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Multimodal Sensing and Information Integration for Multiple Object Tracking

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The funded research designed methods to improve multiple object tracking using measurements from multimodal systems.The methods combine sequential Bayesian filtering to estimate the time-varying parameters of physics-based models and Bayesian nonparametric modeling to infer and learn information directly from the measurements. Integrating these methods resulted in robust learning and increased performance when compared to current state-of-the-art methodologies. Multiple challenging scenarios were considered: time-varying number of moving objects, unknown measurement-to-object associations, time-varying environmental conditions, and multiple statistically-dependent measurements.

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Final Performance Report

Multimodal Sensing and Information Integration for Multiple Object Tracking

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Abstract

The funded research resulted in designing statistical signal processing algorithms to improve the performance of tracking multiple objects using measurements from multimodal sensing systems. The algorithms use sequential Bayesian filtering methods to estimate the time-varying parameters of physics-based models; they also use Bayesian nonparametric modeling methods to infer and learn information directly from the measurements. Integrating the two methods resulted in robust learning and increased tracking performance when compared to current state-of-the-art methodologies. Multiple challenging tracking scenarios were considered: time-varying number of objects entering and leaving a scene at different times; unknown measurement-to-object associations; time-varying environmental and operational conditions; multiple statistically-dependent measurements.

1. Research Goals

Multimodal sensing systems can facilitate algorithm development to integrate and learn new information using measurements from multiple asymmetric sensors. The varying modality characteristics of the systems aim to provide significant performance improvements in tracking multiple objects in diverse operational and environmental conditions. Our main goal concentrated on developing statistical signal processing algorithms to improve tracking performance when tracking multiple objects. State-of-the-art methods employ Bayesian parametric methods that represent a system using physics-based models with unknown characteristics or probabilistic models with unknown parameters. Once the models are selected, they do no allow for variability in operational or environmental conditions. If sudden time-varying changes occur in the tracking scene, processing methodologies must rely directly on the available sensor measurements. Recent advances in machine learning promote Bayesian nonparametric modeling methods [1]; these methods allow for an infinite number of parameters to capture data variations and can directly infer and learn information from new data as they become available. Integrating both parametric and nonparametric approaches can be advantageous: knowledge from physics-based models can only further improve tracking performance when integrated with learned information directly from the data.

Toward our main goal, we accomplished multiple challenging tasks that resulted in theoretical advances in the area of multiple object tracking. These tasks include: tracking a time-varying number of objects with unknown identify and unknown measurement-to-object associations; tracking using an unknown number of statistically-dependent measurements from multiple disparate sources; tracking in varying environmental conditions of high clutter; extracting sensor measurements in a coexisting multimodal system; transferring information from learning sources to track object embedded in time-varying measurement noise; and designing computationally efficient tracking algorithms.

The remaining of the report is organized as follows. The general formulation for the multiple object tracking problem is provided in Section 2. Section 3.1 provides a list of the challenging tasks that resulted in our proposed work. Section 3.2 examines three new algorithms on multiple object tracking under dynamic dependency conditions. New algorithms for tracking with dependent measurements and in high clutter scenarios are detailed in Sections 3.3 and 3.4, respectively. Proposed work on extracting measurements from coexisting multimodal systems, using transfer learning methods with time-varying measurement noise levels, and efficiency implementing tracking algorithms are presented in Sections 3.5, 3.6 and 3.7, respectively. The publications derived from this research are listed in Section 4.

2. General Problem Formulation

We adopt the following formulation for the multiple object tracking problem [2]. We assume N_k moving objects at time step k, where N_k is unknown and varies with time. The unknown parameter or state vector of the ℓth object, $\ell = 1, \ldots, N_k$, is denoted by $\mathbf{x}_{\ell,k}$. If we assume that the ℓth object is present in the scene at time step $(k-1)$ and remains in the scene at time step k, then the object state can be obtained using the transition equation

$$\mathbf{x}_{\ell,k} = g(\mathbf{x}_{\ell,k-1}) + \mathbf{u}_{\ell,k-1} \,. \tag{1}$$

The transition function $g(\cdot)$ is determined by the problem-specific dynamic model and $\mathbf{u}_{\ell,k-1}$ is the modeling error random process. We assume a multimodal sensing system that provides M_k measurement vectors $\mathbf{z}_{m,k}$, $m = 1, \ldots, M_k$, at each time step k. The association between objects and measurements is unknown, and unless otherwise stated, measurements are independent and each measurement is generated from a singe object. Assuming the mth measurement originated from the ℓth object, the measurement equation is given by

$$\mathbf{z}_{m,k} = h(\mathbf{x}_{\ell,k}) + \mathbf{w}_{m,k} \,. \tag{2}$$

where $h(\cdot)$ provides the relationship between measurements and object state and $\mathbf{w}_{m,k}$ is measurement noise.

The tracking problem requires the estimation of the state vector $\mathbf{x}_{\ell,k}$ of the $\ell$the object based on the dynamic state space formulation in (1) and (2); these two equations provide the prior transition density $p(\mathbf{x}_{\ell,k} \mid \mathbf{x}_{\ell,k-1})$ and measurement likelihood density $p(\mathbf{z}_{\ell,k} \mid \mathbf{x}_{\ell,k})$, respectively. Bayesian filtering methods can then be used to estimate the posterior density $p(\mathbf{x}_{\ell,k} \mid \mathbf{z}_{\ell,k})$, whose mean is the estimated object state [2]. Also assuming high signal-to-noise-ratio (SNR) conditions and statistical knowledge of $\mathbf{u}_{\ell,k-1}$ and $\mathbf{w}_{m,k}$, the ℓth object can be successfully tracked. However, the tracking problem becomes more challenging with multiple objects and unknown time-varying operational and environmental conditions.

3. Theoretical Research Advances

3.1. Contributions

Listed below are the challenging tasks we accomplished on this project on multiple object tracking. The tasks are then discussed in detail in this section.

