Use of Hierarchical Dirichlet Processes to Integrate Dependent Observations From Multiple Disparate Sensors for Tracking

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Challenges of multimodal sensing system

Multimodal framework allows for integration of complementary information in analyzing a scene

Challenges:

- **Synchronous transmit/receipt leads to highly correlated observations, view same scene and relative sensor locations**
- **Time-varying number of observations (unknown at each time step)**
- **Observations are unordered: no measurement to-model association**
- Multiple environmental conditions: high noise levels, clutter, interference

STING-EO Mk2 system (Thales): 3 data sources

- I-band radar: angular accuracy
- K-band radar: short ranges
- electro-optical (EO) infrared camera: target identification and observation

Tracking formulation using measurements from multiple sensors

- **Unknown object state vector:** $\boldsymbol{x}_k = f(\boldsymbol{x}_{k-1}) + \boldsymbol{u}_{k-1}$

state transition function

modeling error

- **Measurement vector from m th sensor (total L_m measurements)**

$$\mathbf{z}_{m,k}^{(i)} = h_m(x_k) + \boldsymbol{w}_{m,k}\,, \quad m = 1, \dots, M$$

relation between m th sensor measurement & target state (m th model)

m th sensor measurement noise

- **Require joint PDF of measurements $p(Z_k|\, x_k)$ where**

$$\mathbf{Z}_k = \left[\mathbf{Z}_{1,k} \;\; \mathbf{Z}_{2,k} \;\; \dots \;\; \mathbf{Z}_{M,k}\right] = \left[\left[\mathbf{z}_{1,k} \;\; \dots \;\; \mathbf{z}_{L_1,k}\right] \; \left[\mathbf{z}_{2,k} \;\; \dots \;\; \mathbf{z}_{L_2,k}\right] \;\; \dots \;\; \left[\mathbf{z}_{M,k} \;\; \dots \;\; \mathbf{z}_{L_M,k}\right]\right]$$

- **Measurements are unordered, can correspond to different models, and assumed dependent (even from same sensor)**

Processing dependent measurements by exponential embedding

- **Exponential embedding of multiple probability density functions (PDFs) or exponentially embedded family (EEF):** approximate joint PDF of dependent measurements; extended to multimodal sensor processing **(S. Kay 2005, 2010)**
- **Multi-modal tracking with dependent measurements:** approximate joint PDF of dependent RF and EO measurements using EEF to improve tracking performance **(J. Zhang, Papandreou-Suppappola, Kay 2010)**

Joint variables: $\mathbf{Z}_k = \begin{bmatrix} \mathbf{Z}_{1,k} & \mathbf{Z}_{2,k} \end{bmatrix}$, **assumed known marginals** $p\left(\mathbf{Z}_{1,k}\right) p\left(\mathbf{Z}_{2,k}\right)$

Then, joint PDF $p\left(\mathbf{Z}_{1,k},\ \mathbf{Z}_{2,k}\right)$ **estimated from exponential family that is closest to it using Kullback-Leibler divergence measure**

➔ **parametric form and requires optimization**

Proposed approach: hierarchical Dirichlet process

- **Bayesian nonparametric modeling to capture dependency among measurements that originated from different sensors**

- **Hierarchal Dirichlet process (HDP) framework:**

form clusters that are shared among multiple related groups

- **Use HDP to form measurement clusters that are shared among multiple sensors/groups (related by dependency)**

- **A parameter, for each measurement of each sensor, is drawn from a discrete random probability measure, Dirichlet process (DP), with probability one to ensure dependency among measurements**

Proposed approach: hierarchical Dirichlet process

- **Parameter** $\phi_{m,k}^{(i)}$ **of i th measurement of m th sensor $z_{m,k}^{(i)}$ is drawn from a random probability measure G_m**

$$z_{m,k}^{(i)} \,|\phi_{m,k}^{(i)} \sim F\left(\phi_{m,k}^{(i)}\right), \qquad \phi_{m,k}^{(i)} \,|G_m \sim G_m \;, \quad i = 1, \dots, L_m$$

distribution related to sensor model

- **G_m is a DP drawn from base distribution G_0 & hyper-parameter γ**

$$G_m \,|\, G_0 \sim \mathrm{DP}(\gamma, G_0), \quad m = 1, \dots, M$$

where $G_0 \sim \mathrm{DP}(\eta, H)$ is a DP with base distribution H and hyper-parameter η

