexity and is robust to rotation. A new subpixel template matching approach that combines the parametric template method and the ring projection transform process is proposed. It not only achieves subpixel accuracy in location, but also offers rotation invariance in the subpixel template matching. Furthermore, our approach is conceptually simple, easy to implement, and very efficient because no iterative steps are involved. The simulated results show that our approach enjoys very high precision in the presence of image rotations. Experiments with real-world scenes demonstrate that the proposed method can reach subpixel accuracy for finding the distance between two target objects in the presence of rotations and translations. This indicates that our approach is suitable for accurate on-line template matching with scene rotations and translations.
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Subject terms: subpixel; rotation invariance; normalized correlation; template matching; ring projection transformation; parametric template.

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1 Introduction

Template matching means matching an image with a template that is known. The need for accurate and efficient computation of template matching prevails in many applications, including remote sensing 3-D reconstruction, photogrammetry, and automatic inspection in industry. However, the accuracy of template matching is limited by the resolution of the CCD camera, which can be increased only at very high cost. The possibility has been suggested of using subpixel feature localization algorithms in order to reach superresolution performance with low-cost CCD cameras.[1]

In order to achieve very precise pattern alignment, normalized correlation (NC) has been proven to be a robust and reliable template-matching technique used in industry.[2,3] Nevertheless, there are two major problems in the traditional template-matching method. One is that the position estimation accuracy is limited to one pixel, and the other is that the matching result is sensitive to rotation.

Among the workers who report subpixel matching precision, Wu, Zhou, and Shi[4] proposed an algorithm that combines resampling with surface fitting: it resamples the model first, and then matches the image exactly by the surface-fitting method. The advantage of this method is that not only can subpixel accuracy be obtained by resampling, but also matching time can be saved by the surface-fitting method. The matching accuracy depends on how accurately the new reference image approximates (by resampling) the original image. Gleason, Hunt, and Jatko[5] described a correlation interpolation method that uses a set of NC data generated by correlating a stored reference template against a test-image search area that is believed to contain the feature of interest. A three-dimensional paraboloidal surface is fitted to the data to interpolate the precise point of maximum correlation, or degree of similarity. Normalizing the correlation surface makes the algorithm robust in the presence of illumination variations and local flaws. The accuracy of this method depends on how well the correlation function around the peak approximates a parabola. Foroosh, Zerubian, and Berthod[6] derived analytic expressions for the phase correlation of downsampled images and showed that for downsampled images the signal power in the phase correlation is not concentrated in a single peak, but rather in several coherent peaks close to each other. These coherent peaks correspond to the polyphase transform of a filtered unit impulse centered at the point of registration. The analytic results provide a closed-form solution to subpixel translation estimation. The advantage of the phase correlation is that it can be used when images are seriously distorted in either geometry or intensity. The method provides a very efficient means of registering images at subpixel accuracy across different spectral bands. Its main drawback is its limitation to translations. Indeed, among all the schemes mentioned, none can overcome the changes due to rotation.

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Stone et al.[7] developed a direct Fourier-based algorithm for performing image-to-image registration to subpixel accuracy, where the image differences are restricted to translations and uniform changes of illumination. The algorithm detects the Fourier components that have become unreliable estimators of shift due to aliasing, and removes them from the shift-estimate computation by the frequency-masking method. In the presence of aliasing, the average precision of registration is a few hundredths of a pixel. Cole-Rhodes et al.[8] demonstrated that mutual information may be better suited for subpixel registration in that it produces consistently sharper optimal peaks than correlation. Thévenaz, Ruttiman, and Unser[9] reported an elegant pixel-based iterative algorithm that is able to register to high precision. Although these algorithms can be adapted to deal with rotations, the computations become iterative rather than direct. The parametric template method proposed by Tanaka et al.[10] provides a subpixel matching scheme that yields a high-precision estimation of the object position. However, the computational cost becomes very high when the template matching involves compensation for rotations. Therefore one of the challenges in template matching is how to obtain high accuracy with less computation complexity and robust to rotation.

In this paper, we are interested in the refinement of coarsely matched images to subpixel accuracy. Therefore we confine our attention to the problem of subpixel translation and rotation. A new approach that enables fast subpixel matching between a reference template and a scene image with rotations and translations is proposed. The method combines the parametric template (PT) method[10] with the ring projection transform (RPT) process. The RPT process converts the 2-D template in a circular region into a 1-D gray-level signal as a function of radius. The advantages of the RPT process are that it offers rotation invariance in the template matching and reduces the computational complexity of NC.[11] Subpixel template matching is achieved more accurately than with the conventional method by constructing a PT that interpolates between images of an object shifted by one pixel.[10] Therefore, the merits of our approach are that not only can subpixel accuracy be obtained by the PT method, but also rotation invariance is achieved by the RPT process. It does not need feature-based matching of corresponding points, and it allows estimation of subpixel accuracy by a direct linear calculation rather than an iterative calculation.

