Intention-Aware Multi-Human Tracking via Particle Filtering over Sets

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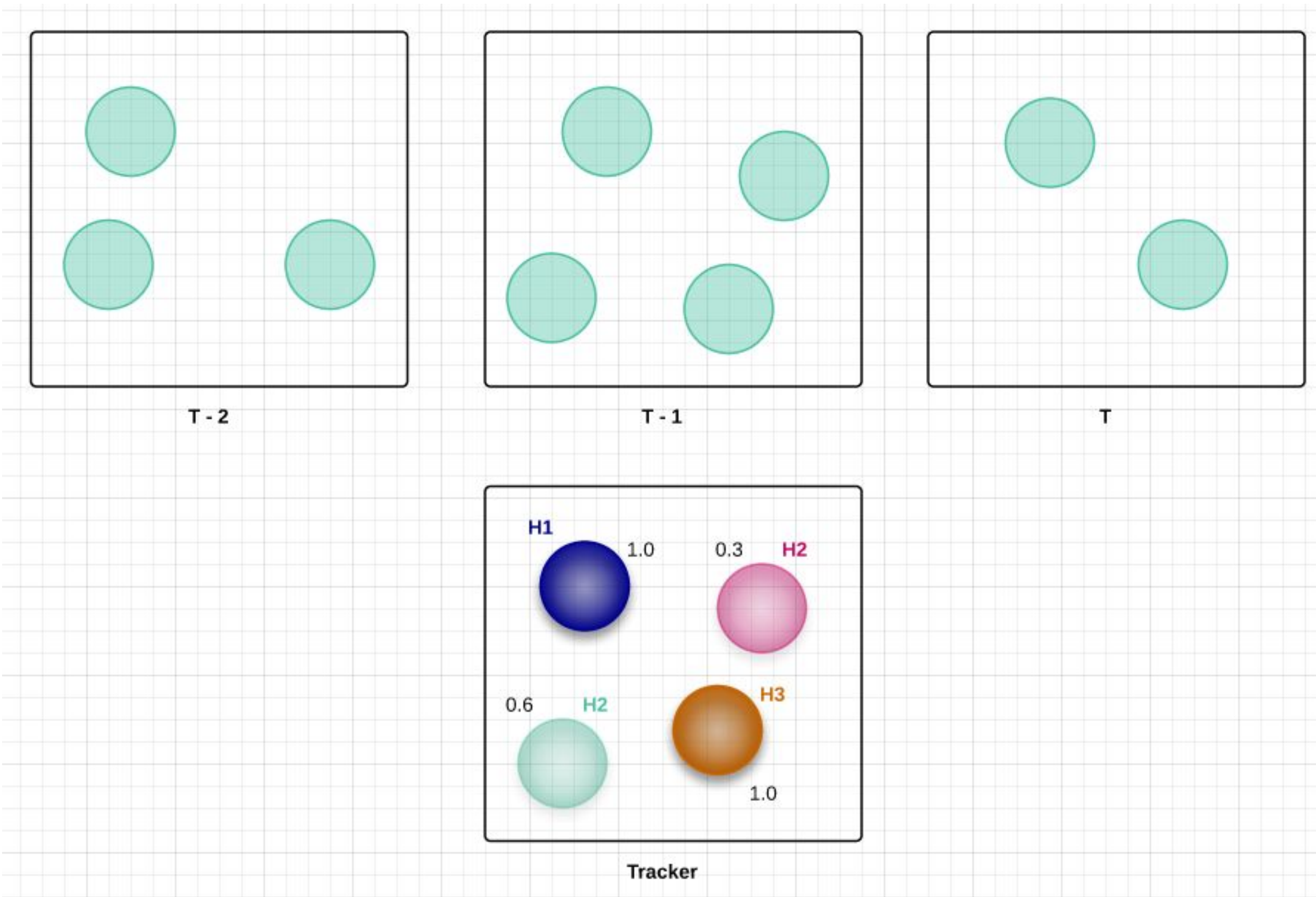
The IMHT Problem

- Intention-Aware Multi-Human Tracking
  - Track multiple humans
  - Understand their motion intentions
- Human-Robot Interaction Tasks
  - Entering an elevator with humans occupation
  - Following a human in crowded environments
  - Staying inside a team of moving humans

The Challenges

- Non-perfect human detectors
  - Inevitable false and missing detections
  - Can not distinguish different people
  - A demo
- Complex human dynamics
  - Unpredictable motion models
  - Move in to and out from FOV stochastically
- The robot navigates from place to place
- Real-time constraints

An Example



The PFS Approach

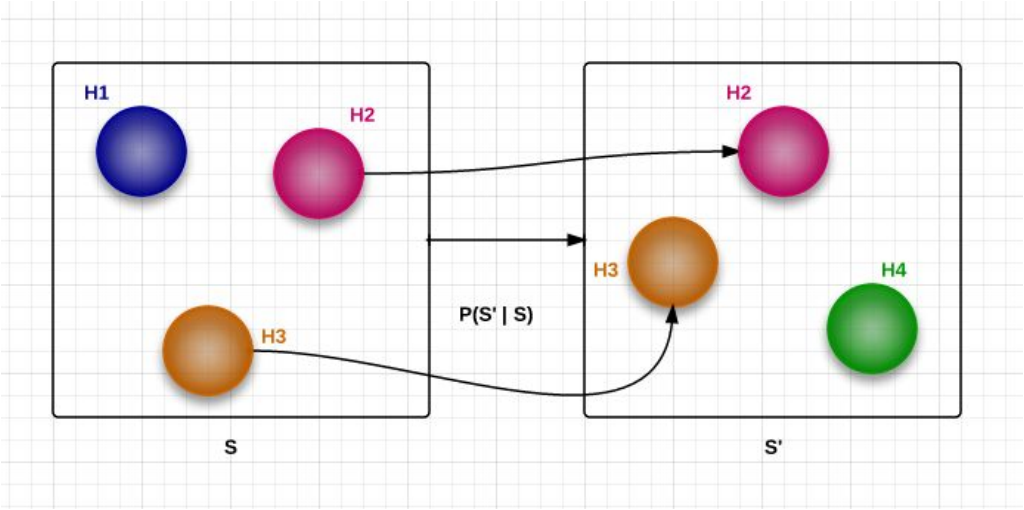
- Hidden Markov Modelling
  - States: $S = \{h_1, h_2, \ldots, h_n\}$
  - Observations: $O = \{o_1, o_2, \ldots, o_m\}$
  - Motion function: $P(S' \mid S)$
  - Observation function: $P(O \mid S)$

The Intention-Aware Motion Model

- A human: h = (s, i, ID)
- Choose action: P(a | s, i)
- Change intention: P(i' | s, i)
- Motion model: P(s' | s, a)

$$P(s', i' \mid s, i) = \sum_{a \in \mathcal{A}} P(s' \mid s, a) P(a \mid s, i') P(i' \mid s, i). \quad (1)$$

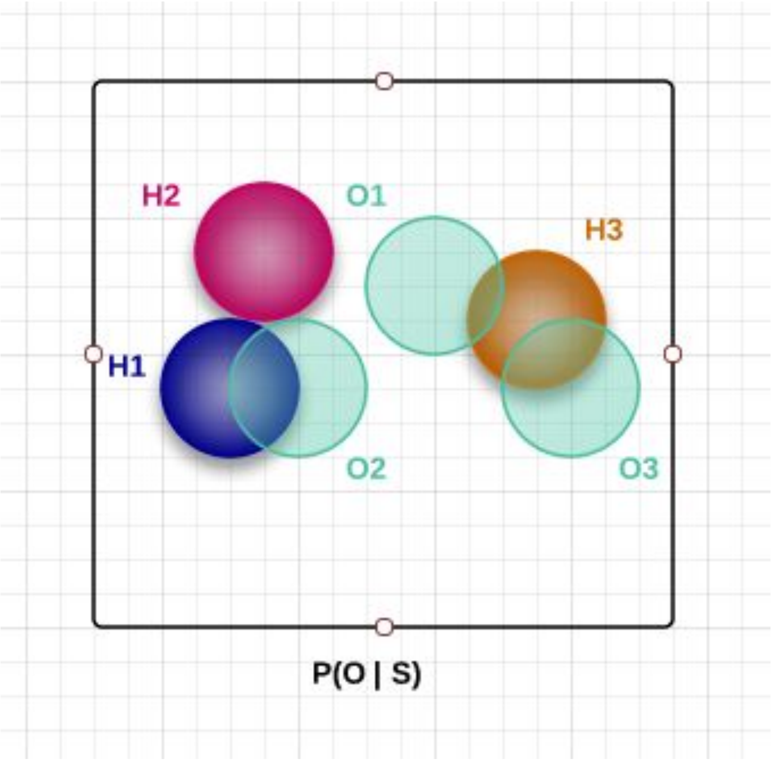
The Motion Function



- Number of humans follows a birth-death process
- Humans behave independently
- P(S' | S) = P(H1 left) P(H4 arrived) P(H2' | H2) P(H3' | H3)
- Not necessary to explicitly represent the motion function
- Only need to draw samples from motion model