- **Parameters are needed to place prior on dependent measurements from same sensor so structure/identity is inherited within sensor measurement**

➔ model captures: dependency among measurement sets & sensor identify

Hypothesis testing for target detection

- **Detection binary hypothesis: object present in given measurements**

$$\mathcal{H}_0 : \mathbf{Z}_{m,k} = \mathbf{w}_{m,k}$$
$$\mathcal{H}_1 : \mathbf{Z}_{m,k} = h_m(\mathbf{x}_k) + \mathbf{w}_{m,k}$$

- **Neyman-Pearson: detected in measurements of m th sensor if test statistic**

$$\mathcal{T}_m\Big(\mathbf{Z}_{m,k}, \phi_{m,k}; \mathbf{x}_k\Big) = \frac{p\Big(\mathbf{Z}_{m,k} \mid \mathbf{x}_k; \mathcal{H}_1\Big)}{p\Big(\mathbf{Z}_{m,k}; \mathcal{H}_0\Big)}$$

with $\phi_{m,k} = \left\{\phi_{m,k}^{(1)}, \ldots, \phi_{m,k}^{(L_m)}\right\}$

exceeds a threshold (from given probability of false alarm)

- **Return object generated measurements** $\mathcal{Z}_k = \{\mathcal{Z}_{1,k}, \ldots, \mathcal{Z}_{M,k}\}$

for $\mathcal{Z}_{m,k} \subset \mathbf{Z}_k$

Compute posterior distribution

To obtain posterior distribution to obtain state estimate:

$$p(\mathbf{x}_k|\mathcal{Z}_1,\ \ldots,\ \mathcal{Z}_k) \propto p(\mathcal{Z}_k|\mathbf{x}_k)\, p(\mathbf{x}_k|\mathcal{Z}_1,\ldots,\mathcal{Z}_{k-1})$$

measurements $\mathcal{Z}_k = \{\mathcal{Z}_{1,k},\ldots,\mathcal{Z}_{M,k}\}$
from sensors modeled using HDP

prediction equation

$$p(\mathbf{x}_k|\mathcal{Z}_1,\ldots,\mathcal{Z}_{k-1}) = \int Q_{\boldsymbol{\theta}}\big(\mathbf{x}_{k-1},\mathbf{x}_k\big) p(\mathbf{x}_{k-1}|\mathcal{Z}_1,\ldots,\mathcal{Z}_{k-1}) d\mathbf{x}_{k-1}$$

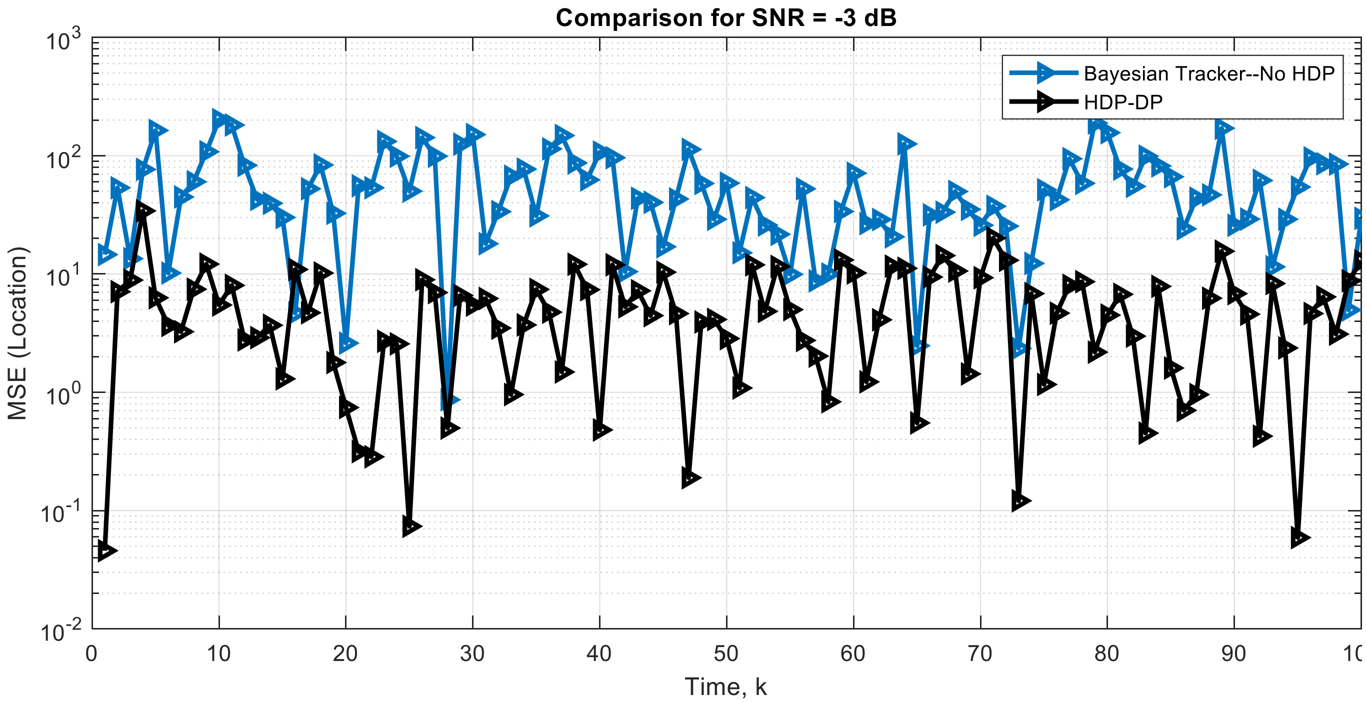
Using HDP estimated density:

