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Designing and Implementation of an Efficient Object Tracking System Using Modified Mean Shift Tracking

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Abstract: Because of image-databases and "live" video information is growing more and more widespread, their intelligent or automatic examining is becoming exceptionally important. Object tracking, in general, is a challenging problem. In this project work an efficient object tracking system is presented based on Modified mean shift tracking (MMST) algorithm. This project work basically deals with how to address the problem to estimate the scale and orientation changes of the target under the mean shift tracking framework. In the mean shift tracking algorithm, the location of the target can be sound estimated, though the scale and orientation changes cannot be adaptively estimated. Taking into consideration that the weight image derived from the target model and the candidate model can represent the possibility that a pixel belongs to the target. The proposed method adaptively estimates the height, width, and orientation changes of the target. Experiments are performed to testify the proposed method and validate its robustness to the scale and orientation changes of the target.

Keywords: Object Tracking, Modified mean shift tracking (MMST) algorithm, scale and orientation changes, Mean shift tracking framework, target model, candidate model.

I. INTRODUCTION

Object tracking refers to method to track an object (or multiple objects) over a sequence of images. Mean shift analysis is a possible forward-tracking technique because it estimates the positions of the regions in the current frame from the previous frame. Mean-shift tracking is a technique for following an object of interest as it moves through a video sequence. The mean shift method is a non-parametric feature space analysis technique. It works with a search window that is situated over a section of the distribution. The mean shift technique is an application independent tool .It is suitable for real data analysis because it does not assume any prior shape (e.g. elliptical) on data clusters. Therefore, there are numerous approaches employing the mean shift algorithm in object tracking [1].

II. RELATED WORK

Real-time object tracking is a critical task in computer vision, and many algorithms have been proposed to overcome the difficulties arise from clutters, noise, occlusions, and changes in the foreground object and/or background environment [9]. Among various tracking methods, the mean shift tracking algorithm is a popular one due to its simplicity and efficiency. The mean shift algorithm was originally developed by Fukunaga and Hostetler [2] for data analysis, and later Cheng [3] introduced it to the field of computer vision. Bradski [4] modified it and developed the Continuously Adaptive Mean Shift (CAMSHIFT) algorithm for face tracking. Comaniciu and Meer fruitfully apply mean shift algorithm to image segmentation [6] and object tracking [5, 7]. Some optimal properties of mean shift were discussed in [8, 10]. In the classical mean shift tracking algorithm [7], the estimation of scale and orientation changes of the target is not solved. Though it is not robust, the CAMSHIFT algorithm [4], as the earliest mean shift based tracking scheme, could truly deal with a variety of types of movements of the object. .

III. PROBLEM IDENTIFICATION

Significant research effort has focused on video-based motion tracking [11] [12] [13] [14] and attract the interest of industry. Performance evaluation of motion tracking is important not only for the comparison and further development of algorithms from researchers, but also for the commercialization and standardization of the technology.. Although the mean shift tracking algorithm is able to provide good results but it cannot able to deal with the scale and orientation of targets. So the most important problem identified for this project is to modify mean shift tracking algorithm to resolve scale and orientation problems of target tracking system.

IV. METHODOLOGY

This section presents the description of the proposed Modified Mean shift tracking algorithm.
The detailed description of the project work is as follows –

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A. Mean Shift Tracking Algorithm

1. Target Representation :

At present, a commonly used target representation is the color histogram because of its independence of scaling and rotation and its robustness to partial occlusions [16],[19]. Denote by $\{X_i^*\}_{i=1\cdots n}$ the normalized pixels in the target area, which is thought to be centered at the origin point and have *n* pixels. The probability of the feature *u* (*u*=1, 2… *m*) in the target model is computed as [16].

$$\begin{cases} \hat{q} = \{\hat{q}_u\}_{u=1\ldots m} \\ \hat{q}_u = C\sum_{i=1}^{n} k(\|x_i^*\|^2)\,\delta[b(x_i^*) - u] \end{cases} \qquad (4.1)$$

