ECSE 626

Statistical Methods for Computer Vision

Literature Review

on

Sequential Monte Carlo Methods in Computer Vision

Junaed Sattar

McGill ID 110248462

Introduction

Sequential Monte Carlo methods have found a number of applications in recent years in Computer Vision, mostly in the form of Particle Filtering methods. Visual tracking of single and multiple targets is one of the primary application areas. This document is a review of five such papers that cover different techniques of tracking based on the Sequential Monte Carlo method. The papers chosen for review here fall into two basic categories. Three papers cover techniques that track a single object. The other two discuss different approaches to tracking multiple objects.

1. ICONDENSATION: Unifying low-level and high-level tracking in a stochastic framework

Based on the original CONDENSATION (CONditional DENSity propagATION) algorithm[1], the authors extend their work to combine CONDENSATION with Importance Sampling to increase the efficiency of visual tracking.

Low-level approaches in visual tracking are fast and robust, but they do not provide much fine-scale information. High-level approaches are excellent for tracking deformations in high-dimensional spaces, but they trade off speed for robustness. The goal of this paper is to combine the best of both approaches by utilizing the importance sampling technique together with the CONDENSATION algorithm. The end result is a framework which the authors call ICONDENSATION [2]. The algorithm combines low-level visual observations with high-level auxiliary measurements to predict current position and motion of the object being tracked. The authors present an example hand-tracker which operates by using a low-level blob tracker and a high-level contour tracker specialized for hands. The blob tracker uses color segmentations to track skin-colored segments, and the tracker is speedy and robust. The contour tracker, being the auxiliary source of measurement, enables the system to track when the hands are obscured momentarily or when the color blobs merge. The system runs in real time, with 400 samples taken at 30 Hz, which is every other frame for the NTSC standard.

2. Partitioned Sampling, articulated objects, and interface-quality hand tracking

This paper introduces another extension to the classic CONDENSATION algorithm. The main drawback of CONDENSATION is the computational cost of the sampling process required for effective tracking. The sampling process takes up a significant number of machine cycles due to the number of particles required for effective tracking and therefore is a major performance bottleneck for the CONDENSATION algorithm or even the ICONDENSATION algorithm presented above. The technique described here uses an approach known as partitioned sampling[3,6]. Partitioned sampling is an a variant of hierarchical search. The paper talks about two new concepts, namely survival diagnostic and survival ratio. The survival diagnostic is defined for a given particle set, and it is the number of particles that survive the resampling mechanism. Survival rate, on the other hand, is a property of a given prior and posterior. The survival diagnostic indicates the reliability of the tracking algorithm. A lower survival diagnostic means the tracker is about to lose track on its target. The survival diagnostic and survival ratio serves as performance measures of the tracker. The authors show that the survival rate, when multiplied with the number of samples, gives the survival diagnostic. Therefore, a low value of survival rate also indicates poor tracker performance. Importance sampling methods also scale poorly with the dimensionality of the configuration space. Partitioned sampling helps out in such cases, by effectively partitioning the configuration space and assigning a varied number of particles to each segment of the space according to the application's demand. This makes the algorithm suitable for tracking articulated objects, where more particles are applied to track the parts of the object that may be subject to rapid and unpredictable motion. The initialization and re-initialization of the process is done using the ICONDENSATION algorithm described in the last section. The authors also show that by using this algorithm on articulated objects, the performance can be improved by a factor of two. A vision-based hand tracker was designed to test and implement this algorithm. This tracker has been interfaced to a drawing package to draw primitives on the screen based on hand gestures.

3. An adaptive color-based particle filter

A variant of the particle filter algorithm incorporating color information is described in this paper. Instead of using the traditional technique of using a shape-based observation, this approach uses an adaptive color model of the tracked object. The technique described here takes the color histogram of the object and compares it to the histograms obtained from the samples positions.

The model of the tracked object is represented by a weighted histogram calculated from both the color and the shape of the object. The similarity (or dissimilarity) of the histograms is measured using the Bhattacharyya distance. The tracker initializes itself either by using a manual, automated or an a-priori target model. A certain number of samples are taken accordingly, and their color distributions are calculated. The Bhattacharyya coefficients of each sample is calculated next. These coefficients are used to weight each sample of the set and estimate the mean state of the sample set. The filter assigns weights based color histograms to elliptical regions, and it assigns smaller weights to samples at the boundary. That is, samples are weighted less as they drift further away from the region center.

The tracker has a top-down design, *i.e.* it generates object hypotheses and tries to verify them by using the image at the sample positions. The choice of color distribution for object tracking has the advantage that it is robust against non-rigidity, rotation and particle occlusion. The authors compare their tracker against the mean shift tracker and the Kalman filter based trackers. The tracker proposed here is more adaptable to scale changes and is also more suited to tracking rapidly moving objects, albeit being somewhat slower than the other two trackers when the object being tracked is fully visible.

