Scale-invariant object tracking method using strong corners in the scale domain

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Abstract. The object tracking method using the scale-invariant feature transform (SIFT) is applicable to rotated or scaled targets, and also maintains good performance in occluded or intensity-changed images. However, the SIFT algorithm has high computational complexity. In addition, the template size has to be sufficiently large to extract enough features to match. This paper proposes a scale-invariant object tracking method using strong corner points in the scale domain. The proposed method makes it possible to track a smaller object than the SIFT tracker by extracting relatively more features from a target image. In the proposed method, strong features of the template image, which correspond to strong corner points in the scale domain, are selected. The strong features of the template image are then matched with all features of the target image. The matched features are used to find relations between the template and target images. In experimental results, the proposed method shows better performance than the existing SIFT tracker. [DOI: 10.1117/1.3070665]

Subject terms: feature matching; object tracking; scale-invariant feature transform (SIFT); scale space.

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1 Introduction

Object tracking methods are widely used for intelligent visual surveillance systems, perceptual user interfaces, and object-based video compression. The template matching method is a procedure to find the highest similarity between a template image and a target image. The sum of absolute differences, sum of squared differences, and correlation are usually used as measures of similarity.[1–3] The correlation provides good accuracy and reliability in template matching, but involves huge computational costs. The kernel-based mean shift method is also used for template matching.[4,5] It generates a histogram with pixel and position information and matches the given template and a target image. All these template matching methods entail some problems when the template or target images have occlusion or noise. Furthermore, if an object is geometrically deformed to a high degree, and thus the object's shape in the template is considerably different from that in the target image, it is difficult to match the two images.

There are also many feature-based tracking methods including the Kanade-Lucas-Tomasi (KLT) tracker[6] and the scale-invariant feature transform (SIFT) tracker.[7] The SIFT tracker has a wider tracking range than the KLT. In addition, the KLT tracker is relatively sensitive to variation of intensity in the image, whereas the SIFT tracker is robust to this disturbance. Therefore, the SIFT tracker is preferable when the object size varies or a given image has noise. The SIFT tracker is also useful in tracking physical movements like hand gestures[8] and head motions.[9]

The SIFT algorithm has also been applied to robot vision.[10] However, it involves a heavy computational cost and also requires that the object in the image be of moderate size for successful tracking. Therefore, some researchers have tried to reduce the computational complexity of the SIFT algorithm.[11,12] In particular, Liefhebber and Sijs[10] searched for SIFT features just within a region of interest (ROI) designated within the object area, and adjusted the image size for controlling the number of features. This method can reduce the image size, computational complexity, and computing time. In this paper, we also reduce the computational cost of the SIFT tracker and make possible the tracking of even small objects.

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First, we review the SIFT algorithm in Sec. 2. The proposed object tracking method is described in Sec. 3. Section 4 presents experimental results with IR and CCD image sequences. Finally, conclusions are given in Sec. 5.

2 Scale-Invariant Feature Transform

The SIFT algorithm[7] generates scale-space images in a Gaussian scale space.[13,14] The scale space contains images of various resolutions, and smoothed images in the Gaussian scale space can replace the original images. Starting from an original image I, smoothed images I_σ are successively generated by applying Gaussian filtering as follows:

$$I_\sigma = G_\sigma * I, \tag{1}$$

where $*$ represents the linear convolution operation and G_σ is a Gaussian function defined as

$$G_\sigma = \frac{1}{2\pi\sigma^2}\exp\left(\frac{x^2+y^2}{2\sigma^2}\right). \tag{2}$$

Here I_σ is equivalent to the resized image $I_{1/\sigma}$ obtained from the original image by a resizing ratio of $(1/\sigma)\times(1/\sigma)$. Initially σ is set to 0.5, so that the corresponding smoothed image is interpolated doubly from the original image.

After generating every smoothed image in the scale domain σ, images in the scale space have three dimensions, corresponding to the image domain (x and y axes) and scale domain. The size of the i'th scale image is double that of the $(i+n)$th scale image, where the scale parameter is given as follows:

$$\sigma = 2^{i/n}. \tag{3}$$

In order to reduce the computational complexity for generation of the entire scale space, every n'th scale image is downsampled by a factor of two. In this case, n images having the same image size are said to be in the same octave. Figure 1 shows the imaginary scale space and the real scale space. Every image $I_{1/\sigma}$ of the imaginary scale space has a different size according to the resizing ratio, and the image of the real scale space is smoothed by Gaussian filtering rather than resizing by a noninteger σ.

