International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:12, No:3, 2018

Object Tracking in Motion Blurred Images with Adaptive Mean Shift and Wavelet Feature

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Abstract**—**A method for object tracking in motion blurred images is proposed in this article. This paper shows that object tracking could be improved with this approach. We use mean shift algorithm to track different objects as a main tracker. But, the problem is that mean shift could not track the selected object accurately in blurred scenes. So, for better tracking result, and increasing the accuracy of tracking, wavelet transform is used. We use a feature named as blur extent, which could help us to get better results in tracking. For calculating of this feature, we should use Harr wavelet. We can look at this matter from two different angles which lead to determine whether an image is blurred or not and to what extent an image is blur. In fact, this feature left an impact on the covariance matrix of mean shift algorithm and cause to better performance of tracking. This method has been concentrated mostly on motion blur parameter. transform. The results reveal the ability of our method in order to reach more accurately tracking.

Keywords**—**Mean shift, object tracking, blur extent, wavelet transform, motion blur.

I. Introduction

OBJECT tracking is an important and applicable topic in computer vision and image processing. Accurate surveillance system has been a critical issue which has attracted a lot of attention in recent years. Intelligent surveillance system has numerous potential applications in various fields, such as protecting security from important locations and buildings, controlling and monitoring traffic in cities and roads, identifying military targets, and so on [1], [2]. Moving is an important feature in video images. Generally, there are three important strategies for calculating motion parameters in the image, which are divided into methods based on matching, frequency domain techniques, and differential methods [3].

Mean Shift Algorithm is a nonparametric gradient estimator based on the maximization in clustering and region search. This algorithm is a nonparametric method for clustering and is used in large image segmentation [4]. The superiority of this algorithm to similar algorithms, such as K-Means, is that here the number of categories is not considered as inputs [4], [5]. Of course, this kind of algorithm is used to track objects in the image. Contrary to the classic K-Means clustering method, there are no predetermined assumptions on the distribution function of the mean shift, and not the number of clusters [6].

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The mean shift was initially proposed by Fukunaga and Hostetler in 1975, and later adapted by Cheng in 1995 with the aim of analyzing the image and more recently by Meer and Ramesh in 2002 to resolve machine vision problems such as segmentation and tracking [1], [2], [6].The main idea of the behavior of the mean shift algorithm is to deal with a series of points in an n-dimensional dimension space as a probability density function, the denser region in which this feature space is related to the local maximum or fundamental distribution state. For each point of the data in the feature space, the gradient operation runs on the estimated local density until it reaches a convergence [7], [8].

The work of Ning et al. in [1] proposed a scale and orientation adaptive mean shift tracking (SOAMST) algorithm under the mean shift framework. Contrary to CAMSHIFT, that uses the weight image which determined by the target model, this proposed method (SOAMST) estimates the target scale by weight image derived from the target model and the target candidate model in the target candidate region [1].

It should be noted that no work has been done in this regard in recent years that we can directly mention it in the references, but we are going to be able to heighten the estimation accuracy of blur target tracking using blur information. Nonetheless, Park et al. [9] worked in handling motion-blur in 3D tracking. Their method proposes an image formation model that explicitly considers the possibility of blur, and shows its results in a generalization of the original ESM algorithm [9] (ESM is a powerful algorithm for template matching-based tracking). Also, Wu et al. [10] introduced a novel BLUR-driven tracker (BLUT) frame-work for tracking motion blurred targets. BLUT actively uses the information from blurs without performing deblurring.

One of the most common problems which occur in object tracking through out the video sequence is that our target region is blurred; hence this phenomenon causes tracking to occur with error. In these cases, the target is usually lost, and tracking is not good. In order to alleviate this problem, we were looking for a way to find the amount of blur extent at the region of target candidate. Regarding different object tracking methods which are model based such as mean shift, it is of vital importance that the histogram of target model and target candidate have had high similarity for better tracking. Unfortunately, some things such as full and partial occlusion, blurring of image and similarity of the background colour make it difficult to track how it should be done. On the other hand, object detection is the task of localization of objects in an input image, but when a pixel records lights from multiple sources, image blur is caused. Image degradation occurs due to various reasons. Camera shake and object motion are two common types of blur which may occur during the tracking. Unfortunately, sometimes during the exposure time, camera motion produces global motion blur therefore some points on the scene are observed by multiple moving pixel sensors. So, in this paper, we propose new method to track the object in blurred image.