The remainder of this paper is organized as follows: Section 2 first introduces the RPT process for a 2-D gray-level template and the similarity measure of NC. Section 3 describes the principle of subpixel template matching by the combination of the PT method and the RPT process. Section 4 presents generation of simulated images with subpixel translations and rotations by the downsampling algorithm. In Sec. 5, various simulation results are reported and compared. The experiments with real-world scenes are tested and reported in Sec. 6. Finally, concluding remarks are found in Sec. 7.

2 Ring Projection Transformation (RPT)

In order to make matching invariant to rotation, the RPT[11–14] process was proposed. The RPT process reduces a 2-D image to a 1-D vector. Let us denote a template, whose size is $M \times N$, by $T(x,y)$. The RPT process of the template is given as follows: First, the center point of $T(x,y)$, denoted as (x_c, y_c), is derived, and subsequently, the template $T(x,y)$ Cartesian frame is transformed into a polar frame based on the following relations:

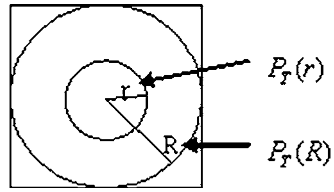

Fig. 1 Concept of RPT for a template.

$$x = r \cos \theta, \tag{1}$$

$$y = r \sin \theta, \tag{2}$$

where $r=\text{int}([(x-x_c)^2+(y-y_c)^2]^{1/2})$, $r \in [0,R]$, $R=\min(M,N)$, $\theta \in (0,2\pi]$.

The RPT of the template $T(x,y)$ at radius r, denoted as $P_T(r)$, is defined as

$$P_T(r) = \frac{1}{S_r} \sum_k T(r \cos \theta_k, r \sin \theta_k), \tag{3}$$

where S_r is the total number of pixels falling on the circle of radius $r=0,1,2,\ldots,R$. Since $P_T(r)$ is defined as the mean of pixel intensities along the circle, centered on the template, whose radius is r (as shown in Fig. 1), $P_T(r)$ values of all rings in the template have equal importance in the computation of correlation.[11] Furthermore, since a RPT is constructed along circular rings of increasing radii, the derived 1-D ring projection template is invariant to rotation of its corresponding 2-D image template. Figure 2 shows a template image in two distinct orientations and the plots of RPT values as functions of the radius r. It can be seen from the figure that the two ring projection plots are almost identical, despite the orientation difference. In order to find the RPT along concentrate circles effectively, we use a lookup table whose diameter is set to the size of the template.[14] Then the RPT is obtained simply by summing the pixel

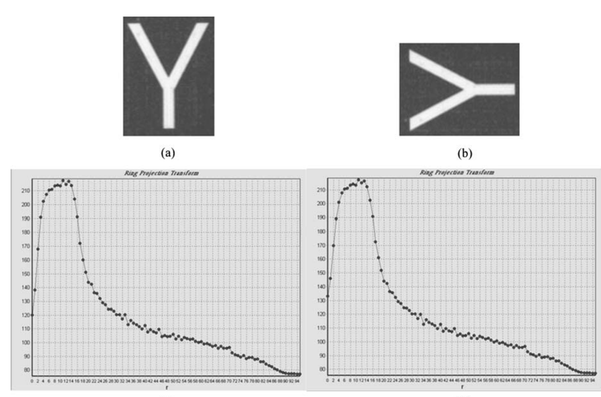

Fig. 2 Image of character Y in two different orientations: (a), (b) the original images; (c), (d) the corresponding plots of RPT.

values along a concentric circle within the template results.

For the matching process, the NC is adopted in the measurement of similarity. Let

$$\mathbf{P}_T=[P_T(0),P_T(1),\ldots,P_T(R)] \tag{4}$$

and

$$\mathbf{P}_S=[P_S(0),P_S(1),\ldots,P_S(R)] \tag{5}$$

represent the ring projection vectors of the reference template and the scene subimage, respectively. The NC between the ring projection vectors $\mathbf{P}_T$ and $\mathbf{P}_S$, denoted by $\langle \mathbf{P}_T,\mathbf{P}_S\rangle$, is defined as

$$\langle \mathbf{P}_T,\mathbf{P}_S\rangle = \frac{\left[(R+1)\sum_{r=0}^{R} P_T(r)P_S(r)-\sum_{r=0}^{R} P_T(r)\sum_{r=0}^{R} P_S(r)\right]^2\times 100}{\left\{(R+1)\sum_{r=0}^{R} P_T(r)^2-\left[\sum_{r=0}^{R} P_T(r)\right]^2\right\}\left\{(R+1)\sum_{r=0}^{R} P_S(r)^2-\left[\sum_{r=0}^{R} P_S(r)\right]^2\right\}}. \tag{6}$$

With this definition, the value of $\langle \mathbf{P}_T,\mathbf{P}_S\rangle$ is unaffected by rotations and linear changes (constant gain and offset) in the reference template and the scene subimage. In addition, the dimensional length of the ring projection vector is only $R+1$. This significantly reduces the computational complexity for $\langle \mathbf{P}_T,\mathbf{P}_S\rangle$.

