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A ROBUST APPROACH FOR OBJECT TRACKING BASED ON PARTICLE FILTER AND OPTIMIZED LIKELIHOOD

Amr M. Nagy[1], Ali Ahmed[2] and Hala H. Zayed[3]
[1,3]Faculty of Computers and Informatics
Benha University
Benha, Egypt
[2]Faculty of Computers and Information
Menofia University
Shubin el Kom, Menufia, Egypt

Abstract: *Robust tracking of non-rigid objects is a challenging task. Particle filter is a powerful tool for vision tracking based on sequential Monte Carlo framework and proved very successful for non-linear and non-Gaussian estimation problem. This paper proposes a tracking algorithm based on particle filter and optimized Likelihood. Colour distributions are applied as they are robust to partial occlusion, rotation, scale invariant and computationally efficient. As the colour of an object can vary over time dependent on the illumination, the target model is adapted during temporally stable image observation. Particle filter approximates a posterior probability density of the state by using samples which are called particles. Here, the state is treated as the position of the object and the weight is considered as the likelihood of each particle. For this likelihood, we calculate the similarity between the colour histogram of the tracked object and the region around the position of each particle by using Bhattacharya distance. To enhance the results, a new parameter is multiplied by the previous likelihood to increase the particles weight. The system proves to be robust against problems of partial occlusion, full occlusion and illumination changes. Finally the mean state of the particles is treated as the estimated position of the object. The correctness as well as validity of the algorithm is demonstrated through the experiments results.*

Keywords: *Particle Filter; Colour Histogram; Nonlinear/NonGaussian; Object Tracking; Optimized Likelihood*

I. Introduction

Tracking is an essential step in many computer vision related applications. Object tracking is the task of detecting and following an object of interest, over period of time. Vision based tracking system detects and tracks objects in a sequence of images. Object Tracking is required by many vision applications such as surveillance [1], human computer interfaces and video communications/ compression. To define your Object of interest it depends on the specific application at hand. For example, in a building surveillance application, targets may be people, whereas in an interactive gaming application may be hands or the face of a person. Numerous approaches have been proposed to improve the performances of target tracking, which have achieved significant improvement in the past decades. They can be roughly classified into two categories: deterministic methods and stochastic methods. Deterministic methods typically track the object by performing an iterative search for a similarity between the template image and the current one. The algorithms which utilize the deterministic method are background subtraction [2,3] inter-frame difference [4,5], optical flow [6], skin colour extraction [7,8] and so on. On the other hand, the stochastic methods use the state space to model the underlying dynamics of the tracking system such as Kalman filter [9], particle filter [10–14] Hybrid Blob and Particle Filter Tracking Approach for Robust Object Tracking, Object Tracking Using Hybrid Mean Shift and Particle Filter and Hybrid Iterated Kalman Particle Filter [15-17]. Probabilistic methods have become popular among many researchers. The Kalman filter is a common approach for dealing with target tracking in a probabilistic framework, but it cannot resolve a tracking problem where the model is nonlinear and non-Gaussian. The extended Kalman filter can deal with this problem, but still has a problem when the nonlinearity and non-Gaussian cannot be approximated accurately.

Recently, the particle filter method, a numerical method that allows finding an approximate solution to the sequential estimation has proven very successful for nonlinear and non-Gaussian estimation problems. It approximates a posterior probability density of the state such as the object position by using samples which are called particles. An important issue in particle filtering is the selection of the proposal distribution function. In general, it is hard to design such proposals. Now many proposed distributions have been proposed in the literature. For example, the prior, the EKF Gaussian approximation and the UKF proposal are used as the proposal distribution for particle filter [16–18].

In this paper, a new proposal distribution generating scheme for the particle filtering framework is proposed. The algorithm obtained is named as particle filter with optimized likelihood. In this algorithm, we propose to use such a particle filter with color-based image features. Color histograms in particular have many advantages for tracking non-rigid objects as they are robust to partial occlusion, rotation, scale invariant and are calculated efficiently. A target is tracked with a particle filter by comparing its histogram with the histograms of the sample positions using the Bhattacharyya distance, which consequently improves the performance of particle filters to estimate the new state of the tracked object.