The remainder of this paper is organized as follows: Section II presents object tracking and principal method of adaptive mean shift algorithm. Section III presents feature extracting and explains how we can be able to use wavelet domain for estimating the amount of blur in an image. In Section IV, the proposed algorithm will be described. Section V provides experimental results and shows the performance of this method. And finally, the paper is concluded in Section VI.

II. Object Tracking Algorithm

A. Classic Mean Shift Algorithm

Object tracking is considered one of the most important issues of machine vision. Tracking is done to identify the location of a target in a series of consecutive images. A specific target is usually determined by using a rectangular or elliptical area in the image around the location, and its area properties are used to obtain a distribution pixel histogram. This histogram identifies the probability density of the distribution of different characteristics in the area. Of course, to get this histogram, the kernel function plays an important role [9]. Normalized colour distribution of target model is defined as:

$$\hat{q}_u = c\sum_{i=1}^{n} k(\| x_i^* \|^2)\delta\left[\left(b(x_i^*\right)-u\right] \quad (1)$$

where $q=\{q_u\}1...m$ and m is the number of bins. The normalized colour distribution of target candidate, centered at the point y, is obtained from (2).

$$\hat{p}_u(y) = c_h \sum_{i=1}^{nh} k(\| \frac{y-x_i}{h} \|^2)\delta\left[b(x_i)-u\right] \quad (2)$$

where $\{x_i\}i=1...nh$ and $k(x)$ is the kernel function with the bandwidth h and C_h is the normalized function.

$$c_h = \frac{1}{\sum_{i=1}^{nh} k(\| \frac{y-x_i}{h} \|^2)\delta\left[b(x_i)-u\right]} \quad (3)$$

To get the similarity between the original model and the candidate image, we need a similarity function or criterion to determine the distance between the model and the candidate. The measure of the comparison between the normalized histograms $p(y)$ and q is the Bhattacharyya coefficient [11] calculated according to formula (4).

$$\rho\left[p(y), q\right] = \sum_{y=1}^{m} \sqrt{p_u(y) q_u} \quad (4)$$

The result of this comparison is a number between 0 and 1, indicating a greater similarity between the target model and target candidate and vice versa.

$$\rho\left[p(y), q\right] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p(y)q_u} + \frac{c_h}{2}\sum_{i=1}^{n} w_i k\left(\| \frac{y-x_i}{h} \|^2\right) \quad (5)$$

where w_i are the weights of the equation calculated from (6).

$$w_i = \sum_{u=1}^{m}\delta\left[b(x_i)-u\right]\sqrt{\frac{q_u}{p_u(y)}} \quad (6)$$

Note that (5) estimates the target density in the center of y in the current frame, calculated with the kernel $k(x)$ and w_i weights [12]. The maximum density in the local neighborhood gives us the most probable location of the target in the current frame, which is obtained by applying the mean shift algorithm. During this procedure, the target center can shift in accordance with (7) in different directions.

$$\hat{y} = \frac{\sum_{i=1}^{n} x_i w_i g(\| \frac{\hat{y}_0 - x_i}{h} \|^2)}{\sum_{i=1}^{n} w_i g(\| \frac{\hat{y}_0 - x_i}{h} \|^2)} \quad (7)$$

where y_0 is the current position of the target candidate center, and $g(x)$ is the derivative function of $k(x)$. As mentioned, the density of the object is weighed by the Epanechnikov decreasing kernel.

$$k(x) = \begin{cases} \frac{1}{2} C_d^{-1}(d+2)(1-x) & if \quad x \le 1 \\ 0 & otherwise \end{cases} \quad (8)$$

where C_d is the value of the n-dimensional space and x are the normalized pixels coordinates within the target area. Because we deal with a two-dimensional image, then our kernel will be in the form of (9).