To allocate a dominant point in a bandpassed signal to a feature in a corresponding scale domain, Laplacian images are computed in the scale space as follows:

$$\sigma\nabla^2 I_\sigma = \frac{\partial I_\sigma}{\partial\sigma} \approx \frac{I_{k\sigma}-I_\sigma}{k\sigma-\sigma}. \tag{4}$$

This shows that the Laplacian function can be replaced with the difference of Gaussians (DoG) function normalized by $(k-1)\sigma^2$. The extremum pixel having the maximum or minimum value is then extracted from the DoG images, where it is compared with the adjacent 26 pixels in image and scale domain. Therefore, two adjacent DoG images differing only in the value of σ should have the same size for the comparison. The extremum point is estimated with floating-point accuracy on the image and scale axes.

Finally, each feature descriptor is defined at the extremum point. For scale invariance, the descriptor includes

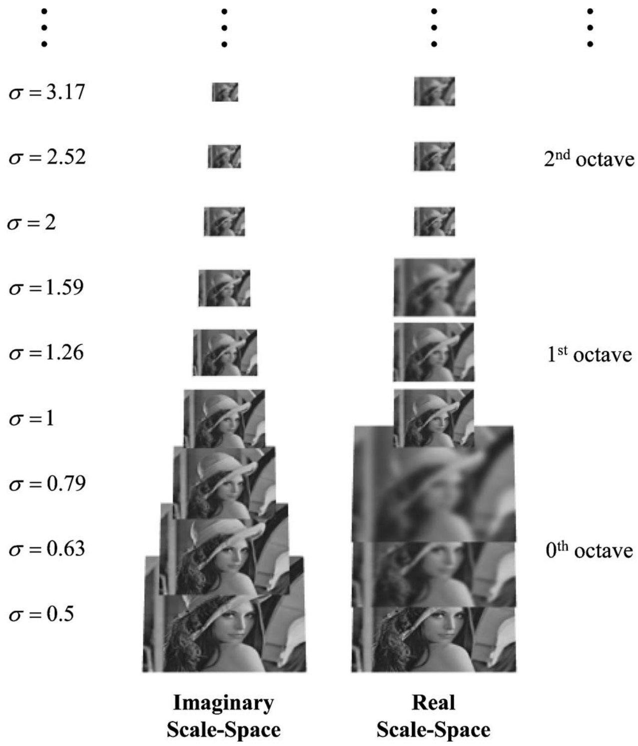


Fig. 1 Imaginary scale space consisting of $I_{1/\sigma}$ resized by $(1/\sigma)\times(1/\sigma)$, and real scale space consisting of Gaussian smoothed images I_σ with scale parameter $\sigma=2^{i/n}$ for $n=3$.

information within a circle of radius σ. This information includes the orientation and magnitude of the gradient of every pixel within that circle. For rotational invariance, the descriptor collects information and finds the dominant orientation of the gradient whose magnitude is the largest, and then rotates every pixel within its circle in order to place the dominant orientation at zero degrees.

3 The Proposed Object Tracking Method

The proposed object tracking method performs feature-based matching and updates the aiming point and template at every sequential frame, as shown in Fig. 2. In this paper, an object area in a previous frame is called a template image, and its next frame is called a target image. The aiming point and template are manually defined in the first image by the user. Scale-invariant features are then extracted from the target image and matched with features of the template image. The number of features of the template image is fixed to 15, and thus 15 features among the features of the target image can be matched with those of the template image. In the next step, an optimum relation between the template and the target image is found using the 15 matched features, and the distances of the matched features for the optimum relation are computed. We select six smallest-distance features among the 15 matched features and nine features of the target image corresponding to strong corners in the scale domain; these features then become new template features for tracking of the next frame. The final step in the loop is to update the aiming point and template with the optimum relation; this is used to continuously track the next frame.