Where $\hat{q}$ is the target model, $\hat{q}_u$ is the probability of the u^{th} element of $\hat{q}$, δ is the Kronecker delta function, and $b\{X_i^*\}$ associates the pixel X_i^* to the histogram b_{in} in above equation and $k(x)$ is an isotropic kernel profile. C is a Constant which is a normalization function defined by

$$C=1/\sum_{i=1}^{n} k(\|x_i^*\|^2) \qquad (4.2)$$

Similarly, the probability of the feature *u* in the target candidate model from the candidate region centered at position y is given by

$$\begin{cases} \hat{p}(y) = \{\hat{p}_u(y)\}_{u=1\ldots m} \\ \hat{p}_u(y) = C_h\sum_{i=1}^{n_k} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta[b(x_i\ )u] \end{cases} \qquad (4.3)$$

and –

$$C_h = 1/\sum_{i=1}^{n_k} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \qquad (4.4)$$

Where $\hat{p}(y)$ is the target candidate model, $\hat{p}_u(y)$ is the probability of the u^{th} element of $\hat{p}(y)$. $\{X_i\}_{n=1\cdots n_h}$ are pixels in the target candidate region centered at y, and *h* is the bandwidth and C_h is the normalization function which is independent of y [16].

In order to calculate the likelihood of the target model and the candidate model, we use a metric based on the Bhattacharyya coefficient [15] is defined by using the two normalized histograms $\hat{p}(y)$ and $\hat{q}$ as follows

$$\rho[\hat{p}(y),\hat{q}] = \sum_{u=1}^{m}\sqrt{\hat{p}_u(y)\hat{q}_n} \qquad (4.5)$$

The distance between $\hat{p}(y)$ and $\hat{q}$ is then defined as –

$$d[\hat{p}(y),\hat{q}] = \sqrt{1-\rho[\hat{p}(y),\hat{q}]} \qquad (4.6)$$

Minimizing the distance $d[\hat{p}(y),\hat{q}]$ in Eq. (4.6) is equivalent to maximizing the Bhattacharyya coefficient $\rho[\hat{p}(y),\hat{q}]$ in Eq. (4.5). The optimization process is an iterative process and is initialized with the target position, denoted by y_o in the previous frame. Now by using the Taylor expansion around coefficient $\hat{p}_u(y_o)$, the linear approximation of the Bhattacharyya in Eq. (4.5) can be obtained as:

$$\rho[\hat{p}(y),\hat{q}] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{\hat{p}(y_0)\hat{q}} + \frac{C_h}{2}\sum_{i=1}^{n_h} wk\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \qquad (4.7)$$

Where,

$$w_i = \sum_{u=1}^{m}\sqrt{\frac{\hat{q}_u}{\hat{p}_u(y_0)}}\,\delta[b(x_i)-u] \qquad (4.8)$$

Since the first term in Eq. (4.7) is independent of y, to minimize the distance in Eq. (4.6) is by maximize the second term in Eq. (4.7). In the mean shift iteration, estimated target moves from y to a new position y_1, which is define by –

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i w_i g\left(\left\|\frac{y-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} w_i g\left(\left\|\frac{y-x_i}{h}\right\|^2\right)} \qquad (4.9)$$

When we choose the kernel $k(x)$ with the Epanechnikov profile, there is $g(x)$ =-$k(x)$ =1, and Eq. (4.9) can be reduced to [20].

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i w_i}{\sum_{i=1}^{n_h} w_i} \qquad (4.10)$$

By using Eq. (4.10), the mean shift tracking algorithm finds in the new frame the most similar region to the object. From Eq. (4.10) it can be observed that the key parameters in the mean shift tracking algorithm are the weights w_i.

B. Modified Mean Shift Tracking for Scale and Orientation of target.

In this section, we first analyze how to calculate adaptively the scale and orientation of the target,.

1. The Weight Images for Target Scale Changing:

In the CAMSHIFT and the mean shift tracking algorithms, the evaluation of the target location is actually obtained by using a weight image [17], [21]. In the mean shift tracking algorithm, the weight image is defined by Eq. (4.8) where the weight of a pixel is the square root of the ratio of its color probability in the target model to its color probability in the target candidate model. The mean shift tracking algorithm can have better estimation results. That's why, the weight image in the mean shift tracking algorithm is more reliable than that in the CAMSHIFT algorithm.

