Animal tracking in wildlife footage with Quantum Particle Filter (QPF)

Prajna Parimita Dash
Dept. of ECE
Birla Institute of Technology, Mesra
Ranchi,India
ppdash@bitmesra.ac.in

Sudhansu Kumar Mishra
Dept. of EEE
Birla Institute of Technology, Mesra
Ranchi,India
sudhansumishra@bitmesra.ac.in

Dipti Patra
Dept. of Electrical Engineering
National Institute of Technology
Rourkela, India
dpatra@nitrkl.ac.in

***Abstract*—Animal behavior analysis in wildlife footage is a preoccupying domain in the society of wildlife biologist. In wildlife video, tracking of a particular animal in a herd is very challenging task due to its unpredictable motion, as well as analogous appearance with others. In order to deal with these issues, in the work we have proposed a maneuvering tracker that uses the notion of quantum measurement in Particle filter. The proposed Quantum Particle Filter (QPF) based tracking technique efficiently handles the abrupt motion of the animal in a video. Subjective and objective evaluation of the proposed method has been accomplished and compared with other state-of-the-art methods. Some wildlife videos from the publicly available benchmark data sets are used for experiments. The results shows the superiority of the proposed method over others.**

***Index Terms*—Animal tracking, Particle filter, Quantum Particle Filter**

I. Introduction

Study and analysis of animal behavior and their habitats remain a key interest of many environmental scientists and wildlife biologists from several decades. In this domain, tracking a single or many animals in a wildlife footage is an abetment step. Tracking of an animal, wandering in a herd is very challenging due to its unpredictable motion and behavior. Partial and total occlusion, analogous appearance with other members of the herd etc. escalate the difficulty in tracking. In visual object tracking, the estimation and localization of the position and motion of the target object, in the subsequent frames is the most crucial task. The prime objective of the tracker is to generate the trajectory of an object over time, by localizing its position in every frame of the video. The task of detection and tracking is accomplished by jointly estimating the object region and its correspondence. Statistical correspondence is an effective approach, which figures out the tracking problem as a state estimation problem by taking the model uncertainties and measurements into account. The statistical methods use the state space approach to model the object properties like position, velocity, acceleration etc. The most popularly used statistical approaches for object tracking are the Kalman Filter (KF) [1] and Particle Filter (PF) [2]. KF works with the linear Gaussian model where the estimation of state is performed by computing the parameters of the posterior in a recursive 递归的 manner. But, in many real time applications, the object state is not Gaussian and the estimation with KF is not acceptable. Furthermore, posteriors in computer vision are never unimodal. In such scenario, the state estimation is performed using PF.

The rest part of the paper is organized as follows. Section II includes the related work, section-III contains some prerequi- 先决条件 site to the proposed work. In section-IV Proposed method has been described briefly followed by the experimental results in section-V. The conclusion is presented in section VI.

II. Related Work

The uncertainty associated with the visual data together with the uncertainty associated with the target′s dynamics [3] is a major difficulty in visual tracking. In contemplation of these uncertainties, Recursive Bayesian Filtering (RBF) is a potential approach, that continuously estimates the posterior probability density function (pdf) over the parameter space of the target model [4]. The mean of the posterior is taken as the estimate of the target′s state, i.e., the position. The first solution to the Bayesian estimate approximates the posterior by a single mode Gaussian distribution is the Kalman Filter (KF) [5]. The KF has been adopted extensively in various object tracking problems in the past decades [6]–[10]. In [11], Baxter *et al.* proposed the Extended Kalman Filter (EKF), by combining the motion information along with a prior assumption about the person's position. However, these approaches are limited to the constraint that the posterior need to be uni-modal and in some cases, distribution has to be Gaussian. These constraints usually violated in visual tracking problems.

Particle Filter (PF) is a potent solution to the aforesaid problems of KF in the field of tracking and is extensively used by many researchers [12]–[14]. In PF the approximation of the posterior distribution in each step is carried out by multiple weighted particles. Therefore, PF based trackers are included in Multiple Hypothesis Trackers (MHT) family. Afterward, the posterior is computed through two steps: sampling, and propagating the particles through the dynamic model and weight updating according to the appearance of the target object.The variance of the estimated state, number of particles and the strategy of allocation determine the performance of the tracker. As a consequence, more number of particles, and effective strategies for particle allocation are the requisites