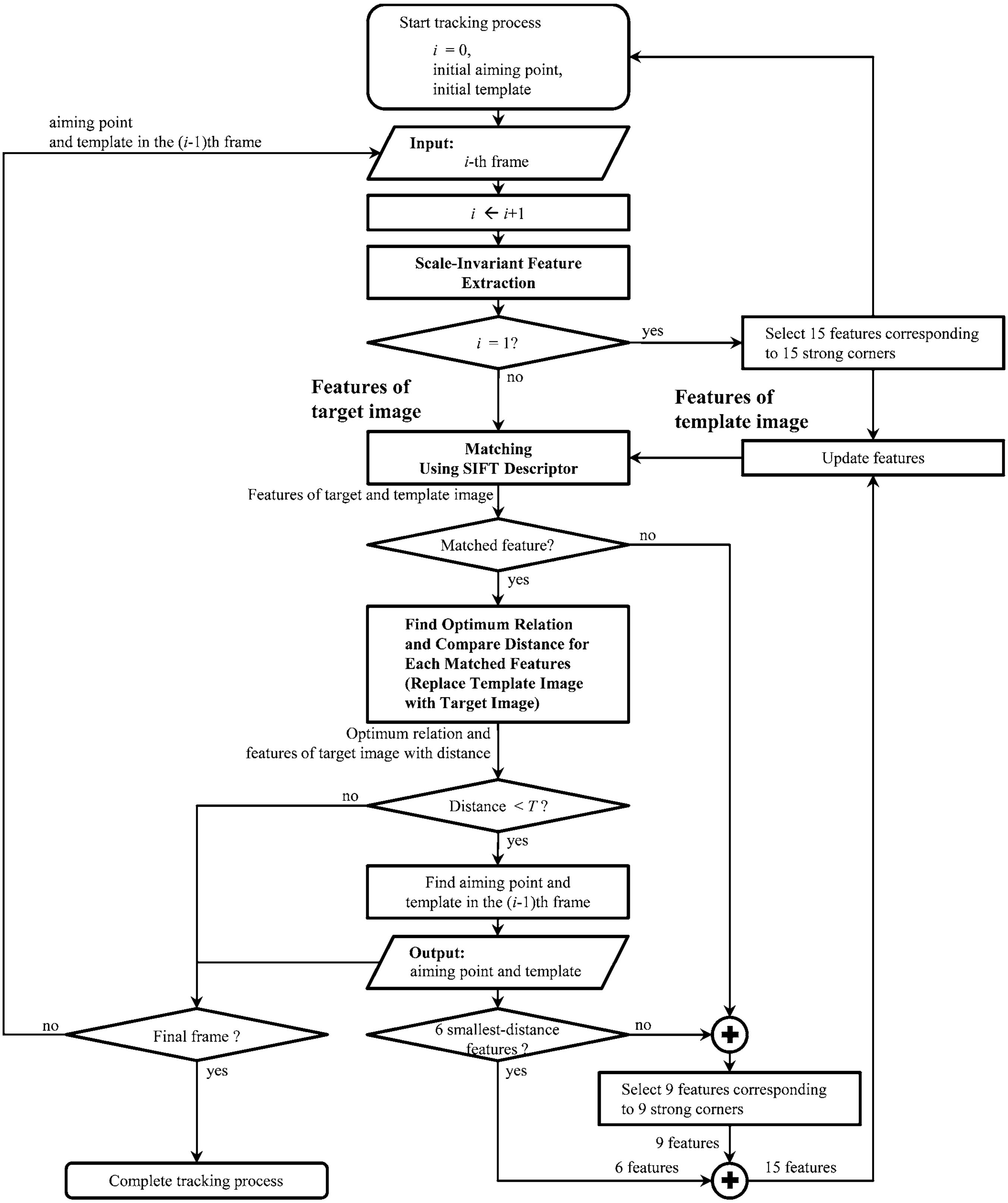


Fig. 2 Flow chart illustrating the proposed tracking procedure.

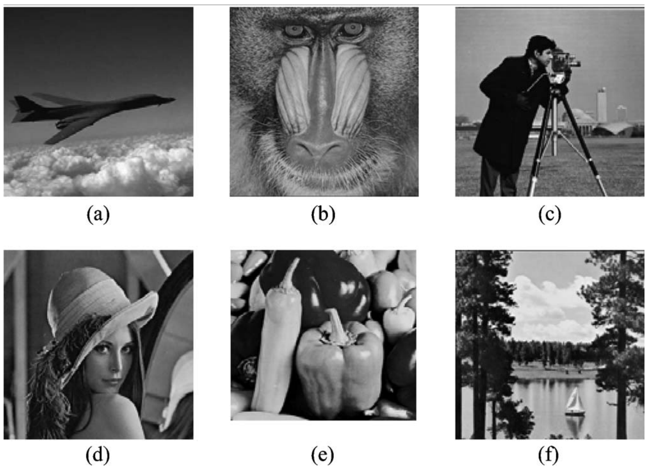


Fig. 3 Test images for comparing numbers of features extracted by the SIFT algorithm and the proposed method: (a) "Airplane" (256×256), (b) "Baboon" (256×256), (c) "Cameraman" (256×256), (d) "Lena" (256×256), (e) "Peppers" (250×230), and (f) "Sailboat" (256×256).