The Observation Function

- P(O | S) = P(O2 | H1)P(O1 | H2)P(O3 | H3) + P(O2 | H1)P(• | H2)P(O1 | •)P(O3 | H3) + P(O2 | H1)P(• | H2)P(O1 | H3)P(O3 | •) + ...
- So many possibilities



Data Associations

- φ: all possible false detections, missing detections and matched assignments given S and O
- P(O | S) = ∑ P(O, φ | S) (2)

$$\Omega\left(\left(\frac{\max\{|O|,|S|\}}{e}\right)^{\min\{|O|,|S|\}}\right)$$

- Assume false and missing detections follow Poisson distributions

The Observation Function (Cont'd)

- False detections F ⊆O
- Missing detections M ⊆S
- |O - F| = |S - M|

$$P(O \mid S) = \sum_{\langle F, M \rangle \in O \circ S} P(O - F \mid S - M)$$

$$\cdot\, (\nu\tau)^{|F|} e^{-\nu\tau} \prod_{o \in F} P_f(o) \frac{(|S|\xi\tau)^{|M|} e^{-|S|\xi\tau}}{|M|!} \frac{1}{\binom{|S|}{|M|}}, \quad (4)$$

$$P(O-F \mid S-M) = \sum_{\psi \in \Psi_{S-M}^{O-F}} \prod_{h \in S-M} P_o(\psi(h) \mid h), \ (5)$$

Approximate Observation Function

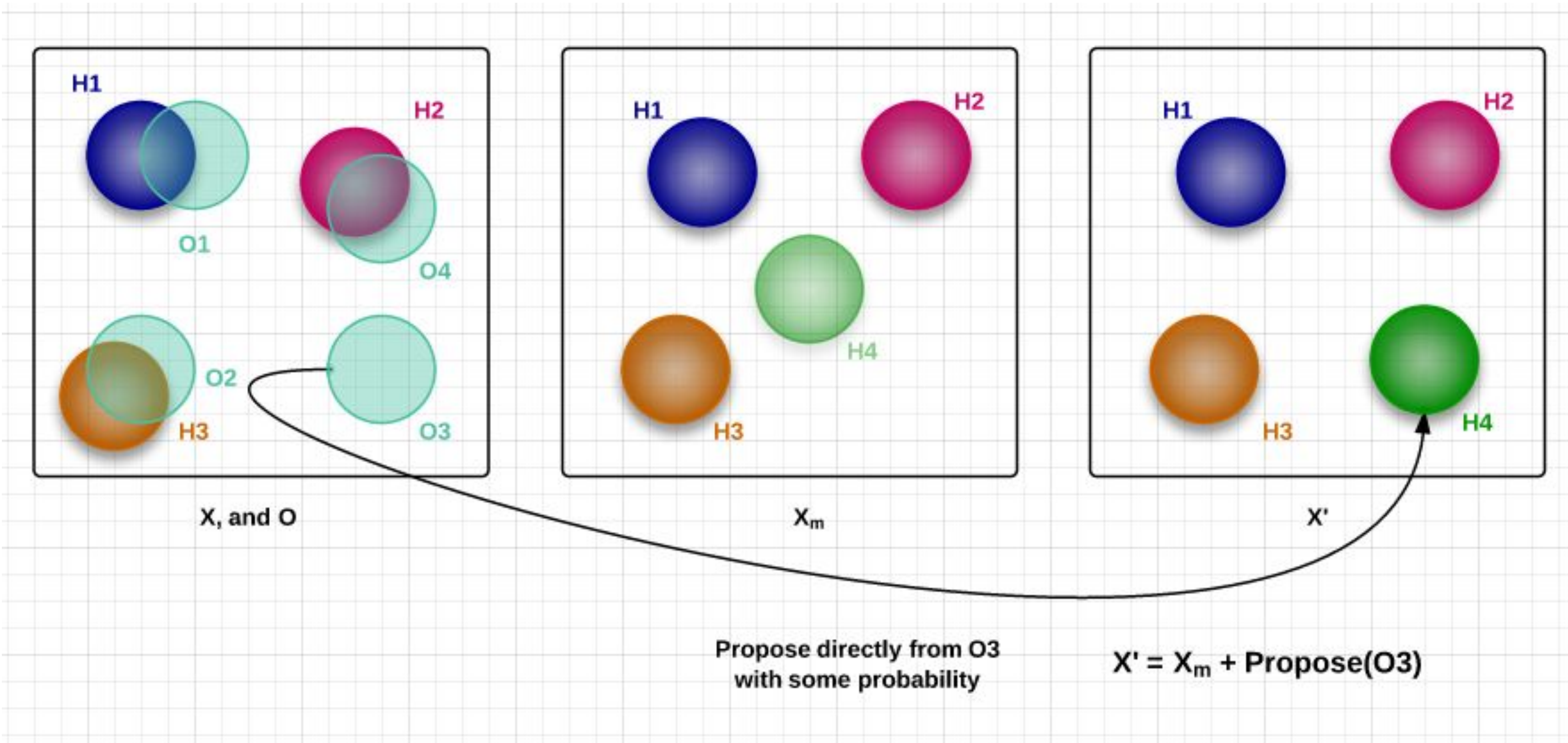
- Assignment Pruning
  - Find assignments in Equation 5 in probability decreasing order until a ratio threshold
  - Murty's algorithm for top-k best assignment problem
- False-Missing Pruning
  - Find F-M pairs in Equation 4 in probability decreasing order until a threshold
  - Implemented by using priority queue

Particle Filtering

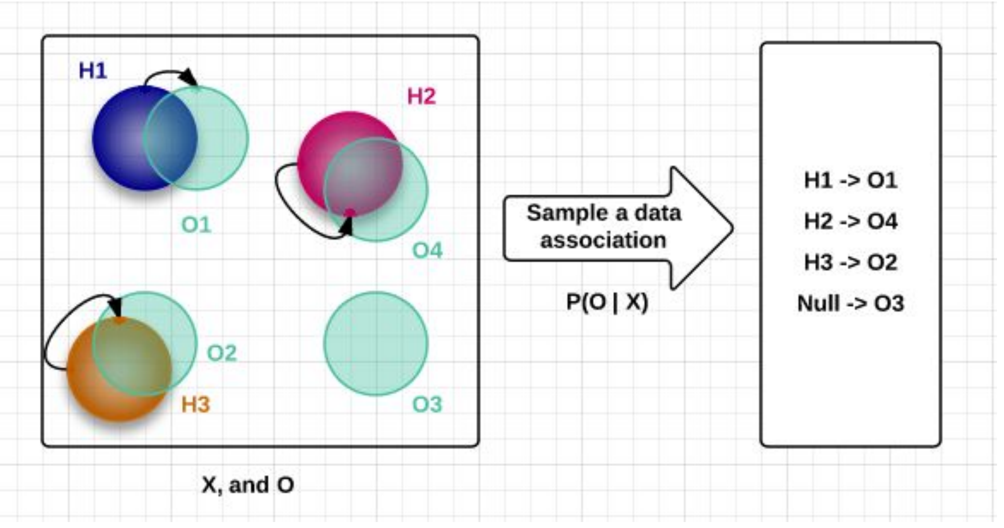
- Propose
  - $X' \sim \pi(\bullet \mid X, O)$
- Update Weights:
  - $w' = w * P(X' \mid X) * P(O \mid X') / \pi(X' \mid X, O)$
- Normalize
- Resample

