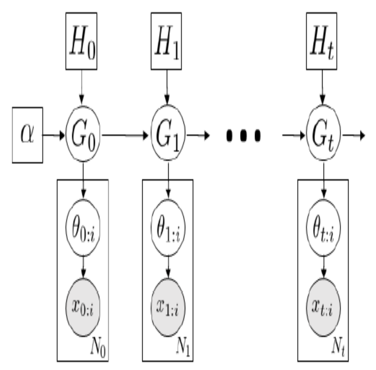

Tracking Multiple Objects with Dependent Measurements using Bayesian Nonparametric Modeling

Bahman Moraffah, Cesar Brito, Bindya Venkatesh, and Antonia Papandreou-Suppappola

School of Electrical, Computer, and Energy Engineering, Arizona State University, Tempe, AZ

Problem Statement

- Tracking a time-dependent number of objects using dependent measurements collected from multiple sensors
- Using statistically dependent measurements to determine object-state association and at each time step time-varying object cardinality.

➢ **Goals:**

- ❑ Jointly estimate the object cardinality and identity
- ❑ Accuracy in both object identity and object-state association
- ❑ Tractability as objects are evolving
- ❑ Efficiency of algorithms to track and update
- ❑ Simplicity in implementation

➢ **Our Contribution: Dependent Dirichlet Process - Hierarchical Dirichlet Process (DDP-HDP)**

- ❑ Place a prior on temporally evolving objects states
  (a) Survival, (b) Birth, and (c) Death
- ❑ Bayesian nonparametric modeling; dependent Dirichlet process as a prior on the object states that captures birth, death, and survival.
- ❑ Adjust the weights among new and transitioned objects
- ❑ Inference: Hierarchical Bayesian modeling to cluster measurements and track objects
- ❑ Inference through Gibbs sampler
- ❑ Tracking algorithm that does NOT require high SNR
- ❑ Achieve higher estimation accuracy and lower computational intensity

Related Approaches:

➢ **Bayesian Nonparametric Models**

- Dependent Dirichlet process as prior [Moraffah 2018]
- Dependent Pitman-Yor process [Moraffah 2019]
- Dependent infinite Poisson diffusion tree [Moraffah 2019]
- Hierarchical Diriclet process for maneuvering [Fox 2011]
- Dynamic Clustering via DDP [Campbell 2013]
- Bayesian Inference for linear dynamic model [Caron 2007]
- k-means-like: Based on asymptotic analysis of DPM

➢ **Random Finite Set**

- Utilizes RFS to represent uncertainty in the number of objects as well as the state of objects [Mahler 2007]
- These methods are approximations of Multi-object filter
- For instance: Labeled multi-Bernoulli filtering [Bryant 2017]

➢ **Evolutionary Clustering**

- Does not capture birth and death [Chakrabarti 2006]
- Number of cluster is known
- Does not include the dependence from time to time

DDP-HDP Model

➢ Dependent Dirichlet process Construction

Given the configurations at time (k-1): Transition from time (k-1) to k as fellows:

✓ **Transition from time (k-1) to k:** Each object may leave the scene w.p and $1 - P_{k|k-1}$ stays and transitions w.p. $P_{k|k-1}$

✓ **At time k:** The choice of DDP on the object state distribution is based on the following dynamic dependencies:

- **[Case 1]** The nth object from time (k-1) remains in the scene at time k, and it is reassigned to a cluster that has already been selected by one of the (n-1) previous objects at time k. The probability of choosing such a cluster:

$$\Pi_1(\text{Select } l\text{th assigned cluster}|\Theta_k) = \left([V^*_{k|k-1}]_l + [V_k]_l\right) \Big/ \left(\sum_m [V^*_{k|k-1}]_m + [V_k]_m + \alpha\right)$$