3 Principle of Subpixel Template Matching by the Combination of PT and RPT

The proposed method for subpixel template matching is inspired by the PT method in Ref. 10. However, the PT method incurs an increase of computational complexity when the scene images involve the changes of rotation. In order to achieve rotation invariance and computational efficiency, a new method using the combination of PT and RPT (CPTRPT) is proposed. In CPTRPT, a PT $\mathbf{P}_{T_p}$ is constructed from a set of base ring projection vectors $(\mathbf{P}_{t_0},\mathbf{P}_{t_1},\ldots,\mathbf{P}_{t_8})$ that are the RPTs at the center point (x_c,y_c), and its eight surrounding points of the template image as given by

$$\mathbf{P}_{T_p}=\frac{\mathbf{P}_{t_0}\omega_0+\mathbf{P}_{t_1}\omega_1+\cdots+\mathbf{P}_{t_8}\omega_8}{|\mathbf{P}_{t_0}\omega_0+\mathbf{P}_{t_1}\omega_1+\cdots+\mathbf{P}_{t_8}\omega_8|},\quad 0.0\le\omega_i\le 1.0, \tag{7}$$

$\sum_{i=0}^{8}\omega_i=1.$

Figure 3 shows the construction of a PT $\mathbf{P}_{T_p}$ in CPTRPT. The NC between the scene subimage vector $\mathbf{P}_O$, whose center (x_0,y_0) is the optimal matching point, and a PT $\mathbf{P}_{T_p}$ becomes $\langle \mathbf{P}_{T_p},\mathbf{P}_O\rangle$. Consequently, the problem we want to solve becomes a constrained optimization, that is

$$\max_{(\boldsymbol{\omega})}\langle \mathbf{P}_{T_p},\mathbf{P}_O\rangle \quad \text{subject to} \quad \sum_{i=0}^{8}\omega_i=1. \tag{8}$$

This problem can be solved by the Lagrange multiplier method. The solution $\boldsymbol{\omega}$ is given by

$$\boldsymbol{\omega}=\frac{H^{-1}\mathbf{G}}{\mathbf{n}\cdot H^{-1}\mathbf{G}}, \tag{9}$$

where $\boldsymbol{\omega}$, H, $\mathbf{G}$, $\mathbf{n}$ are

$$\boldsymbol{\omega}=\begin{bmatrix}\omega_0\\ \vdots\\ \omega_8\end{bmatrix}, \tag{10}$$

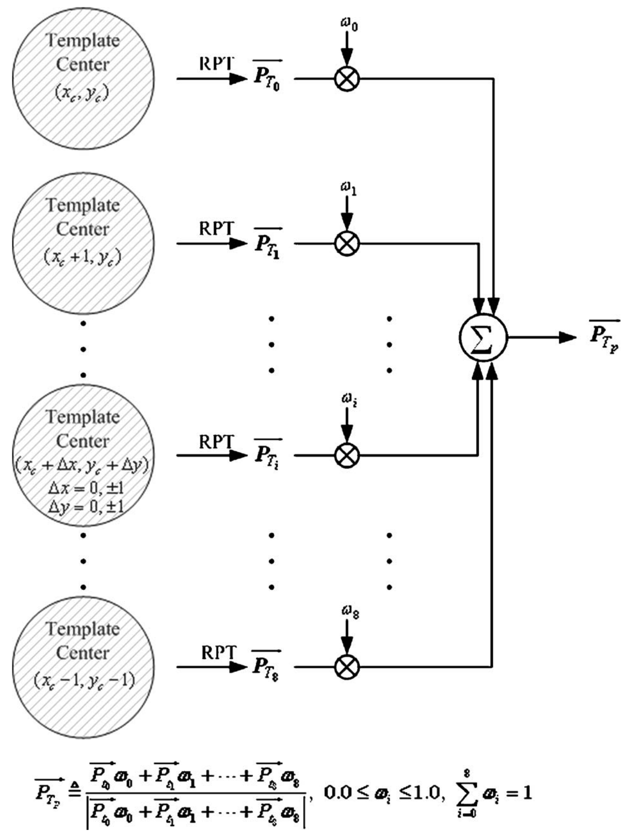

Fig. 3 Diagram of a parametric template space in CPTRPT.