- If propose from motion model
  - $X' \sim P(X' \mid X)$
  - $w' = w * P(O \mid X')$

Particle Refinement



Particle Refinement (Cont'd)



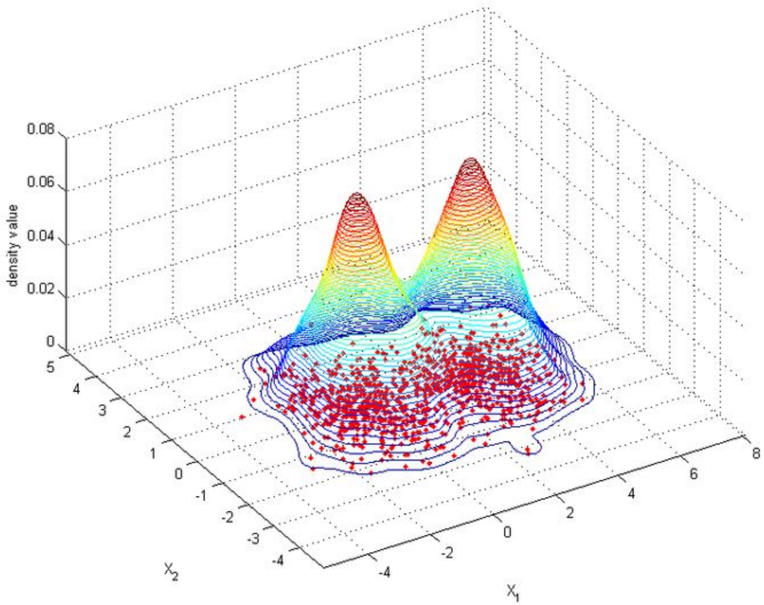
- Sample $X_m \sim P(X_m \mid X)$
- Sample $\varphi \sim P(O, \varphi \mid X) / P(O \mid X)$
- Find a false detection o in φ if any
- Propose $X' = X_m + \text{Propose}(o)$ with some probability

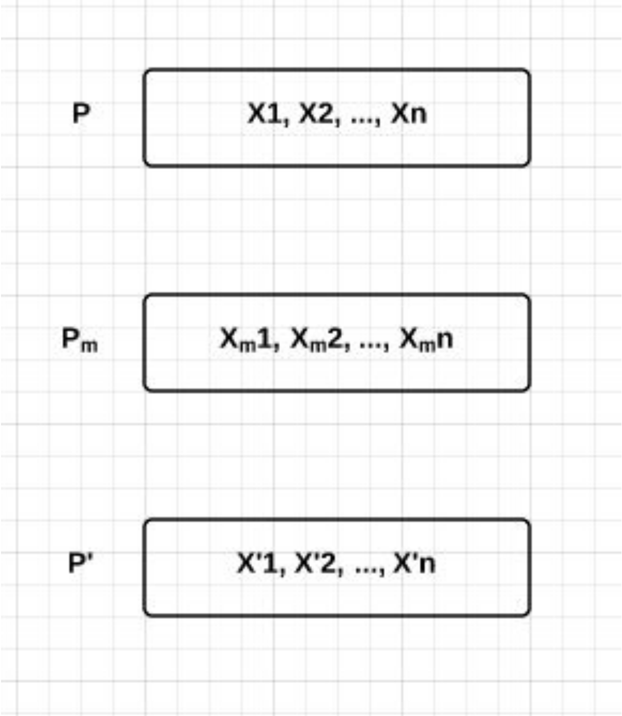
Update Weights

- Given X, X', and O
  - Observation weight $P(O \mid X')$
  - Motion weight $P(X' \mid X)$
  - Proposal weight $\pi(X' \mid X, O)$

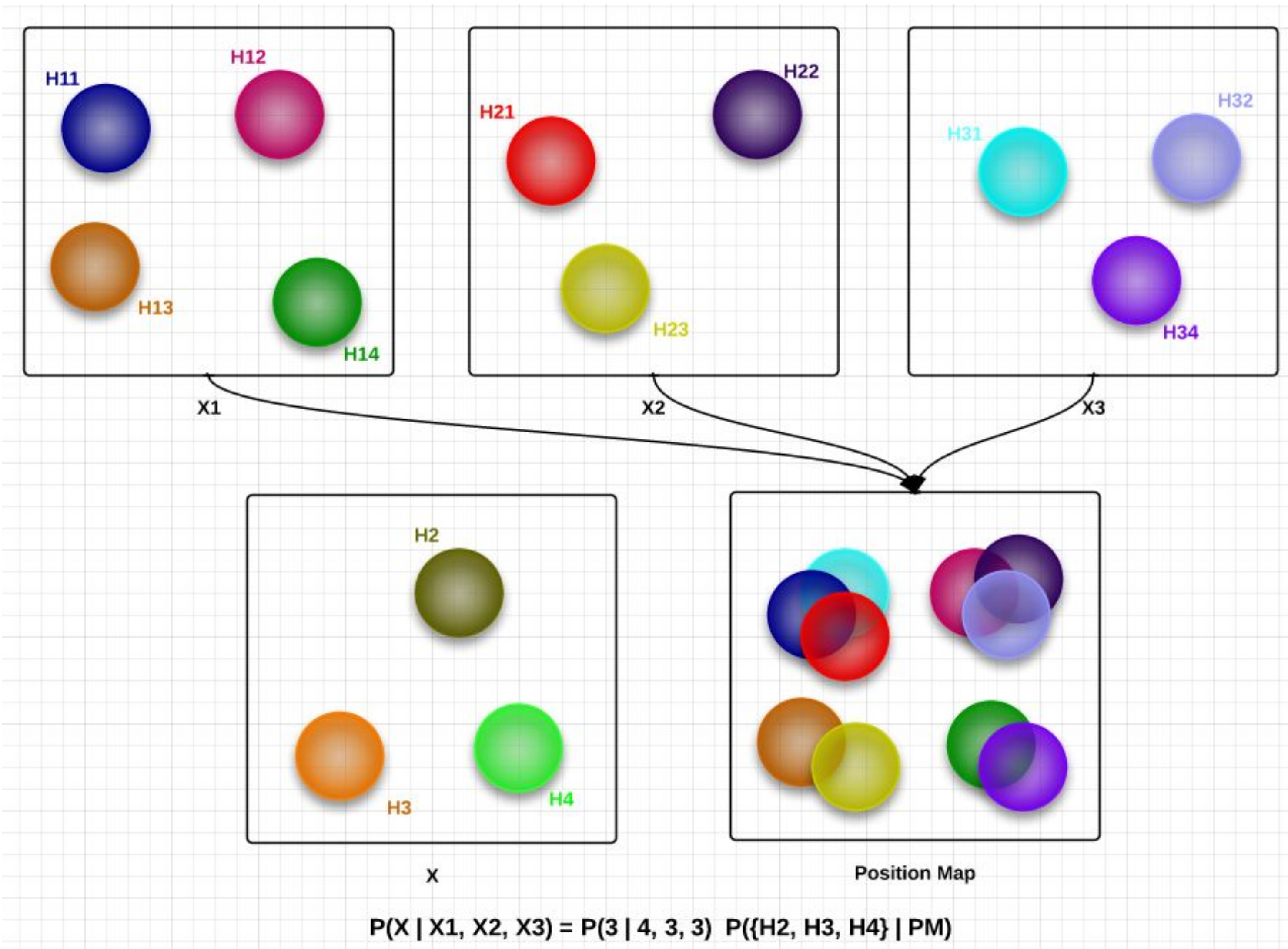
Kernel Density Estimation

- $P(X' \mid X) \approx KDE(X' \mid P_m)$
- $P(X' \mid X, O) \approx KDE(X' \mid P')$