- **[Case 2]** The nth object from time (k-1) remains in the scene at time k and is assigned to a cluster that has been survived from time (k-1) but has not yet been selected by the previous (j-1) objects. The probability of choosing such cluster is given by:

$$\Pi_2(\text{Select } l\text{th unassigned cluster}|\Theta_k) = [V^*_{k|k-1}]_l \Big/ \left(\sum_m [V^*_{k|k-1}]_m + [V_k]_m + \alpha\right)$$

- **[Case 3]** The jth object is a new arrival object at time k and creates its own cluster with probability

$$\Pi_2(\text{Create a new cluster}|\Theta_k) = \alpha \Big/ \left(\sum_m [V^*_{k|k-1}]_m + [V_k]_m + \alpha\right)$$

✓ **Density Estimate:** The state distribution is given by :

$$p(\mathbf{x}_{n,k}|\text{rest}) = \begin{cases} p_\theta(\mathbf{x}_{n,k}|\mathbf{x}_{n,k-1})\nu(\theta^*_{n,k-1}, \theta_{n,k}) f(\mathbf{x}_{n,k}|\theta^*_{n,k}), & \text{w.p. } \Pi_1 \\ p_\theta(\mathbf{x}_{n,k}|\mathbf{x}_{n,k-1} f(\mathbf{x}_{n,k}|\theta^*_{n,k}), & \text{w.p. } \Pi_2 \\ \int_\theta f(\mathbf{x}_{n,k}|\theta) dH(\theta), & \text{w.p. } \Pi_3 \end{cases}$$

➢ Hierarchical Mixture Modeling and Inference

Upon receiving measurements, exploit the hierarchical dependent Dirichlet process mixture modeling to make use of dependency among measurement.

✓ Hierarchical Dirichlet process over the dependent measurements

$$G_0|\eta, H_0 \sim \text{DP}(\eta, H_0)$$
$$G_\ell|G_0 \sim \text{DP}(\gamma, G_0), \quad \ell = 1, \ldots, L$$
$$\phi^{(\ell)}_{m,k}|G_\ell \sim G_\ell, \quad m = 1, \ldots, M_k$$

✓ For mixing distribution R, distribution on the measurements is thus

$$\mathbf{z}^\ell_{m,k}|\phi^\ell_{m,k}, \mathbf{x}_{1,k}, \ldots, \mathbf{x}_{N_k,k} \sim R(\cdot|\phi^\ell_{m,k}, \mathbf{x}_{1,k}, \ldots, \mathbf{x}_{N_k,k})$$

✓Measurements collected from each sensor are clustered and utilized to robustly track trajectory of each object.

Experimental Results:

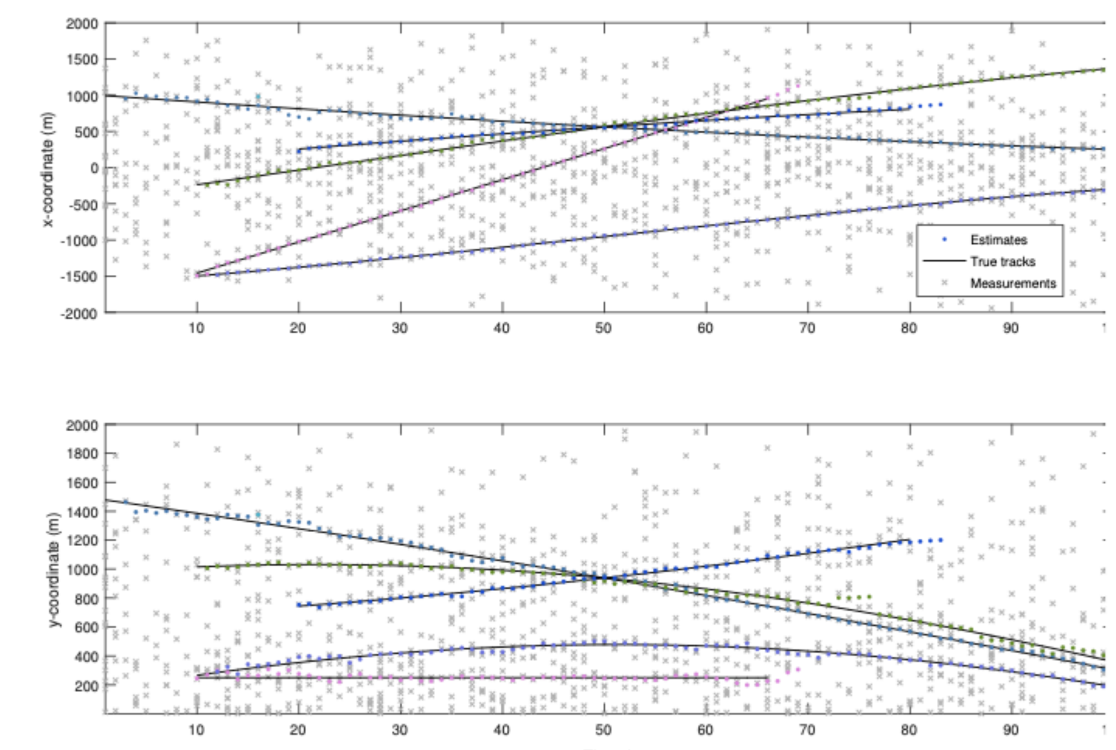

Figure: Actual and estimated x(top) and y(bottom) position against time through DDP-HDP algorithm.

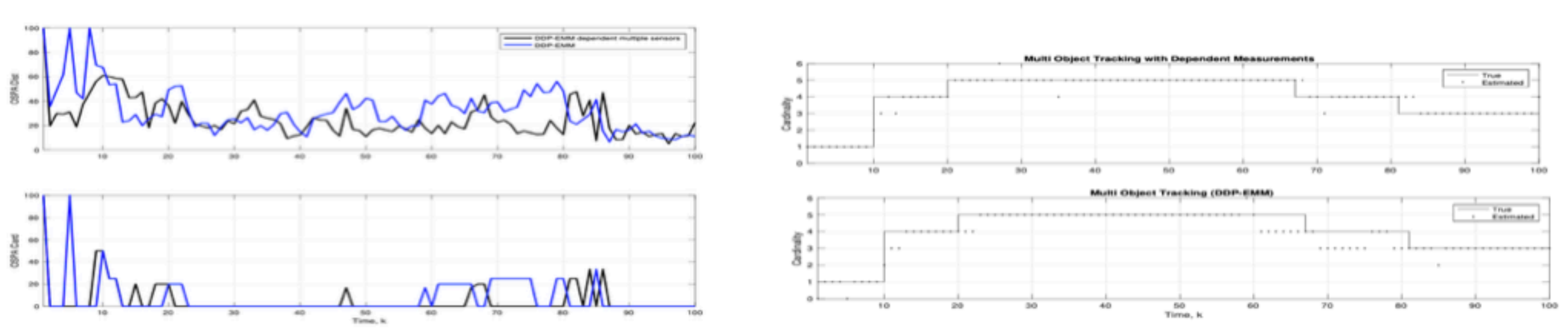

Figure: (left) OSPA comparison between DDP-HDP and DDP-EMM: OSPA range(top) and time-dependent cardinality (bottom); (right) Comparison between learned cardinalities for DDP-HDP(top) and DDP-EMM(bottom).

*Comparison between this model and LMB is provided in the paper.

Summary

- We proposed a class of random measures to efficiently and robustly track multiple objects upon receiving measurements.
- A hierarchical mixture model is employed to account for the dependency among the measurements and make use of dependency to robustly estimate the object trajectory.
- Trajectory of time-varying objects can be estimated by integrating the proposed nonparametric prior (Dependent Dirichlet process) with a hierarchal Dirichlet process to estimate the trajectory of objects.
- The proposed dependent Dirichlet process prior integrated with hierarchical Dirichlet process introduces more flexibility to the modeling, and thus there is a significant improvement over existing tracking compared to other tracking methods, particularly, dependent Dirichlet process prior and labeled multi-Bernoulli.
- The algorithm is efficient to implement.