Tasks

(a) *Object labeling:* match the object state estimate to the correct object

(b) *State dependency:* formulate and integrate inherent dependency on object states

(c) *Measurement-to-noise association:* match each measurement to the correct object

(d) *Time-varying existence:* estimate time-varying number of objects and measurements

(e) *Dependent measurements:* formulate and integrate statistical dependence of measurements

(f) *Environmental conditions:* account for high clutter or high noise in the measurements

(g) *Coexisting modalities:* extract tracking measurements from coexisting sensing systems

(h) *Transfer learning:* transfer information learned from similar sources

(i) *Computational cost:* reduce cost in implementing Bayesian inference algorithms.

3.2. Time-Variability in Multiple Object Tracking

We proposed three different algorithms to address Tasks (a)-(d) and solve the problem of tracking a time-varying and unknown number of moving objects that enter and leave a scene at different time steps; a time-varying and unknown number of measurements is provided at each time step but with unknown object association. Current state-of-the-art methods include the use of probability hypothesis density filtering, multi-Bernoulli filtering, random finite sets and labeled random finite sets [3–5]. Some of these methods are computationally intensive and require high SNR. They also do not take into account the time-dependent evolution that is inherent in multiple object tracking. The new algorithms integrate Bayesian filtering with Bayesian nonparametric methods to model prior distributions by capturing the full time-dependency among object states.

Dependent Dirichlet Process Modeling [6–10]

We proposed an approach to model the prior distribution of multiple dynamic object states and learn multiple object labels (or clusters) over dependent information using the dependent Dirichlet process (DDP) [11]. The DDP forms clusters associated with different object states using the Dirichlet process (DP) at each time step.

A DP is a distribution over probability measures that forms a class of Bayesian nonparametric models for density estimation. A random distribution G that is DP-distributed is defined on an infinite dimensional space and denoted by $G{\sim}\mathrm{DP}(\alpha, G_0)$; here, G_0 is a (possibly continuous) base distribution (e.g., Gaussian distribution) and α is a concentration positive scalar parameter. The random probability measure G is a discrete distribution made up of a countably infinite number of samples and has the same support set Θ as G_0. Any finite set of partitions $\theta_1, \ldots, \theta_N$ of Θ follows $\{G(\theta_1), \ldots, G(\theta_L\}{\sim}\mathrm{Dir}(\alpha\, G_0(\theta_1), \ldots, \alpha\, G_0(\theta_L))$. Note that a Dirichlet distribution with parameters $\mathrm{b} = \{b_1, \ldots, b_L\}$ of sequence $\mathrm{y} = \{y_1, \ldots, y_L\}$ is denoted by $\mathrm{y}{\sim}\mathrm{Dir}(\mathrm{b})$ and has probability density $p(\mathrm{y}) = \frac{1}{B(\mathrm{b})} \prod_{\ell=1}^{L} y_\ell^{b_\ell - 1}$, where $B(\mathrm{b})$ is the beta function. The DP $G \sim \mathrm{DP}(\alpha, G_0)$ can also be defined by the stick-breaking construction as [12]

$$G(\theta) = \sum_{\ell=1}^{\infty} \Big(V_\ell \prod_{i=1}^{\ell-1} (1 - V_i) \Big) \, \delta(\theta - \theta_\ell)$$

where θ_ℓ, $\ell = 1, 2, \ldots$, are independent and identically distributed samples of G_0 and $V_\ell \sim \mathrm{Beta}(1, \alpha)$.

The new DDP approach learns multiple parameters by exploiting inherent dependencies in the state transition. The dependencies include the relationship between the number of objects present at the previous time step $(k-1)$ and the current time step k; and the relationship between the clustering indices of the ℓth object state and the previous $(\ell-1)$ object states at the same time step k. The clustering property of the DP prior is used to model the states of new objects entering the scene so no prior knowledge on the expected number of objects is needed. The iterative DDP construction of the state prior distributions at time step k is described as follows.

- At time step $(k-1)$, the ℓth object cluster parameter $\boldsymbol{\theta}_{\ell,k-1}$ as well as the lth cluster assignment indicator $c_{l,k-1}$ and object cardinality (number of objects) $v_{l,k-1}$ are assumed available from the previous iteration.

- During transition from time step $(k-1)$ to time step k, the object transition indicator $\mathrm{s}_{\ell,k|k-1}$ is modeled as a Bernoulli process with parameter $\mathrm{P}_{\ell,k|k-1}$. This parameters is the probability that the object transitions according to the Markov transition kernel $F_{\boldsymbol{\theta}}(\mathbf{x}_{\ell,k-1}, \mathbf{x}_{\ell,k})$, which depends on the transition equation in (1). If $v_{l,k-1} \geqslant 1$, the binary cluster transition indicator $\lambda_{\ell,k|k-1}$ is used to keep track of the number of transitioning clusters.

- At time step k, three different cases are considered to formulate the distribution of the DDP cluster parameter $\boldsymbol{\theta}_{\ell,k}$ and its corresponding predicted object state $\mathbf{x}_{\ell,k}$. Each of these case depends on the selection of the cluster to be assigned to the ℓth object. The existence probability of each object depends on the object cardinality, cluster transition and assignment indicators and the DP concentration parameter.