$$k(x) = \frac{2}{\pi}(1 - \| x \|^2) \quad (9)$$

B. Adaptive Mean Shift

One of the most significant part of the task of tracking is object's scale estimation [1]. Equation (7) can be reduced to (10) since we use Epanechnikov kernel and there is $g(x) = -k(x) = 1$.

$$\hat{y} = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i} \tag{10}$$

From (10), it can be concluded that weights play an important role in mean shift algorithm. Because the weight value of a pixel indicates the probability that it belongs to the target region, zero order moment can be used as the weighted area of the target region [3].

$$Cov = \begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix} \tag{11}$$

The first order moment order denoted by:

$$M_{01} = \sum_{i=1}^{n} w_i x_{i,2} \quad M_{10} = \sum_{i=1}^{n} w_i x_{i,1} \quad M_{11} = \sum_{i=1}^{n} w_i x_{i,1} x_{i,2} \tag{12}$$

where *n* is the number of pixels in target candidate region and $x_{i,1}$ and $x_{i,2}$ are the coordinate of pixel *i* in the candidate region and denote the *i*'th *x* and *y* value, respectively. The second order moments which describe the scale of the object are determined by:

$$M_{02} = \sum_{i=1}^{n} w_i x_{i,2}{}^2 \quad M_{02} = \sum_{i=1}^{n} w_i x_{i,2}{}^2 \tag{13}$$

And second order central moments are calculated by (14):

$$\mu_{02} = \frac{M_{02}}{M_{00}} - x_2{}^2 \quad \mu_{20} = \frac{M_{20}}{M_{00}} - x_1{}^2 \quad \mu_{11} = \frac{M_{11}}{M_{00}} - x_1 x_2 \tag{14}$$

Also, the second order central moments can be written as a covariance matrix which represents height and width of the object.

$$Cov = \begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix} \tag{15}$$

For better estimating the height and width of object, the matrix denoted by (15) should be decomposed by singular value decomposition (SVD).

$$Cov = U \times S \times U^T = \begin{bmatrix} u_{12} & u_{12} \\ u_{21} & u_{22} \end{bmatrix} \times \begin{bmatrix} \lambda^2{}_1 & 0 \\ 0 & \lambda^2{}_2 \end{bmatrix} \times \begin{bmatrix} u_{12} & u_{12} \\ u_{21} & u_{22} \end{bmatrix}^T \tag{16}$$

λ_1 and λ_2 are directly scale changes parameters, but in order to more accurately estimating of height and width of object, λ_1 and λ_2 should be optimized. If we suppose that *a* is the height and *b* is the width of rectangular bounding box around the target instead of using λ_1 and λ_2 as a height and width, we can show that these parameters could be well approximated with $a = k\lambda_1$ and $b = k\lambda_2$. So, we can estimate the target area *A:*

$$A = ab = (k\lambda_1)(k\lambda_2) \tag{17}$$

Then it can be easily derived that:

$$k = \sqrt{A/(\lambda_1 \lambda_2)} \tag{18}$$

And,

$$a = \sqrt{\lambda_1 A / \lambda_2}\,,\ b = \sqrt{\lambda_2 A / \lambda_1} \tag{19}$$

Then, covariance matrix converts to (20).

$$Cov = U \times S \times U^T = \begin{bmatrix} u_{12} & u_{12} \\ u_{21} & u_{22} \end{bmatrix} \times \begin{bmatrix} a^2 & 0 \\ 0 & b^2 \end{bmatrix} \times \begin{bmatrix} u_{12} & u_{12} \\ u_{21} & u_{22} \end{bmatrix}^T \tag{20}$$

Equation (20) shows that for width and height estimation of target, the area of target with covariance matrix should be combined.

$$Cov = U \times S \times U^T = U \times \begin{bmatrix} (a+\Delta d)^2 & 0 \\ 0 & (b+\Delta d)^2 \end{bmatrix} \times U^T \tag{21}$$

After we estimate the location and size of the target candidate region in the current frame, for better tracking, we need to estimate these parameters in the next frame too. Therefore, covariance matrix of (21) is defined to indicate the size of the target candidate region in the next frame and Δd is the increment of the target candidate region in the next frame.