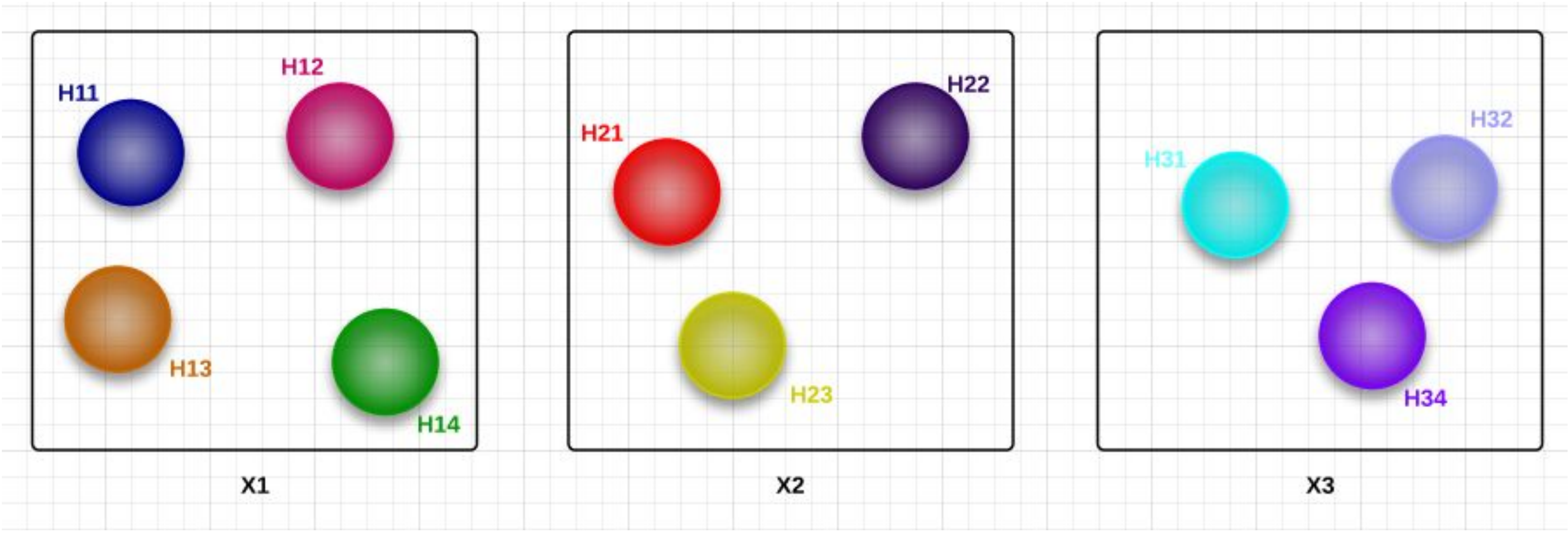


KDE over Sets

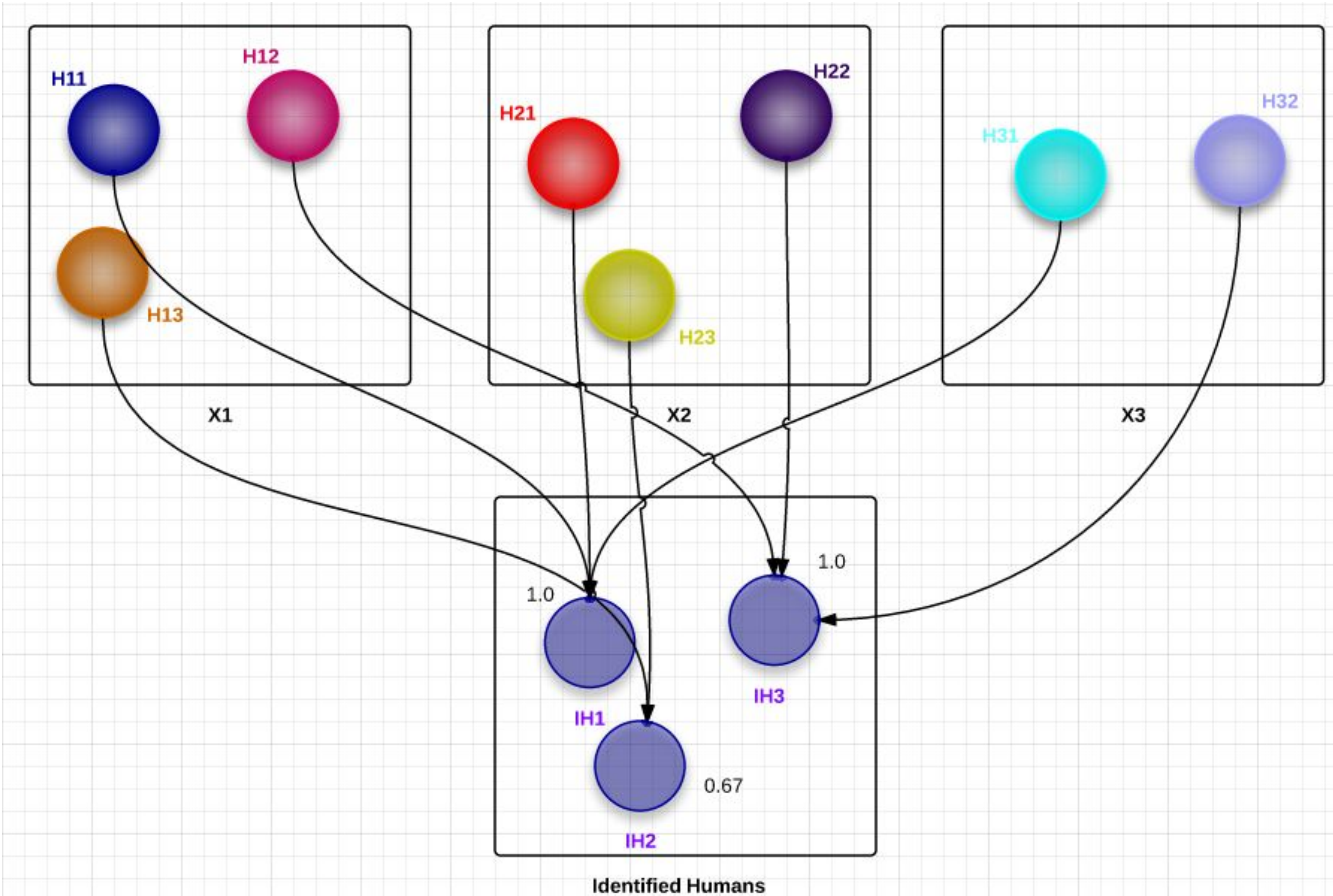


Human Identification

- Identify individual humans from updated particles