  Case 1: The ℓth object selects a transitioned cluster that is already occupied by at least one of the $(\ell-1)$ previous objects. The cluster parameter $\boldsymbol{\theta}_{\ell,k}$ is drawn from the cluster transitioning kernel $\varphi(\boldsymbol{\theta}_{\ell,k-1}, \boldsymbol{\theta}_{\ell,k})$ that is related to Equation (1); the state prior distribution is then obtained as

$$p_1\Big(\mathbf{x}_{\ell,k} \mid \mathcal{X}_{\ell-1,k}, \mathcal{X}_{\ell,k|k-1}, \Theta_{\ell,k}, \Theta_{\ell,k-1}\Big) = F_{\boldsymbol{\theta}}(\mathbf{x}_{\ell,k-1}, \mathbf{x}_{\ell,k}) \, p(\mathbf{x}_{\ell,k} \mid \boldsymbol{\theta}_{\ell,k}),$$

  where $\mathcal{X}_{\ell,k} = \{\mathbf{x}_{1,k}, \ldots, \mathbf{x}_{\ell,k}\}$, $\Theta_{\ell,k} = \{\boldsymbol{\theta}_{1,k}, \ldots, \boldsymbol{\theta}_{\ell,k}\}$, $F_{\boldsymbol{\theta}}(\mathbf{x}_{\ell,k-1}, \mathbf{x}_{\ell,k})$ is the transition kernel in (1), and $p(\mathbf{x}_{\ell,k} \mid \boldsymbol{\theta}_{\ell,k})$ is the object state density given the cluster parameter $\boldsymbol{\theta}_{\ell,k}$.

Case 2: The ℓth object selects a transitioned cluster that has not yet be occupied by any of the previously considered objects. The cluster parameter $\boldsymbol{\theta}_{\ell,k}$ is drawn from $\varphi(\boldsymbol{\theta}_{\ell,k-1}, \boldsymbol{\theta}_{\ell,k})$ and the state prior distribution is

$$p_2\Big(\mathbf{x}_{\ell,k} \mid \mathcal{X}_{\ell-1,k}, \mathcal{X}_{\ell,k|k-1}, \Theta_{\ell,k}, \Theta_{\ell,k-1}\Big) = F_{\boldsymbol{\theta}}(\mathbf{x}_{\ell,k-1}, \mathbf{x}_{\ell,k}) \, p(\mathbf{x}_{\ell,k} \mid \boldsymbol{\theta}_{\ell,k}) \, \varphi(\boldsymbol{\theta}_{\ell,k-1}, \boldsymbol{\theta}_{\ell,k})$$

Case 3: The ℓth object does not belong to an existing cluster and a new cluster is formed with parameter $\boldsymbol{\theta}_{\ell,k}$. Using a $\mathrm{DP}(\alpha, H)$ with concentration parameter α, $\boldsymbol{\theta}_{\ell,k}$ is drawn from the base distribution H. The state prior distribution is given by

$$p_3\Big(\mathbf{x}_{\ell,k} \mid \mathcal{X}_{\ell-1,k}, \mathcal{X}_{\ell,k|k-1}, \Theta_{\ell,k}, \Theta_{\ell,k-1}\Big) = \int_{\boldsymbol{\theta}} p(\mathbf{x}_{\ell,k} \mid \boldsymbol{\theta}) \, dH(\boldsymbol{\theta}) \, .$$

Using the independent sensor measurements $\mathbf{z}_{m,k}$, $m = 1, \ldots, M_k$, at time step k, the DDP modeled prior distribution is used with a Markov chain Monte Carlo (MCMC) method to update the object state estimate. As DDP clustering is used to label the object states, Dirichlet process mixtures (DPMs) are used to learn and assign each measurement to its associated object identity. The DPM mixing measure is drawn from the DDP to infer the density $p(\mathbf{z}_{m,k} \mid \boldsymbol{\theta}_{\ell,k}, \mathbf{x}_{\ell,k})$, which depends on the measurement likelihood function in Equation (2).

The posterior distribution is efficiently implemented using a Gibbs sampler inference scheme that iterates between sampling the object states and the dynamic DDP parameters. The Bayesian posterior is given by

$$p(\mathbf{x}_{\ell,k} \mid \mathcal{Z}_k) = \int p(\mathbf{x}_{\ell,k} \mid \mathcal{Z}_k, \Theta_{D_k,k})\, dG(\Theta_{D_k,k} \mid \mathcal{Z}_k)$$

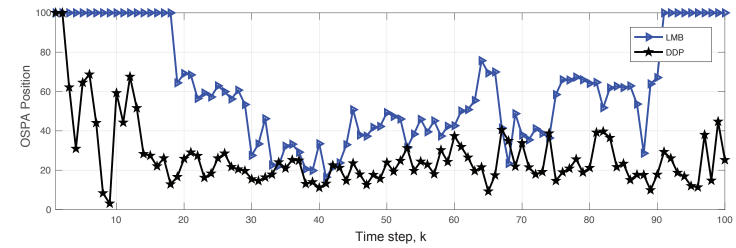
where $\mathcal{Z}_k = \{\mathbf{z}_{1,k}, \ldots, \mathbf{z}_{M_k,k}\}$, $G(\Theta_{D_k,k} \mid \mathcal{Z}_k)$ is the cluster parameter posterior distribution given the measurements, and D_k is the number of non-empty clusters; its computation using Gibbs sampling is provided in [8]. The posterior distribution is then used to estimate the object states and find the time-dependent object cardinality.

Dependent Pitman-Yor Process Modeling [7–10, 13]