Table 1 Numbers of features extracted from six images by the SIFT algorithm and the proposed method for full template and 20×20 template.

	Size		Full template size		20×20 template size	
Image	Width	Height	SIFT	Proposed	SIFT	Proposed
"Airplane"	256	256	2138	7619	4	15
"Baboon"	256	256	2411	9687	8	62
"Cameraman"	256	256	2020	8652	8	52
"Lena"	256	256	2070	7002	10	50
"Peppers"	250	230	1780	5942	22	69
"Sailboat"	256	256	2508	8540	23	42

3.1 *Scale-Invariant Feature Extraction*

Using the SIFT algorithm,[7] the scale- and rotation-invariant features can be extracted. Even if there are affine, viewpoint, and illumination changes in a given image, it is possible to match the given image with the changed image by extracting and matching the SIFT features from the two images. However, the SIFT algorithm has some limitations, such as high computational complexity and ability to cope only with moderate size of the objects. In order to overcome these drawbacks, we propose a new method, whereby the number of features is increased and strong features among them, which correspond to strong corners in the scale space, are selected. In addition, we restrict the range of the scale space, thereby reducing the computational complexity. The selection of strong corners in the scale space among numerous features can also reduce the computational complexity for one-to-one correspondence matching. Since this approach guarantees sufficient features, it can also be successfully applied to small-object tracking.

While the SIFT algorithm employs the extremum in 3-D of both the image and the scale space, the proposed method extracts the extremum only from the image domain at each scale domain. Therefore, the proposed method does not need the two adjacent DoG images for one comparison. We compare numbers of features extracted by the SIFT algorithm and the proposed method from six test images, which are familiar to image-processing experts: "Airplane," "Baboon," "Cameraman," "Lena," "Peppers," and "Sailboat" shown in Fig. 3. The test results are summarized in Table 1. While the SIFT algorithm uses three different octaves each of which has three DoG images, the proposed method uses only one octave with three DoG images, assuming that the object size can vary by less than a factor of 2 between two adjacent frames. In practice, the SIFT algorithm generates 18 Gaussian smoothed images for three octaves. However, the proposed method uses only four Gaussian smoothed images, generating three DoG images. This reduces the computational complexity for generating the scale space. Furthermore, the proposed method extracts more features than the SIFT algorithm. As shown in Table 1, when the template size is 20×20, the SIFT algorithm cannot extract sufficient features for tracking the "Airplane," "Baboon," and "Cameraman" images. On the other hand, the proposed method can extract sufficient features from all images.

In order to reduce the computational complexity, the proposed method selects good matching features among all features. Strong corners in every scale domain can be a good criterion to select good matching features, since they are invariant to scale. A corner can be estimated by a Hessian matrix[15] defined as follows:

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}, \tag{5}$$

where D_{ab} is the second derivative of the scale space image along the a and b directions. The eigenvalues of H are proportional to the principal curvatures. The trace and determinant of H equal the sum and product of the eigenvalues, respectively, as follows:

$$\mathrm{Tr}(\mathbf{H}) = D_{xx} + D_{yy} = \alpha + \beta,$$

$$\mathrm{Det}(\mathbf{H}) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha\beta, \tag{6}$$

where α and β are the larger and the smaller eigenvalue, respectively. The following corner coefficient then represents how strong the corner is in scale space:

$$\frac{\mathrm{Tr}(\mathbf{H})^2}{\mathrm{Det}(\mathbf{H})} = \frac{(\alpha+\beta)^2}{\alpha\beta}. \tag{7}$$

The corner coefficient is at a minimum when the two eigenvalues are equal, and it increases as α/β, the ratio of eigenvalues, increases. A point at which the two curvatures are both dominant is considered as a corner. Therefore, the smaller the corner coefficient is, the stronger the corner is.

