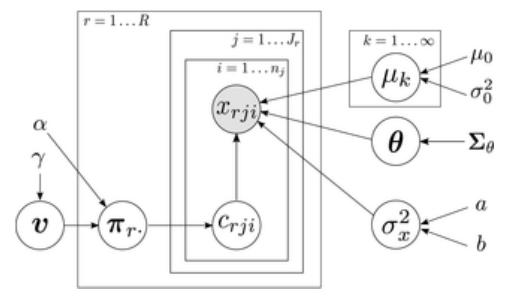

Dependent Dirichlet Process Modeling and Identity Learning for Multiple Object Tracking

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Problem Statement

- Tracking a time-dependent number of objects
- Using measurement sets to determine object-state association at each time step as well as 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

➢ **Our Contribution: DDP-EMM**
- ❑ Place a prior on temporally evolving objects states
  (a) Survival, (b) Birth, and (c) Death
- ❑ Bayesian nonparametric model, DDP prior on the object states that captures birth, death, and survival.
- ❑ Inference using Gibbs sampler
- ❑ Adjust the weights among new and transitioned objects
- ❑ Update: DPM clustering the measurement
- ❑ Tracking algorithms that does not require high SNR
- ❑ Concurrently infer the number of objects and its state
- ❑ Achieve higher estimation accuracy and lower computational intensity

Related Approaches:

➢ **Random Finite Set**
- Utilizes RFS to represent uncertainty in the number of objects as well as the state of objects
- These methods are approximations of Multi-object filter
- For instance: Multi-Bernoulli Filtering

➢ **Hierarchical Dirichlet Process**
- Maneuvering target tracking problem
- Uncertainty on the number of modes and their associated statistics
- Kalman Filter

➢ **Dirichlet Process Mixtures**
- Bayesian Inference for linear dynamic model
- k-means-like: Based on asymptotic analysis of DPM
- Does not include evolution

➢ **Evolutionary Clustering**
- Does not capture birth and death
- Number of cluster is known

Theoretical Results

➢ Dependent Dirichlet Process Modeling For State Prior

- DDP-EMM is to learn and label over related information
- Related information such as object labeling at the previous step and labeling of previously considered objects at the current time
- The choice of DDP on the object state distribution is based on the following dynamic dependencies:

a. The jth 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 (j-1) previous objects at time k.

b. The jth 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.

c. The jth object is a new arrival object at time k.

THEOREM :

The distribution on the jth object state at time k is :

$$\mathbf{p}(\mathbf{x}_{\mathbf{j,k}}|\mathbf{x}_{\mathbf{j,k-1}},\mathbf{a},\mathbf{b},\mathbf{c}) = \mathbf{p}(\mathbf{x}_{\mathbf{j,k}}|\mathbf{x}_{\mathbf{j,k-1}},\mathbf{a}) + \mathbf{p}(\mathbf{x}_{\mathbf{j,k}}|\mathbf{x}_{\mathbf{j,k-1}},\mathbf{b}) + \mathbf{p}(\mathbf{x}_{\mathbf{j,k}}|\mathbf{c})$$

➢ Dirichlet Process Mixtures Learning

Inference

$$\theta_{\mathbf{j,k}}|\alpha \sim \mathbf{DDP}(\alpha, \mathbf{G_0})$$

$$\mathbf{x}_{\mathbf{j,k}}|\mathbf{x}_{\mathbf{j,k-1}}, \theta_{\mathbf{j,k}} \sim \mathbf{F}(\theta_{\mathbf{j,k}})$$

$$\mathbf{z}_{\mathbf{l,k}}|\mathbf{x}_{\mathbf{j,k}}, \theta_{\mathbf{j,k}} \sim \mathbf{G}(\mathbf{x}_{\mathbf{j,k}}, \theta_{\mathbf{j,k}})$$

Use Gibbs sampling method to update labels and parameters.