2. Estimating the Target Area :

Since the weight value of a pixel in the target candidate region represents the probability that it belongs to the target, the sum of the weights of the entire pixels, i.e., the zero[th] order moment, can be measured as the weighted area of the target in the target candidate region:

$$M_{00} = \sum_{i=1}^{n} w(x_i) \qquad (4.11)$$

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The Bhattacharyya coefficient (referring to Eq. (4.5)) is an indicator of the similarity between the target model $\hat{q}$ and the target candidate model $\hat{p}(y)$. If we take M_{oo} as the estimation of the target area, then according to Eq. (4.11), while the weights from the target turn out to be bigger, the estimation error by taking M_{00} as the area of the target will be bigger, vice versa. So, the Bhattacharyya coefficient is a good indicator of how reliable it is by taking M_{00} as the target area. We can see that with the increase of the Bhattacharyya coefficient, the estimation accurateness by taking increase (e.g., the estimation error will decrease). M_{00} as the target area will also based on the on top of analysis, we see that the Bhattacharyya coefficient can be used to adjust M_{00} in estimating the target area, denoted by A. We recommend the following equation to estimate it:

$$A = c(\rho)M_{00} \ldots\ldots\ldots\ldots(4.12)$$

Where $c(\rho)$ is a monotonically increasing function with respect to the Bhattacharyya coefficient $\rho(0 \le \rho \le 1)$ always greater than the real target area and it will monotonically approach to the real target area with ρ increasing. Hence we require that $c(\rho)$ should be monotonically increase and reach maximum 1 while ρ is 1, Such correction function $c(\rho)$ is possible to shrink M_{00} back to the real target scale.

There can be alternative candidate functions of $c(\rho)$, such as linear function $c(\rho)=\rho$, Gaussian function, etc. Now we select the exponential function as $c(\rho)$ based on our experimental experience:

$$c(\rho) = \exp\left(\frac{\rho-1}{\sigma}\right) \ldots\ldots\ldots\ldots(4.13)$$

From Eqs. (4.12) and (4.13) we can see that when ρ approaches to the upper bound 1, when the target candidate model approaches to the target model, $c(\rho)$ approaches to 1. In this case it is more reliable to use M_{00} as the estimation of target area. When ρ decreases, the candidate model is not identical to the target model, M_{00} will be much bigger than the target area but $c(\rho)$ is less than 1 so that A can avoid being biased too much from the real target area. When ρ approaches to 0, the tracked target gets lost, $c(\rho)$ will be extremely small so that A is close to zero.

3. The Moment Features in Mean Shift Tracking:

We can simply calculate the moments of the weight image as follows:

$$M_{10} \sum_{i}^{n_k} w_i x_{i,1} \qquad M_{01} \sum_{i=1}^{n_k} w_i x_{i,2} \ldots\ldots(4.14)$$

$$M_{20} \sum_{i=1}^{n_k} w_i x_{i,1}^2 , \quad M_{02} \sum_{i=1}^{n_k} w_i x_{i,2}^2 , \quad M_{11} \sum_{i=1}^{n_k} w_i x_{i,1} x_{i,2}$$

$$\ldots\ldots\ldots\ldots(4.15)$$

Where pair ($x_{i,1}$, $x_{i,2}$) is the coordinate of pixel i in the candidate region. Comparing Eq. (4.10) with Eqs. (4.11) and (4.14), we can find that y_1 is actually the ratio of the first order moment to the zero[th] order moment:

$$y_1 = (\bar{x}_1, \bar{x}_2) = (M_{10}/M_{00}, M_{01}/M_{00}) \ldots\ldots\ldots(4.16)$$

Where $(\bar{x}_1, \bar{x}_2)$ represents the centroid of the target candidate region. The second order center moment can describe the shape and orientation of an object. By using Eqs. (4.10), (4.11), (4.15) and (4.16), we can convert Eq. (4.9) to the second order center moment as follows

$$\mu_{20} = M_{20}/M_{00} - \bar{x}_1^2$$

$$\mu_{11} = M_{11}/M_{00} - \bar{x}_1\, \bar{x}_2$$

$$\mu_{02} = M_{02}/M_{00} - \bar{x}_2^2 \ldots\ldots\ldots\ldots(4.17)$$

Eq. (4.17) can be rewritten as the following covariance matrix in order to estimate the height, width and orientation of the target:

$$Cov = \begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix} \ldots\ldots\ldots\ldots(4.18)$$