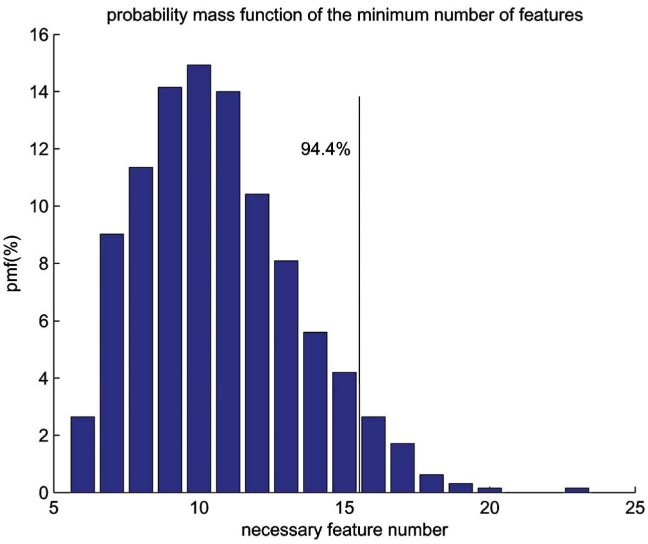


Fig. 4 The probability mass function (pmf) of the minimum number of features including six strongly matched features.

3.2 *Matching Using the SIFT Descriptor*

The proposed object tracking method is applied to video sequences for object tracking. Therefore, we perform the matching process between two adjacent frames. The best match for the features of the template image is found by searching its nearest neighbor for the features in the target image. The nearest neighbor is defined as the one whose features have the minimum Euclidean distance from the invariant descriptor vectors.

A certain number of features are selected in the template image by using Eq. (7) in order to reduce the computational complexity; in this paper 15 features of the template image are used. In the target image, we extract SIFT features in the search area. The search area is determined by plus or minus the maximum movement range from the object position of the template image along the horizontal and vertical directions. We set the maximum movement range to six pixels in our experiment.

3.3 *Finding the Optimum Relation*

The proposed method finds an optimum relation between the template and target images in a similar manner to random sample consensus (RANSAC).[16] RANSAC provides poor results if inliers (i.e., well-matched features) comprise less than half of the overall matched features. Our method selects a suitable number of features, and then calculates the optimum relation between the template and target images using the selected features.

The relation between two images is defined by a 3-by-3 matrix with four degrees of freedom as follows[17]:

$$\mathbf{R} = \begin{bmatrix} s_x & 0 & -d_x \\ 0 & s_y & -d_y \\ 0 & 0 & 1 \end{bmatrix}, \tag{8}$$

where s_x and s_y are the scale factors of the x and y axes, respectively, and d_x and d_y are the translation factors of the x and y axes, respectively.

Table 2 Image size, frame length, and target object of two IR and CCD image sequences, which are used in the experiments.

Sequence	Image size	Frame length	Object
IR sequence 1	128×128	1000	Approaching car
IR sequence 2	160×120	750	Approaching car
CCD sequence	160×120	60	Occluded car

At least four matched features are required to find the relation between two images. The proposed method selects four features from the overall matched features and finds a relation using them. A distance is then computed for all matched features by using the standard relation

$$\mathrm{Dist}(\mathbf{x}_1,\mathbf{x}_2,\mathbf{R}) = |\mathbf{x}_1 - \mathbf{R}\mathbf{x}_2| + |\mathbf{x}_2 - \mathbf{R}^{-1}\mathbf{x}_1|, \tag{9}$$

where the 2-D position vectors $\mathbf{x}_1$ and $\mathbf{x}_2$ are the matched features of the template and target images, respectively, and R is the relation between the two images. The distances are computed for every relation that is generated using four features selected from all matched features. We selected only six matched features, which have smallest distance among all matched features. Among the six smallest-distance matched features, four are used to find the relation between the two images, and we compute the distances from the other two to evaluate the relation's suitability. Finally, the relation having the lowest distance value, which is the sum of two distances, becomes the optimum relation between two images.

After the optimum relation is obtained, the aiming point in the target image is obtained by multiplying the optimum relation matrix and the aiming point in the template image. In addition, the template image is updated for tracking the next frame by multiplying the optimum relation matrix with the four corners of the object area in the template image. The 15 features of the new template image are updated with 6 smallest-distance matched features and 9 new features that have strong corner coefficients in the template image.

For determining the number of features required in the template image, we evaluated the matched features in the order of the corner coefficients of Eq. (7) for a given image sequence consisting of 1000 frames. We found the minimum number of template features in which six reliably matched features can be successfully included. Figure 4 shows the probability mass function (pmf) of the minimum number of features including six reliably matched features among them. Though the computational complexity in the template image increases, a more optimal relation between the template and target images can be obtained as the number of features increases. We set the number of features to 15, resulting in a 94.4% rate of finding a suitable relation.