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for a PF based tracker. These strategies are used in auxiliary PF [15], boosted PF [16] and likelihood-adjusted PF [17]. Increased number of particles outgrowth 增加 the computational burden and deteriorates the tracking performance. In order to improve the efficiency of PF Matej *et al.* [3] have adopted a n efficient dynamic model for tracking different types of motion of pedestrians, where they have constructed an efficient two-stage dynamic model by combining two different models named as: a liberal 自由的 model and a conservative 保守的 model. The first model handles the larger perturbation 扰动 and the other handles the smaller perturbation. Although this two-stage approach improves the accuracy as well as handles the abrupt motion up to some extent, but it fails in the case of very frequent abrupt motion. Some multiple trackers based methods for tracking motion of the pedestrians are presented in literature [18], [19]. However, higher computational complexity becomes the bottleneck for the mode estimation delay problem. Quantum filtering is an open up area for handling this non-linear, non-deterministic estimation problem. Quantum Filtering stands on the theory of quantum mechanics. As per the quantum theory, any description of the phenomena on a small scale is inherently nondeterministic in nature. It entails that the observations of quantum systems are naturally noisy. Quantum filtering (QF) was used in the early work of Davies in 1960s [20], [21] as a quantum measurement problem. The work of the QF is to estimate the state of the target by using indirect measurements [22]. A survey of quantum inspired computational intelligence has been delineated in [23]. Bradley A. Chase and J. M. Geremia proposed the Quantum Particle Filter (QPF), and experimented for the single-shot parameter estimation [24]. The QPF approach can be applied for the target state estimation in video object tracking. The informations like angular momentum and velocity of the object can be used along with the information of the previous position. One successful approach has been claimed recently in [25], for handling the abrupt motion as well as the mode estimation delay problem. In this letter, A. Khalili *et al.* have simulated the idea of the uncertainty principle of electrons around the nucleus in quantum mechanics and successfully applied it to the propagation of particles in the PF based tracking approach. Motivated by this concept, in this paper we have proposed a QPF based tracking method for tracking animal in wildlife video.

III. PREREQUISITES

Visual tracking can be formulated as an estimation problem, where the state of the system that changes over time needs to be estimated with a sequence of noisy measurements of the system. This estimation can be performed robustly using PF, which is nothing but the approximation of the Recursive Bayesian Filter(RBF) through Monte Carlo simulation.

A. Recursive Bayesian estimation

The state estimation of a discrete time varying system can be solved by using Baye's theorem [26], the law of total probability and employing the following assumptions. For a current state $\mathbf{x}_t$, the given set of observations $\mathbf{Y}_t = \{\mathbf{y}_0, \mathbf{y}_1, ..., \mathbf{y}_t\}$, the goal of Bayesian tracking is to estimate $p(\mathbf{x}_t | \mathbf{Y}_{1:t})$.

Assumptions1: *The observation signal given the last state is independent of the previous observation signals:*

$$p\left(y_t | x_t, y_{1:t-1}\right) = p\left(y_t | x_t\right) \quad (1)$$

Assumption2: *The state is independent of the previous observation signals, if the previous state is given:*

$$p\left(x_t | x_{t-1}, y_{1:t-1}\right) = p\left(x_t | x_{t-1}\right) \quad (2)$$

Then the posterior can be computed as

$$\begin{aligned} p\left(\mathbf{x}_t | \mathbf{Y}_{1:t}\right) &= \tfrac{p(\mathbf{Y}_t|\mathbf{x}_t)p(\mathbf{x}_t|\mathbf{Y}_{1:t-1})}{p(y_t|\mathbf{Y}_{1:t-1})} \\ &\propto p\left(\mathbf{Y}_t | \mathbf{x}_t\right) \int p\left(\mathbf{x}_t | \mathbf{x}_{t-1}\right) p\left(\mathbf{x}_{t-1} | \mathbf{Y}_{1:t-1}\right) dx_{t-1} \\ &= K.\, p\left(\mathbf{Y}_t | \mathbf{x}_t\right) \int p\left(\mathbf{x}_t | \mathbf{x}_{t-1}\right) p\left(\mathbf{x}_{t-1} | \mathbf{Y}_{1:t-1}\right) dx_{t-1} \end{aligned} \quad (3)$$

where K is the normalization constant independent of x_t. As this is a recursive equation, the initial state density $p(\mathbf{x}_1)$ is known and the posterior $p\left(\mathbf{x}_t | \mathbf{Y}_{1:t-1}\right)$ is to be estimated through the above formulation. Complexity of the model restricts the exact solution, except in some special cases like the case of the linear Gaussian model or the Hidden Markov model. Therefore, usually an approximate solution is adopted to find the estimate of the posterior. The Sequential Monte-Carlo (SMC) method based approximation, i.e., PF is one of the best feasible solutions.