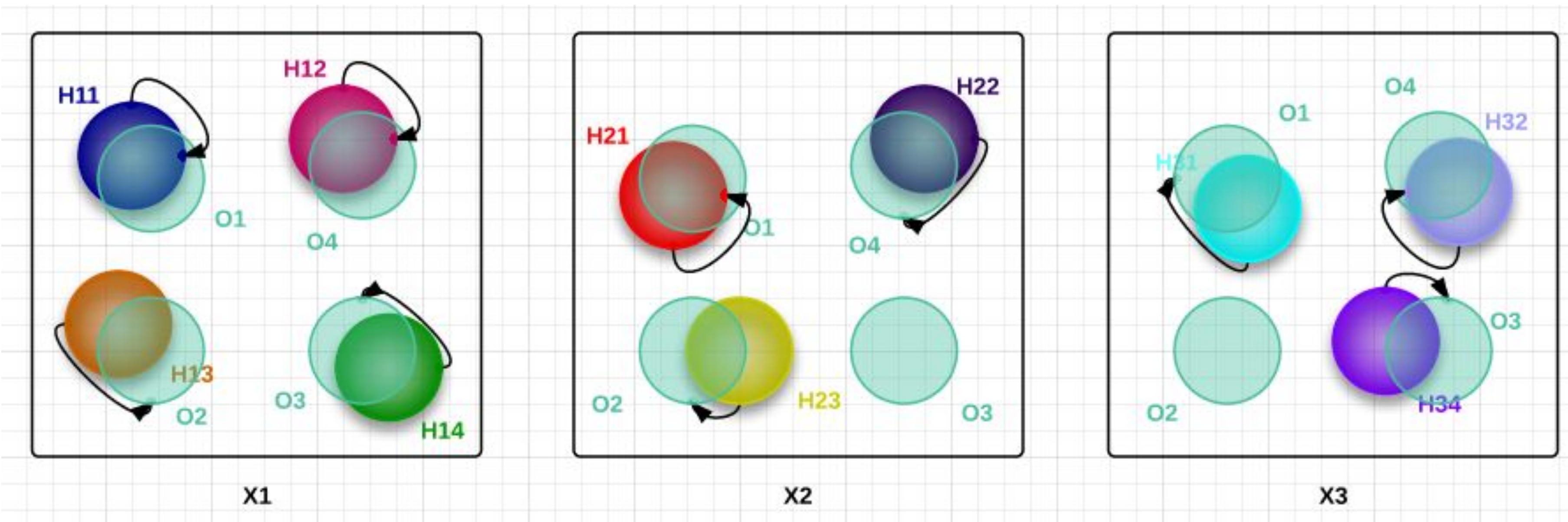


An Example

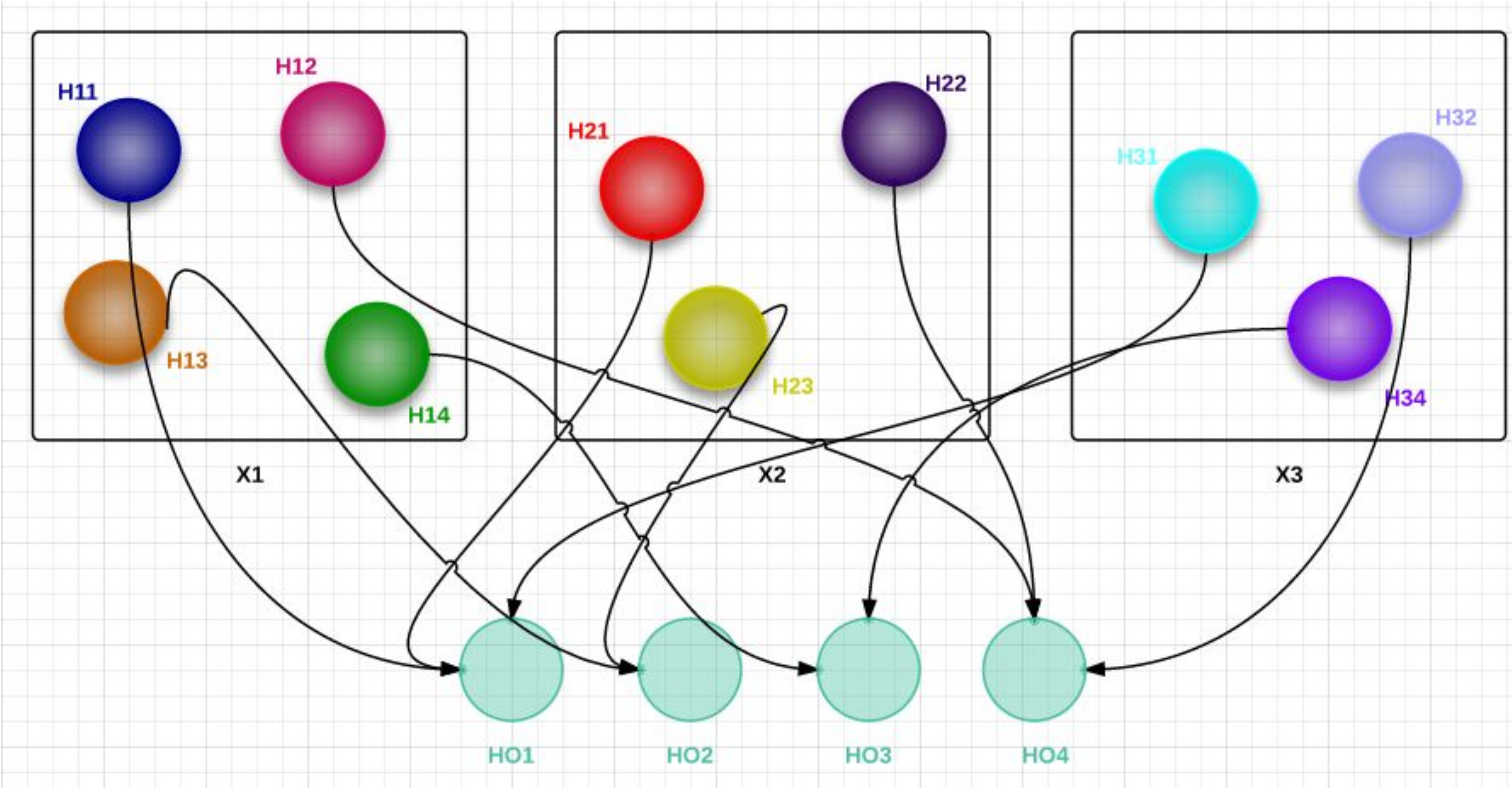


H11
H12
H13
X1
H21
H22
H23
X2
H31
H32
X3
1.0
1.0
IH1
IH3
IH2
0.67
Identified Humans

