PARTICLE FILTER APPLIED IN AIRCRAFT TRACKING SYSTEMS

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ABSTRACT

Particle filtering techniques have captured the attention of many researchers in variety of fields like image processing and signal processing. The Kalman filter (KF) is one of the most widely used method for tracking and estimation. The basic KF is limited to a linear assumption. To overcome these limitations, Particle Filter (PF) has proposed lately which is a nonparametric filter and hence can easily deal with non linearity and non-Gaussian noises. Particle filtering is particularly useful in dealing with nonlinear state space models and non-Gaussian probability density functions. This paper presents new methods for efficient tracking in video sequences using particle filtering. The underlying principle of methodology is the approximation of relevant distributions with random measures composed of particles and their associated weights.

***Keywords**: Image Processing, Kalman Filter, Particle Filter, Tracking*

I. INTRODUCTION

Over the past 40 years many Kalman filtering techniques has developed for target tracking in a mess environment. A detailed explanation of Kalman filters has given by Anderson.B.D and J.B.Moore [1]. Target tracking has always been a challenging problem in image or signal processing. Although significant work has been done in this area by the research community, the problem is still considered challenging. Recent growth in adhoc wireless communications and sensor technology has given a new dimension to the sensor based tracking problem. Comaniciu.D, V.Ramesh and P.Meer [2] has proposed a method for real time tracking of a non rigid object observe from moving camera. Current applications of sensor based tracking include tracking of climatic conditions in remote places such as mountain slopes, activity tracking across sensitive areas such as defense and surveillance areas like airports. In this work, target tracking and detection problems are usually formulated using linear state space models with additive Gaussian noise. The complete statistics of linear Gaussian problems can be computed with Kalman filtering technique. Julier.S.J and J.K.Uhlmann [3] has developed and demonstrated a new linear estimator. Kalman.R.E [4] has developed a new approach to linear filtering problems. However in reality, problems involving target and object tracking require nonlinear models with non Gaussian noise. Nonlinear non Gaussian models would necessitate the adoption of a particle filtering technique. The basic idea behind particle filtering is to sample a continuous posterior density function of interest into a set of weighted particles. If the weights are chosen appropriately, then this weighted equivalent set of particles can very closely approximate the posterior density function (PDF).

II. PARTICLE FILTERING

The main task of particle filtering is to assign appropriate weights and update the weights as time progresses. N.Gordon, D.Salmond and A.F.M.Smith [5] has published a novel Approach to nonlinear or non-Gaussian Bayesian State estimation known as bootstrap filter, which provides the implementation of the Particle filters or Sequential Monte Carlo (SMC) methods used today. Arulampam.S, S.Maskell, N.Gordon, and T.Clapp [6] has explained the particle filters for on-line non-linear or non-Gaussian Bayesian tracking. Gustafsson.F et al [7] has explained how the particle filter can used to positioning for integrated navigation on aircraft and for target tracking. Problems dealing with particle filtering involve making inferences on the state vector $\mathbf{s}_t$, based on $\mathbf{z}_{0:t}$, the observations from time 0 to t. Using sequential importance sampling particle filters can approximate the posterior density function, regardless of the nature of the underlying model. The continuous density function is descretized by sampling the function. Sampling is performed by choosing an appropriate sampling function called the importance sampling function. The continuous density function is represented by sample sets. The selection of the sampling function is the major concept and the important condition for this concept is that the density function also sampling function must have the same support. The correctness of the particle filtering approach depends on proper particles selection. Another important feature of particle filtering is resampling, in which the weights that have a very low value are eliminated and replaced with weights that have a higher value. Resampling the particles allows the particles to represent the probability density function with greater accuracy. This step allows more particles or samples to focus on high prospect areas and less on low precedence regions and overall effect of this step is that the particles with high relative weights after the observation have a high probability of remaining in the set, possibly multiple times, and the particles with low weights have a high probability of being removed from the set. Fig. 1 shows the region of high density samples.

