Advance in Electronic and Electric Engineering.
ISSN 2231-1297, Volume 4, Number 6 (2014), pp. 669-674

http://www.ripublication.com/aeee.htm

Comparative Study on Filtering Techniques of Digital Image Processing

Aanchal Pathak[1] and Esmita Singh[2]

[1]*Student, ABES, Enggineering Collage*
[2]*Faculty, ABES, Enggineering Collage.*

Abstract

This paper presents an approach to supervise two types of filter technique for localizing and tracking the position of single and multiple objects by means of particle filter. It ensures a comparative study based on filtering technique of object tacking, it also include various advantages and disadvantages of particle filtering technique & their benefits.

1. Introduction

Particle filter technique is used for positioning, navigation & tracking. Particle Filter is concerned with the problem of tracking single and multiple objects. Particle Filter is a hypothesis tracker,that approximates the filtered posterior distribution by a set of weighted particles. It weights particles based on a likelihood score and then propagates these particles according to a motion model. . The particle filter-based trackers have the theoretical possibility of tracking multiple hypotheses, and kalman filter –based on single object tracking. We show that KPF performs robust multiple object tracking. . Particle filtering is a promising technique because it allows fusion of different sensor data, to incorporate constraints and to account for different uncertainties. The algorithm based on likelihood factor as a product of the likelihoods of different object. We show the Benefit of using multiple object compared to color-based tracking only and texture-based tracking only.

Types of filtering

Various types of filtering involve kalman filter, kernel particle filter , Monte Carlo method ,accelerating particle filter ,filtering for stochastic particle, ,determinatively particle filter.

2. Kernel Particle Filter-multiple object tracking

The idea of kernel-based tracking was originally published in where kernels are used for object representation and localization. Recently, mean shift is used with a particle filter to find the *likelihood* modes [9]. We have used mean shift as a mode-seeking procedure to locate the *posterior* modes .

2.1 Kernel-based Posterior Estimation

Denote the target state and the observation at (discrete) time

2.2 Posterior Gradient Estimation

Given the posterior estimation, we now estimate its gradient and move particles along the gradient direction toward the modes of the posterior. This can be achieved using the mean shift procedure [5]. In this procedure, each particle is moved to its sample mean.

2.3 Particle Re-weighting

The mean shift can be applied repeatedly to a particle set. A problem arises when particles change their positions: the new particles do not follow the posterior distribution anymore. This is compensated in KPF by re-weighting the particles. Denote the particle set after the mean shift procedure at time .After each mean shift procedure, the weight is re-computed as the posterior density evaluated, at the new particle positions augmented with a particle density balancing factor.

3. Kalman(KPF) filter for single object tracking

KPF is applied to head tracking to test its ability in tracking with a weak dynamic model. The test videos involve various motions such as sudden acceleration, rotation, abrupt changes of direction, jump, and out-of-plane rotation. The first test video sequence, 1FACE, consists of 797 frames of a human face moving in a typical laborat or environment. The face is modeled as an ellipse with a vertical major axis and a fixed aspect ratio of 1.4. Trackers are initialized manually. A few frames of the tracking results using PF and KPF are shown in Fig. 4. The PF tracker with the same dynamic model tends to lag behind the object and eventually loses the head at the #373rd frame. A PF tracker is able to succeed after doubling the dynamic noise and uses 250 particles to saturate the search region. On the other hand, KPF with 30 particles and 3 iterations, despite being occasionally distracted by the background clutter, is able to track the face throughout the sequence. The intermediate samples of KPF in processing frame #27.Starting from a poor prediction, the KPF is able to move particles toward the correct direction through mean shift filteration and gives a better estimate. In the FIGURE SKATE sequence shown,the KPF successfully tracks the female skater’s head as she performs out-of-plane rotation followed by a sudden acceleration.

4. Monte Carlo Method

They are sequential Monte Carlo methods based on point mass representations of probability densities, which are applied to any state model. Over the past fifteen years, particle methods for filtering and smoothing have been the most common examples of SMC ALGORITHMS. INDEED, IT HAS BECOME TRADITIONAL TO present particle filtering and SMC the same thing in much of the literature. Here, we wish to emphasis that SMC actually encompasses a broader range of algorithms and by doing so we are able to show that many more advanced techniques for approximate filtering and smoothing can be described using precisely the same framework and terminology as the basic algorithm.

SMC methods are a general class of Monte Carlo methods that sample sequentially from a sequence of target probability densities f(n) (x1:n)g of increasing dimension where each distribution f(n) (x1:n) is defined on the product space X_n.

4.1 Benefits of filtering

Particle filtering is a technique that is very suitable for object tracking in video sequences while we are tracking multiple object . Tracking of aircraft positions from radar. Estimating communications signals from noisy measurements .Predicting economic data. Tracking of people or cars in surveillance videos.Track car position in given road map.Track car position from radio frequency measurements.Track aircraft position from estimated terrain elevation.Collision Avoidance (Prediction). Replacement for GPS .Recovery of signal from noisy measurements even if signal may be absent (e.g. synaptic currents) & mixture model of several hypotheses.

