A Graphical Model Representation of the Track-Oriented Multiple Hypothesis Tracker

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Motivation

- The track-oriented MHT (TOMHT) consists of three main components:
  - A (partial) enumeration of possible tracks.
  - Constraints identifying mutually exclusive tracks.
  - An optimization algorithm for finding the most likely hypothesis.
- Marginalization, useful for tasks such as parameter estimation and model selection, requires an intractable summation over the space of hypotheses.
- By formulating the TOMHT as a graphical model, we can use belief propagation and related algorithms to perform efficient, approximate marginalization.

Track-Oriented MHT

- Observations arrive in sets and are stored in track trees:
- Each leaf represents a possible track.
- Associated with each track $\tau_i$ is a track score $s_i$.
- The track score is a function of the dynamics, observation, noise, and target birth & death models. Typically these are chosen such that $s_i$ is efficiently and incrementally computable.
- The posterior distribution over tracks is given by

$$\Pr(\tau \mid z_{1:k}, \theta) \propto \prod_{i=1}^{T} \exp(s_i)^\tau_i$$  \hspace{1cm} (1)

Factor Graph Representation of the Track Posterior Distribution

- The structure of the factor graph mirrors that of the track trees, each observation node now a binary variable indicating whether it is part of a true track:

- Each variable in the factor graph is a binary indicator for the partial track extending from the root of its track tree down to itself.

- By construction, the product of all factors is exactly the track posterior distribution (1).

Factor Graphs

- A factor graph is a bipartite graph consisting of factor nodes and variable nodes, e.g.
- Each factor is a non-negative function defined over its adjacent variables.
- Together, the factors define a joint probability distribution:

$$\Pr(x_1, \ldots, x_n) = \frac{1}{Z} \prod f_i(x_{\mathcal{N}(i)})$$

- Many approximate inference algorithms exist to efficiently compute MAP estimates,

$$\tilde{x}^* = \arg \max_x \Pr(x)$$

marginal probabilities,

$$\Pr(x_i) = \sum_{j \neq i} \Pr(x)$$

and the partition function:

$$Z = \sum_{x_1, \ldots, x_n} \prod f_i(x_{\mathcal{N}(i)})$$

Parameter Estimation

- Proper setting of model parameters is critical to tracker performance.
- Parameter estimation from unlabeled data is useful in cases where
  - Labeled data is difficult or expensive to obtain.
  - Optimal parameter values may drift over time.
- In single target tracking, such estimation is commonly performed using the EM algorithm, which requires computing moments of the target state variables.
- In the multitarget setting, we also require moments of the track indicator variables, e.g.:

$$\mathbb{E}[\tau^i_x h(x)] = \Pr(\tau^i_x = 1 \mid z^{1:k}, \theta) \int h(x) \Pr(x^{1:k} \mid \tau^i_x = 1, z^{1:k})$$

Marginal probability of a "leaf" track indicator variable.

- Thus, any modeling choices that yield practical EM for single target tracking can be extended to multitarget tracking with this approach.
- Using simulated data we show that an online EM-based estimation scheme increases robustness to parameter misspecification.

Experimental Results

- A sample simulated dataset:

- Performance as a function of misspecification:

  - Solid and dashed lines indicate performance with and without online estimation, respectively. The dotted black line corresponds to minimal pruning and no online estimation.