$$H=\begin{bmatrix}\langle \mathbf{P}_{t_0},\mathbf{P}_{t_0}\rangle & \cdots & \langle \mathbf{P}_{t_0},\mathbf{P}_{t_8}\rangle\\ \vdots & \ddots & \vdots\\ \langle \mathbf{P}_{t_8},\mathbf{P}_{t_0}\rangle & \cdots & \langle \mathbf{P}_{t_8},\mathbf{P}_{t_8}\rangle\end{bmatrix}, \tag{11}$$

$$\mathbf{G}=\begin{bmatrix}\langle \mathbf{P}_{O},\mathbf{P}_{t_0}\rangle\\ \vdots\\ \langle \mathbf{P}_{O},\mathbf{P}_{t_8}\rangle\end{bmatrix}, \tag{12}$$

$$\mathbf{n}=\begin{bmatrix}1\\ \vdots\\ 1\end{bmatrix}. \tag{13}$$

Next, the subpixel location is found with the following equations:

$$x=x_0+\sum_{i=0}^{8}\omega_i\,\Delta x_i, \tag{14}$$

$$y=y_0+\sum_{i=0}^{8}\omega_i\,\Delta y_i, \tag{15}$$

where $(\Delta x_i,\Delta y_i)$, $0\le i\le 8$, denote the offset values of the one-pixel step shift relative to the center point (x_c,y_c) of the template at (x_c,y_c) and the eight surrounding points.

This optimal matching solution algorithm is listed as follows:

1. Select a template, and transform to a 1-D vector template by RPT.
2. Construct the set of templates $\mathbf{P}_{t_0},\mathbf{P}_{t_1},\ldots,\mathbf{P}_{t_8}$.
3. Calculate the correlation matrix H by using Eq. (11).
4. Transform the 2-D image to a 1-D vector using RPT in the scene subimage of interest, and determine the best integer pixel (x_0,y_0) matching by moving the 1-D vector of the template step by step.
5. Calculate the correlation vector $\mathbf{G}$ by using Eq. (12).
6. Determine $\boldsymbol{\omega}$ according to Eq. (9).
7. Find the subpixel value by using $\boldsymbol{\omega}$ and Eqs. (14) and (15).

Our approach enables fast matching in the subpixel matching algorithm. Since the correlation matrix H can be determined in the training phase, the optimal parameters $\boldsymbol{\omega}$ and the subpixel value are directly obtained from the correlation vector $\mathbf{G}$ and the correlation matrix H in the matching phase. No iterative steps are involved, and the execution time is deterministic. The interpolation method of CPTRPT is not based on the correlation values themselves, but on image data. Therefore it gives a more accurate estimation result.[10]

4 Generation of Simulated Images by the Downsampling Algorithm

Simulated images created by the downsampling algorithm[6,7] are used for verification of the proposed algorithm, due to their well-controlled image features. The execution of the downsampling algorithm creates a simulated image pair from a single high-resolution image by filtering and downsampling. First, a high-resolution image is shifted by integer amounts Δx and Δy, and rotated through an angle θ with respect to each other by using cubic B-spline interpolation[15] at the center of the template, and then a pair of low-resolution images, which are subsequently downsampled by a factor of M in each dimension, are generated. The relative shifts and the rotation angle of this simulated image pair become fractional shifts of size $\Delta x/M$, $\Delta y/M$ and an angle θ, respectively. If the downsampling rate M is larger than the maximum shifts, the correspondence between the simulated image pair is reduced to the subpixel level.

For the purpose of this research, the two main variables of the digitization process, resolution and accuracy, were chosen to be 1280×1024 and 8 bits per pixel, respectively. The resolution of the image is high, and the downsampling factor M is 4 in each dimension. Every simulated image pair is created on the basis of this downsampling algorithm. The simulated image size is therefore 320×256.

5 Verification of the Proposed Algorithm Using Simulated Images

In this section, we report a series of experiments conducted under various translations and rotations. Many simulated image pairs generated from the previous section were tested, and the results are reported. In the experimental procedures, a reference template was first selected in a simulated image without translation and rotation, and then the center position (x_c,y_c) was recorded. Subpixel template matching was performed between the reference template and other simulated images involving different subpixel shifts or different rotated angles. The region from (x_c-5,y_c-5) to (x_c+5,y_c+5) was searched exhaustively. All the computations were performed with C++ Builder 6.0 under the same conditions on a PIII1000 mainframe with 256 Mbyte of memory, and the computation times were recorded.