III. Feature Extraction

A. RGB Color Feature

The most reliable feature which could have best description of scale changes of the object in different situation is RGB color features.

RGB color model is invariant to illumination changes and changes of the object's scale. A form is very much used in the shape of the target is a color (RGB) histogram, due to its non-dependence on scaling and rotation, as well as its strength when minor occlusions occur. We determine the desired target model as a normalized color histogram. Consequently, as the main feature for tracking, we separate the target region and make RGB histogram. Both target model and target candidate during the tracking have a RGB histogram. Feature spaces, quantized bins are 16×16×16.

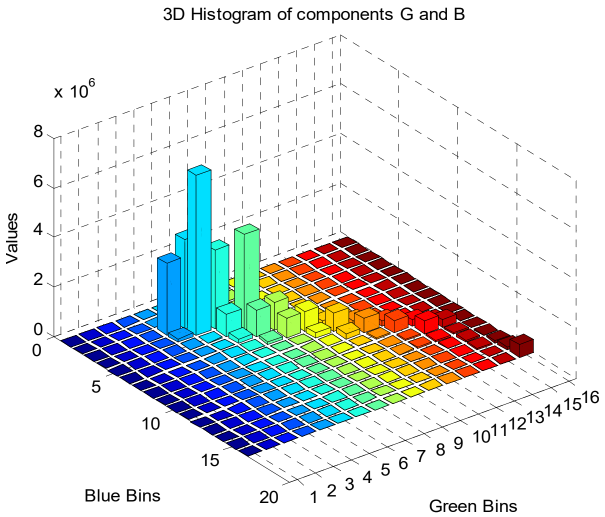


Fig. 1 3D histogram of color blue and green

B. Harr Wavelet Transform

Wavelet transform is another commonly used technique to check the texture in the image. By applying wavelet transforms, the frequency-space information is extracted in the signal. Besides, the main subject of this article which could be useful for us is blur feature of the object. Blur phenomenon can be used as another feature for distinguish of different images. Aside from this fact, blurring may cause by camera motion during the exposure time and tracking in different scene [13]. These blurred scenes include blur length and blur orientation which could have effect on an image and caused image degradation [13], [14]. Therefore, this feature could be very helpful especially for estimating of object motion in miscellaneous frames.

Harr wavelet transform play an important role in both discriminating different types of edges and recovering sharpness from the blurred version [15]-[17]. Taking advantage of the ability of Harr wavelet transform leads to two main aspects: first, it can help us to judge whether a given target region is blurred or not, which is based on edge type analysis, second, by edge sharpness analysis it determines to what extent the given target region is blurred [15].

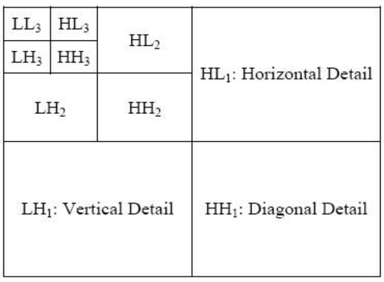


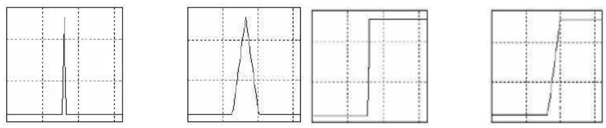
Fig. 2 Three level wavelet transform with related sub-bands

Firstly, Harr wavelet transform is performed to target region and the composition level is 3. Then construct the edge map in each scale:

$$Emap_i(k,l) = \sqrt{LH_i^2 + HL_i^2 + HH_i^2} \quad i = (1,2,3) \tag{22}$$

The local maxima ($Emax_i$) of the blurred target region is computed by partitioning the edge maps and taking a window and find local maxima in each window. Window size in the highest scale is 2×2. In the next edge map window size is 4×4 and in the next edge map window size is 8×8. The result is denoted as $E\max_i$ (i = 1, 2, 3). In fact, $E\,max_i$ describes the relationship between edges and intensity of this region. The larger $E\max_i$, the more intense the edge. It is considered a threshold whether computed $Emax_i$ is an edge point or not.