If an occlusion occurs in the target image or sufficient matched features are not selected for finding the optimum relation, the distance of the optimum relation will be larger than a threshold value. In this paper, the threshold value is determined to be 5 pixels in the first frame, and in the next frame it is obtained by multiplying by a scale factor for the optimum relation, $s=(s_x{}^2+s_y{}^2)^{1/2}$. If the distance of the op-

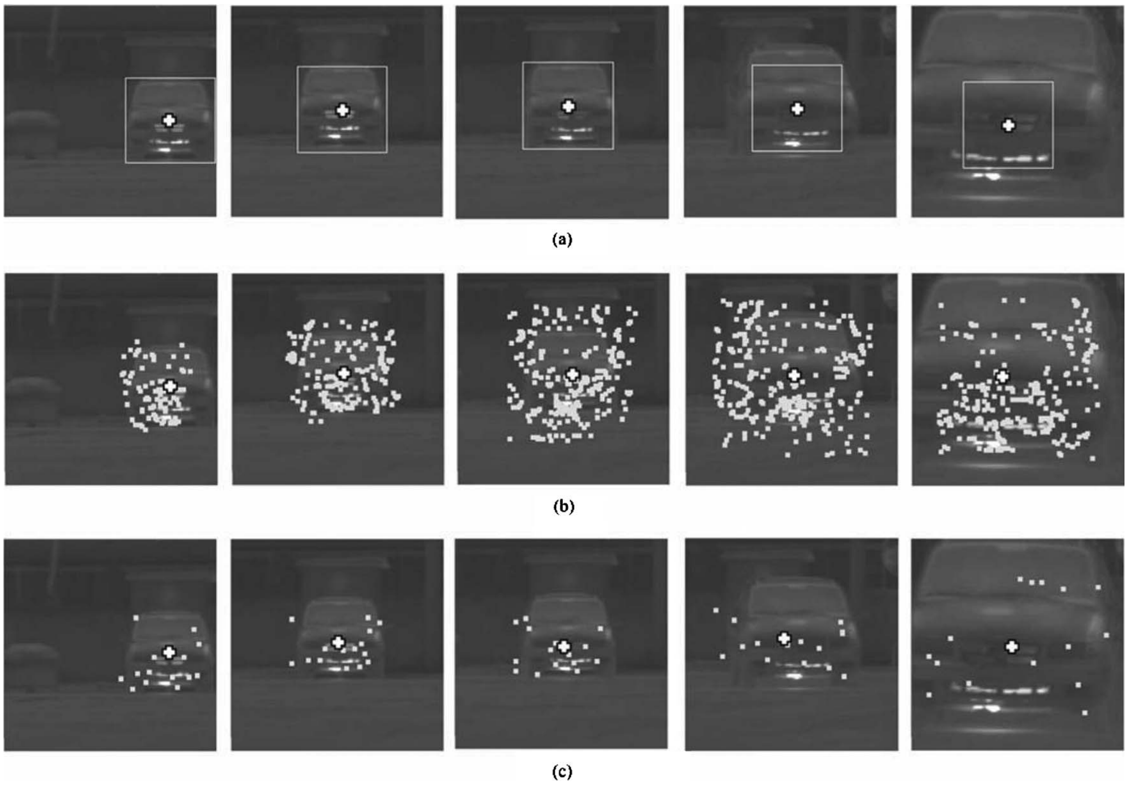


Fig. 5 Experimental results of three tracking methods in 0th frame, 200th frame, 400th frame, 600th frame, and 800th frame of an IR image sequence 1: fast template matching using (a) correlation-based adaptive predictive search, (b) the SIFT tracker, and (c) the proposed method. The plotted squares, square boxes, and crosses indicate features, templates, and aiming point, respectively.

