Object Tracking in Video using Mean Shift Algorithm including Effect of AWGN channel

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Abstract:- One of the analytic ventures in object tracking is the tracking of fast-moving objects in arbitrary movement, mainly in the area of video vision applications. Thus a technique of mean shift (MS) algorithm in visual video tracking is put forward. In this suggested method, arbitrary motion and partial occlusion of an object can be managed due to its capacity in estimating the object position with modifying motion model. Although the techniques like particle filter (PF) is able to manage numerous hypotheses to manipulate clutters in background and short-term breakdown. However, on the other hand, it needs a huge number of particles to estimate the actual posterior of the target dynamics. Therefore, MS algorithm is employed to the sampling process of the PF to carry these particles in gradient ascent direction. As a result of this, a little sample size will be adequate to constitute the system dynamics precisely. The proposed algorithm is directed to track the moving object in arbitrary directions under altering states with reasonable computational time. The dissimilarity between the target model and the target candidates is expressed by a metric derived from the Bhattacharya Coefficient.

Keywords: *kernel-based, object tracking, particle filter, mean shift, Bhattacharya Coefficient.*

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I. INTRODUCTION

In common, object tracking is an exacting issue because of the partial occlusions, abrupt object motion, scene illumination changes, camera motion, and varying appearance of the object and background. There are two main categories in a typical object tracker:

1. Target estimation and localization
2. The filtering and data association.

The first one is a kind of bottom-up process which deals with the appearance variations of the target; and the second one is a kind of top-down process which deals with the dynamics of the tracked object [1]. There are various categories of object tracking, which includes point tracking, kernel tracking and silhouette tracking [2]. Kernel tracking is performed by estimating the movement of target object with primitive object region representation. Due to the computational cost of brute force search is large, more applicable techniques have been derived to limit the object search within the neighborhood of its initial location [3]. The mean shift (MS) applications were first suggested in reference [4]. The MS algorithm widens the look similarity iteratively by equating the histograms of the target candidate and the hypothesized object model. Histogram likeliness is given in words of the Bhattacharya coefficient. The coefficient is enlarged at every iteration in the estimation of MS vector as soon as convergence is gained [5].However, kernel tracking is hopped to the condition that at least some parts of the object exist in the region of the former position of the target. Kalman filter (KF) or particle filter (PF) technique is employed in combination with MS tracker to increase the prediction of the target object position [6]. A nonlinear dynamic model where PF was used for state calculation is suggested in reference [7].

II. MEAN SHIFT BASED TRACKING ALGORITHM

2.1 Mean Shift Object Tracking

The MS algorithm is introduced to optimize the smooth similarity function and obtain the direction of the target's movement.

$$g(a) = -K_E(a) = \begin{cases} \frac{2}{\pi} & if\,|a|<1 \\ 0 & otherwise \end{cases} \qquad (1)$$

Epanechnikov outline is chose as the kernel mask in place of other kernel outlines like Gaussian since its derivative is a constant, which clarifies the use of the gradient optimization method. The similarity distance estimated between the target and current distribution is the sign to discover the target object in the current frame.

2.2 Prediction of Target Movement using Mean Shift Calculation

The similarity between the current target distribution and the next frame candidate distribution require to be enlarged to estimate the direction of the target's motion. The distance evaluation metric between the two discrete distributions is defined in (2).

$$d(b) = \sqrt{1 - \rho[p(b), q]} \qquad (2)$$

The Bhattacharya coefficient is chose to find the quantity of relative similarity, which is shown in (3),

$$\rho(p(b), q) = \sum_{u-1}^{m} \sqrt{p_u(b) q_u} \qquad (3)$$

Where ρ is the cosine of the angle between m-dimensional unit vectors. Using Taylor expansion around the value $p_u(x_0)$, the linear approximation of the Bhattacharya coefficient can be estimated as shown in (4).