5.1 *Accuracy and Computation-Time Comparisons for Image Translations*

The first experiment is a comparison of the precision and total run time as a function of subpixel displacement for three methods. These three methods are the correlation surface-fitting (CSF) method in Ref. 5, the PT method in Ref. 10, and the proposed method CPTRPT. For these experiments, we used three different test images. The images and the corresponding template images are shown in Fig. 4. The results are presented in Table 1. The error in displacement is defined as

$$Er=[(\Delta x_e-\Delta x)^2+(\Delta y_e-\Delta y)^2]^{1/2}, \tag{16}$$

where $(\Delta x_e,\Delta y_e)$ denotes the estimated value and $(\Delta x,\Delta y)$ is the preassigned displacement.

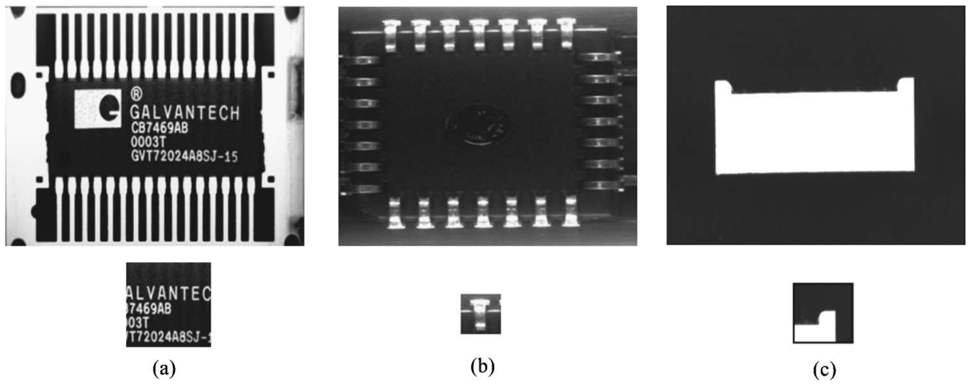

Fig. 4 Three different test images and the corresponding reference templates used in the experiment: (a) "IC Mark" test image and reference template with size 91×91, (b) "PLCC Lead" test image and reference template with size 41×41, (c) "Rigid Body" test image and reference template with size 61×61.

From the results, we can see that the proposed algorithm does not perform as well as the other algorithms. The main reason is that in the RPT process a 2-D image is reduced to a 1-D vector. This reduction process is adopted to overcome image rotation. However, the accuracy of CPTRPT is quite close to that of CSF and PT. The mean error is 0.0883 pixels, and the corresponding standard deviation is 0.051 pixels. Moreover, it can be found from the last row of Table 1 that our method is faster than the other methods in average computation time. That the model parameters become 1-D vectors, due to the RPT process, allows estimation by a direct linear calculation rather than an iterative calculation. Therefore, the matching time of the proposed algorithm is reduced.

5.2 *Accuracy Comparisons for Image Rotations and Translations*

In this part of the experiments, the subpixel matching accuracy is to be compared under combinations of image rotations and translations. For each high-resolution test image in Fig. 4, nine translated images with 1 to 3 pixels in the X direction and the Y direction, just the same as in the first experiment, are created. Every translation image is rotated with respect to the center of the template, and the rotation angles are varied from -175 to $+180$ deg in steps of 5 deg. Therefore, six hundred forty-two 320×256 simulated images with different subpixel translations and rotations are produced by the downsampling algorithm described in Sec. 4. The mean error values of nine translation images are calculated for every 5 deg of rotation in every test image class. Figures 5 to 7 show the comparison results of the three methods for the three test images.

As shown in these figures, our proposed method is superior to the traditional interpolation method CSF and outperforms the PT method in the presence of rotations. From Figs. 5 and 7, it can be seen that the mean error values of CPTRPT are less than 0.1 pixel for rotations ranging from -10 to $+10$ deg, on the order of 0.2 pixels from -25 to $+25$ deg, and no more than 0.5 pixels from -60 to $+60$ deg. Almost none of the mean error values exceed 1 pixel for rotations ranging over $[-175, 180 \text{ deg}]$. This means the accuracy of the proposed method can reach subpixel range and the subpixel template matching is robust to image rotations. However, the performance of CPTRPT in Fig. 6 is not as good as in Figs. 5 and 7 . The reason is that the template image size of the "PLCC Lead" test image in Fig. 4(b) is 41×41. It is smaller than the other test images. Obviously, the template image size will affect the accuracy of the subpixel matching. This phenomenon will be studied in future work.

