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A scalable method of tracking targets with dependent distributions

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Introduction

- Multiple target trackers generally make the approximation that the target distributions are independent
- We wish to improve tracking accuracy by relaxing this approximation
  - Aim to reduce track loss and track swapping
  - Application to fusing occasional measurements which include target identity information
- Storing the whole joint distribution is computationally prohibitive
  - Approximate the joint by a tree-based representation
- We generalize an existing algorithm which efficiently and exactly implements the Joint Probabilistic Data Association Filter to deal with dependent components

Dependent Target Distributions

- We model the motion of the targets as being independent of each other
- The posterior probability distribution of target t at time step k is therefore a mixture over discrete component variables c_t^k:

$$p(\mathbf{x}_t^k | Y^{1:k}) \quad = \quad \sum_{c_t^k} p(\mathbf{x}_t^k | Y^{1:k}, c_t^k) p(c_t^k | Y^{1:k}).$$

- The componer
  - Generally merged to avoid exponential number of components
- The states of the targets are conditionally independent given their measurement assignment histories

Representing the Target Distributions

- The component variables will be dependent in general
- To store the distribution exactly requires us to store the complete joint distribution of the component variables
  - Computational cost grows exponentially in the number of targets, so this is infeasible
- Instead, we maintain a tree over the targets and store the joint distributions of adjacent targets:
- We adapt our exi

$$p(c^k_{1:T}|Y^{1:k}) \approx \prod_{t=1}^{T} p(c^k_t|c^k_{pa(t)}, Y^{1:k}).$$

pendent distributions

Mathematical Problem

- Represent the distribution over the component variables $c_1,\ldots,c_T$ for each target as on the previous slide
- For each target i we have a discrete random variable a_i representing the measurement assigned to the target
  - Only consider feasible measurements for each target (gating)
  - 0 represents the null hypothesis (i.e. target is not detected)
- The distributions $P(a_i \mid c_i)$ are known and the assignments are assumed to be independent given the components
- We have a constraint A that all the nonzero a_i are distinct (Mutual Exclusion constraint)
- Our aim is to efficiently calculate $p(a_i, a_{pa(i)}, c_i, c_{pa(i)} \mid A)$ for each i

Previous Data Association Algorithm

- We recap the earlier EHM / EHM 2 algorithms
  - These do not consider component variables
  - We later generalize these to deal with dependent components
- Consider a small example with the following measurement hypotheses

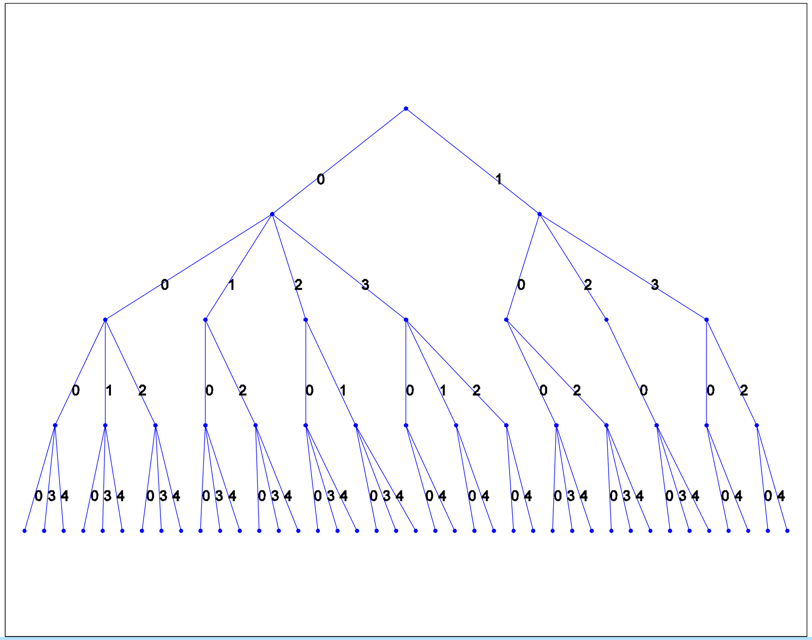
Target Number	Measurement Hypotheses
1	0, 1
2	0, 1, 2, 3
3	0, 1, 2
4	0, 3, 4