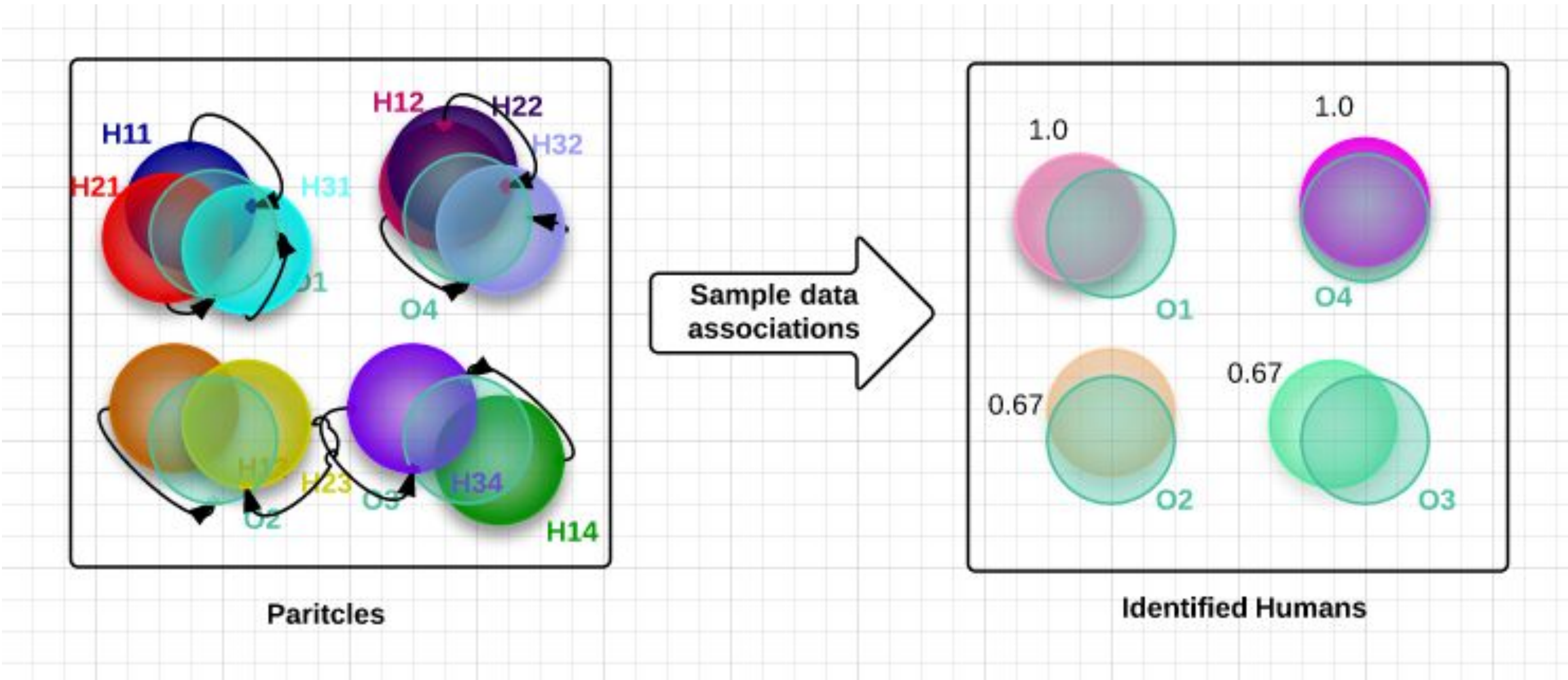
Sample Data Associations



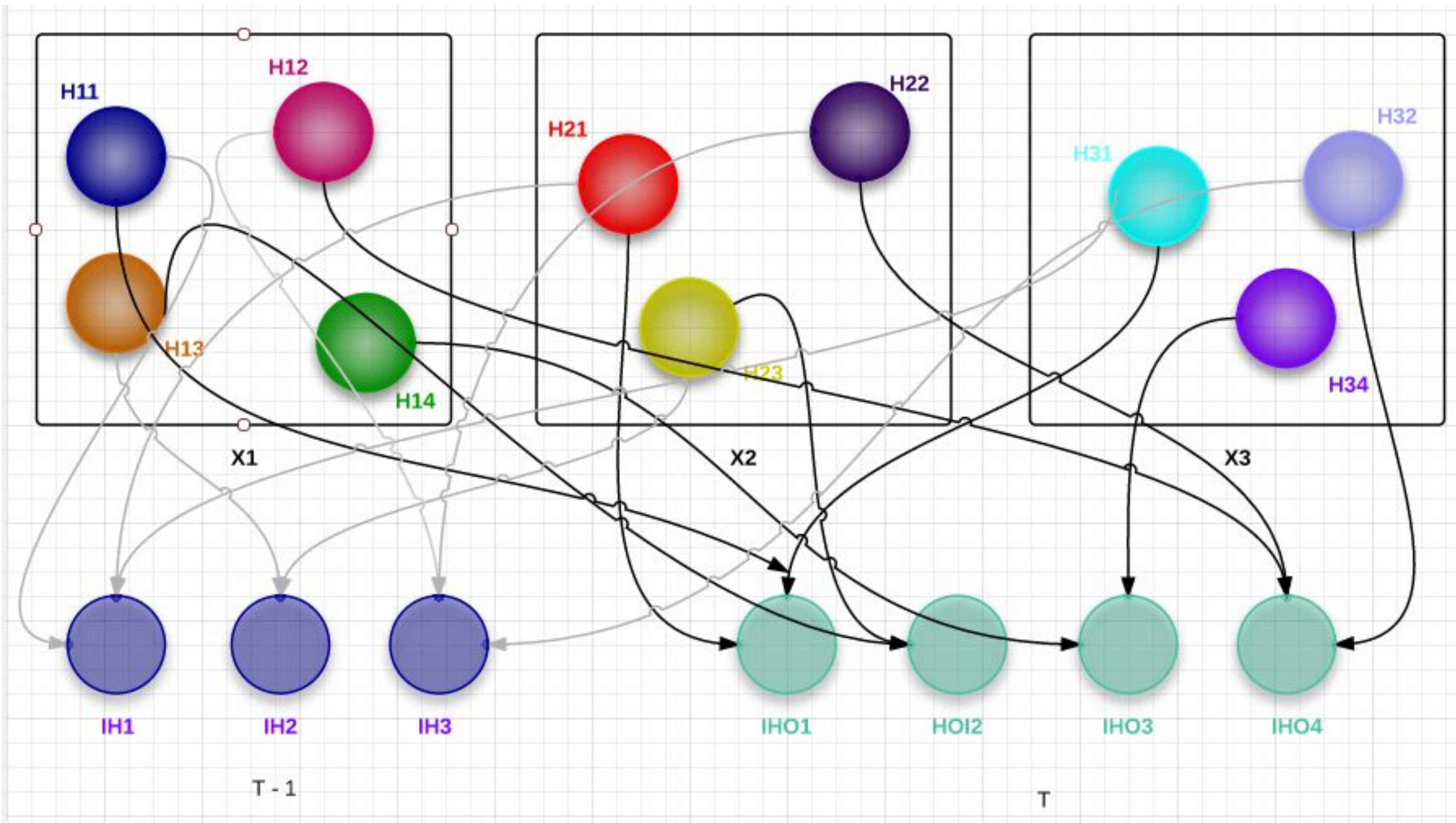
Identify Humans at Cycle 0



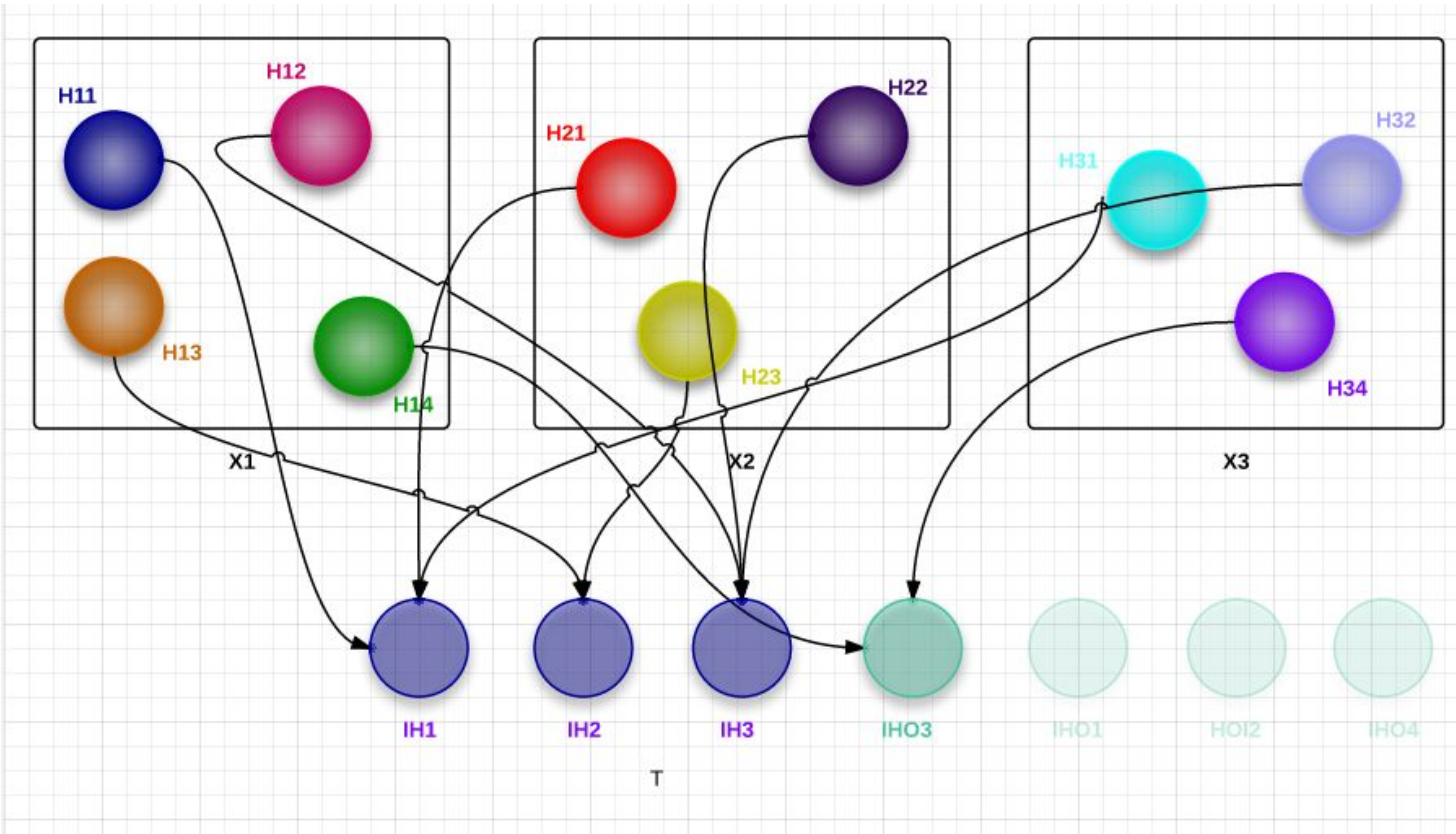
The Resulting Identified Humans



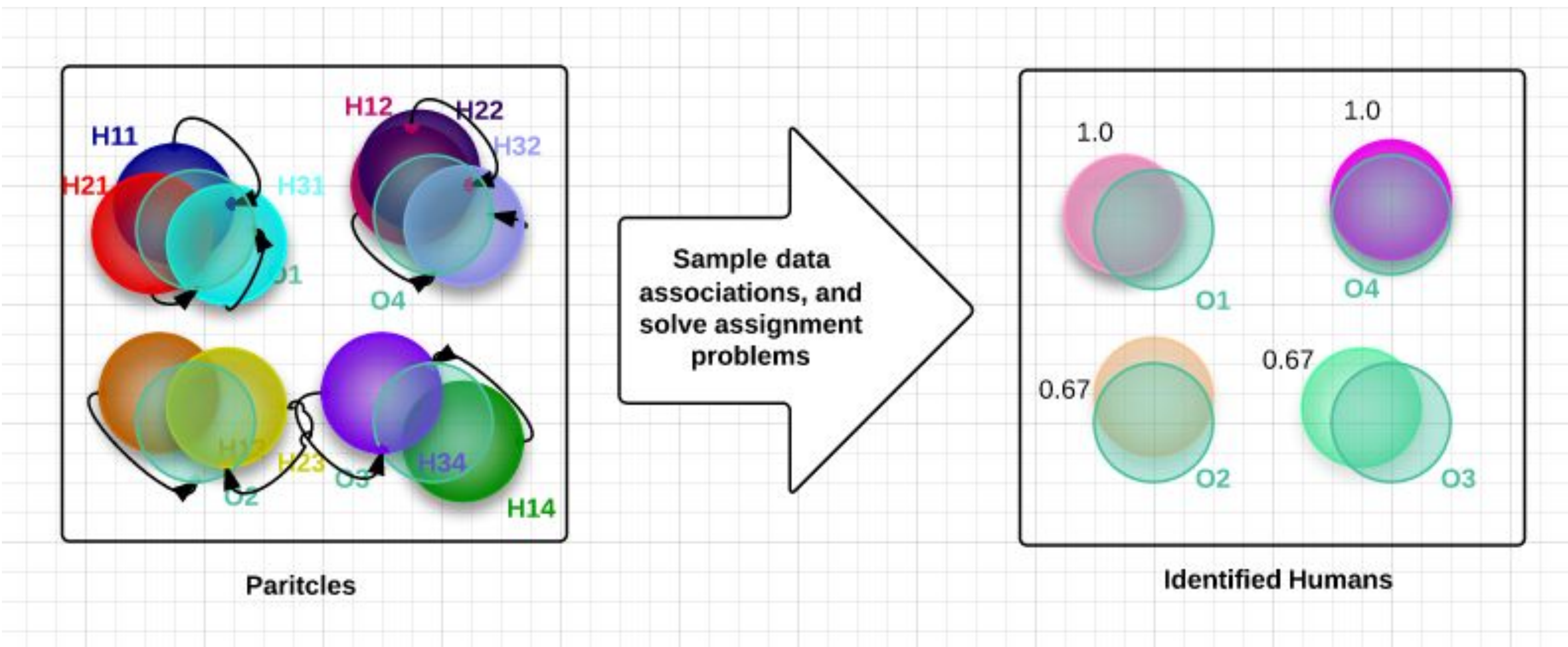
Identify Humans at Cycle T != 0



Solve a Linear Number of Assignment Problems



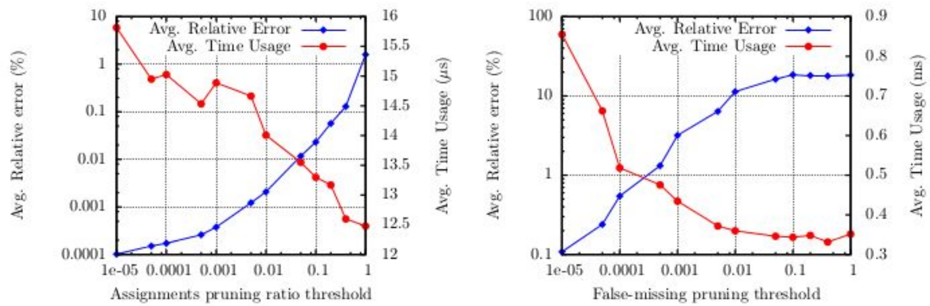
The Resulting Identified Humans



Experimental Evaluation

- Simulation Experiments
  - Approximation error test
  - Overall performance test