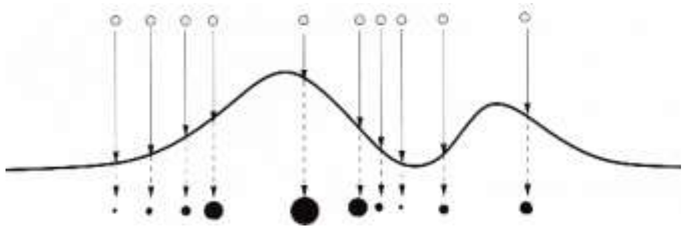

Fig. 1: Region of High Density Samples

With advancements in compression and video coding, image and video over wireless channels or sensor networks are gaining popularity. Image and video sensors include webcams, pan-zoom-tilt cameras, infra-red cameras, etc. These sensors capture the information from the environment where they are deployed. Visual data provides very rich information compared to other types of sensor data. Since image data is highly correlated, efficient correlation based tracking algorithms may be employed to increase the overall efficiency of the sensor network. The numerous advantages involved in using image and video sensors along with advances in adhoc network systems.

III. TARGET TRACKING USING PARTICLE FILTERING

Jepson.A, D.D.J.Fleet and T.El-Maraghi [8] has proposed a model used for motion based tracking the natural objects. Ikoma.N, N.Ichimura, T.Higuchi and H.Maeda [9] has explained the target tracking using particle filter. As per Carpenter.J, P.Cliord and P.Fearnhead [10] Kalman filter has provide effective solutions to linear Gaussian filtering problems. However, most non trivial systems are nonlinear. The non linearity can be associated either with the process model or with the observation model or with both have introduced new approach called the extended Kalman filter (EKF). In EKF, the state transition and observation models need not be linear functions of the state but instead may be non linear functions. These non linear functions are used for calculating the predicted state from previous estimate and the predicted measurement from predicted state. Over the years EKF has led to a general consensus within the tracking and control community that it is difficult to implement and only reliable for systems that are almost linear on the time scale of the update intervals have developed a new linear estimator called unscented Kalman filtering (UKF).

Fig. 2: Tracking Aircraft in Video Sequence Using MATLAB

Tracking targets is a very challenging and multi faceted problem. Various algorithms with varying levels of complexity are developed for this purpose. In this paper, the authors described and tested four maximum likelihood (ML) techniques that localize (or triangulate) a moving target and compare these methods with a linear least-squares approach through a number of simulations at various signal-to-noise levels. Multiple object tracking (MTT) deals with state estimation of an unknown number of moving targets. Addressing the problem of tracking multiple objects encountered in many situations by signal or image processing. In this paper a new method has proposed by extending the classical filter, in which the estimation of stochastic vector is achieved by a Gibbs sampler. Six of them are well known and widely used: the autonomous multiple model algorithms generalized pseudo-Bayesian algorithm of first order and of second order interacting multiple-model algorithm, Viterbi based MM algorithm and B-best-based MM algorithm. A.Averbuch, S.Itzkowitz, and T.Kapon [11] has compared the Viterbi-based and Interacting Multiple Model (IMM) algorithms for Radar target tracking. Reweighted interacting multiple model algorithm also considered, which was developed recently. The aim was to track a maneuvering target, e.g., a ship or an aircraft. The authors used a state-space representation to model this situation. The dynamics of the target was represented by a system model in continuous time, although a discredited system model was actually to be used in practice. The position of the target was measured by radar and the process described by a nonlinear observation model in polar coordinates. The authors proposed the use of heavy-tailed non-Gaussian distribution for the system noise to follow the rapid changes in motion of the targets. Consequently, the nonlinear non-Gaussian state-space model was used. A particle filter was used to estimate the target state of the nonlinear non-Gaussian model. Developed a framework using particle filters consisted of motion models and a general nonlinear measurement equation in position.