4.2 Comparative study on kalman and particle filter

The Extended Kalman Filter (EKF) and the Particle Filter (PF) are two widely used tools for solving non-linear state estimation problems. The EKF is a sub-optimal approach, which implements a Kalman filter. For a system dynamics that result from the linearization of the original non-linear filter dynamics around the previous state estimates. But it has been defined on the assumption that both, the process and sensor noises, are Gaussian distributed. The particle filter is a more generalized scheme and does not require either of the noises to be Gaussian, as the posterior probabilities are represented by a set of randomly chosen weighted samples. This work aims to compare the use of the particle filter and the EKF for a two dimensional state estimation problem, that is, estimating the position and velocity of an autonomous surface craft, from measurements of the velocity corrupted by Gaussian noise.

Comparative study on both types of particle filter technique

NATURE	Kalman filter	Kernel particle filter
Type of object tracker	Single object tracker	Multiple object tracker
Method type	Recursive system based on non linear.	Recursive implementation of monte carlo

Mean sqaure error	MSE obtain through this is almost the same.	Decreases.
Processing	Based on Gaussian distributed.	Based on probability distribution .
Computation time	Takes less time on executing the state.	Takes more time.

4.3 Advantages /Disadvanges of Partcle filter:

Advantages:

1. Non-Gaussian distributions e.g. multi-modal
2. Estimation of full PDFs
3. Non-linear state and observation model
4. Parallelizable

Disadvantages

1. Degeneracy problem
2. High number of particles needed
3. Computationally expensive
4. Linear-Gaussian assumption is often sufficient
5. Non-linear Models
6. Non-Gaussian Noise or Posterior
7. Multi-modal Distributions

5. Conclusion

Over the past few years, Kalman and particle filters have become a popular topic. There have been a large number of papers (arguably too many) demonstrating new applications and algorithm developments for tracking various objects. This popularity may be due to the simplicity and generality of the basic algorithm - it is easy to get started. Particle filters include a random element and almost surely converge to the true posterior pdf if the number of samples is very large. While the strong point of particle filters is that they can be used for non-Gaussian noise too, in the case that the Gaussian assumptions in some model hold, no particle filter can outperform the Kalman filter if the dynamic model is linear. Or in case the system is nonlinear, the EKF may produce satisfactory results at a lower computational cost, as the results obtained confirms.

6. Future work

Future work may address situations when we can use the advantage of both the model and create a model which can be better provide functionality to the motion pattern of objects within one group changes dramatically, especially during long and continuous full occlusion, in which case the proposed association technique may fail. It is possible to improve the tracker by forcing a larger dynamic noise and keeping all detected

modes during occlusion. However, we believe the problem is inherent to any purely motion based association techniques and a more robust solution would be to employ both motion continuity and appearance. Future work may also address on RoboCup: Multi-robot localization and tracking.

References

[1] A Tutorial on Particle Filters for on-line Non-linear / Non-Gaussian Bayesian Tracking

[2] B. Ristic, S. Arulampalam, and N. Gordon, Beyond the Kalman filter: particle filters for tracking applications. Artech House, 2004.

[3] Y. Bar-Shalom and A. G. Jaffer. Tracking and Data Association.Academic Press, San Diego, CA, 1988.

[4] . Cham and J. M. Rehg. A multiple hypothesis approach to figure tracking. In IEEE CVPR, June 1999.

[5] C. Chang and R. Ansari. Kernel particle filter: iterative sampling for efficient visual tracking. In IEEE ICIP, 2003.

[6] P. Pérez, J. Vermaak, A. Blake, Data Fusion for Tracking with Particles, Proc. IEEE, **92**:3, 2004, 495-513.

[7] P. Brasnett, L. Mihaylova, N. Canagarajah, D. Bull Object Tracking by Particle Filtering Techniques in Video Sequences1, IEEE Trans. on Image Proc., submitted, 2005.

[8] A. Doucet, N. Freitas, N. Gordon, Eds., Sequential Monte Carlo Methods in Practice, New York: Springer- Verlag, 2001.

[9] M. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A Tutorial on Particle Filters for Online Nonlinear/ Non- Gaussian Bayesian Tracking, IEEE Trans. Sign. Proc., **50**: 2, 2002, 174-188.

[10] J. Liu, Monte Carlo Strategies in Scientific Computing, Springer Verlag, 2001.

[11] M. Isard and A. Blake, Contour Tracking by Stochastic Propagation of Conditional Density, European Conf. on Comp. Vis., Cambridge, UK, 1996, 343-356.

[12] M. Isard, A. Blake, Condensation -- Conditional Density Propagation for Visual Tracking, Intl. Journal of Computer Vision, **28**:1, 1998, 5-28.

[13] C. Shen, A. van den Hengel, A. Dick, Probabilistic Multiple Cue Integration for Particle Filter Based Tracking, Proc. of the VIIth Digital Image Comp.: Techniques and Appl., 2003.