According to above algorithm, three types of edges will obtain: Dirac-Structure, Step-Structure, and Roof-Structure. Also, whether the change of intensity is gradual or not, Step-Structure is classified into Astep-Structure and Gstep-Structure [15]. We know that most natural images contain all types of edges. For the sake of this reason, we review some attributes of different edges. Both Dirac-Structure and Astep-Structure will disappear and both Gstep-Structure and Roof-Structure tend to lose their sharpness. Hence, it does not matter whether blurred image is caused by Out-of-focus or Linear motion. To put in a nutshell, according to the fact that primary target region has either Dirac-Structure or Astep-Structure our procedure judges whether this region is blurred or not, and then uses the percentage of Gstep-Structure and Roof-Structure which are more likely to be in a blurred region to determine the blur extent feature.



(a) (b) (c) (d)

Fig. 3 Graphic description of edge type [(a)Dirac-Structure, (b)Roof-Structure, (c)Astep-Structure and (d)Gstep-Structure]

IV. Proposed Algorithm

For tracking the object in blur scene, blur extent of image should be calculated from Harr wavelet transform. So, we crop the target candidate region in size of 128×128 to calculate this parameter. Moreover, as mentioned before, the local maxima ($Emax_i$) of the blurred image are computed by partitioning the target candidate region and taking a window and finding find local maxima in each window. We should first realize the kind of edge that exists in the target region and then should calculate the amount of blur extent according to the edge types. So, we should look at this matter from two main aspects. First, we use an algorithm to find out target region which is blurred and second we use another algorithm to find out the blur extent and then use this feature for cooperating with covariance matrix of mean shift tracking algorithm. Hence, significant properties of Harr wavelet transform lead to the following step:

1) All of the edge point will calculated if $Emax1(k, l)$

>threshold or $Emax_2(k, l)$>threshold or $Emax_3(k,l)$ >threshold.

2) Dirac-Structure and Astep-Structure will obtaine if $Emax_1(k,l)>Emax_2(k,l)>Emax_3(k,l)$ for any edge point (k,l).
3) Roof-Structure and Gstep-Structure will obtaine if $Emax_1(k,l)<Emax_2(k,l)<Emax_3(k,l)$ for any edge point (k,l).
4) Roof-Structure will onbtain if $Emax_2(k,l)>Emax_1(k,l)$ and $Emax_2(k,l)>Emax_3(k,l)$ for any edge point (k,l).
5) if $Emax_1(k, l)<threshold$ for any Gstep-Structure or Roof-Structure edge point, (k,l) is more likely to be in a blurred image.

For finding out whether a given image is blurred or not and calculating the blur extent, we follow the bellow procedure:

1) Find total number of all edge points. We named it N_{edge}.
2) Find total number of all Dirac-Structure and Astep-Structure edge points. We named it N_{da}.
3) Find total number of all Roof-Structure and Gstep-Structure edge points. We named it N_{rg}.
4) Find total number of all Roof-Structure and Gstep-Structure edge points that have lost their sharpness. We named it N_{brg}.
5) Calculate the ratio of Dirac-Structure and Astep-Structure to all the edges:

$$per = \frac{N_{da}}{N_{edge}} \quad (23)$$

If $Per > MinZero$, judge that the target region is un-blurred and vice versa, where $MinZero$ is a positive parameter close to zero.