$$p(\mathcal{Z}_{m,k} \mid \mathbf{x}_k) = \sum_{j=1}^{\infty} \pi_{m,j}\, F(\boldsymbol{\theta}_{j,k})$$

(details in the paper)

Simulation: Dependent EO and RF measurements

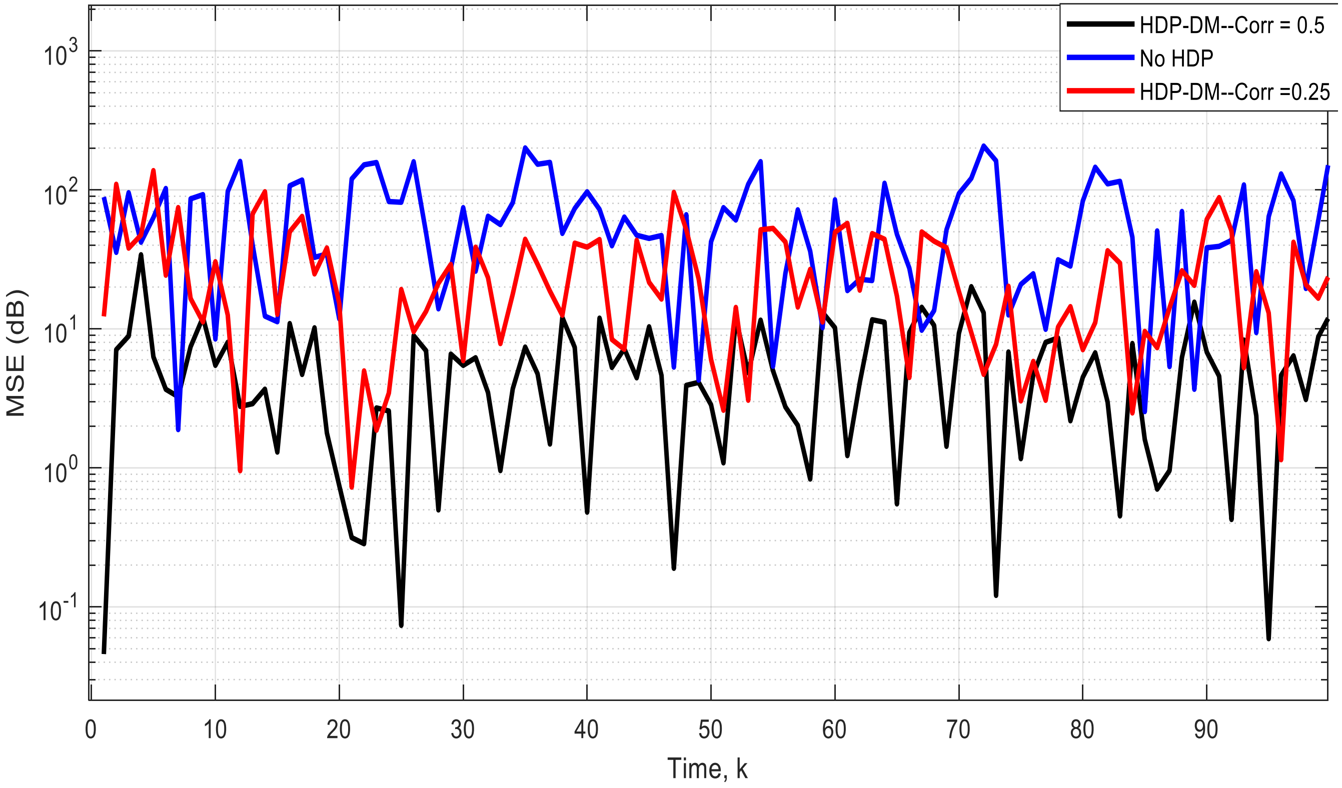
Object location estimation mean-squared error (MSE)