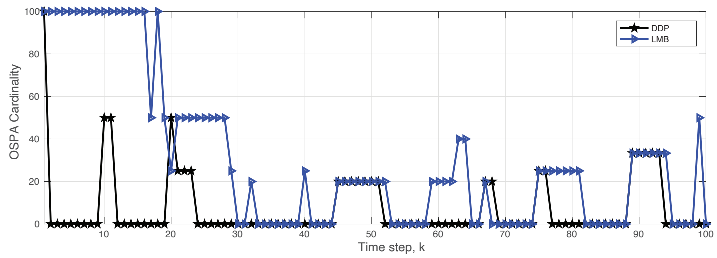
We extended the work on DDP state priors to modeling using the dependent Pitman-Yor process (DPYP) in order to introduce more flexibility in the nonparametric formation of object clusters. The expected number of unique clusters during transitioning is $\alpha \log(N_k)$ when the DDP is used; here, α is the DP concentration parameter and N_k is the time-varying number of objects. The corresponding expected number of unique clusters for the DPYP formulation follows the power law $\alpha\, N_k^d$, where d is a discount parameter. With this additional parameter, the DPYP allows for a higher probability of having a large number of unique clusters [14]. Also, clusters with only a small number of objects have a lower probability of selecting new objects. As such, the DPYP model is better matched to tracking a time-varying number of objects as it ensures that the larger number of available clusters can capture all dependencies. Note that the Pitman-Yor process (PYP) forms a large class of distributions on random probability measures that contains the DPs. Similar to the DP, it defines a prior on the space of probability distributions on an infinite dimensional space. The DPYP prior construction is similar to that of the DDP; however, the probability of an object selecting a particular cluster is different. Note that this work was in collaboration with Dr. Muralidhar Rangaswamy, Technical Lead for Radar Sensing at Air Force Research Laboratory, Wright-Patterson Air Force Base.

Dependent Poisson Diffusion Process Modeling [7–10, 15]

We proposed a method to track a dynamically varying number of objects by making use of information from previously tracked objects. The method is based on Bayesian nonparametric modeling that uses diffusion processes and random trees to robustly associate object states on a new scene with previously estimated object states. The Dirichlet diffusion tree (DDT) is a nonparametric prior over tree structures for computing posterior distributions; it is a generalization of Dirichlet processes that can be used to capture hierarchical structure when estimating latent parameters [16]. The proposed approach uses the dependent Poisson diffusion tree (D-PoDT) that extends the capability of Dirichlet diffusion trees of modeling hierarchies to also capture dependencies among the object states. The approach considers a class of priors on trees whose terminal nodes are the object state parameters and whose nonterminal nodes represent clustering of the state parameter in a hierarchy. The state prior includes the number of objects at the current time step and the object label at the previous time step. Thus, inference on



(a)



(b)

Figure 1: OSPA (a) position and (b) cardinality comparison between the LMB and new DDP.

the labels of object states over dependent information can be made by tracing random tree paths.

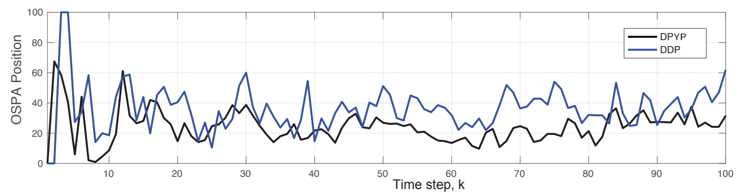
Simulations

Using multiple simulations, we demonstrated the improved performance of the three proposed algorithms as compared to the state-of-the-art labeled multi-Bernoulli (LMB) filtering approach. The coordinated turn motion model was selected to track targets moving in two dimensions. The unknown target state parameters are the coordinates for position and velocity as well as the turn rate; the measurements are bearing and range. The following simulations used 100 times steps, -3 dB SNR, and 10,000 Monte Carlo realizations. The optimal sub-pattern assignment (OSPA) metric is used to compare the overall estimated target state position and cardinality (number of targets). For the OSPA metric, the lower the metric value the higher the performance.

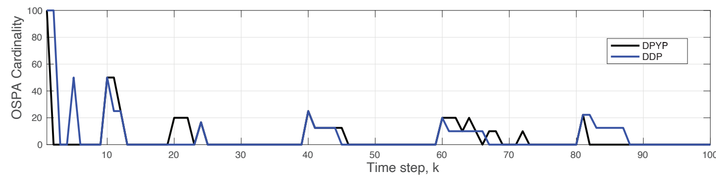
DDP Simulation We used 5 targets moving in close proximity to each other, following the same trajectory but entering and leaving the scene at different time steps. The OSPA metric for the estimated target position is shown in Figure 1a and the cardinality in Figure 1b. As shown, the DDP performs much higher than the LMB even for closely-spaced targets. Additional examples were simulated to demonstrate the DDP performance for a higher number of time-varying targets and for varying SNRs.

DPYP Simulation To demonstrate that the DPYP is better matched to the multiple object tracking problem than the DDP, we used a simulation with a maximum of 10 moving targets. The increased performance of the DPYP, as compared to the DDP, is shown using the OSPA comparison for position and cardinality in Figures 2a and 2b, respectively.

D-PoDT Simulation Using a simulation with 5 moving targets, the new D-PoDT approach is compared to the LMB. The increased performance of the D-PoDT, as compared to the LMB, is shown using the OSPA comparison



(a)



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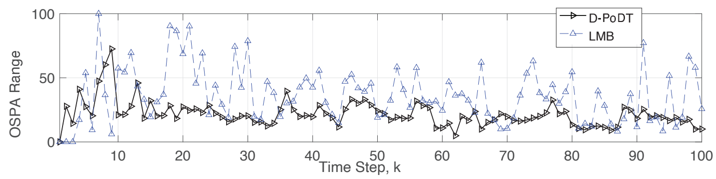

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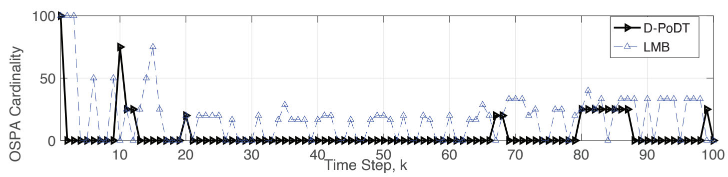


(d)

Figure 2: OSPA (a) position and (b) cardinality comparison between the DDP and DPYP; OSPA (c) range and (d) cardinality comparison between the D-PoDT and LMB.

for range and cardinality in Figures 2c and 2d, respectively. The highest errors for the D-PoDT are observed when targets enter the scene at $k = 0, 10, 20$.