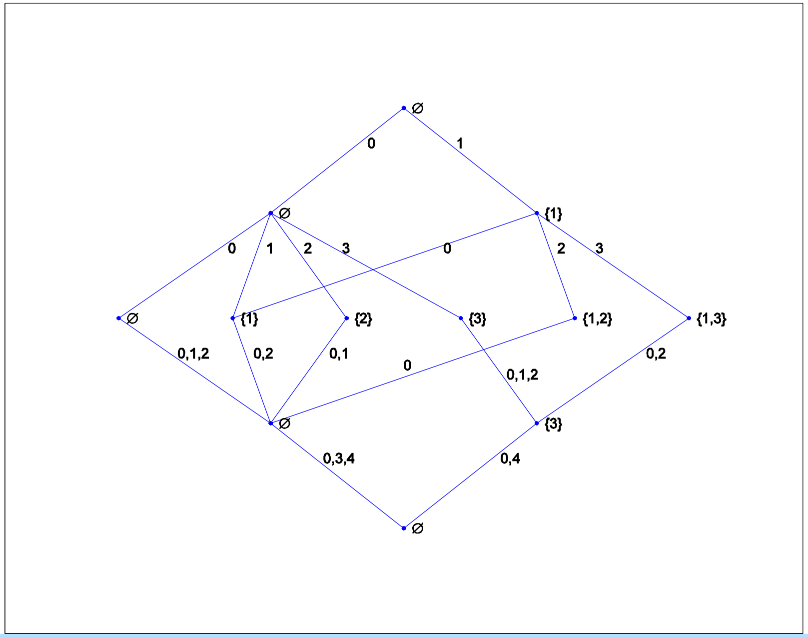
Original Efficient Hypothesis Management

- A naïve implementation of JPDAF can be performed as follows:
  - Build a tree of possible assignments, considering each target in turn
  - At each node, only consider assignments which have not already been used on that branch to enforce the constraint
- This tree grows exponentially with the number of targets
- The EHM algorithm notes that
  - Only need to remember the assignments used, not their order
  - Do not need to remember assigned measurements which are infeasible for all future targets

Original Efficient Hypothesis Management

- Each node in the EHM net is identified by
  - The target number
  - The set of measurements used by previous targets