References

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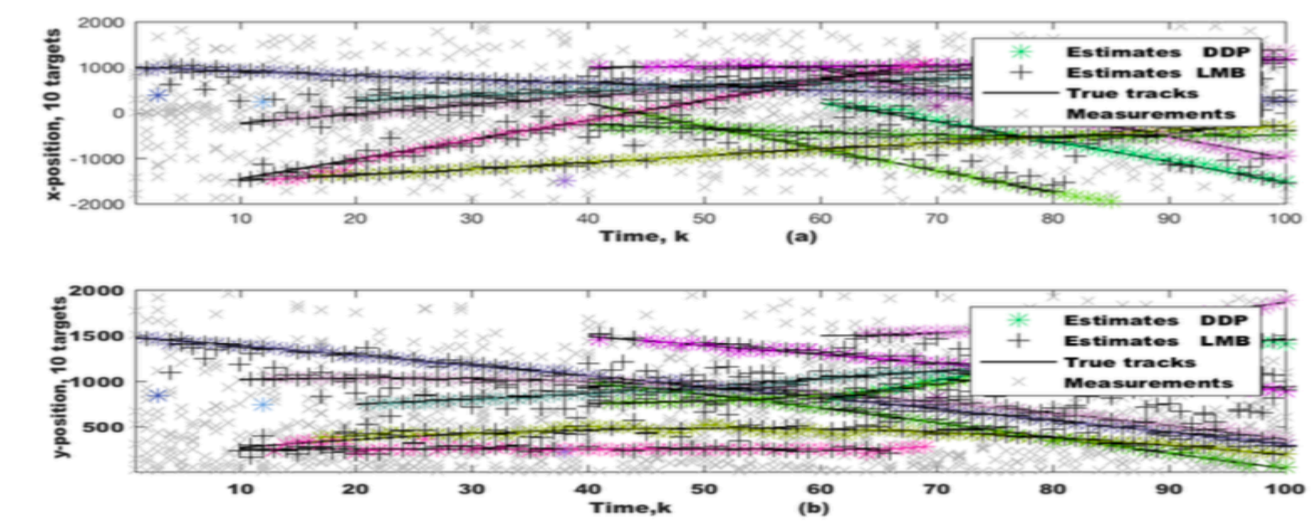
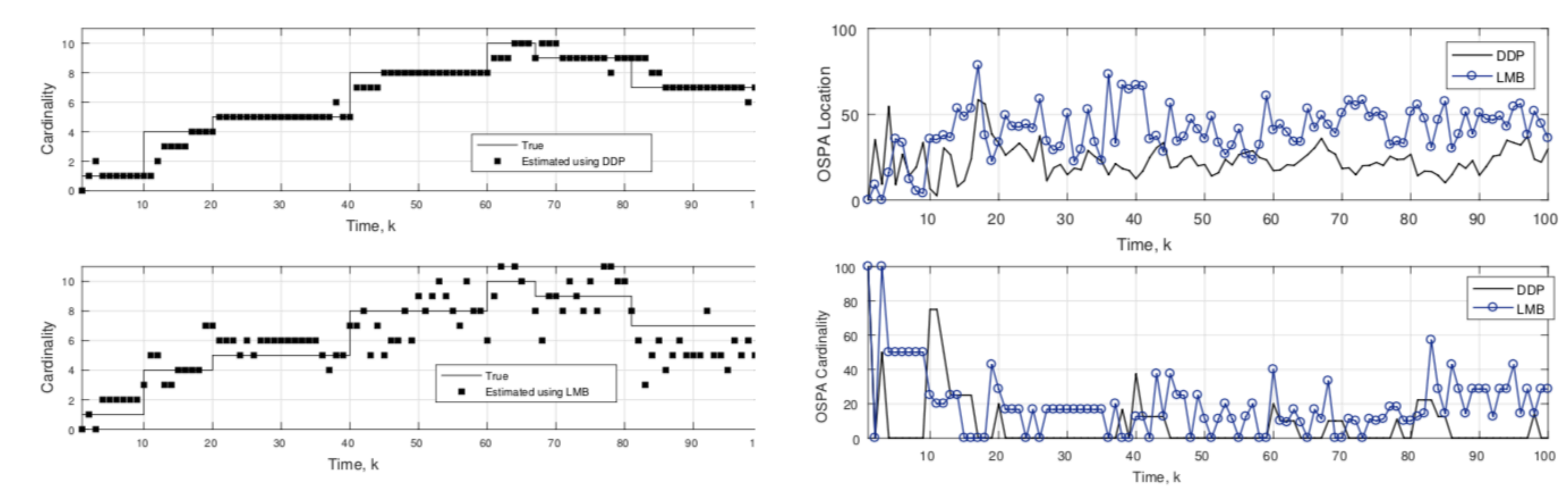
DDP-EMM Algorithm: Experimental Results



Actual and estimated x(top) and y(bottom) position against time for DDP-EMM and LMB.



(a) (b)

- ❑ (a) Comparison between cardinality estimation for DDP(top) and LMB(bottom)
- ❑ Comparison between DDP and LMB: OSPA location (top) and cardinality (bottom) of order p=1 and cut-off=100

Summary

- We have introduced the DDP-EMM algorithm to model object evolution that along with the measurement sets may infer the object identity and the time-dependent object cardinality.
- The DDP-EMM algorithm can be integrated, for example, into Dirichlet process mixture models for estimation of source location.
- The DPM model to update the time-dependent object cardinality.
- Significant gains over existing algorithms such as labeled multi Bernoulli.