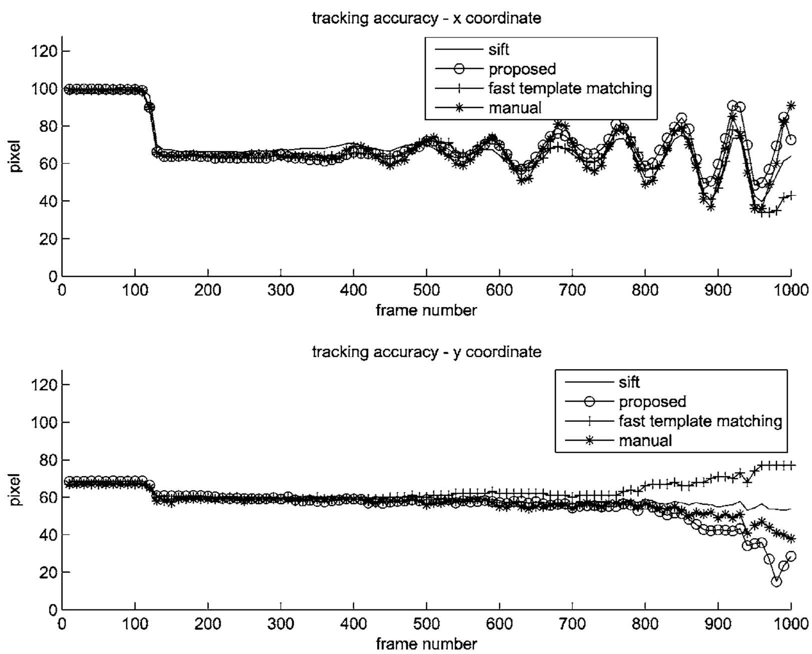


Fig. 6 Tracking accuracy of three algorithms; the fast template matching algorithm using correlation-based adaptive predictive search, the SIFT tracker, and the proposed method. The line with asterisks indicates the manually marked aiming point.

Table 3 Frame rates of the IR image sequence computed in a second; fast template matching using correlation-based adaptive predictive search, the SIFT tracker, and the proposed method.

	Fast template matching		SIFT tracker		Proposed method	
Frame numbers	Processing time (s)	Frame rate (Hz)	Processing time (s)	Frame rate (Hz)	Processing time (s)	Frame rate (Hz)
1–100	7.25	13.79	62.56	1.60	28.66	3.49
101–200	7.20	13.88	141.25	0.70	35.98	2.78
201–300	7.26	13.77	187.35	0.53	38.92	2.57
301–400	7.31	13.69	219.05	0.46	43.78	2.39
401–500	7.38	13.55	276.26	0.36	40.13	2.49
501–600	7.81	12.80	322.01	0.31	43.96	2.27
601–700	7.89	12.67	322.03	0.31	50.10	2.00
701–800	8.75	11.42	322.34	0.31	63.81	1.57
801–900	17.77	5.63	304.89	0.33	74.55	1.34
901–1000	23.94	4.18	254.36	0.39	73.83	1.35

timum relation is larger than the threshold value, we do not update the aiming point and template. Instead, the previous template is used to match with the next frame.

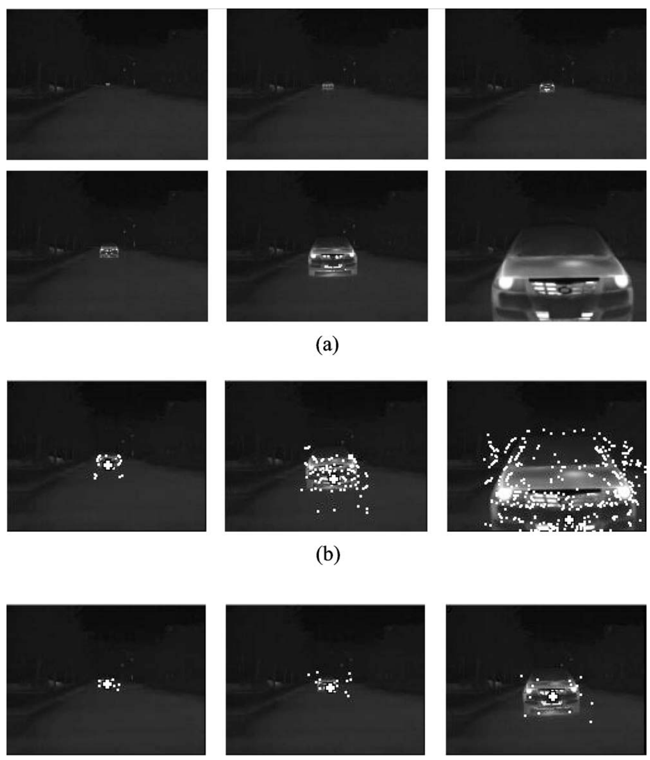
4 Experimental Results

The first experiment shows the tracking accuracy of the proposed method. We applied the SIFT algorithm and the proposed method to IR and CCD image sequences. Table 2 depicts the image size, frame length, and target objects of three sequences.