$$\rho(p(b), q) = \frac{1}{2}\sum_{u-1}^{m}\sqrt{p_u(a_0)q_u} + \frac{1}{2}\sum_{u-1}^{m}\sqrt{\frac{q_u}{p_u(a_0)}} \quad (4)$$

Equation (4) can be expressed as in (5) also,

$$\rho(p(b), q) = \frac{1}{2}\sum_{u-1}^{m}\sqrt{p_u(a_0)q_u} + \frac{1}{2}\sum_{i-1}^{n} w_i\, k\left(\left|\frac{a-a_i}{h}\right|^2\right) \quad (5)$$

$$\text{Where, } w_i = \sum_{u-1}^{m}\sqrt{\frac{q_u}{p_u(a_0)}}\,\delta(y(a_i)-u) \quad (6)$$

The terms q_u and p_u in (6) are the values of the target and candidate histograms correlating to pixel x_i of the candidate object. This mapping is to see the alterations of the target object over a period and the correlating distribution of weights for it.

From (5), the first term does not depend on x, so in order to diminish the distance in (2); the second term has to be enlarged. By using the MS estimation, the center of the target candidate is separately moved according to (7),

$$a_{new} = \frac{\sum_{i-1}^{n} a_i w_i g\left(\left|\frac{a_0-a_i}{h}\right|^2\right)}{\sum_{i-1}^{n} w_i g\left(\left|\frac{a_0-a_i}{h}\right|^2\right)} \quad (7)$$

Where x_0 is the present position of the candidate and g(x) is the derivative function k(x). According to (1), the derivative of Epanechnikov kernel is a constant and hence (7) can be reduced to a weighted distance average as shown in (8).

$$a_{new} = \frac{\sum_{i-1}^{n} a_i w_i}{\sum_{i-1}^{n} w_i} \quad (8)$$

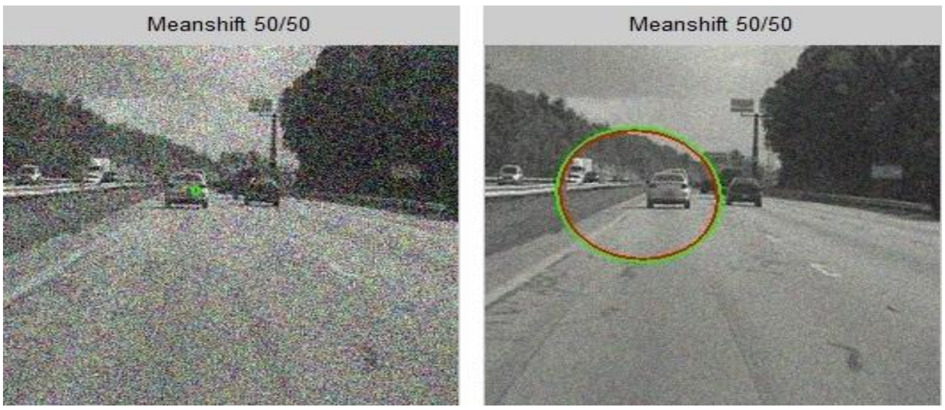
III. EXPERIMENTAL RESULTS

The interpretation of the MS algorithm is assessed on picked video to illustrate multiple situations. Experiments are performed to examine for its skill to manage partial occlusion, velocity changes and overlapping as well as abrupt direction with like-colored background.

This procedure points to examine and assess the staging of MS algorithm in tracking the target shaky car which repeatedly feels random direction and velocity alteration, as given in Figure 1. This outcome illustrated consecutive tracking of the car by MS algorithm. The purpose of this algorithm in chasing with random motion and velocity variations of fast moving object helps the utilization of the tracker in tracking random moving object.