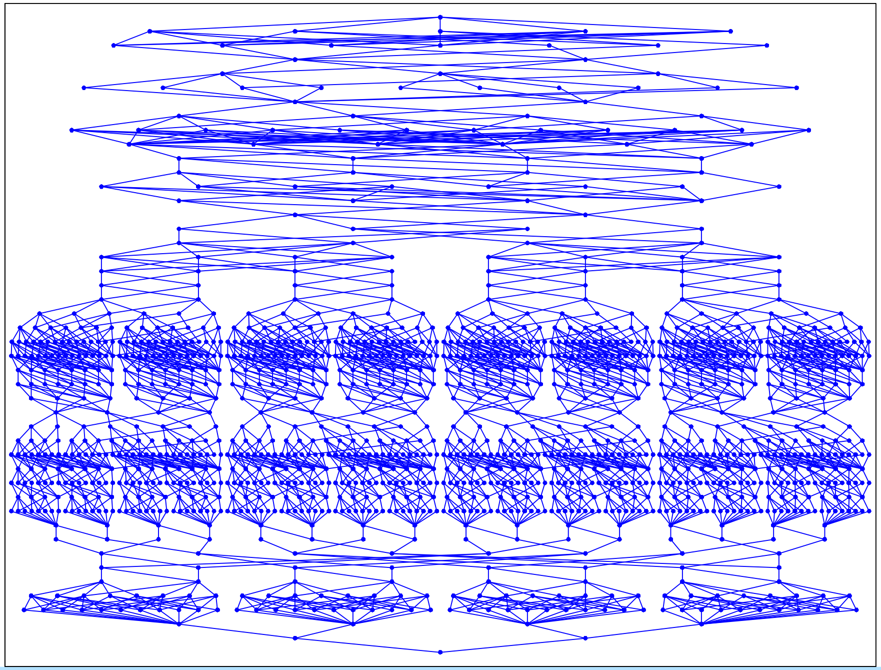


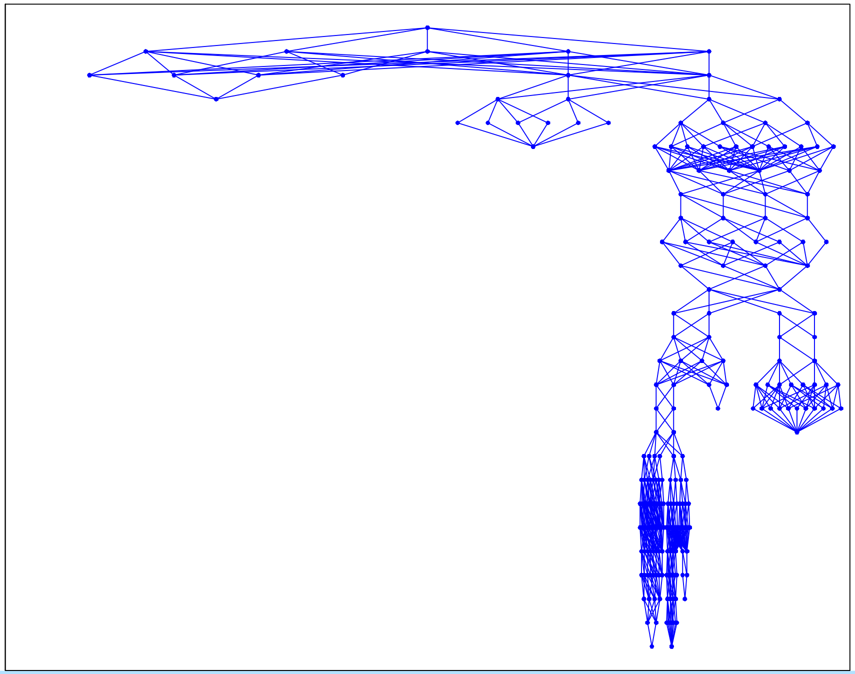
EHM 2

- We previously made the following improvement to EHM:
- Suppose we have two or more groups of targets, each group having no (non-null) measurement hypotheses in common with any of the others
- The assignments of these groups are then conditionally independent, given the assignments of the other targets
- Instead of processing the targets linearly, we can process them in a tree

EHM 2

- EHM graph (1365 nodes) and the corresponding EHM 2 graph (238 nodes) for an example scenario with 45 targets





Applying EHM 2 To Dependent Components

- We approximate the joint distribution over the component variables using a tree which satisfies the conditional independence conditions needed for EHM 2
- The tree is chosen to preserve as much information in the joint distribution as possible:
  - For each pair of targets, compute a measure of the information which would be lost by treating the target component distributions as independent (based on Kullback-Leibler divergence)
  - Construct a tree which maximizes this preserved information and satisfies the EHM 2 constraint

Applying EHM 2 To Dependent Components

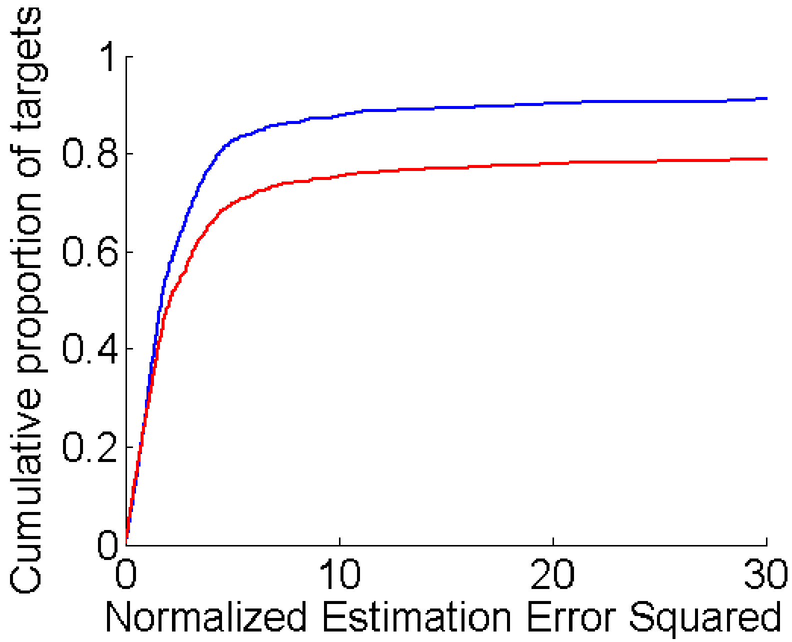
- We can generalize the existing EHM 2 net to deal with a tree-based approximation to the joint component variables
  - At each node, store probabilities for each component of the parent target
  - This is sufficient to compute probabilities for the descendent targets
- Rather than compute the marginal probabilities for each target from the net, need to compute the joint probabilities of each target with its parent
  - This can be obtained from the net

Example Scenario

- We track 10 targets for 20 measurement epochs
- After each measurement update, target distribution components which have the same most recent measurement associations are merged
- At the end of the run, we take a less accurate position measurement of each target which includes an identifier of which target it came from
  - Motivated by applications where conventional measurements are fused with identification measurements with a lower data rate
- Compare results over 100 runs in the cases where
  - Component distributions are approximated as independent
  - Component dependencies are represented as a tree