- Cobot Experiments

Approximation Error Test



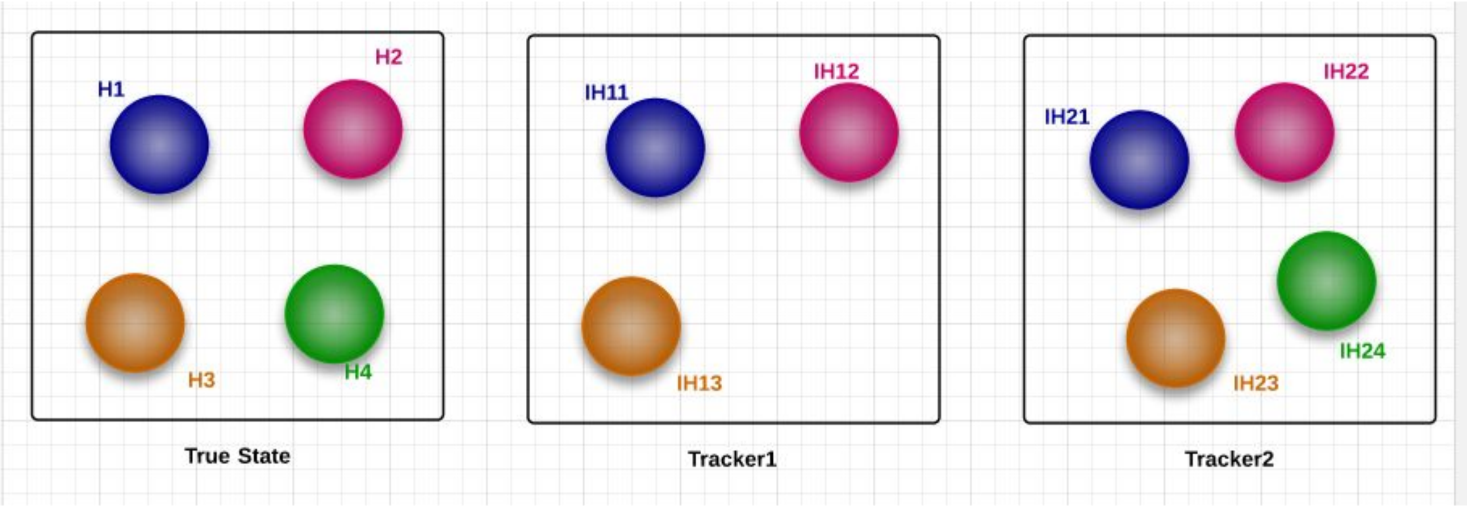
(a) Assignment pruning (b) False-missing pruning

Figure 1: Pruning approximation error test.

Before pruning	Equation 5	Equation 4
Avg. terms	32.66 ± 0.09	1466.52 ± 34.77
Max. terms	5040	2.5018×10^6
After pruning		
Avg. terms	2.11 ± 0.01	29.23 ± 0.13
Max. terms	145	3043
Pruning rate	93.50%	97.95%
Relative error	0.026%	3.30%

Table 1: Detailed results of pruning experiments when $T_a = 0.1$ and $T_{fm} = 0.001$.