3.3. Statistically-dependent Measurements in Multiple Object Tracking

In a multimodal sensing platform, as disparate sensors observe the same scene, their measurements can be statistically dependent and correspond to different measurement models. To address Task (e), we proposed a Bayesian nonparametric framework to track a time-varying number of moving objects using disparate sensor measurements. The DDP is first used to estimate the object states and then hierarchical modeling is used to take advantage of the dependency among the measurements at each time step. The method was first developed to track one object [17] and then extended to track a time-varying number of moving objects [18]. In both cases, the hierarchical Dirichlet process (HDP) mixture model [19] is used to cluster the dependent measurements and estimate their joint density.

The measurements are assumed to be synchronously received, statistically dependent, and can correspond to different measurement models. In addition, we assume no knowledge of object-to-measurement associations.

At time step k, we assume that there are M_k measurements, $\mathcal{Z}_{k,l} = \{\mathbf{z}^{(l)}_{1,k,l}, \ldots, \mathbf{z}_{M_k,k,l}\}$, from the lth sensor, $l = 1, \ldots, L$. Thus, the measurement equation in (2) is modified to

$$\mathcal{Z}_{k,l} = h_l(\mathbf{x}_{\ell,k}) + \mathbf{w}_{k,l} \tag{3}$$

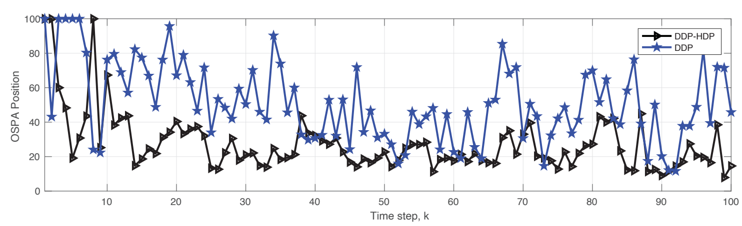
where $h_l(\cdot)$ and $\mathbf{w}_{k,l}$ are the measurement function and measurement noise associated with the lth sensor. Each measurement can only be generated from one object, and the lth sensor generates measurements $\mathcal{Z}_{k,l}$ according to the likelihood function $p\big(\mathcal{Z}_{k,l} \mid \mathbf{x}_{\ell,k}\big)$. Also, measurements from different sensors, $\mathcal{Z}_{k,l}$ and $\mathcal{Z}_{k,i}$ for $l \neq i$, and measurements from the same sensor, $\mathbf{z}_{m,k,l}$ and $\mathbf{z}_{n,k,l}$ for $m \neq n$, are dependent and thus highly correlated.

Each sensor parameter is drawn from a discrete (local) random probability measure with probability one to ensure dependency among measurements. We assume a global probability measure G_0 drawn from $\mathrm{DP}(\eta, H)$, which has concentration parameter η and base distribution H. We then draw the lth sensor local probability random measure G_l, $l = 1, \ldots L$, from $\mathrm{DP}(\gamma, G_0)$, with parameters γ and G_0. The measurement parameters $\psi_{m,k,l}$ are then drawn from G_l. Using the HDP mixture model, the joint likelihood measurement is given by

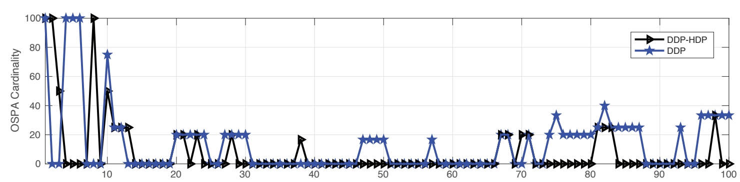
$$p(\mathbf{z}_{m,k,l} \mid \psi_{m,k,l},\ \mathbf{x}_{1,k}, \ldots, \mathbf{x}_{N_k,k}),\ m = 1, \ldots, M_k$$

and depends on the lth sensor measurement function $h_l(\cdot)$ in (3). The posterior distribution at time step k is then obtained using this joint measurement likelihood and the prior obtained using the DDP.

To demonstrate the performance of this new approach, we simulated five targets moving according to the coordinated turn model. The measurements from two different sensors were range and bearing and bearings from a Gaussian model; all measurements were generated to be highly correlated. The integrated DDP and HDP approach was compared to the DDP that assumes independent measurements. The OSPA metric for position and cardinality is compared in Figures 3a and 3b, respectively. As it can be seen, the performance is improved when the HDP is used to account for dependency among the measurements.



(a)



(b)

Figure 3: OSPA (a) position and (b) cardinality comparison between the DDP-HDP and DDP.

3.4. Object Tracking with Multiple Measurements in High Clutter

We proposed a robust generative approach to effectively model multiple sensor measurements for tracking a moving object in high clutter to address Task (f). We assumed a time-dependent number of measurements with unknown origin; some of the measurements contain only clutter and have no information on the object. As the presence of clutter measurements can greatly reduce tracking performance, we used joint Bayesian nonparametric modeling to construct the joint prior distribution of target and clutter measurements [20].

We considered a single object moving in an environment with an unknown number of clutters. As multiple measurements are received whose origin is unknown, the measurement model in (2) is modified to provide the mth measurement vector, $m=1,\ldots,M_k$, as

$$\mathbf{z}_{m,k} = \begin{cases} \mathbf{z}^{(t)}_{m,k} = h(\mathbf{x}_k) + \mathbf{w}_{m,k}, & \text{object measurement} \\ \\ \mathbf{z}^{(c)}_{m,k}, & \text{clutter measurement} \end{cases}$$