4. Estimating the Width, Height and Orientation of the Target:

By using the estimated area and the moment features (, the width, height and orientation of the target can be well estimated. The covariance matrix in Eq.(4.18) can be decomposed by using the singular value decomposition (SVD) [20] as follows :

$$Cov = U \times S \times U^T \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix} \times \begin{bmatrix} \lambda_1^2 & 0 \\ 0 & \lambda_2^2 \end{bmatrix} \times \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix}^T$$

$$\ldots\ldots\ldots\ldots(4.19)$$

Where $U = \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{bmatrix}$ and $S = \begin{bmatrix} \lambda_1^2 & 0 \\ 0 & \lambda_2^2 \end{bmatrix}$. λ_1^2 and λ_2^2 are the Eigen values of Cov. The vectors $(u_{11}, u_{21})^T$ and $(u_{12}, u_{22})^T$ represent, correspondingly, the orientation of the two main axes of the real target in the target candidate region.Suppose that the target is represented by an ellipse, whose lengths of the semi-major axis and semi-minor axis are denoted by a and b, respectively, as an alternative of using and λ_1 and λ_2 directly as the width a and height b, it has been made known that the ratio of λ_1 and λ_2 can well approximate the ratio of a to b, i.e., $\lambda_1/\lambda_2 \approx a/b$ Thus we can set $a = k\,\lambda_1$ and $b = k\,\lambda_2$, where k is a scale factor. Since we have estimated the target area A, there is $\pi ab = \pi (k\,\lambda_1)(k\,\lambda_2) = A$. Then it can be simply derived that :

$$k = \sqrt{A/(\pi\,\lambda_1\,\lambda_2)} \ldots\ldots\ldots\ldots(4.20)$$

$$a = \sqrt{\lambda_1 A/(\pi\,\lambda_2)} \qquad , b = \sqrt{\lambda_2 A/(\pi\,\lambda_1)} \ldots\ldots(4.21)$$

Now the covariance matrix becomes..

$$Cov = \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix} \times \begin{bmatrix} a^2 & 0 \\ 0 & b^2 \end{bmatrix} \times \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix}^T \ldots\ldots (4.22)$$

The adjustment of covariance matrix *Cov* in Eq. (4.22) is a key step of the proposed algorithm. It should be keep in mind that the EM-like algorithm by Zivkovic and Krose [18] estimates iteratively the covariance matrix for each frame based on the mean shift tracking algorithm. Not like the EM-like algorithm, our proposed algorithm combine the area of target, i.e., *A*, with the covariance matrix to estimate the height , width and orientation of the target.

5. Determining the Candidate Region in Next Frame:
We define the following covariance matrix to represent the size of the target candidate region in the next frame

$$Cov_2 = \begin{bmatrix} (a + \Delta d)^2 & 0 \\ 0 & (b + \Delta d)^2 \end{bmatrix} \times U^T \ldots\ldots\ldots\ldots\ldots (4.23)$$

where Δd is the increment of the target candidate region in the next frame. The location of the initial target candidate region is defined by the following ellipse region

$$(x - y_1) \times Cov_2^{-1} \times (x - y_1)^T \leq 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.24)$$

6. Implementation of the MMST Algorithm :
Based on the above analyses the scale and orientation of the target can be estimated and then orientation and scale adaptive mean shift tracking algorithm, means the MMST algorithm, can be developed.

V. EXPERIMENTAL RESULT

This section evaluates the proposed MMST algorithm. We selected RGB color space as the feature space and it was quantized into 16×16×16 bins. In this section, the results of applying the modified mean shift tracking (MMST) methods on various test sequences are shown. The experimental results are presented to show that the proposed method can achieve promising performance. Videos are homemade video. We have taken 5 home made video containing similar background and 5 containing dissimilar background. The detection rate and processing time is calculated for each case.

A. *Experimental Result in similar foreground and background color:*

Figure 1 shows the result of MMST method on five test sequence. In this example, the color of the objects (Green dice, Black rectangular cap, red dice, black round cap & blue showpiece) being tracked, has similarity with its background. In such case, the other algorithm fails to track the object; relatively it keeps on adapting its window to include the background. They works well only when the object significantly differs from its background in color. Their Processing time and Detection rate are also calculated in Table.