B. Particle filter

Particle filter is a suboptimal filter for handling nonlinearity as well as multimodality, through the Sequential Mante-Carlo (SMC) based sampling of the posterior. The fundamental steps of the PF based estimation are presented in Fig. 1. The PF consists of three elementary stages: Propagation, Resampling and Estimation. The CONDENSATION algorithm proposed by Micheal Isard and Andrew Blake [27] is briefly depicted as follows. Particles are chosen randomly to represent posterior

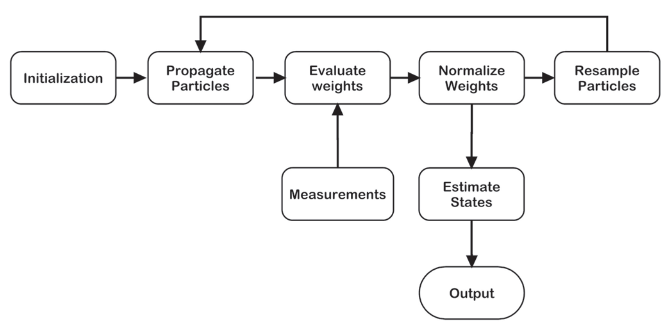

Fig. 1. Block diagram of Particle Filter

distribution. The formal Bayesian recursive iteration consists of a prediction and an update operation. The prediction operation propagates the posterior pdf of the state vector from time step $t-1$ to time step t. To update the prior samples in the light of measurement y_t, a weight w_t^j is calculated for each particle. This weight is the measurement likelihood evaluated at the value of the prior sample: $w_t^j = p\left(y_t | \, x_t^j \right)$. The weights are then normalized, so they sum to unity and the prior particles are resampled (with replacement) according to these normalized weights to produce a new set of particles. For a given set of weighted samples $\mathbf{S} = \left\{ x_t^j, w_t^j \right\}_{j=1}^N$ in the previous frame and the new observation $\mathbf{y}_t$, the state can be estimated as $\hat{x}_t \approx \sum_{j=1}^{N} w_t^j . x_t^j$ through the resampling and measurement update. The simple algorithm that contains the concept of PF is called Importance Sampling as described below. The visual representation of the sampling concept of PF is presented in Fig. 2 for a better understanding.

1) Importance sampling: PF uses the importance sampling method [28] for drawing the particles from the distribution, in order to resample a new set without destroying the original distribution. This method is applicable, when prior information about the location in the state-space which contains the information about the posterior is available. Usually this prior information is termed as an importance function and is closely associated with the weight assignment of the particles. The weights associated with the particles are defined as

$$w_t^j \propto \frac{p_{t|t} \left(x_t^j \middle| \, y_{1:t} \right)}{q_t \left(x_t^j \middle| \, y_{1:t} \right)} \qquad j = 1, 2, ..., N \tag{4}$$

where $q_t(.)$ denotes the importance density function that generates the current set of particles. Let us assume that $p_{t-1|t-1} \left(x_{t-1} | \, y_{1:t-1} \right)$ is approximated by a set of particles associated with the weights $\left\{ w_{t-1}^j, \, x_{t-1}^j \right\}_{j=1}^N$.

$$p_{t|\,t-1} \left(x_t | \, y_{1:t-1} \right) \approx \sum_{j=1}^{N-1} w_{t-1}^j f_{t|t-1} \left(x_t | \, x_{t-1}^j \right) \tag{5}$$

The recursive formulation for propagating the particles and weights as in [28] is given as,

$$w_t^j \; \propto \; \frac{g_t \left(y_k | \, x_k^j \right) \sum\limits_{j=1}^{N} w_{t-1}^j f_{t|t-1} \left(x_t^j \middle| \, x_{t-1}^j \right)}{q_t \left(x_t^j \middle| \, y_{1:t} \right)} \tag{6}$$

As per the CONDENSATION algorithm, the particles are drawn from the predicted prior i.e.

$$q_t \left(x_t | \, y_{1:t} \right) = p_{t|t-1} \left(x_t | \, y_{1:t-1} \right) \tag{7}$$

Solving the Eq. 6, the reduced form can be expressed as follows, where the weights of the particles are proportional to the likelihood.