6) Calculate how many Roof-Structure and Gstep-Structure edges are blurred

$$BlurExtent = \frac{N_{brg}}{N_{rg}} \quad (24)$$

To reach more accuracy and more reliable scale the blur extent parameter which was achieved from wavelet transform earlier is used in (25)

$$\Delta d = \Delta BE = k \times BlurExtent \quad (25)$$

where k is an experimental constant

$$Cov = U \times S \times U^T = U \times \begin{bmatrix} (a+\Delta BE)^2 & 0 \\ 0 & (b+\Delta BE)^2 \end{bmatrix} \times U^T \quad (26)$$

With this approach, the location and scale of the object are determined in the current frame, but we need to estimate the location and scale of this object in next frame too. Hence, we considered the ΔBE that comes from blur extent parameter which defined before. Blur extent is between 0 and 1, and the one which is close to 1 shows more blur in the image.

V. Experimental Results

We perform the proposed algorithm in MATLAB. The algorithm was implemented on a PC (core i7 with 8 GB RAM). The images used in the experiment are standard images of PET dataset. We used 16×16×16 RGB colour histogram for determining the target model and target candidate. First, we select the region of interest (ROI) and then tracking algorithm starts to run. As the figures demonstrate, bounding box of adaptive mean shift has been much bigger or smaller in different frames because it uses the same Δd for all frames but the proposed method uses a unique $\Delta d = \Delta BE$ for each frame which comes from wavelet feature and it leads to more accurate tracking in the region of interest. In fact, this sort of update in covariance matrix not only prevents the bounding box from getting smaller or bigger haphazardly but also controls the real scale. Fig. 4 shows that when blur extent increases then Bhattacharyya decreases. It means that similarity coefficient in blurred scenes has been reduced.

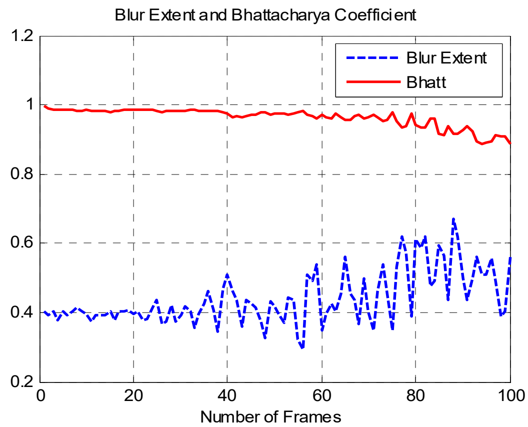


Fig. 4 The relationship between blur extent parameter and Bhattacharyya coefficient for first 100 frames of blur car

The estimation result and accuracy of the width, height in blur condition has been demonstrated in Table I. Fig. 5 illustrates 28,48,58,74 and 93 frame of blur car which their blur extents are respectively 0.2787, 0.5469, 0.3810, 0.7937, 0.9377 and 0.9111. Blur owl's frames 1, 27, 40, 47, 63, and 82 are represented in Fig. 6 and blur extent corresponding with them are 0.5246, 0.8906, 0.9688, 1, 1, 0.9206. Fig. 7 shows 1, 27, 59, 66, 76, and 84 frame of blur face and their blur extents of them are respectively 0.3607, 0.3770, 0.5938, 0.5156, 0.5873, and 0.5238.

Clearly from Table I and the figures, we can conclude that when the camera speeds up and stops suddenly, this leads to motion blur in the image and sudden changes of the camera increase in different directions, and consequently error gets bigger. In all images, the red bounding box represents the adaptive mean shift tracker and green bounding box shows our proposed method. As we can see, green bounding box has good performance in all images. Frame indexes are shown in the top left of each figure.

TABLE I
ESTIMATION RESULTS

Data set	Frame no	Real Width	Esti Width	Error (%)	Real height	Esti height	Error (%)
car	28	51	50	1.97	47	47	0
car	*48*	45	41	8.89	42	38	10.63
car	*58*	48	47	2.09	45	44	2.33
car	*74*	39	38	2.57	36	35	2.80
car	*93*	41	39	4.88	39	35	10.26
Average error over 100 frames				4.08			5.20
owl	*27*	48	48	0	59	59	0
owl	*40*	48	49	2.08	59	63	6.70
owl	*47*	48	51	6.25	60	63	5.00
owl	*63*	50	51	2.00	60	59	1.77
owl	*82*	49	48	2.05	58	66	13.79
Average error over 100 frames				3.07			5.45
face	*27*	38	36	5.36	44	45	2.27
face	*59*	36	37	2.70	45	45	0
face	*66*	37	37	0	45	45	0
face	*76*	36	37	2.70	45	44	2.33
face	*84*	36	37	2.70	46	44	4.35
Average error over 100 frames				2.69			1.79