where $\mathbf{z}^{(t)}_{m,k}$ and $\mathbf{z}^{(c)}_{m,k}$ indicate the target and clutter measurement, respectively. In order to account for the presence of clutter, we first factorize the joint measurement prior $p\big(\mathbf{z}^{(t)}_{m,k}, \mathbf{z}^{(c)}_{m,k}\big) = p\big(\mathbf{z}^{(t)}_{m,k} \mid \mathbf{z}^{(c)}_{m,k}\big)\, p\big(\mathbf{z}^{(c)}_{m,k}\big)$ into two marginal distributions. The marginals are then modeled as two conditionally independent DPs to be used as priors on $\mathbf{z}^{(t)}_{m,k}|\mathbf{z}^{(c)}_{m,k}$ and $\mathbf{z}^{(c)}_{m,k}$. The clutter prior is first independently modeled as $G^{(c)}_k \sim \mathrm{DP}(\alpha_c, H_c)$, with concentration parameter α_c and base distribution H_c. To model the target prior, first the set $\Theta_k = \{\theta_{1,k}\ldots,\theta_{M_k,k}\}$ of independent and identically distributed samples $\theta_{m,k}$ is drawn from the clutter prior $G^{(c)}_k$; given Θ_k, the target prior $G^{(t)}_k$ is defined as a DP with concentration parameter α_t and base distribution

$$H_t + \sum_{m=1}^{M_k} \delta(\theta - \theta_{m,k})\,.$$

The target prior $G^{(t)}_k$ is then used to draw the independent and identically distributed sample set $\Phi_k = \{\phi_{1,k}\ldots,\phi_{M_k,k}\}$. Using sets Θ_k and Φ_k, the target and clutter measurements are then drawn, respectively, as

$$\mathbf{z}^{(t)}_{m,k} \mid \Phi_k, \Theta_k \;\sim\; p(\cdot \mid \Phi_k),\; m = 1,\ldots,M_k$$

$$\mathbf{z}^{(c)}_{n,k} \mid \Phi_k, \Theta_k \;\sim\; p(\cdot \mid \Theta_k),\; m = 1,\ldots,M_k$$

To only provide the tracker with target-based information, we cluster the $M^{(\mathrm{t})}_k$ target measurements into set $\mathbf{Z}^{(t)}_k = \{\mathbf{z}^{(t)}_{1,k},\ldots,\mathbf{z}^{(t)}_{M^{(\mathrm{t})}_k,k}\}$ and form the likelihood ratio as

$$L\Big(\mathbf{Z}^{(t)}_k; \Phi_k, \mathbf{x}_k\Big) = \frac{\prod_{m=1}^{M_k} p\Big(\mathbf{z}^{(t)}_{m,k} \mid \mathbf{x}_k; \text{target present}\Big)}{\prod_{m=1}^{M_k} p\Big(\mathbf{z}^{(c)}_{m,k} \mid \mathbf{x}_k; \text{target absent}\Big)}\,.$$

This is then integrated into a Bayesian tracker to estimate the posterior density as

$$p\Big(\mathbf{x}_k \mid \mathbf{Z}^{(t)}_k\Big) \propto p\Big(\mathbf{Z}^{(t)}_k \mid \Phi_k, \mathbf{x}_k\Big)\, p\Big(\mathbf{x}_k \mid \mathbf{Z}^{(t)}_{k-1}\Big). \tag{4}$$

We compared the new approach with a Bayesian filter that incorporated both target and clutter measurements. Using 5.9 dB signal-to-clutter ratio, the improved mean-squared error (MSE) for estimating the target position is demonstrated in Figure 4.

Some additional work on clutter involved the development of an efficient method for estimating model parameters of sea clutter in thermal noise [21].

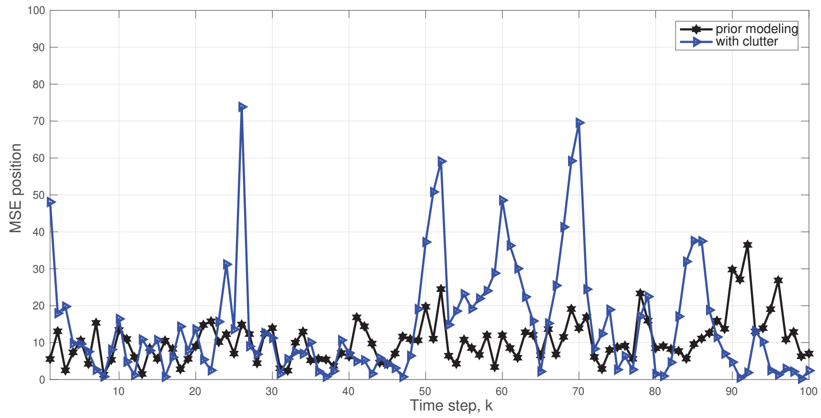


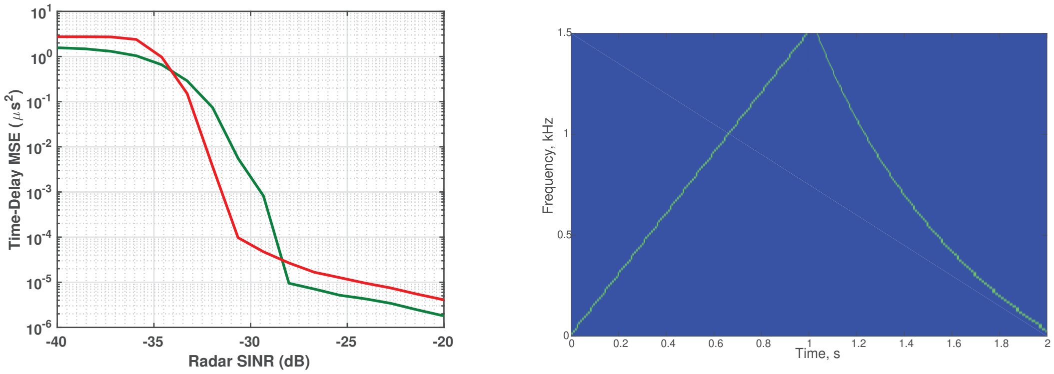
Figure 4: Comparison of MSE of target position estimate when tracking using all measurements (with clutter) and using new Bayesian nonparametric prior modeling .