$$w_t^j \; \propto \; g_k \left(y_t | \, x_t^j \right) \tag{8}$$

2) Effective sample size: Effective Sample size: The CONDENSATION PF is also termed as Bootstrap PF where, N samples are replaced from the set of $\mathbf{S} = \left\{ x_t^j, w_t^j \right\}_{j=1}^N$. The probability to choose sample *j* is w_t^j. According to importance sampling, if the effective number of samples (N_{eff}) is less than the threshold value (N_{th}) then $w_t^j = {}^1/_N$.

$$N_{eff} = \frac{1}{\sum\limits_{j} \left(w_t^j \right)^2}, \qquad 1 \leq N_{eff} \leq N \tag{9}$$

The upper bound is acquired when all particles have the same weight and the lower bound is acquired when all the probability mass is at a single particle. Usually the value of N_{th} is preferred as $\frac{2N}{3}$. The visual representation of the propagation of particles is shown in Fig. 2 .

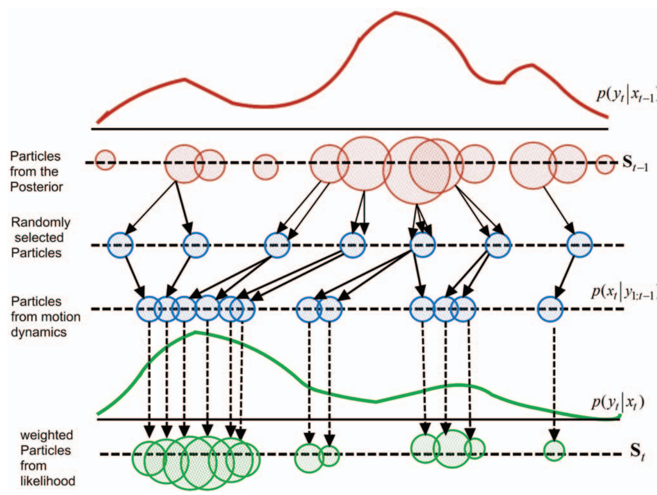

Fig. 2. Visual representations of steps in CONDENSATION algorithm [28]

IV. Quantum Particle Filter (QPF) based tracking

Recently a thought-provoking example has been presented by Michael S. Helfenbein of Yale University [http://phys.org/news/2016-11-tracking-quantum.html] to simplify the concept of the quantum objects. We are simply highlighting the same here: ˝objects in motion are like rain water flowing through a gutter and landing in a puddle, then quantum objects in motion are like rain water that might end up in a bunch of puddles, all at once˵. It clarifies that it is difficult to understand where the quantum objects land and when they are transmitted. As per the fundamental principle of nature, an object will move until it reaches the minimal energy state or ground. But in the case of the quantum system, an object can exist in multiple states at the same time. Motivated by the quantum theory and establishing an analogy between the abrupt motion of the object in the visual tracking problem and quantum object, we have formulated the tracking problem with the QPF.

One prime drawback of the PF based tracking method is that, it fails to estimate the target state whenever there are abrupt changes in direction or velocity. Usually in the wildlife videos the motion of animals speed and direction of the target animals are highly erratic. To overcome the limitations of the unmodeled dynamics , the traditional PF needs to be upgraded in the prediction step. Except for the prediction step, all other steps remain same as in the PF. In the QPF based approach, when there is an abrupt change in speed or direction, the prediction of the position of the next state is accomplished by allocating the particles in the required positions. In the conditions when the object stops suddenly, runs suddenly or changes its direction abruptly, then the particles are propagated uniformly in all directions simultaneously to redress the effect of the abrupt changes. However, if there is no abrupt motion, the particles are propagated in the current direction with the current speed to enforce the current dynamics. Figure 3 shows the propagation of particles in the cases of abrupt motion and steady motion. The tracking of object in a sequence of images is accomplished with the steps as follows.

- The target object is initialized with a rectangular bounding box by assigning the width, height, pixel coordinates of one corner. This represents the state of the particles
- In the next frame, 10 particles are distributed with gaussian random distribution.
- The particles are distributed according to their speed and direction as per the algorithm presented in the following part.