B. *Experimental Result in Dissimilar foreground and background color :*

Figure 2 shows the result of MMST method on five test sequence . In this , the color of the objects (Green dice, Black rectangular cap, red dice, black round cap & blue showpiece) being tracked, has no similarity with its background. Their Processing time and Detection rate are also calculated in Table

C. *Calculation of Detection Rate*

Detection rate is the ratio of the number of frames the object location is accurately estimated to the total number of frames in the sequence. The detection rate of MMST method applied to ten different video sequences are shown in Table 1. The method is efficient in both the situation, when the object has similar color with its background and when the object has dissimilar color with its background. The traditional tracking methods are not efficiently work when the background color is similar to the color of object

D. *Calculation of Processing Time*

Processing time is defined as the time taken by the system to process the video , that is to track the interested object in a sequence of Frames. The Table 2 and Table 3 shows the processing time from first frame to last frame of video contained in Figure 1 and Figure 2.

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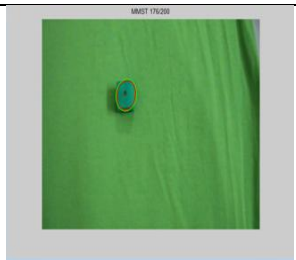
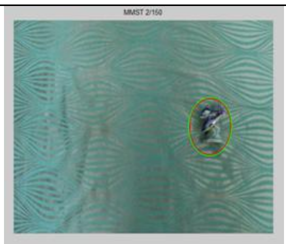
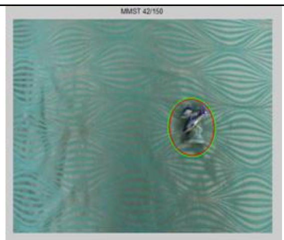
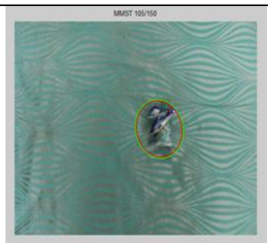
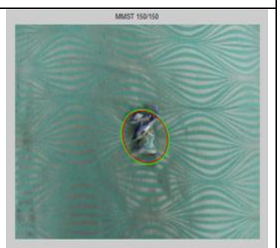
S.N	Sequence of Frames in a Video			
1.	 Frame 11	 Frame 100	 Frame 176	 Frame 200
2.	 Frame 7	 Frame 34	 Frame 79	 Frame 300
3.	 Frame 5	 Frame 52	 Frame 75	 Frame 200
4.	 Frame 4	 Frame 30	 Frame 82	 Frame 200
5.	 Frame 2	 Frame 42	 Frame 105	 Frame 150

Fig 1. Similar Foreground object and Background scene color.

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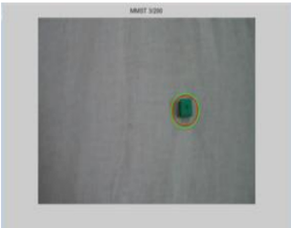
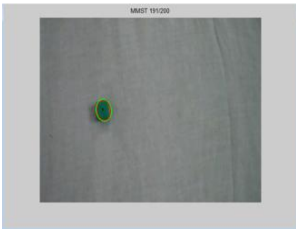
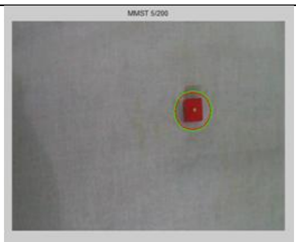
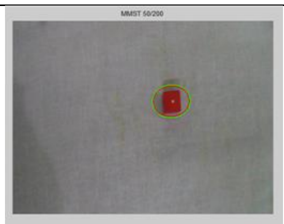
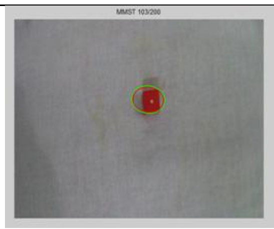
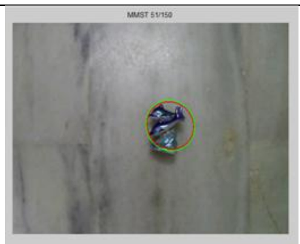
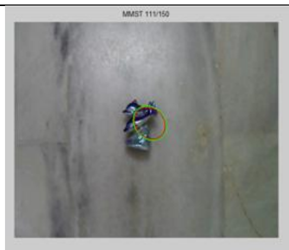
S.N.	Sequence of Frames in a Video			
1.	 Frame 3	 Frame 42	 Frame 191	 Frame 200
2.	 Frame 4	 Frame 42	 Frame 71	 Frame 300
3.	 Frame 5	 Frame 50	 Frame 103	 Frame 200
4.	 Frame 3	 Frame 46	 Frame 81	 Frame 190
5.	 Frame 2	 Frame 51	 Frame 111	 Frame 150