3.5. Object Tracking in Coexisting Sensing Systems

A multimodal system with disparate sensors can be used to track different types of information while sharing the same operational conditions, such as available spectrum. However, when different sensing modalities coexist, their transmit waveforms need to be appropriately designed to avoid interference, and thus loss of performance, at the receiver. Such a multimodal system can include a radar tracking multiple targets and a multiuser wireless communications system. In some recent work [22], we designed different system transmit waveforms with unique time-varying phase functions and parameters selected to optimize desirable performance metrics. Figure 5a shows the time-delay estimate MSE as a function of radar signal-to-interference-plus-noise ratio (SINR) for tracking an object while sharing spectrum with multiple wireless communications users. One of the MSE curves (red) resulted from minimizing the interference between the two systems; the other one resulted from minimizing the MSE from estimating target position [22]. In order to address Task (g) for object tracking in a coexisting system, we developed a time-frequency based approach to extract tracking measurements based on their unique time-frequency signature with minimum amount of interference [23,24]. The approach uses a modified synchrosqueezing transform to extract and reconstruct individual time-frequency signal components [25]. As shown in Figure 5b, this reconstruction is possible due to the highly localized time-frequency signatures offered by the transform.

3.6. Transfer Learning in Bayesian Filtering

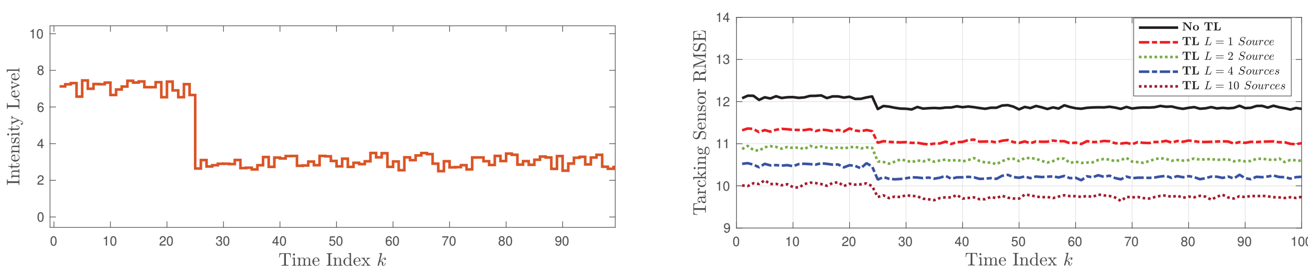
To address Task (h), we proposed an algorithm that integrates Bayesian filtering with transfer learning. This is a method used to improve inference performance when the data provided is not sufficient or is difficult to label [26]. We used transfer learning to improve the tracking performance of an object moving under unknown time-varying environmental conditions. The primary source performs Bayesian filtering to track a moving object



(a) (b)

Figure 5: (a) MSE estimation in a coexisting system for varying SINR obtained by minimizing interference (red) and position MSE; (b) Modified synchrosqueezing transform of waveforms from two different sensors.

when the measurement noise intensity varies at each time step. To improve its tracking performance, the primary source uses knowledge learned from other multiple tracking sources (learning sources) with known noise intensity variability. We modeled the measurement likelihood of each learning source using Gaussian mixtures whose parameters are learned from conjugate priors. The learned parameter distributions are used as a basis to form a linear weighted combination to model the measurement likelihood of the primary source. The basis weights are learned from a Dirichlet distribution prior [27]. Initial results demonstrated the improved tracking performance for a target moving with constant velocity. The measurement noise intensity level is shown in Figure 6a as it varies with time. The root MSE of the estimated object's position is shown in Figure 6b to decrease as the number of learning sources increases.



(a) (b)

Figure 6: (a) Time-varying intensity level of measurement noise; (b) position root MSE (RMSE) when tracking without transfer learning (TL) and with TL and a varying number of learning sources.

3.7. Fast Computation of Bayesian Inference

We developed a two-stage parallel update scheme for a fast implementation of the Gibbs sampling algorithm for Bayesian inference to address Task (i). As its direct computation is often intractable, Gibbs sampling estimates the posterior distribution $p(\mathbf{x}_k \,|\, \mathbf{z}_1, \ldots, \mathbf{z}_k)$ by iteratively drawing samples from the conditional posterior distributions

$p(\mathbf{z}_k \,|\, \mathbf{x}_k)$ and $p(\mathbf{x}_k \,|\, \mathbf{z}_1, \ldots, \mathbf{z}_{k-1})$. The conditionals are then used to draw samples of the posterior density

$$p(\mathbf{x}_k \,|\, \mathbf{z}_1, \ldots, \mathbf{z}_k) = \frac{p(\mathbf{z}_k \,|\, \mathbf{x}_k)\, p(\mathbf{x}_k \,|\, \mathbf{z}_1, \ldots, \mathbf{z}_{k-1})}{\int p(\mathbf{z}_k \mid \mathbf{x}_k)\, p(\mathbf{x}_k \,|\, \mathbf{z}_1, \ldots, \mathbf{z}_{k-1})\, d\mathbf{x}_k}$$

In our aforementioned Bayesian nonparametric approaches, we used Gibbs sampling to determine how much structure can be inferred directly from available measurements. The fast computation of Gibbs sampling is thus important, especially as more measurements become available. Existing parallel implementations of Gibbs sampling concentrate on reducing communication between computing units, thus resulting in loss of performance. As a trade-off between cost and performance, we developed a two-stage process to map the design onto a parallel architecture when the number of computing units is large [28]. In the first stage, the parallel computing units share information with each other, and in the second stage, the parallel units work independently. The advantage of the new design is demonstrated in Figure 7, where the computation time of various proposed parallel implementation schemes is compared to that of the direct implementation. The multiple schemes provide different trade-offs between performance accuracy and computational speed.