Results

- Measure consistency of the tracker distribution using Normalized Estimation Error Squared (NEES)
- High NEES is indicative of track loss or track swapping



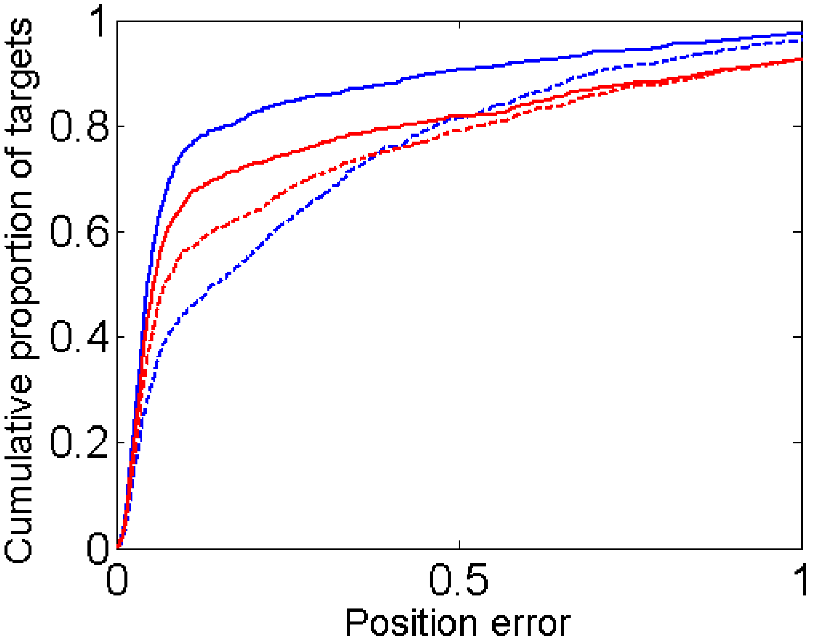
Blue line: Dependent components

Red line: Independent components

Using dependent components gives a greater proportion of consistent tracks

Results

- The accuracy of the track estimates after using the identification measurements is much higher with the dependent components method