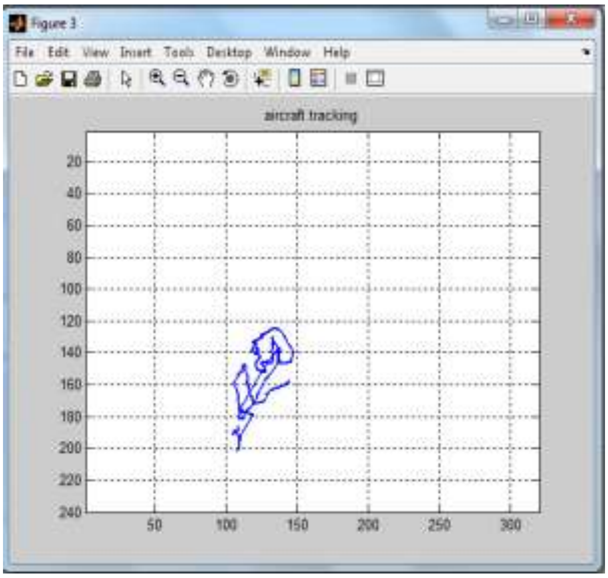

Fig. 3: Aircraft Tracking Path in 2-d Graph View

A general algorithm has presented based on marginalization, to estimate position derivatives by enabling KF. Based on simulations, the authors argued how the particle filter could be used for positioning based on cellular phone measurements. Recent approaches for tracking objects in video sequences have involved better algorithms and robust solutions. A particle filtering algorithm has introduced for tracking of appearances in images instead of using contours. An adaptive appearance model was used as the observation or the measurement model. The appearance model based on intensity was used instead of the model based on phase of intensity. The EM algorithm was used to update the appearance model adaptively from the obtained posterior density. Motion vectors have calculated from the current image block observations and new block to be selected from the next frame was obtained by using first order linear approximations. The number of particles selected was also adaptive. Prediction error is a measure of forecast quality. If the forecast error is high, then the noise is spread widely, forcing the model to cover large jumps in motion state. Thus, more particles are selected if the noise discrepancy is more. As the likelihood function, the standard multi dimensional normal density was used and occlusion detection was implemented by keeping track of the pixels obtained from the appearance model. The model update was stopped if occlusion has detected.

IV. PREDICTION USING PARTICLE FILTERING

Particle filtering is a sequential Monte Carlo technique that recursively computes the posterior probability density function using the concept of importance sampling. Doucet A, J. F. G. de Freitas, and N. J. Gordon [12] has explains the perfect Monte Carlo sampling method. It can be used to solve a state-space estimation problem that involves nonlinear state measurement models and non-Gaussian noise models. The classical solution to the state space estimation problem is given by the Kalman filter in which the state model and the measurement or the observation models are assumed to be linear, If it is nonlinear, then model has approximated to a linear model so that Kalman filter can be applied. The extensions of the Kalman filter include an extended Kalman filter and an unscented Kalman filter, in which the nonlinear term is approximated up to first order and second order terms. In KF approach, the underlying density functions are assumed to be Gaussian, hence, estimation of the mean and variance characterizes the complete density function. Real models for an application are generally nonlinear and non-Gaussian. Mean and variance do not characterize the complete density function. In order to handle these cases, the complete density function is considered by its samples.

Hue.C, J.-P. Le Cadre and P.Perez [13] has proposed an extension of traditional particle filters where the assigned stochastic vector has projected by a Gibbs sampler. Prediction using particle filtering is presented in this section, followed by a detailed analysis of the sampling function. Let a system be denied by parameters represented by X_k and the observations be represented by Z_k. Let the state evolution be represented by

$$X_k = f_{k-1}(X_{k-1}, V_{k-1}) \quad (1)$$

Where f_k is a nonlinear function of the state, and v_{k-1} is an i.i.d noise sequence. Let the observation model be given by

$$Z_k = h_k(X_k, W_k) \quad (2)$$

Where h_k is a nonlinear function and h_k is an i.i.d observation noise.

The aim of prediction is to recursively estimate the State parameters X_k from the observations given in equation. The posterior density function over the State parameters, given by $p(X_k \; Z_k)$, gives the measure of the State parameters from the observations. This posterior density function is predicted using the Bayesian framework. It is assumed that the system follows a first-order Markov process. If the posterior density function $p(X_{0:k} \; Z_{0:k})$, is sampled and the samples $X_{0:t}$ are drawn from the importance function π $(X_{0:k} \; Z_{0:k})$, then weights denied in equation become

$$w_k = \frac{p(x_k, z_{1:k})}{\pi(x_k, z_{1:k})} \quad (3)$$

If the importance density function can be factorized as

$$\pi(x_{0:k}|z_{0:k}) = \pi(x_{0:k}|x_{0:k-1}, z_{0:k})\pi(x_{0:k-1}|z_{0:k-1}) \quad (4)$$

and if

$$x_{0:k}^m \sim \pi(x_{0:k}|z_{0:k}) \quad (5)$$

Prediction: Predict next state PDF from current estimate.

