On line Bayesian Tracking and Detection of Multiple Objects

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Agenda

Detection and tracking of multiple objects

- Automated video analysis has three main steps:
  1. Detection of interesting moving objects.
  2. Tracking objects from frame to frame
  3. Behaviourial pattern recognition from tracked objects.
- Applications of object tracking are found in video surveillance, automatic annotation for multimedia information retrieval, human-computer interaction, traffic monitoring and vehicle navigation.

Bayesian filtering

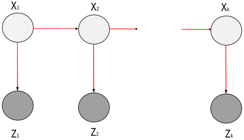


Figure: State space model

- A Bayesian approach consists of two steps:
  - **Filtering :** Predict current target state x_k given past states $x_{1:k-1}$.
  - **Update :** Update the conditional distribution of the predicted target state x_k given measurements $z_{1:k}$ up to time k.
- Estimation can be carried with Kalman filters, extensions of the Kalman filter or Sequential Monte Carlo methods.

Multiple Target Tracking

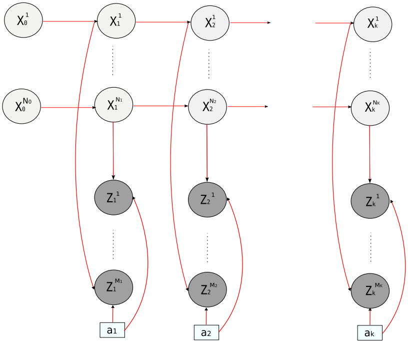


Figure: Switching factorial hidden Markov model (Ghahramani and Jordan, 1997.)

Multiple Target Tracking

- Data association methods like joint probabilistic data association (JPDA) and multiple hypothesis tracking (MHT) enumerates all possible associations.
- Objects may present similar features or can be occluded, so measurement to track association can be even more challenging.
- Enumerating and combining multiple hypothesis can also be difficult when having multiple appearing objects and clutter observations.

Random finite sets and point process theory for tracking applications

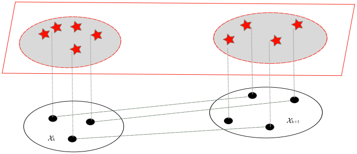


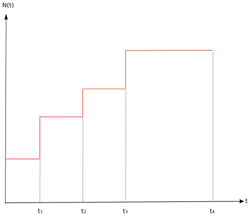
Figure: Random sets for tracking

- Random finite sets and point process theory can be used for representing the time-varying number of states and observations.
- A set of hidden target states is observed with a set of measurements and the cardinality of the random finite sets are Poisson point processes.

Poisson point process

Definition ($N(T), T \geq 0$ represents the total number of events that have occurred prior to time T)

$N(0) = 0$
$N(t + \Delta_t) - N(t) \sim \text{Poisson}(\lambda \Delta_t)$
$N(T)$ has independent increments



Basic properties of Poisson point processes

A Poisson process is closed under superposition and independent thinning

- **Superposition :** The sum of independent Poisson processes with intensities λ_1 and λ_2 is a Poisson process with intensity $\lambda = \lambda_1 + \lambda_2$.
- **Thinning :** If each point x survives with probability $0 \leq \pi(x) \leq 1$, then the probability of survival of x is a Poisson process with intensity $\lambda_{thin}(x) = \lambda(x)\pi(x)$.

Non-homogeneous spatio-temporal Poisson process

Figure: Spatial Poisson process

- The number of points to be observed is Poisson distributed $N_{\Xi}(S) = |\Xi \cap A| \sim \text{Poisson}(N_{\Xi}(A), \Lambda_A)$, where $A = T \times S$.
- **Intensity function :** $\lambda(x) = \mathcal{X} \to \mathcal{R}^+, x \in \Xi, \mathcal{X} = \mathcal{B}(x)$
- **Intensity measure :** $\Lambda_A = \int_A \lambda(x) dx$.

Probability Hypothesis Density Filter

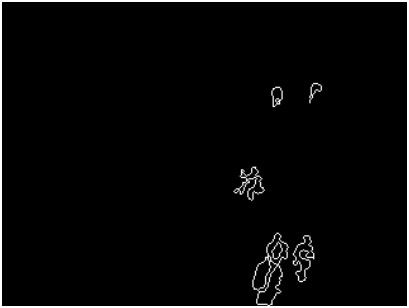
- The PHD filter resembles the Kalman filter defining two operators Φ_k and Ψ_k for filtering and update.
- Filtering :

$$\lambda_k(dx) = (\Phi_k \hat{\lambda}_{k-1})(dx) = (\phi_k \hat{\lambda}_{k-1})(dx) + \gamma_k(dx) \qquad (1)$$

- Update :

$$\begin{aligned} \hat{\lambda}_k(dx) &= (\Psi_k \lambda_k)(dx) \\ &= \left[\nu(x) + \sum_{z \subset Z_k} \frac{\psi_{z,k}(x)}{< \psi_{z,k}, \lambda > + \kappa_k(z)} \right] \lambda_k(dx) \end{aligned}$$

Background Subtraction



PHD filter for detection and tracking

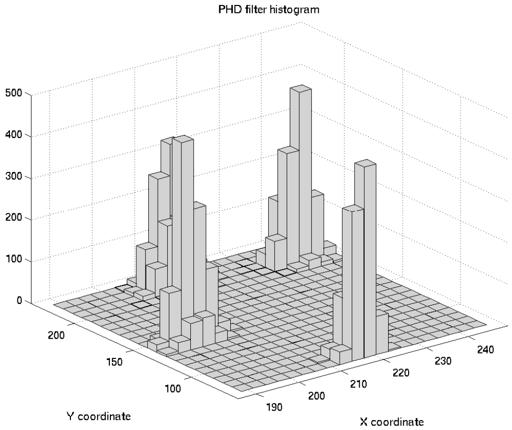


Figure: PHD filter with spatial discretization. ("Multi-target tracking with point procesess observations". Hernandez, S. and Teal, P. 2007)

Conclusions

- Moments of the filtering distribution can be computed from the intensity measure, giving a set of non-interacting or *complete spatially random* (CSR) points where the targets are located.
- Explicit target identification is required for estimating trajectories, so an smoothing algorithm for would be useful for calculating optimal target trajectories.
- The set of CSR points may not be enough for understanding complex scenes. In that case, the PHD can be used for estimating larger regions where interacting point patterns can be used for a more comprehensive analysis.

Thanks

New website available

http://randomsets.eps.hw.ac.uk/index.html