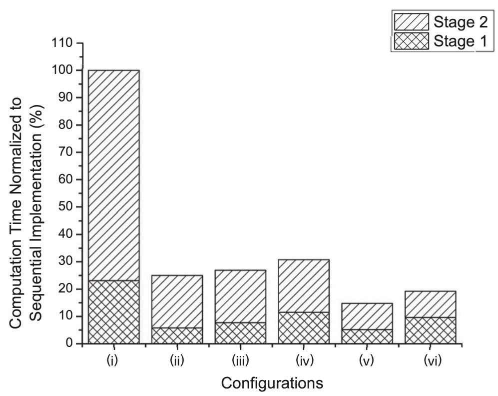


Figure 7: Computation time: (i) direct implementation and (ii)-(vi) proposed parallel implementation schemes.

4. Publication List

Journal Papers

– B. Moraffah and A. Papandreou-Supppappola, "Bayesian nonparametric modeling for predicting dynamic dependencies in multiple object tracking," arXiv: 2004.10798 [cs.LG], 2020.

– B. Moraffah and A. Papandreou-Supppappola, "Machine learning modeling and clustering algorithms for tracking," *Sensors* (invited, in preparation), 2020.

– B. Moraffah and A. Papandreou-Supppappola, "Integration of Bayesian nonparametric modeling with Bayesian filtering for dynamic object tracking," *Sensors* (in preparation), 2020.

– J. Zhou, A. Papandreou-Suppappola, and C. Chakrabarti, "Parallel Gibbs sampler for wavelet-based Bayesian compressive sensing with high reconstruction accuracy," *Journal of Signal Processing Systems*, vol. 92, pp. 1101-1114, 2020.

- J. S. Kota and A. Papandreou-Suppappola, "Joint design of transmit waveforms for object tracking in coexisting multimodal sensing systems," *Sensors, Special Issue on Multiple Object Tracking: Making Sense of the Sensors*, vol. 19, 2019.

Conference Papers

- B. Moraffah, C. Richmond, R. Moraffah and A. Papandreou-Suppappola, "METRIC-Bayes: Measurements estimation for tracking in high clutter using Bayesian nonparametrics," *Asilomar Conference on Signals, Systems and Computers*, November 2020.
- O. Alotaibi and A. Papandreou-Suppappola, "Transfer learning with nonparametric Bayesian modeling for object tracking under varying conditions," *Asilomar Conference on Signals, Systems and Computers*, November 2020.
- B. Moraffah, C. Brito, B. Venkatesh, and A. Papandreou-Suppappola, "Tracking multiple objects with dependent measurements using Bayesian nonparametric modeling," *Asilomar Conference on Signals, Systems and Computers*, pp. 1847-1851, 2019.
- B. Moraffah, A. Papandreou-Suppappola and M. Rangaswamy, "Nonparametric Bayesian methods and the dependent Pitman-Yor process for modeling evolution in multiple object tracking," *International Conference on Information Fusion*, Ottawa, Canada, 2019.
- B. Moraffah, C. Brito, B. Venkatesh and A. Papandreou-Suppappola "Use of hierarchical Dirichlet processes to integrate dependent observations from multiple disparate sensors for tracking," *International Conference on Information Fusion*, Ottawa, Canada, 2019.
- B. Moraffah and A. Papandreou-Suppappola, "Random infinite tree and dependent Poisson diffusion process for nonparametric Bayesian modeling in multiple object tracking," *IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 5217-5221, 2019.
- B. Moraffah and A. Papandreou-Suppappola, "Dependent Dirichlet process modeling and identity learning for multiple object tracking," *Asilomar Conference on Signals, Systems and Computers*, pp. 1762-1766, 2018.
- V. S. Gattani, J. S. Kota, A. Papandreou-Suppappola "Time-frequency separation of matched waveform signatures of coexisting multimodal systems," *Asilomar Conference on Signals, Systems and Computers*, pp. 2086-2090, 2018.

Ph.D. Dissertation

Bahman Moraffah, "Bayesian nonparametric modeling and inference for multiple object tracking"
Arizona State University, Tempe AZ, July 2019.

M.S. Thesis

- Vinett Sunil Gattani, "Separation of agile waveform time-frequency signatures from coexisting multimodal systems," Arizona State University, Tempe AZ, December 2018.
- Bindya Venkatesh, "Uncertainty quantification in predictive modeling," Arizona State University, Tempe AZ, May 2020.

Presentations

– *How can Bayesian Nonparametric Methods, Applied to Machine Learning Problems, Improve Information Learning in Multimodal Sensing Under Time-Varying Conditions*, AFOSR Science of Information, Computation, Learning and Fusion meeting, Boston, MA, June 13, 2019.

– *Radar Target Tracking Under Varying Environmental Conditions*, Air Force Research Laboratory, Wright-Patterson Air Force Base, Dayton, OH, September 7, 2017 (invited by Mark Oxley and Christine Schubert Kabban, U. S. Air Force).

– *Information Learning and Integration for Multiple Object Tracking*, AFOSR Science of Information, Computation, Learning and Fusion meeting, Colorado Springs, CO, June 28, 2017.

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The funded research designed methods to improve multiple object tracking using measurements from multimodal systems.The methods combine sequential Bayesian filtering to estimate the time-varying parameters of physics-based models and Bayesian nonparametric modeling to infer and learn information directly from the measurements. Integrating these methods resulted in robust learning and increased performance when compared to current state-of-the-art methodologies. Multiple challenging scenarios were considered: time-varying number of moving objects, unknown measurement-to-object associations, time-varying environmental conditions, and multiple statistically-dependent measurements.

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Vinett Sunil Gattani, “Separation of agile waveform time-frequency signatures from coexisting multimodal
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14. ABSTRACT
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15. SUBJECT TERMS
Multimodal sensing, multiple object tracking, information integration, Bayesian inference, Bayesian nonparametric modeling, dynamic state-space representation, time-varying environmental and operational conditions

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