II. Basic Particle Filter.

The state equation and measurement equation of the dynamic system are described as follows:

$$x_k = f_k(x_{k-1}, v_{k-1}) \qquad (1)$$

$$y_k = h_k(x_k, u_k) \qquad (2)$$

Where x_k denotes the system state at time k, and y_k denotes the observation at time k. v_k and u_k are the process noise and measurement noise at time k respectively (they obeys the independent and identical distribution). The state model f(.) and observation model h(.) are known and at least one non-linear. The state equation (1) characterizes the state transition probability of the system $P(x_k|x_{k-1})$, and measurement equation (2) characterizes the likelihood probability $P(y_k|x_k)$. From the perspective of Bayesian filter, given that the initial state x_0 is $P(x_0|y_0) \equiv P(x_0)$, the state transition probability $P(x_k|x_{k-1})$ and likelihood probability $P(y_k|x_k)$ the problem-solving core is to estimate the posterior probability density function (PDF) $P(x_k|y_k)$. The particle filter is the Bayesian filter's variety. It uses a set of weighted samples to approximate the posterior probability density function

$$\mathrm{P}(x_k|y_k) \approx \sum_{I=1}^{N} w_k^i \delta\left(x_k - x_k^i\right) \qquad (3)$$

The particle filter algorithm has three important steps: particle production (important sampling), weight computation and resampling.

Step 1 Produce particle (important sampling)

$$x_k^i \approx q\left[\left(x_k^i \middle| x_{k-1}^i\right), y_k\right], i = 1, \dots N \qquad (4)$$

Step 2 Compute weight and normalize weight

$$\widetilde{w}_k^i = \frac{\mathrm{P}\left(y_k \middle| x_k^i\right) \mathrm{P}\left(x_k^i \middle| x_{k-1}^i\right)}{q(x_k^i | x_{k-1}^i, y_k)} \widetilde{w}_{k-1}^i \qquad (5)$$

$$w_k^i = \frac{\widetilde{w}_k^i}{\sum_{j=1} \widetilde{w}_k^j} \qquad (6)$$

Step 3 State estimate

$$\bar{x} = \sum_{i}^{N} x_k^i \;\; w_k^i \qquad (7)$$

Steps 4 Resample.

Duplicate the high weight particle and get rid of the low weight one from the particle set $\left\{x_k^i,\ w_k^i\right\}_{i=1}^N$, obtain the new particle set $\left\{x_k^j,\ w_k^j\right\}_{j=1}^N$.

III. Re-sampling

This step involves discarding samples that have low importance and reassigning weights to the remaining particles. Various approaches have been suggested in the literature for carrying out this step.

IV. The Proposed Tracking System

Before talking about our proposed algorithm (Particle Filter with optimized likelihood), firstly the Color Based Distribution and the Particle filter initialization are introduced.

A. Color Based Distribution

Assume that the distributions are discretized into m bins. The histograms are produced with the function h (xi) that assigns the colour at location xi to the corresponding bin. In our experiments, to make the algorithm less sensitive to lighting conditions, HSV colour space using (8*8*8) bins is used to compute the histogram.

Here to compute the weight of the sample set, we do not use the entire image as a measurement, but rather we compute the colour histogram inside the ellipse that is specified by the state vector. After we compute the histogram, we use the Bhattacharyya distance to compute the similarity between the two colour histograms p = p(u), u = 1, ...,m which taken from the first frame and q = q(u), u = 1, ...,m which taken from the next frame. Bhattacharyya distance are calculated using the following equation

$$d = \sqrt{1-\rho[p,q]} \qquad (8)$$

Where

$$\rho[p,q] = \sum_{u=1}^{m} \sqrt{p^{(u)}.*} \, q^{(u)} \qquad (9)$$

From this equation, when the ρ is large this indicate that the distribution is more similar. If ρ = 1 this indicate a perfect match and we have a two identical histograms

B. Particle filter initialization

For the initialization of the particle filter, we have to find the initial starting values. There are three possibilities depending on the prior knowledge of the target object: manual initialization, automatic initialization using a known histogram as a target modal or an object detection algorithm that finds interesting targets. Whatever the choice, the object must be fully visible, so that a good colour distribution can be calculated.