Figure 5 shows the tracking results of three methods: the fast template matching algorithm, the SIFT tracker, and the proposed method. The fast template matching algorithm is a tracking method using correlation-based adaptive predictive search,[3] which is a fast matching method using correlation. Figures 5(b) and 5(c) show the tracking results of the SIFT algorithm and the proposed method, respectively, for IR sequence 1. In the proposed method, the numbers of features and strongly matched features are 15 and 6, respectively. In order to evaluate the tracking results and tracking errors, we manually marked the center point of the object in every frame. Figure 6 depicts the tracking results in (x,y) coordinates. All methods track the objects with similar tendencies. Exceptionally, in the y coordinate, the template matching method tracks an object far from the manually marked position, since the object size abruptly increases as the object approaches the camera after the 500th frame.

Table 3 shows the processing times of the three methods for 100 frames of the IR image sequence. The fast template matching algorithm is notably fast, and the proposed method is at least two times faster than the SIFT tracker.

Figure 7 shows the tracking results of IR sequence 2, where an object is gradually zoomed from a point source until it covers the whole frame. We applied two methods to IR sequence 2 for finding the minimum applicable object



(a)

(b)

(c)

Fig. 7 (a) 0th frame, 550th frame, 580th frame, 600th frame, 650th frame, and 680th frame of an IR image sequence 2, and the experimental results of two tracking methods: (b) the SIFT tracker (600th frame, and 650th frame, and 680th frame) and (c) the proposed method (550th frame, 600th frame, and 650th frame). The plotted squares and crosses indicate features and aiming points, respectively.

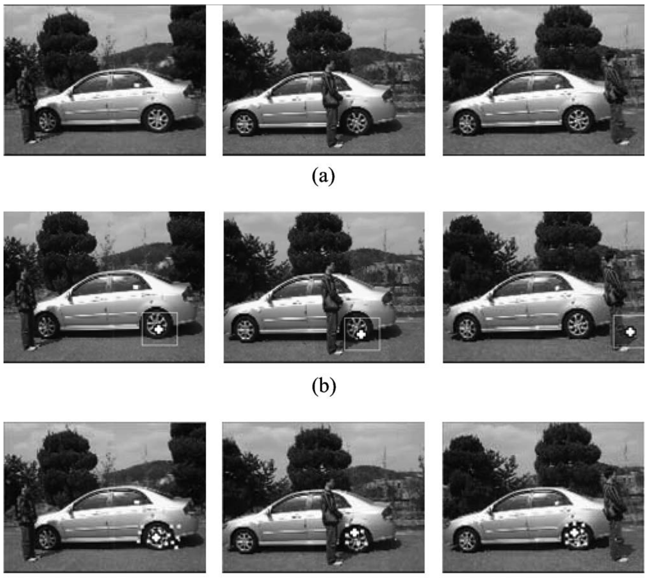


Fig. 8 (a) CCD image sequence that has an occlusion across an object, and experimental results from two tracking methods of the occluded CCD sequence: (b) template matching using correlation, and (c) the proposed method. Square boxes and crosses indicate the template area and aiming point, respectively, in the template matching. Plotted squares sand crosses indicate features and aiming point, respectively, in the proposed method.

size. The SIFT tracker could find the object from the 600th frame, where the object size was approximately 25×20. The proposed method found the object from the 550th frame, where the object size was approximately 20×13.

One of the greatest advantage of the SIFT algorithm is that it is possible to track an object even if the object is partially occluded. In the image shown in Fig. 8, a person occludes a car moving forward. The figure shows the tracking results when the object is partially occluded. While the occluded image affects template matching, the proposed method was fairly robust to occlusion, as shown in the figure.

5 Conclusions

The SIFT tracker provides good performance as an efficient object tracker, even in the case of occluded and intensity-variant images. However, this approach suffers from high computational complexity and limitation on image size. In this work, we have proposed an efficient object tracking method using strong corners in scale space. The proposed method reduces the computational complexity and can be applied to small targets.

The experimental results showed that the proposed method delivers strong performance, and can also be applied to an occluded target. In addition, the proposed method tracked the target at least twofold faster than the SIFT tracker.

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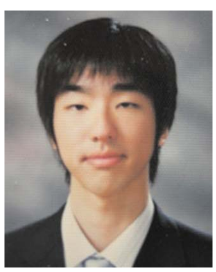

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