Algorithm 1 Algorithm for the Quantum Particle Filter based tracking

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Initialization: Sample ξ_i from the prior distribution (initial position of the target object in first frame)
No. of particles= N
for $i \leftarrow 1$ **to** N **do**
  Create a quantum particle with weight $w_t^{(i)} = 1/N$, parameter state $|\xi_i\rangle \langle\xi_i|$ and the initial atomic state $\rho_0^{(i)}$
end
for $t \leftarrow 1$ **to** $no.\ of\ iteration$ **do**
  Update the ensemble by integrating a time step of the filter .
  if $N_{eff}/N \leq$ Target Threshold **then**
    Create a new ensemble
  end
  Resampling: Sample an index i from the discrete density $\left\{w_t^{(i)}\right\}$.
  Sample a new parameter $\tilde{\xi}_i$ from the Gaussian distribution with mean $\mu^{(i)}$ and variance $\sigma^{2\,(i)}$. Add a quantum particle to the new ensemble with weight $w_t^{(i)} = 1/N$, parameter state $|\xi_i\rangle \langle\xi_i|$ and atomic state $\rho_t^{(i)}$.
end

V. Results and Discussion

The tracking performance of the proposed technique has been evaluated by experimenting on different publicly available wildlife video data sets. The detail of the data set is shown in Table I. The experimental results of some data sets are shown in this paper. In order to achieve the quantitative results detection rate has been evaluated and Cente location Error (CLE) and Pascal Score (PS) are considered for qualitative analysis. The superior performance of QPF over PF is validated through the estimation of the standard Quail function shown in Fig. 4. Furthermore, the sensitivity plot between no. of particles and root mean square error (RMSE) shown in Fig. 5 supports the superiority of QPF over the PF. The proposed method has been compared with the Mean shift (MS) optimization based tracking and Particle filter (PF) based tracking method. The comparative evaluation includes the detection rate shown in Table II, CLE in Table III and PS in Table IV. The performance measures used in the evaluation process are briefly represented in the following section.

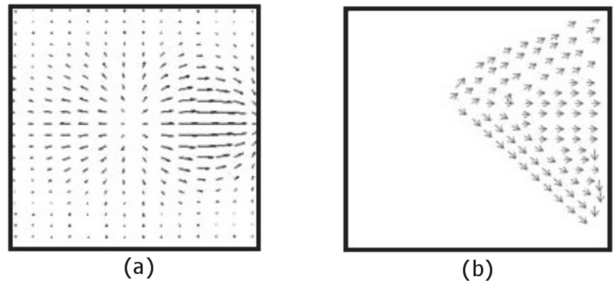

Fig. 3. Propagation of Particles in Quantum Particle Filter. (a) during abrupt motion, (b)during steady motion

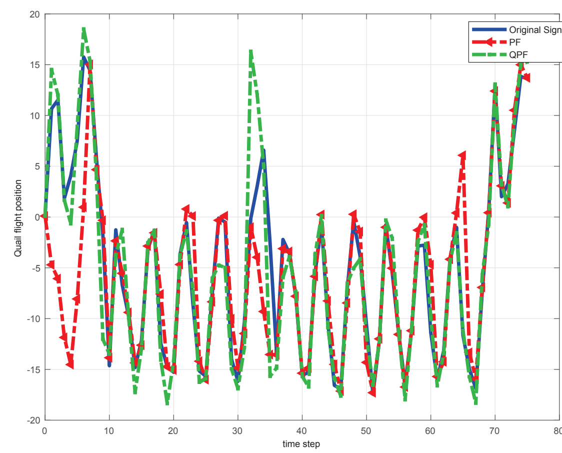

Fig. 4. Estimation of Quail function using PF and QPF

- **Detection Rate (DR):** This measure is used for the quantitative evaluation of the tracking results. DR for a tracker is defined as the ratio of number of frames