C. Particle filter with optimized likelihood.

Our proposed algorithm named particle filter with optimized likelihood. It inherits the excellent properties of the colour histogram, which make it very attractive for the generation of proposal distribution within the particle filtering framework. Our proposed tracking system framework uses the Bhattacharyya distance to update the priori distribution calculated by the particle filter. Before applying the tracking algorithm, we detect an interested object manually to segment it from the background scene. For a new object entering at time instance k, the system initializes its system state $x_k = [u_k, v_k, \dot{u}_k, \dot{v}_k, a_k, b_k, \theta_k]$. Commonly used appearance models are colours values of fitted ellipse (colour matrices), and compact summarization of colour distribution such as histograms. The position (u_k,v_k) is coordinate of an object in image plane. The velocities $\dot{u}_k$ and $\dot{v}_k$ are initialized as zeros. The sizes (a_k, b_k) are the length of the major axis and the minor axis of the ellipse fitted on the visual object and θ_k the corresponding scale change. The sample set is propagated through the application of a dynamic model

$$S_k = A * S_{k-1} + W_{k-1}$$

Where A defines the deterministic component of the model and W_{k-1} is a multivariate Gaussian random variable. In our application we currently use a first order model for A describing a region moving with constant velocity $\dot{u}_k$ and $\dot{v}_k$ and scale change θ_k. After we propagated the particles according to the system modal. The weight is considered as the likelihood of each particle. For this likelihood, we use the Bhattacharyya distance to compute similarity of the colour distribution of the tracked object and the region around the position of each particle. After we compute the likelihood, we multiply it with the proposed parameter α. It consists of multiplication of number of particles, dimensional of the state vector and the number colours of histogram. We use this parameter to increase the weight of each particle.

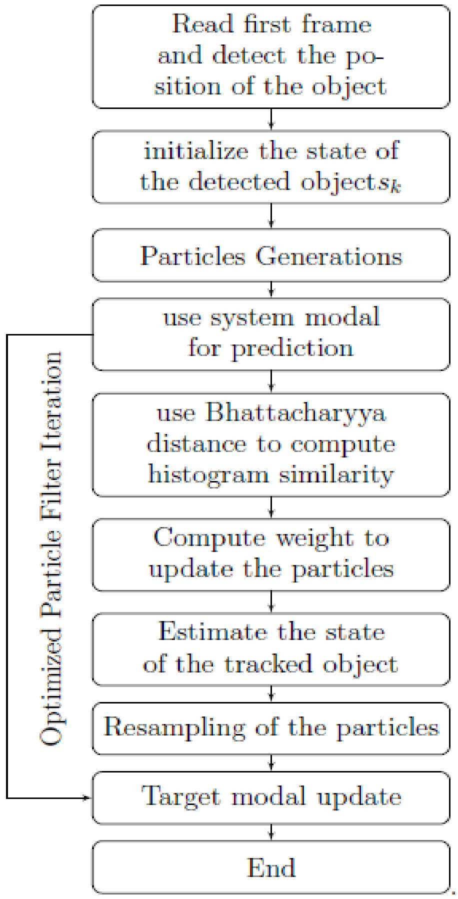
The weight $w^{(i)}$of the i-th state $x^{(i)}$is calculated as

$$w^{(i)} = \frac{1}{\sqrt{2\pi\sigma}} e^{\left(\frac{-d^2}{2\sigma^2}\right)} \quad * \alpha \qquad (10)$$

$$= \frac{1}{\sqrt{2\pi\sigma}} e^{\left(-\frac{1-\rho[p(x^i),q]}{2\sigma^2}\right)} \quad * \alpha$$

where $p(x^i)$ and q are the color histogram of sample and target ,respectively. From this equation, if we obtained a small Bhattacharyya distance, this indicates that we have large weight. During the resample step of the particle filter, samples with high weight are chosen several times, leading to identical copies, while others with relatively small weights are removed.