Fig. 5 The tracking result of selected target for frames 1, 28, 48, 58, 74, and 93 of blur car

VI. CONCLUSION

In this paper, we show that we could have better tracking result in blur images with proposed method. We try to take advantage of Harr wavelet transform in order to estimate the amount of blur extent in target region, and by this fact, we could determine target candidate region more accurately. It has been demonstrated that wavelet feature could have impact on covariance matrix of mean shift tracking algorithm and could lead to better result in tracking. With this approach we defined ΔBE as an incremental target candidate region parameter. This method with blur extent feature handles significant appearance changes such as better detection of object in blur scene and even background clutter. Result shows that our algorithm has good performance in tracking miscellaneous object especially in blur scene. As we can see, the accuracy of estimations is satisfying.

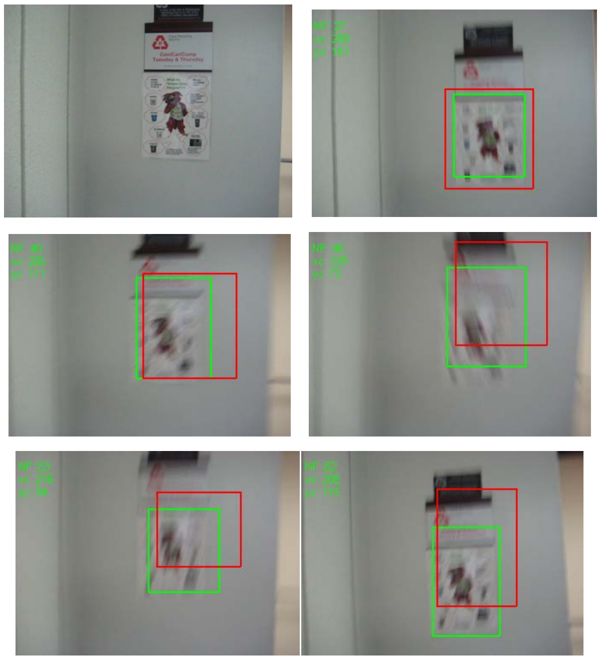


Fig. 6 The tracking result of selected target for frames 1, 27, 40, 47, 63, and 82 of blur owl

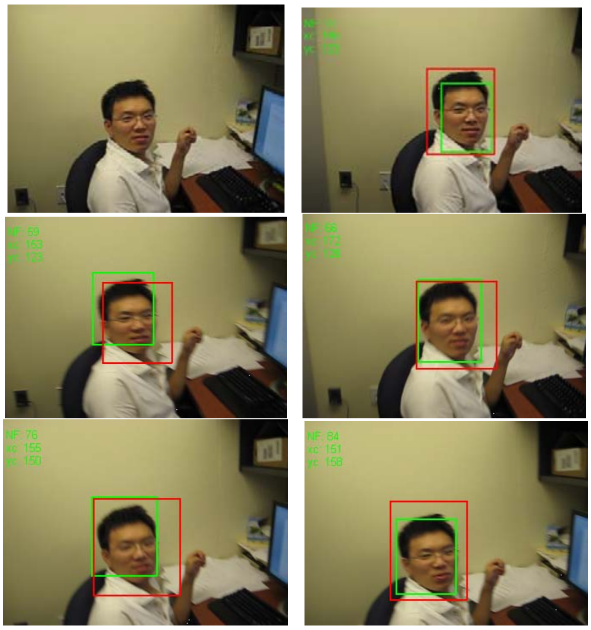


Fig. 7 The tracking result of selected target for frames 1, 27, 59, 66, 76, and 84 of blur face

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