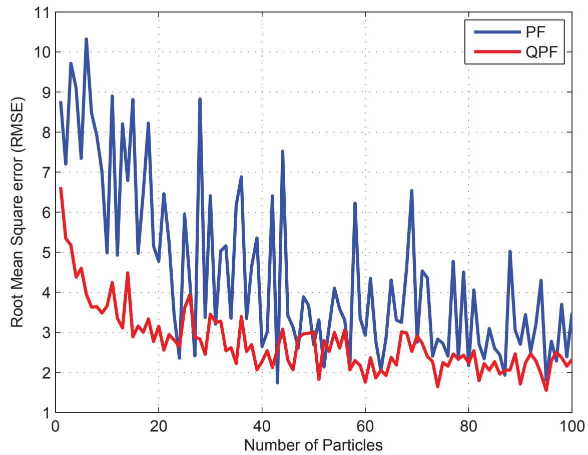

Fig. 5. Sensitivity plots for PF and QPF

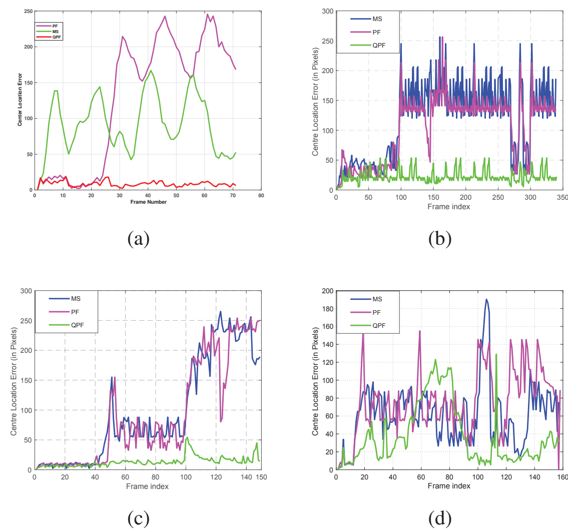

Fig. 6. Comparison of Center location error plots for different methods in various data sets: (a) Deer sequence, (b) Bird1 sequence (c) Butterfly sequence, (d) Rabbit sequence

TABLE I
DETAILS OF THE DATA SETS

Image sequence	Data set	Resolution	frames	Challenges
Deer	CVPR2010	704 × 400	71	Abrupt motion and heavy cluttered background
Bird1	VOT 2016	720 × 1280	339	Abrupt motion, occlusion
Butterfly	VOT 2016	480 × 640	151	Camera motion, Illumination change Motion change, Occlusion
Rabbit	VOT 2016	480 × 640	158	Camera motion, Illumination change Motion change, Occlusion

TABLE II
PERCENTAGE DETECTION RATE (DR) OF DIFFERENT METHODS

Image Sequence	MS	PF	QPF
Deer	15.49%	18.31%	94.36%
Bird1	68.8%	75.6%	94.45%
Butterfly	78.34%	83.2%	97.8%
Rabbit	10.75%	12.65%	34.5%
Avg. %DR	**43.18%**	**47.34%**	**84.41%**

correctly detected to the total number of frames.

$$DR = \frac{\text{No. of frames correctly detected}}{\text{Total no. of frames}} \tag{10}$$

- **Centre Location Error (CLE):** The CLE is defined as the central location of the tracked target and the ground truth.
- **Pascal Score (PS):** In order to compute the success rate, i.e., whether the tracking result is a success or not, PS is used. In PASCAL VOC challenge [29], PS is defined as,

$$PS = \frac{area\left(ROI_T \cap ROI_{GT}\right)}{area\left(ROI_T \cup ROI_{GT}\right)} \tag{11}$$

where, ROI_T is the tracked bounding box and ROI_{GT} is the ground truth bounding box. in any frame the tracking result is considered as success if the PS value is more than 0.5.

VI. CONCLUSION

In this paper, a novel Quantum particle Filter (QPF) based maneuvering tracker has been proposed for tracking of an animal in a wildlife footage. The unpredictable behavior of wild animals create difficulty in tracking. Their abrupt motion, i.e, due to nonuniform speed as well as change in direction usually distract the tracker. This problem has been addressed by the proposed tracking technique by considering the target object as a quantum object. The performance of QPF has been compared with the PF, by estimating a standard Quail function and also with the sensitivity plot. Tracking of the animals in various benchmark videos has been experimented with the proposed QPF based tracking as well as some other state-of-the-art techniques. Superiority of the QPF based method has been shown, by evaluating the detection rate, center location error and pascal score. Although the abrupt motion can be handled by the QPF based method, various issues like multiple similar objects, long duration occlusion, very fast motion etc. need to be reconciled in future work.

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TABLE III
AVERAGE CENTER LOCATION ERROR (CLE) OF DIFFERENT METHODS

Image Sequence	MS	PF	QPF
Deer	122.76	153.6	19.64
Bird1	119.68	104.543	22.281
Butterfly	97.084	93.208	13.404
Rabbit	61.409	73.456	37.188
Avg.	**154.78**	**140.90**	**19.71**

TABLE IV
AVERAGE PASCAL SCORE (APS) FOR CORRECTLY DETECTED FRAMES OF DIFFERENT METHODS

Image Sequence	MS	PF	QPF
Deer	0.621	0.623	0.698
Bird1	0.721	0.752	0.843
Butterfly	0.684	0.562	0.723
Rabbit	0.621	0.653	0.712
Avg.	**0.676**	**0.657**	**0.762**

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