Figure 1 Flow chart of our proposed algorithm



V. Experimental Results.

To demonstrate the improved particle algorithm, we used two different datasets. The first one for indoor dataset taken on our lab which consists of 491 frames and every frame has 480 width and 272 height and the second one for outdoor dataset (PETS2009) S2.L1 collection with scenario walking with elements sparse crowd is investigated which consists of 287 frame and every frame has 768 width and 576 height. We choose the sequences from view 001 for our evaluation due to the wide angle view in order to reduce the possibility of capturing object partially. Dataset view 001 consist more than 8 persons with similar colour properties walking from various directions.

*A. **Results using indoor dataset.***

We test the algorithm for indoor dataset with different number of particles. The tracking results for the proposed system are shown in figure (2, 3) using 100 and 300 particles respectively. The estimated trajectory shows that, the proposed algorithm could track the object under illumination changes. Figure 4, shows the estimated trajectory and the original trajectory of the object through the video sequence. When we use 300 particles in figure 4 (b), we obtain the best trajectory but in figure4 (a), with 100 particles after 300 frames, It’s obvious that the estimated trajectory diverse from original trajectory.

Figure 2 **Tracking result for indoor dataset using 100 particles.**

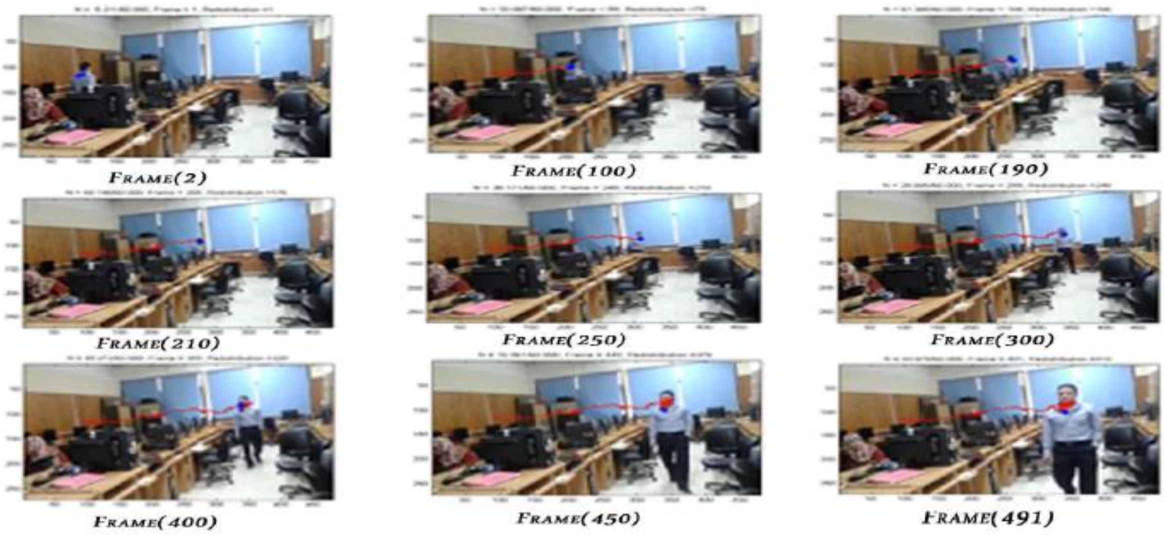
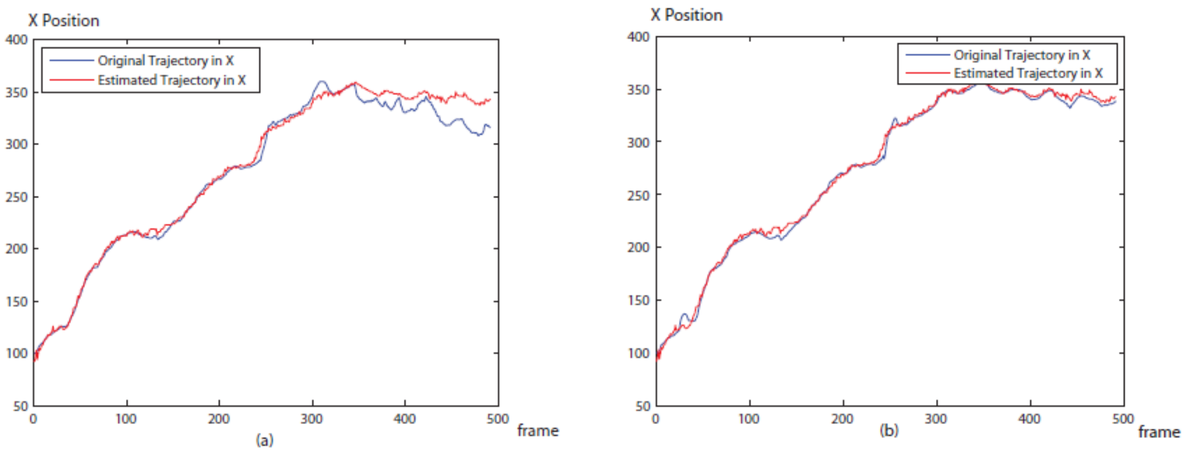