Overall Performance Evaluation



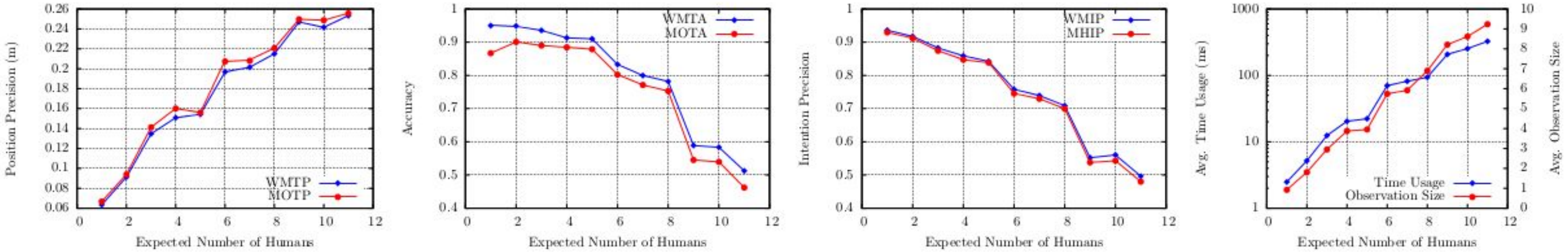
- CLEAR MOT metrics
  - MOTP / MOTA
- Weighted versions
  - WMTP / WMTA / WMIP
  - MOIP

Overall Performance

- Simulator

  Death rate = 0.02/s, variable birth rate

  False rate = 0.5/s, missing rate = 0.5/s



(a) WMTP/MOTP (b) WMTA/MOTA (c) WMIP/MHIP (d) Time and observation

Figure 2: PFS performance in terms of confidence weighted and unweighted CLEAR MOT metrics.

- Some demos

Cobot Experiments

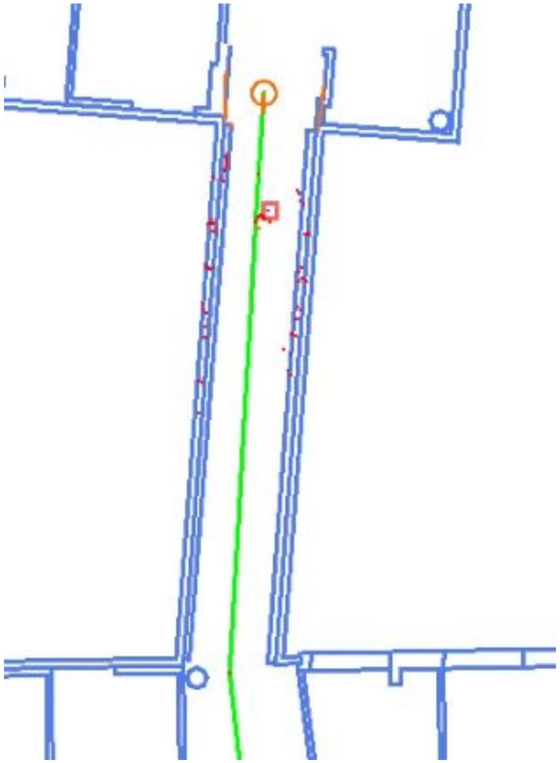
- PFS

  Death rate = 0.01/s

  Birth rate = 0/s

  False rate = 1/s

  Missing rate = 1/s



Data on Feb 28, 2014

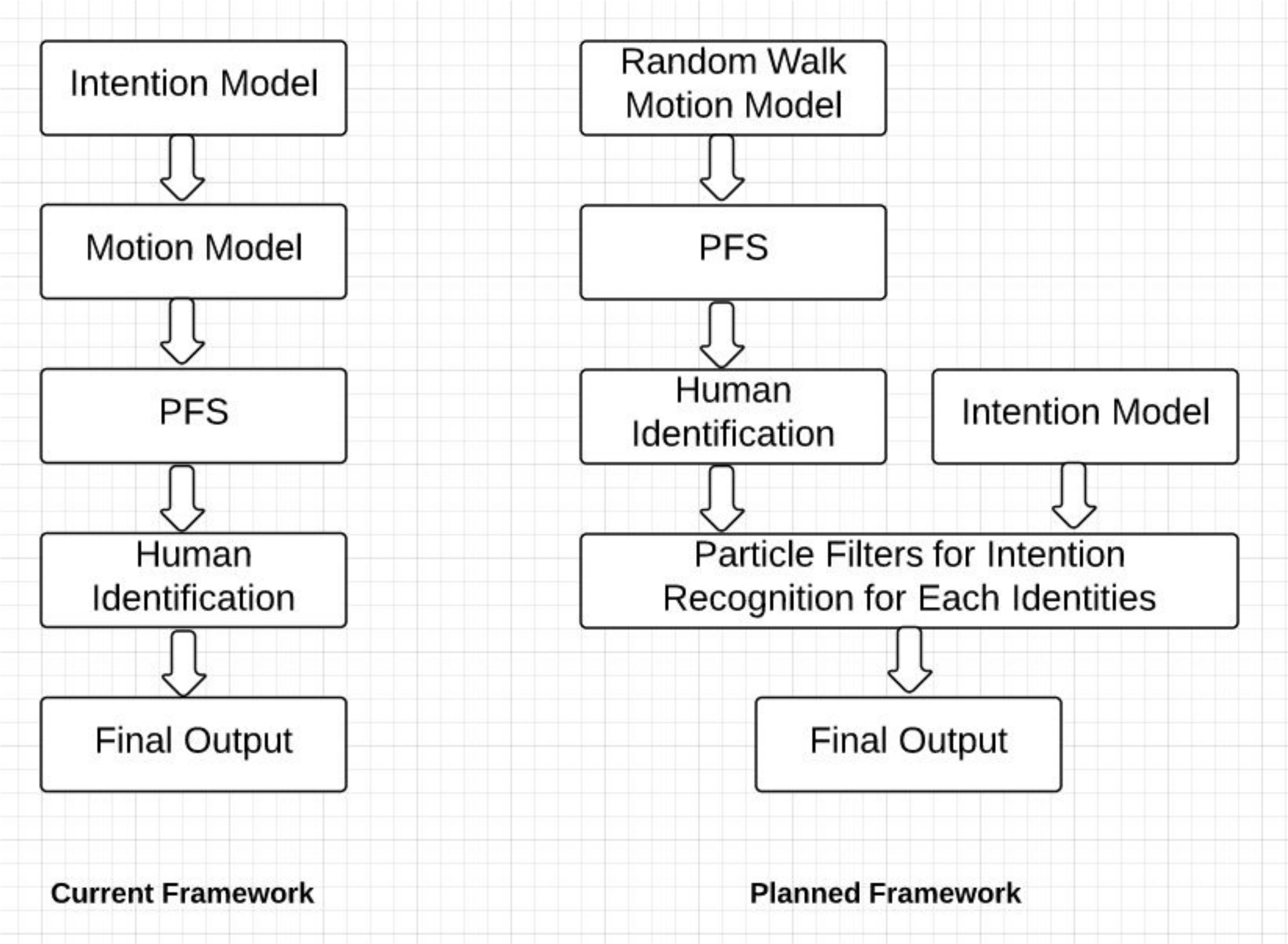
During one deployment, the robot travelled 2,680m within 2.72 hours. The human detector reported totally 11,229 detections. The average non-empty observation size is 1.19. The human tracker reported 936 identities. The average number of identities if any is 1.44. The average survival time for each identity is 4.28s. The longest survival time is 270.60s. The average confidence of identities during the whole time of being tracked is 0.82.

- Some demos

Conclusion

- An intention-aware multi-human tracker
  - Input
    - A set of indistinguishable detections with noises and errors
  - Output
    - Identified humans with
      - Expected positions and velocities
      - Confidence values
      - Intention distributions / dominant intention

Future Work



Intention Model
Motion Model
PFS
Human Identification
Final Output
Current Framework
Random Walk Motion Model
PFS
Human Identification
Intention Model
Particle Filters for Intention Recognition for Each Identities
Final Output
Planned Framework

Future Work

- Discussion