Assumes independent measurements

HDP

Simulations: HDP approach for varying correlation values

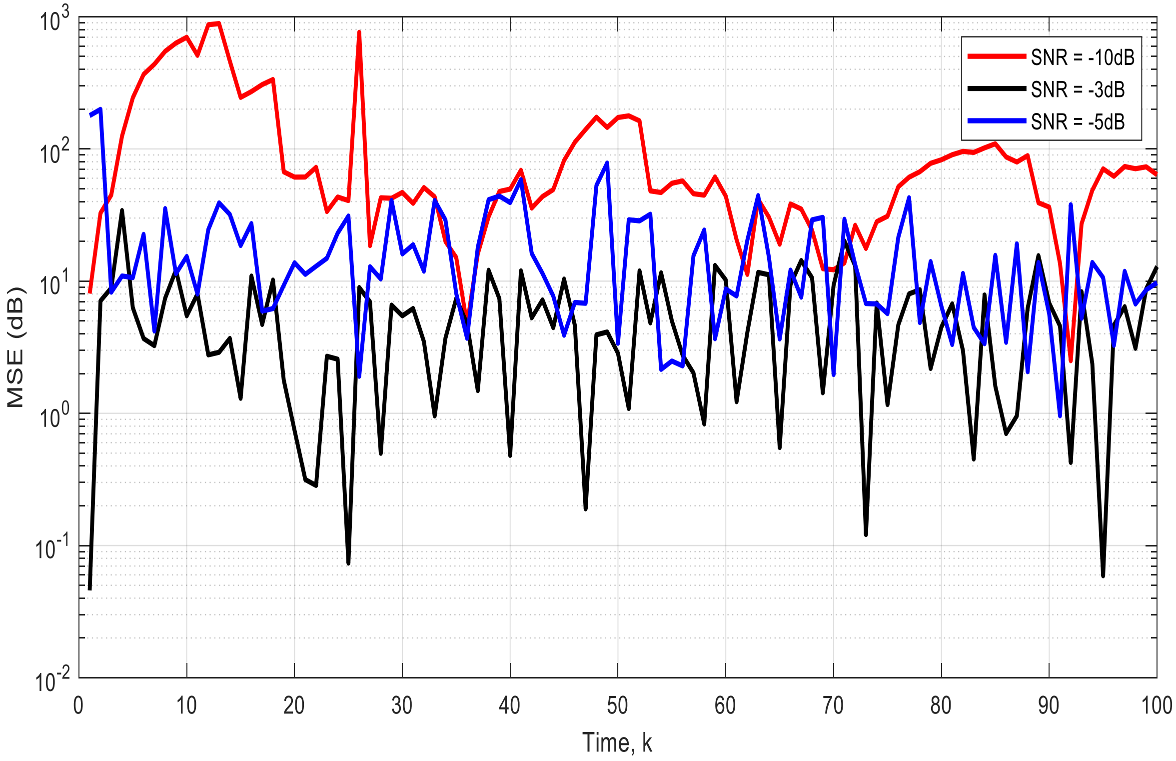


Assumes independent but r=0.5

r = 0.25

r = 0.5

Simulations: HDP approach for varying SNR



-10 dB

-5 dB

-3 dB

Conclusions

- Tracking a target by integrating dependent observations from multiple sources and associated with different measurement models
- Hierarchical Dirichlet process (HDP) models dependency, model association, and time-varying cardinality of the measurements provided by each sensor
- No assumptions needed for prior knowledge of marginal PDFs
- Low computational cost as no optimization necessary
- No parametric model required