$$P(X_k \mid Z_{1:k-1}) = \int P(X_k \mid X_{k-1}) P(X_{k-1} \mid Z_{1:k-1}) dx_{k-1} \quad (6)$$

Update: Update the prediction using sequentially arriving new measurements.

$$P(X_k|Z_{1:k}) = \frac{P(Z_k|X_k)P(X_k|Z_{1:k-1})}{\int P(z_k|X_k)P(X_k|Z_{1:k-1})dx_k} \quad (7)$$

Importance weight:

$$w_k = \frac{p(x_k, z_{1:k})}{\pi(x_k, z_{1:k})} \quad (8)$$

Weight update:

$$W_k^i \, \alpha \, W_{k-1} \frac{P(Z_k|X_k^i)P(X_k^i|X_{k-1}^i)}{\pi(X_k^i|X_{k-1}^i, Z_k)} \quad (9)$$

Resampling is the next step to get the accuracy. This is the particle filter algorithm.

V. PERFORMANCE ANALYSIS

We consider a mock surveillance sequence of 450 frames to demonstrate the efficiency of the color-based particle filter. The system uses cameras to track a aircraft in a open space. The cameras are kept static without any zoom, pan or tilt and their relative exterior orientation is known. To illustrate the differences between the Kalman filter and our proposal we discuss a aircraft video sequences. The experiments have been processed with a Pentium dual core 2.30GHz PC under windows 7, using the RGB color space with 8 x 8 x 8 bins. Fig. 2 shows the tracking aircraft in video sequence using MATLAB. In the open space aircraft is flying, the results of the trackers are illustrated by the paths of the elliptic regions. The image size is 320 x 260 pixels and the initial elliptic search region contains 20 x 20 pixels. Finally, for the particle filter we processed N ¼ 75 samples. In this experiment we used the initialization method based on a known histogram. Both trackers are put into the 'initialization' mode and start tracking as soon as a aircraft enters their field of view.

When the aircraft later leaves the field, the corresponding tracker will return to the 'initialization' mode. The trackers handle the initialization successfully, even when the aircraft is appearing from different sides. To stabilize the tracker, Chellappa.R, S.Zhou, and B.Moghaddam [14] has proposed an observation model arising from an adaptive noise variance and adaptive number of particles. An improvement can be achieved by increasing the number of samples but this affects the computational performance. The particle filter predicts the search region similarly to the Kalman tracker but it can still track the aircraft. To increase the flexibility of the particle filter, it can be further enhanced by switching between multiple motion models. Huang.Y and P.Djuri [15] has projected a particle filtering detector to estimation of channel model coefficients, signal detection and channel tracking over flat Rayleigh fading channels. In particle filtering, the object location has to be estimated by calculating the mean value of the sample distribution. Accordingly, the accuracy of the tracker is dependent on the size of the sample set. By increasing the number of samples the discretization error can be decreased. The running time to process one frame depends mainly on the region size for all approaches as many color distributions have to be calculated. To reduce the number of iterations for the best object location the basic mean shift tracker was enhanced by a state prediction using Kalman filtering. If a Kalman filter is used to estimate the new location, the search regions of subsequent frames no longer need to overlap and the tracker is more likely to converge to the correct maxima in case of rapid movements. Fig. 3 shows the aircraft tracking path in 2-d graph view.

VI. FUTURE ENHANCEMENT AND CONCLUSION

Particle filtering is a widely used framework for visual object tracking that is highly extensible and offers the flexibility to handle non-linearity and non-normality in the object models. In future work, we plan to extend our approach to learn the parameters of more complex multi object tracking. . In future, new particle filter-based approaches have been proposed to solve difficult multi object tracking problems. This paper presents a particle filter for aircraft tracking in video sequences. The experimental results from real video sequences show its reliable performance. The proposed algorithm runs comfortably in real time with 15 frames per second without any special optimization on a normal 800 MHz PC. The algorithm is characterized with low computational complexity and is able to cope with partial occlusions and recover after temporary loss. The tracker can efficiently and successfully handle non-rigid and fast moving objects under different appearance changes.

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