6 Experimental Verification

Further experiments were performed using real-world images containing target objects. A PC board with two target objects was placed on a platform. Then, we captured image samples by moving or rotating the PC board repeatedly under the camera. The image size is 768×576 as shown in Fig. 8(a), and the images of the two target objects depicted in Fig. 8(b) were selected as the two matching templates. The actual template locations were unknown for these real-world images. To solve this problem, the distance between the PC board and CCD camera is kept fixed in our experiments, so that the distance between the two target objects will not change due to rotations and translations. Then, the distance between the two target objects without translation and rotation can be used as the standard distance. The performance was evaluated by calculating the absolute error value between the distance of two matching locations with translations and rotations and the standard distance in the matching phase.

In order to verify the performance of CPTRPT for image translations, 50 samples were obtained by moving target object repeatedly in the X direction and Y direction. Similarly, we captured 50 samples by rotating the target object as in the verifying experiment for image rotations. Figures 9(a) and 9(b) show the two extreme images for rotation in the clockwise direction. Similarly, Figs. 9(c) and 9(d) show the two extreme images for rotation in the counterclockwise direction.

The results of the experiment in Sec. 5.2 show that the traditional CSF interpolation method and the PT method cannot overcome the changes due to rotation. During the subpixel verifying process for this part of the experiment, the locations of the two target objects were found by the

Table 1 Comparison results on the accuracy and computation time with image translations for the three methods studied.

Test image	Preassignments $(\Delta x, \Delta y)$	Estimates CSF	Estimates PT	Estimates CPTRPT
"IC Mark"	(0.25, 0.00)	(0.20, 0.00)	(0.36, 0.00)	(0.33, 0.06)
	(0.50, 0.00)	(0.49, 0.01)	(0.65, 0.01)	(0.36, −0.02)
	(0.75, 0.00)	(0.80, 0.01)	(0.66, −0.01)	(0.65, 0.01)
	(0.00, 0.25)	(0.01, 0.23)	(−0.01, 0.32)	(0.02, 0.29)
	(0.00, 0.50)	(−0.01, 0.52)	(0.01, 0.41)	(0.04, 0.41)
	(0.00, 0.75)	(−0.01, 0.79)	(0.00, 0.69)	(0.03, 0.69)
	(0.25, 0.25)	(0.21, 0.24)	(0.36, 0.32)	(0.40, 0.34)
	(0.50, 0.50)	(0.54, 0.43)	(0.66, 0.41)	(0.33, 0.42)
	(0.75, 0.75)	(0.80, 0.78)	(0.65, 0.69)	(0.68, 0.70)
"PLCC Lead"	(0.25, 0.00)	(0.22, 0.01)	(0.26, 0.00)	(0.39, −0.02)
	(0.50, 0.00)	(0.46, 0.01)	(0.51, −0.01)	(0.52, 0.01)
	(0.75, 0.00)	(0.75, 0.01)	(0.69, −0.01)	(0.70, 0.03)
	(0.00, 0.25)	(0.00, 0.20)	(0.00, 0.28)	(0.05, 0.24)
	(0.00, 0.50)	(0.00, 0.47)	(0.00, 0.57)	(−0.03, 0.53)
	(0.00, 0.75)	(0.00, 0.78)	(0.00, 0.67)	(0.04, 0.70)
	(0.25, 0.25)	(0.22, 0.19)	(0.27, 0.28)	(0.43, 0.22)
	(0.50, 0.50)	(0.49, 0.47)	(0.52, 0.57)	(0.46, 0.52)
	(0.75, 0.75)	(0.75, 0.77)	(0.69, 0.67)	(0.70, 0.72)
"Rigid Body"	(0.25, 0.00)	(0.24, 0.01)	(0.27, 0.00)	(0.23, 0.02)
	(0.50, 0.00)	(0.47, 0.01)	(0.50, 0.00)	(0.44, −0.01)
	(0.75, 0.00)	(0.73, 0.01)	(0.70, 0.01)	(0.69, 0.01)
	(0.00, 0.25)	(0.00, 0.19)	(0.00, 0.21)	(0.03, 0.17)
	(0.00, 0.50)	(0.00, 0.55)	(0.00, 0.53)	(0.01, 0.48)
	(0.00, 0.75)	(0.00, 0.85)	(0.00, 0.82)	(−0.04, 0.80)
	(0.25, 0.25)	(0.24, 0.19)	(0.26, 0.20)	(0.26, 0.34)
	(0.50, 0.50)	(0.47, 0.56)	(0.50, 0.53)	(0.39, 0.46)
	(0.75, 0.75)	(0.81, 0.90)	(0.85, 0.89)	(0.83, 0.92)
Mean error value (pixels)		0.0467	0.0719	0.0883
Max error value (pixels)		0.1616	0.1836	0.1879
Min error value (pixels)		0.0100	0.0000	0.0224
Standard derivation (pixels)		0.0315	0.0484	0.0510
Average run time (ms)		20.8	22.9	20.5