The effect of the AWGN channel on the illustration of the MS-based tracker is shown in Figure 2. Maximum Bhattacharya coefficient employs that the calculated target distribution is corresponded with the target model distribution with maximum likeliness. It can be seen that the MS can gain adequately large efficiency when the SNR is kept around 20. Therefore, the result indicates that MS applied can efficiently decrease the number of particles needed for robust tracking by increasing the SNR value (Figure 3).

Figure 1: The Tracking result of MS algorithm in shaky car video



(A) (B)

Figure 2: The Tracking result of MS algorithm in shaky car video for (A) SNR=10 and (B) SNR=20 including AWGN channel

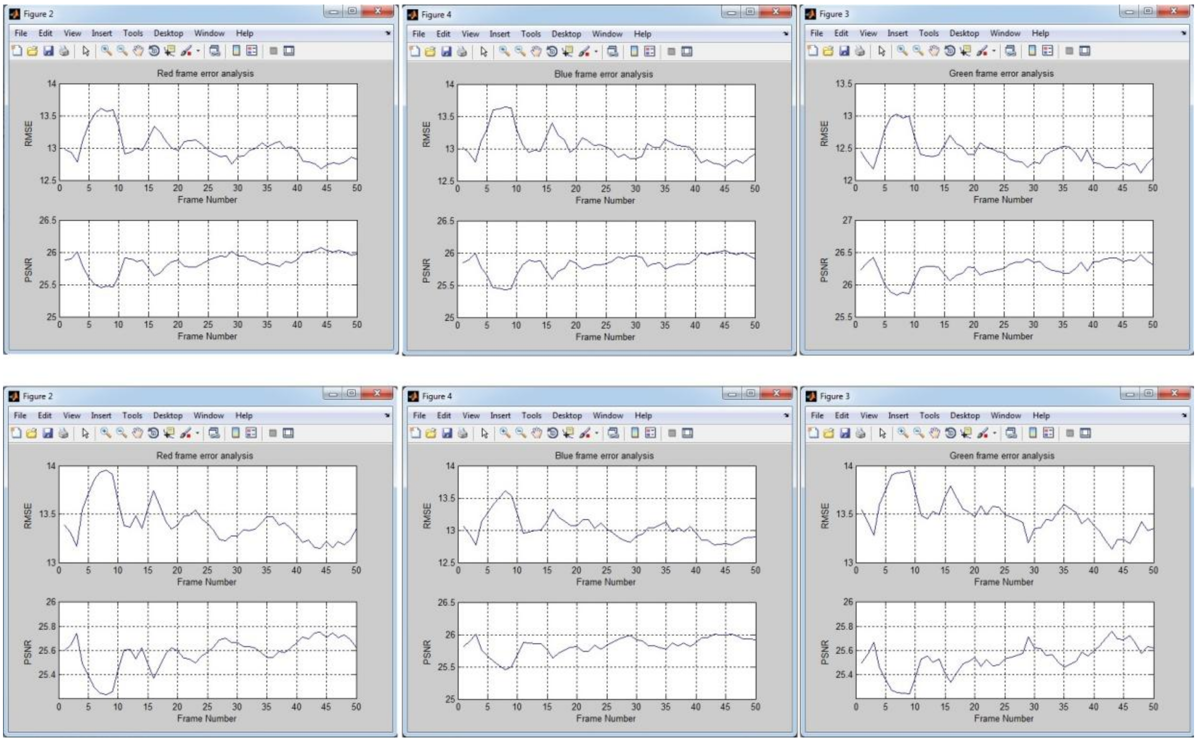


Figure 3: Frame Error Analysis of Red, Blue and Green frames by comparing original video with video including AWGN effect

IV. CONCLUSION

The advanced MS algorithm gives adequate tracking interpretation and being computationally affordable. The execution of the MS tracking algorithm in video is illustrated with the use of AWGN effect on the target. This tracking algorithm is competent to track abrupt direction and velocity varying object. Moreover, illustration indicates that by increasing the SNR value, MS algorithm can highly minimize the number of particles needed for robust tracking corresponding to conventional approaches.

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