4. BraMBLe: A Bayesian Multiple-Blob Tracker

Blob trackers have been proved useful in tracking objects in a scene by modeling it using an elliptical contour and thereby segmenting it from the background. These algorithms have a severe performance bottleneck because background subtraction is usually followed by blob detection and tracking. This paper introduces two theoretical advances in enhancing performances of multi-object trackers: one is a Bayesian correlation based multi-blob likelihood function, and the other is a Bayesian particle filter for tracking multiple objects when the number of objects present in a scene can vary.

The multi-blob likelihood function assigns directly comparable likelihoods to hypotheses containing different number of objects. The observation likelihood is computed as follows: a fixed grid is overlaid on the image and a set of filters are applied to each location on the grid which yields a response value. The response likelihoods are calculated and labeled based on whether that particular patch lies on the background (=0) or foreground (≠0). The foreground label is the number of the object on which the patch lies. The individual likelihoods can be computed from a learned model of the background and the foreground. The response of the background was precalculated using k-means clustering, since the camera in the scene is static. The foreground model is similarly pooled using k-means clustering from the patches of the grid that has been labeled as a foreground patch. The foreground is tracked by following color histograms as explained in the previous summary. To track multiple persons as they appear and disappear from the scene, the system models human figures as cylindrical models.

This multi-blob likelihood function is used as an observation model for a particle filter. The authors use the CONDENSATION algorithm for their purpose to demonstrate the utility of the Bayesian likelihood function. The CONDENSATION algorithm has been augmented here to track distinctly identified objects as they change positions over time. One problem faced by the tracker is when one object being tracked passes in front of the other; in such cases the labels assigned to the objects are switched. In such cases, the tracking algorithm fails to distinguish between different foreground objects. This issue is addressed in the paper summarized next.

5. A Probabilistic Exclusion Principle for Tracking Multiple Objects

A solution to tracking multiple objects with indistinguishable models is proposed by the authors. To that end, the technique described applies a particle filter with two unique features. Firstly, the technique described here uses a probabilistic exclusion principle to suppress simultaneous reinforcement of mutually exclusive object hypotheses by using a single piece of evidence. Secondly, the paper introduces the idea of partitioned sampling for the applied sequential Monte-Carlo method. Method. The partitioned sampling approach serves to reduce the number or particles required to track multiple objects significantly and thereby speeds up the tracking process.

The probabilistic exclusion principle used as observation model inhibits reinforcement if a piece of data was generated by overlapping, *i.e.* mutually exclusive objects. This exclusion principle prevents the locking of object hypotheses on the same object whenever two object are close or even overlapping. The only piece of geometric information required is this the depth information; *i.e.* which objects occlude other objects.

Partitioned sampling increases the efficiency of the resampling step required for particle filtering and thus helps to overcome the effect of dimensionality in case of high-dimensional problem state space. The basic idea is to separate the sampling into two steps. First, the object hypotheses in the foreground, *i.e.* the hypotheses of fully visible objects, are sampled and propagated. Then the remaining hypotheses, *i.e.* those of objects partially occluded by objects of the first subset are processed. This approach leads to a much better approximation of the posterior which allows to decrease the required number of particles.

Conclusion

The papers covered in this review shows various approaches of using the Sequential Monte-Carlo (SMC) methods in object tracking and detection. [2] introduces the concepts of importance sampling; [3] and [6] discusses two ways of using partitioned sampling for tracking one or many objects respectively. Application of color data in tracking is described in [4], whereas [5] incorporates Bayesian inference rules in particle filtering. These papers propose extensions to the fundamental SMC methods of particle filtering by using different statistical methods. Although the review focuses on tracking algorithms, the SMC methods find uses in other areas of computer vision with a steady rise in number of applications in recent years.

References

1. Michael Isard and Andrew Blake. Condensation - conditional density propagation for visual tracking. International Journal of Computer Vision, 29(1):5-28, 1998.

2. Michael Isard and Andrew Blake. ICondensation: Unifying low-level and high-level tracking in a stochastic framework. In European Conference on Computer Vision, volume 1, pages 893-908, 1998.

3. John MacCormick and Michael Isard. Partitioned sampling, articulated objects, and interface-quality hand tracking. In European Conference on Computer Vision, volume 1843 of Lecture Notes in Computer Science, pages 3-19, 2000.

4. Katja Nummiaro, Esther Koller-Meier, and Luc Van Gool. An adaptive color-based particle filter. Image and Vision Computing, 21(1):99-110, 2003.

5. Michael Isard and John MacCormick. Bramble: A Bayesian multiple-blob tracker. In IEEE International Conference on Computer Vision, volume 2, pages 34-41, Vancouver, British Columbia, Canada, 2001. IEEE Computer Society, Los Alamos CA.

6. John MacCormick and Andrew Blake. A probabilistic exclusion principle for tracking multiple objects. International Journal of Computer Vision, 39(1):57-71, 2000.