Figure 3 **Tracking result for indoor dataset dataset using 300 particles**

Figure 4 **Tracking trajectories for indoor dataset using 100 and 300 particles respectively.**



B. **Results using outdoor dataset (PETS2009 dataset).**

We also test the algorithm for outdoor dataset with different number of particles. The tracking results of the proposed system are shown in figure (5, 6) using 100 and 300 particles respectively. Figure 7 show the estimated trajectory and the original trajectory of the object through the video sequence. When we use 300 particles in figure 7 (b), we obtain the best trajectory but in figure 7 (a), with 100 particles after 150 frames, It's obvious that the estimated trajectory diverse from original trajectory. Also the system show best tracking result in case of partial occlusion and full occlusion as seen in figure 5 (frames 196, 197, 230, 233) and in figure 6 (196, 197, 230, 233) .

Figure 5 **Tracking result for outdoor dataset using 100 particles.**

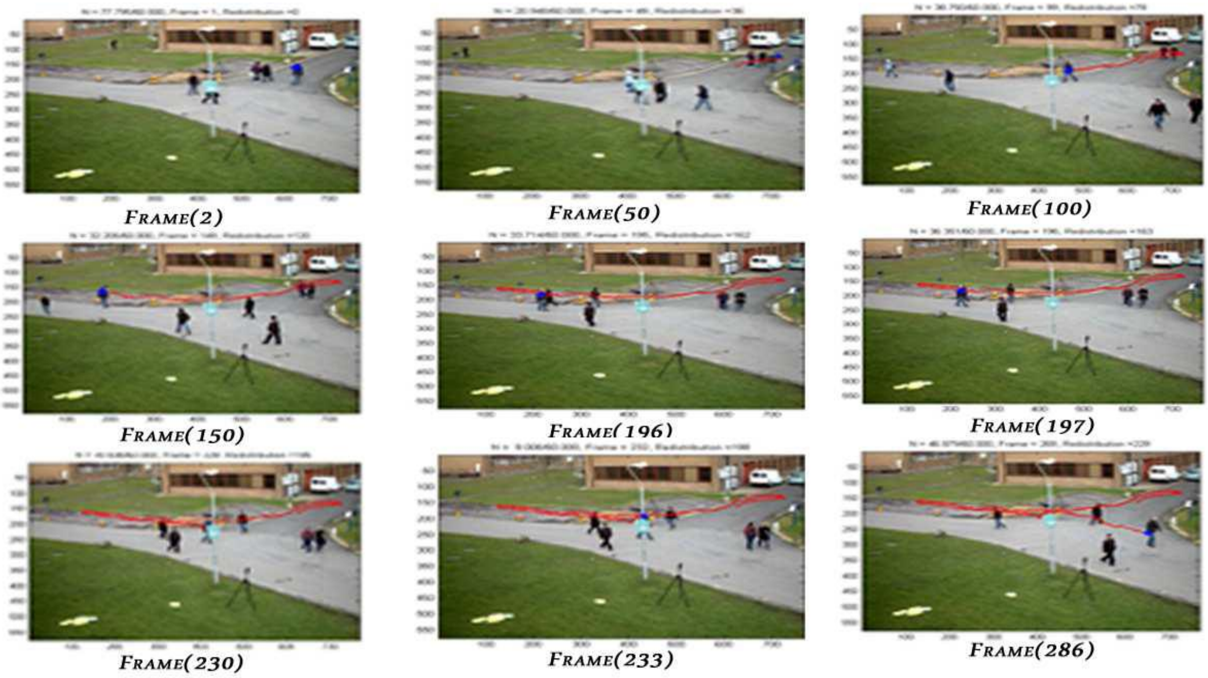


Figure 6 **Tracking result for outdoor dataset using 300 particles.**

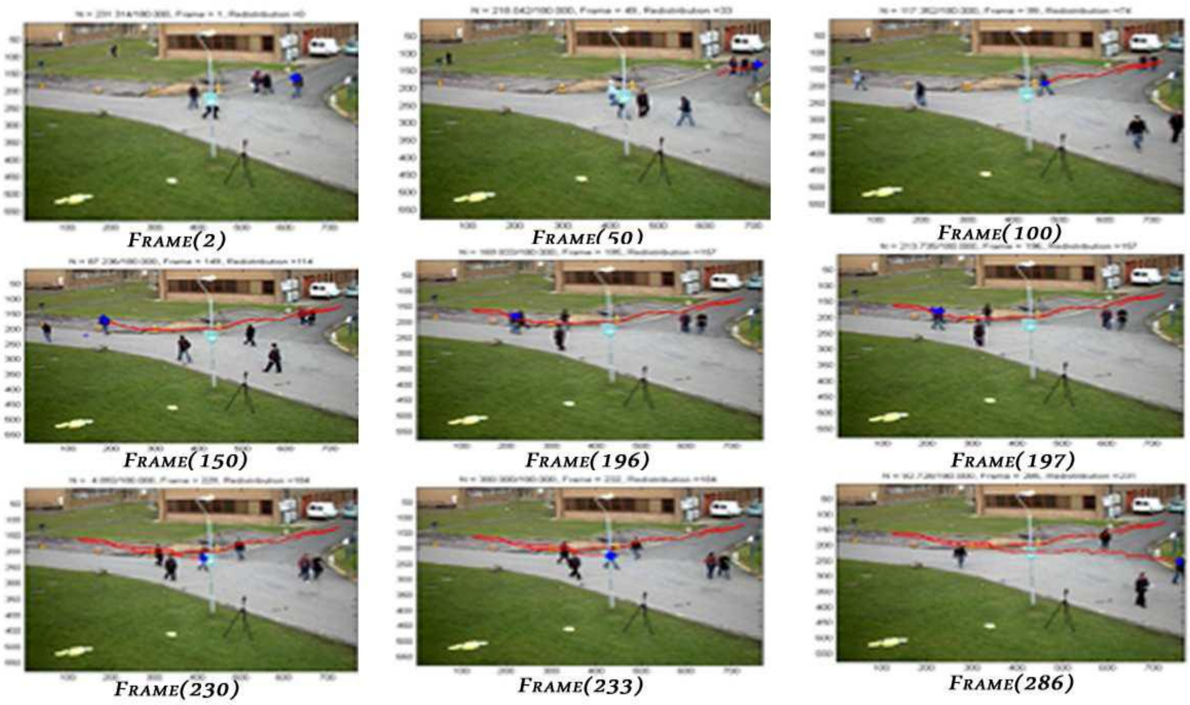
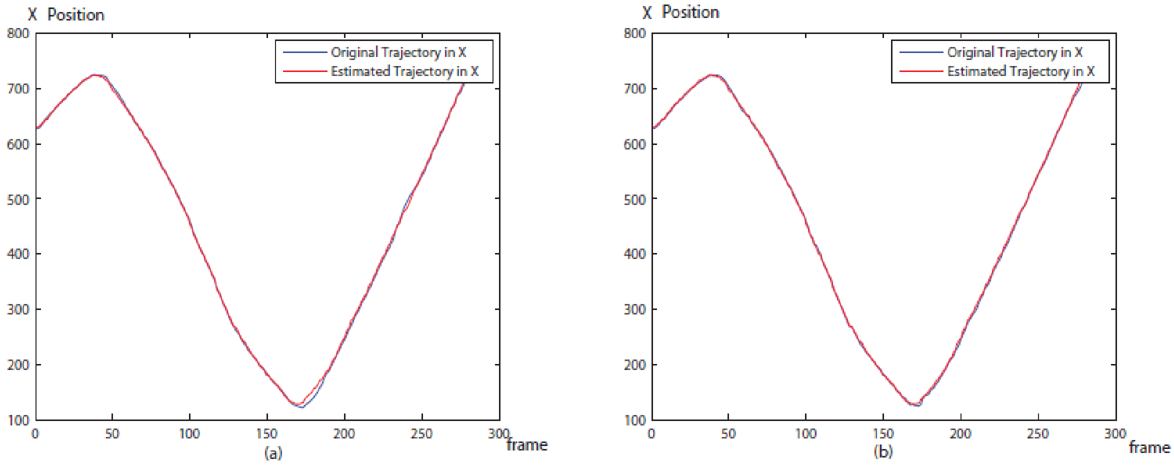