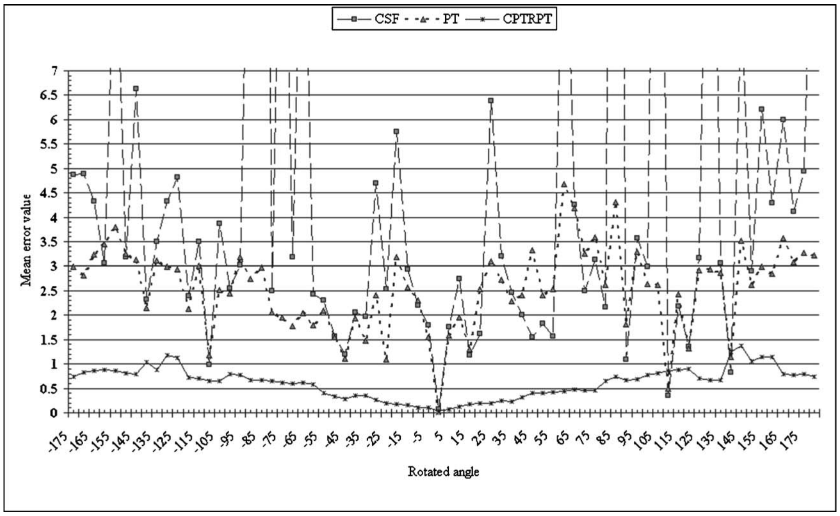

Fig. 5 Accuracy comparisons with image rotations and translations for the three methods studied in the “IC Mark” test image.

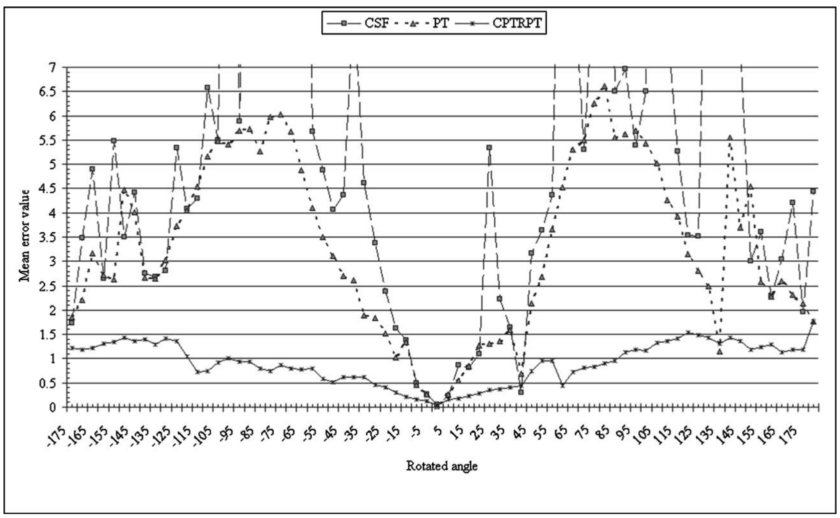

Fig. 6 Accuracy comparisons with image rotations and translations for the three methods studied in the “PLCC Lead” test image.

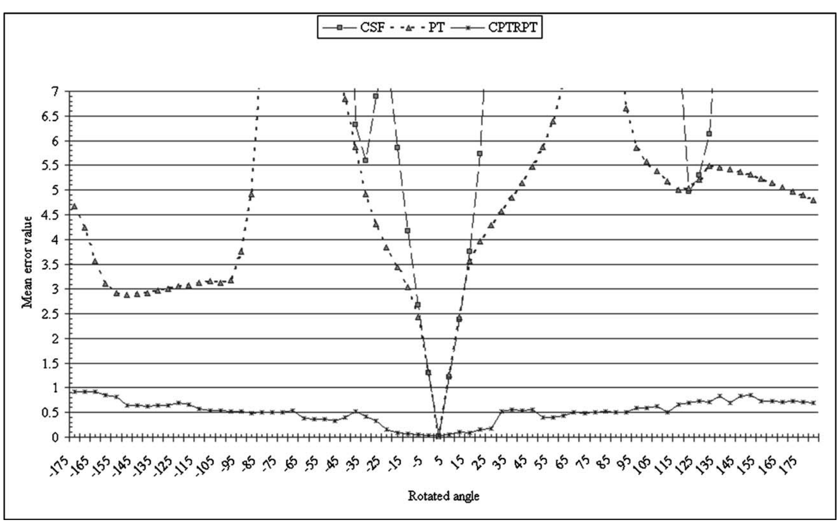

Fig. 7 Accuracy comparisons with image rotations and translations for the three methods studied in the “Rigid Body” test image.