Blue line: Dependent components

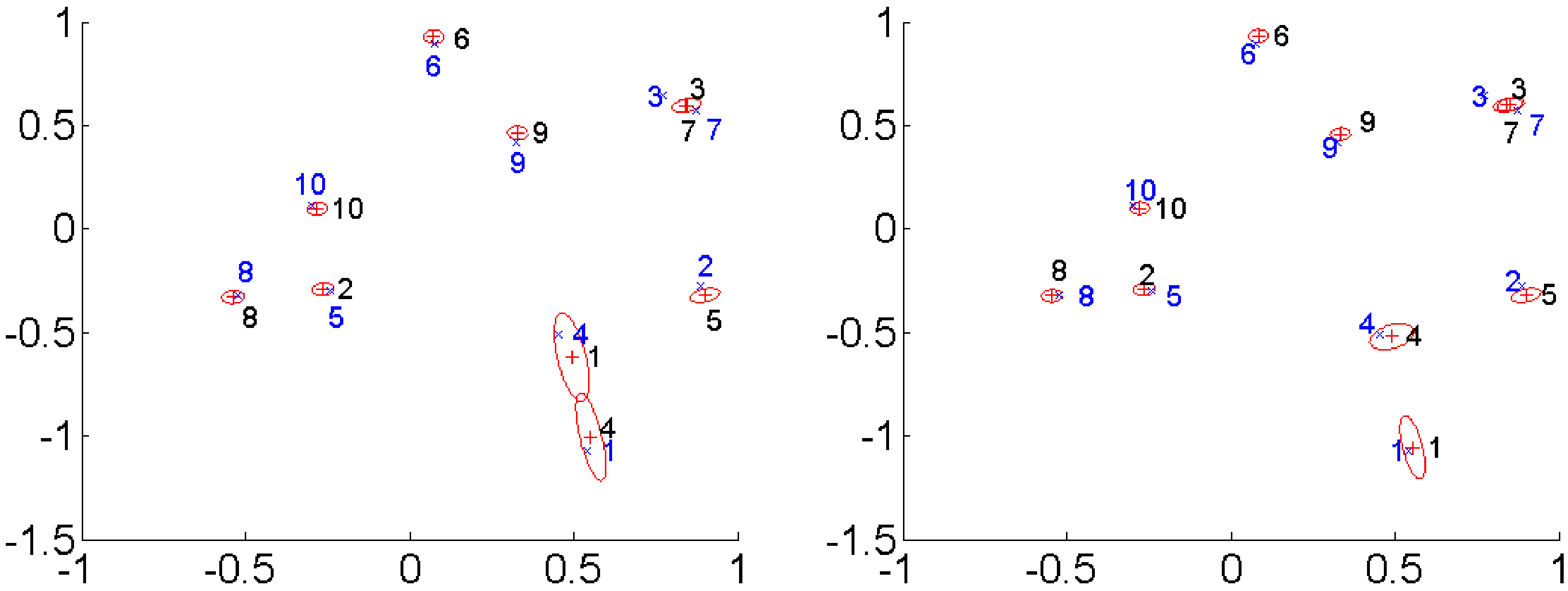
Red line: Independent components

Dashed: Before ID measurements

Solid: After ID measurements

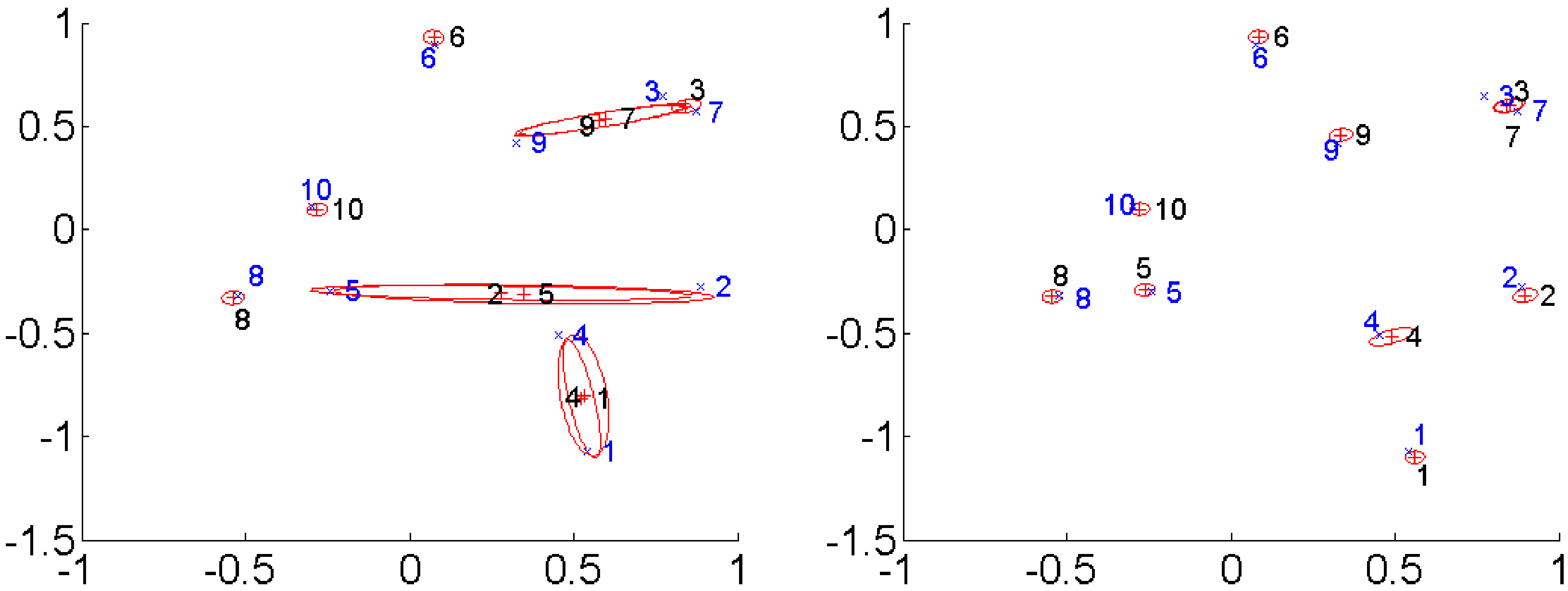
Example Run (Independent Components)

- Tracks 2 and 5 have swapped and are following the wrong targets
- Tracks 1 and 4 have started to swap but identity measurement causes the tracker to recover



Example Run (Dependent Components)

- Ambiguous distributions for targets 2, 5, 3, 7, 9, 4 and 1 which the identity measurement resolves



Conclusions

- We have presented a method of tracking multiple targets which represents the dependency of target distributions
- The method is scalable to many targets
- Compared to approximating the target distributions as being independent, the method has the following advantages
  - The tracker distribution is more consistent with the ground truth
  - Occasional measurements which include target identity information give a greater reduction in estimation error
  - Measurements of some targets may provide information on others

Questions

- Any questions?