Fig 2 . Dissimilar Foreground object and Background scene color

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Table 1 - Comparision of MMST method Tracking result in similar color background and dissimilar color background

S.N.	Object	Similar Background Color		Dissimilar Background Color	
		Frame Missed/ Total	Detection Rate	Frame Missed/ Total	Detection Rate
1.	**Green Dice**	0/200	100%	3/200	98.5%
2.	**Black rectangular cap**	39/300	87%	47/300	84.34 %
3.	**Black Round Cap**	21/200	89.5%	23/200	88.5%
4.	**Red Dice**	13/200	93.5%	11/200	94.5%
5.	**Blue Showpiece**	7/150	95.34%	15/150	90%

Table 2 – Execution Time Analysis For Tracking (Similar color Background)

S.N.	Video	Parameter					
		Frame Height	**Frame Width**	**Number of Frames**	**Frame Rate (FPS)**	**Video Length in Sec.**	**Total Processing time in sec.**
1	**Green Dice**	720	1280	200	10 FPS	20	37
2	**Black Rect. Cap**	720	1280	300	10 FPS	30	42
3	**Black round Cap**	720	1280	200	10 FPS	20	29
4	**Red Dice**	720	1280	200	10 FPS	20	26
5	**Blue showpiece**	720	1280	150	10 FPS	15	46

Table 3 – Execution Time Analysis For Tracking (Dissimilar color Background)

S.N.	Video	Parameter					
		Frame Height	**Frame Width**	**Number of Frames**	**Frame Rate (FPS)**	**Video Length in Sec.**	**Total Processing time in sec.**
1	**Green Dice**	720	1280	200	10 FPS	20	27
2	**Black Rect. Cap**	720	1280	300	10 FPS	30	34
3	**Black Round Cap**	720	1280	200	10 FPS	20	27
4	**Red Dice**	720	1280	200	10FPS	20	27
5	**Blue Showpiece**	720	1280	150	10FPS	15	40

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VI. CONCLUSIONS

By analyzing the moment features of the weight image of the target candidate region and the Bhattacharyya coefficients, we developed an orientation and scale adaptive mean shift tracking (MMST) algorithm. It can well solve the problem of how to estimate robustly the scale and orientation changes of the target under the mean shift tracking framework.

The weight of a pixel in the candidate region represents its probability of belonging to the target, while the zeroth order moment of the weights image can represent the weighted area of the candidate region. By using the zeroth order moment and the Bhattacharyya coefficient between the target model and the candidate model, a straightforward and efficient method to estimate the target area was proposed. After that a new approach which is based on the area of the target and the corrected second order center moments was proposed to adaptively approximate the width, height and orientation changes of the target.

From Experiment following conditions are observed -

1. If the object to be tracked is in any geometric shape like circle, ellipse, square, triangle and rectangle then the detection rate is good otherwise decreases.

2. If we take less background features in the Region of Interest (ROI) we select to track the object , then the performance is good and less chances of false detection.

3. If the object to be tracked is of small size then it takes less processing time in tracking of object. On the other hand is the object to be tracked is large in size, then it takes more processing time in tracking

4. If the video has less FPS (Frame per second) value , then better the accuracy of tracking and detection rate.

5. It is also observed from the experiments that if the video tracking framework takes more processing time to track the object , then it results in more accurate tracking.

6. From experimental result it is also clear that the performance of tracking of object in a shape of circle and ellipse is always better than the other shapes of objects.

The method is tested in 10 video sequence. The test result reveals that the method gives satisfactory result in both the situation i.e. similar foreground and background color and dissimilar foreground and background color.

VII. SCOPE OF FUTURE WORK

The developed MMST method inherits the merits of mean shift tracking, like its simplicity, efficiency and robustness. Extensive experiments were performed and the results showed that MMST can reliably track the objects with scale and orientation changes, which is not easy to achieve by other state-of-the-art schemes. In the future research, we will focus on how to detect and use the true shape of the target, as an alternative of an ellipse or a rectangle model, to achieve more robust tracking.

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