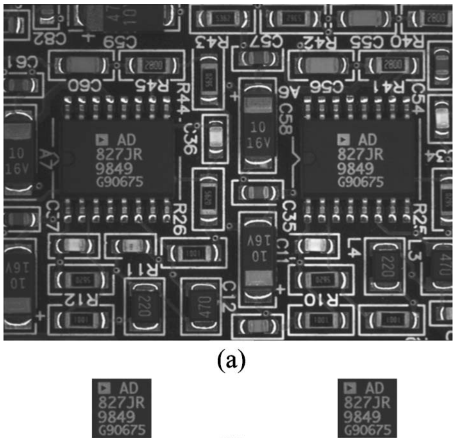

Fig. 8 A PC board image with two target objects obtained by CCD: (a) PC board image, (b) images of the two target objects used as the two matching templates.

proposed method only and the distance between them was calculated for each sample. The statistical results for the absolute error value between the distance of the two locations and the standard distance are summarized in Table 2. From these results for the translation experiments, the mean error of the distance is 0.0301 pixels, and the standard derivation is 0.0265 pixels. For the rotation experiments, the mean error is 0.1123 pixels and the standard derivation is 0.0885 pixels. Obviously, these real application experiments verify that our approach can obtain very high accuracy for scene translations and rotations.

Table 2 The statistical results for the absolute error value between the distance of the two locations and the standard distance in the experiments with real world scenes.

Statistics	Translation	Rotation
Mean error value (pixel)	0.0301	0.1123
Max error value (pixel)	0.0754	0.2084
Min error value (pixel)	0.0049	0.0212
Standard derivation (pixel)	0.0265	0.0885

7 Conclusion

A new subpixel template-matching approach that combines the PT method and the RPT process is proposed in this paper. It not only achieves subpixel accuracy in location, but also offers rotation invariance in subpixel template matching. Furthermore, our approach is conceptually simple, easy to implement, and very efficient because no iterative steps are involved.

In this work, a large number of simulated images with different subpixel shifts and different rotated angles were generated by the downsampling algorithm. They are used to verify the feasibility and validity of the proposed method. The simulated results show that the detection precision of the proposed method is close to and the computational time of image processing is faster than the CSF method and the PT method in the image translations. Moreover, our approach enjoys very high precision in the presence of image rotations. Experiments with real-world

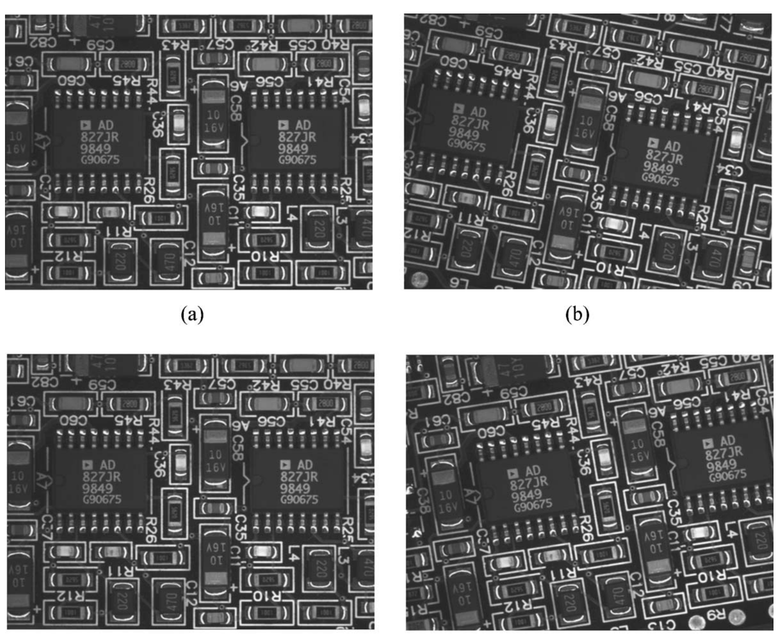

Fig. 9 Images showing the rotation range used in the experiments: (a) and (b), the two extreme images for rotation in the clockwise direction; (c) and (d), the two extreme images for rotation in the counterclockwise direction.

scenes demonstrate that the proposed subpixel template matching method can reach subpixel accuracy for finding the distance between two target objects in the presence of rotations and translations. This indicates that our approach is suitable for accurate on-line template matching with scene rotations and translations.

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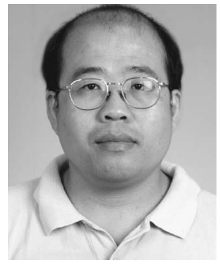

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