Figure 7 Tracking trajectories for outdoor dataset using 100 and 300 particles respectively.



C. System performance.

We measure the performance of the proposed system using the root mean square error (RMSE) for PF with color histogram and PF with optimized likelihood. In case of indoor dataset, we obtained the RMSE 10.34 and 4.10 for 100 and 300 particles with color histogram respectively, and 9.9 and 3.26 for 100 and 300 particles with optimized likelihood respectively.

Using the outdoor dataset, it gives 4.59 and 3.74 for 100 and 300 particles with color histogram respectively, and 4.38 and 2.75 for 100 and 300 particles using optimized likelihood respectively. For both experiments, the system gives high performance when using 300 particles than 100 particles.

Table I Shows RMSE and time at different number of particles for indoor dataset

Sequence with	particles									
	100		150		200		250		300	
	RMSE	Time	RMSE	Time	RMSE	Time	RMSE	Time	RMSE	Time
PF Co. histogram	10.34	30.32	5.99	38.74	4.89	39.19	4.53	40.74	4.10	44.61
PF OP. likelihood	9.90	31.17	5.85	36.81	4.50	39.54	4.27	41.64	3.26	44.89

Table III Shows RMSE and time at different number of particles for outdoor dataset

Sequence with	particles									
	100	150			200		250		300	
	RMSE	Time	RMSE	Time	RMSE	Time	RMSE	Time	RMSE	Time
PF Co. histogram	4.59	28.26	3.98	31.85	3.77	30.52	3.91	34.97	3.74	38.42
PF OP. likelihood	4.38	29.01	3.95	31.20	3.62	30.74	2.95	35.5	2.75	37.8

VI. Conclusions and Future Work.

In this paper, a robust tracking algorithm is presented, which combines particle filter and optimized likelihood. The experimental results demonstrate that the proposed algorithm can effectively overcome the problems of object occlusion and can track the color target efficiently in presence of illumination changes.

To obtain more accurate result, one can use multi features with particle filter such as first and second derivatives edge detection methods to enhance the tracking of the object.

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