Tracking Multiple Moving Objects with a Mobile Robot

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Motivation

For many applications it is highly desirable that a mobile robot can determine the positions of the people in its surrounding:

- Navigation
- Surveillance
- Health care
- Cooperation
- Interaction
- ...

The Problem

- The problem of tracking a single target is relatively well understood:
  - Kalman filtering
  - Bayesian filtering
- In the context of multiple targets we have to answer the following questions:
  - How to represent the state space?
  - Which feature belongs to which object?
  - What are the states of the individual objects?

Joint Probabilistic Data Association Filters (Motivation)

Task:

To keep track of multiple moving objects one generally has to estimate the joint probability distribution of the state of all objects.

Problem:

This is infeasible, since the joint state space grows exponentially in the number of objects being tracked.

Idea:

Factorial, representation of the joint state space by n individual and independent state spaces.

Problem:

How can we determine which measurement or feature is caused by which object in order to update the corresponding filter?

Solution:

Joint probabilistic data association filters (JPDAFs)

JPDAFs

- T objects with states $\mathbf{X}^k = \{\mathbf{x}_1^k, \ldots, \mathbf{x}_T^k\}$ at time k.
- $\mathbf{Z}(k) = \{\mathbf{z}_1(k), \ldots, \mathbf{z}_{m_k}(k)\}$ are the measurements at time k, where $\mathbf{z}_j(k)$ is one feature.
- $\mathbf{Z}^k$ is the sequence of all measurements up to time k.
- Key question: How to assign the observed features to the individual objects?

Joint Association Events

- A joint association event θ is a set of pairs $(j, i) \in \{0, \ldots, m_k\} \times \{1, \ldots, T\}$.
- Each θ uniquely determines which feature is assigned to which object.
- The feature $\mathbf{z}_0(k)$ is used to model situations in which no feature has been found for object i.
- Θ_{ji} denotes the set of all valid joint association events which assign feature j to the object i.
- At time k, the JPDAF computes the posterior probability that feature j is caused by object i according to

$$\beta_{ji} = \sum_{\theta \in \Theta_{ji}} P(\theta \mid \mathbf{Z}^k). \tag{1}$$

Computing the β_{ji}

$$
\begin{aligned}
P(\theta \mid \mathbf{Z}^k) &= P(\theta \mid \mathbf{Z}(k), \mathbf{Z}^{k-1}) \\
&\overset{\text{Markov!}}{=} P(\theta \mid \mathbf{Z}(k), \mathbf{X}^k) \\
&\overset{\text{Bayes!}}{=} \alpha\, p(\mathbf{Z}(k) \mid \theta, \mathbf{X}^k)\; P(\theta \mid \mathbf{X}^k) \\
&\overset{P(\theta|\mathbf{X}^k)\text{ is constant}}{=} \alpha\, p(\mathbf{Z}(k) \mid \theta, \mathbf{X}^k)
\end{aligned}
$$

Computing $p(\mathbf{Z}(k) \mid \theta, \mathbf{X}^k)$

- To determine $p(\mathbf{Z}(k) \mid \theta, \mathbf{X}^k)$ we have to consider false alarms.
- Let γ denote the probability that an observed feature is a false alarm.
- The number of false alarms in an association event θ equals $(m_k - |\theta|)$.
- Thus, $\gamma^{(m_k - |\theta|)}$ is the probability assigned to all false alarms in $\mathbf{Z}(k)$.
- All other features are uniquely assigned to an object.
- Under the assumption that the features are detected independently of each other, we obtain

$$p(\mathbf{Z}(k) \mid \theta, \mathbf{X}^k) = \gamma^{(m_k - |\theta|)} \prod_{(j,i)\in\theta} p(\mathbf{z}_j(k) \mid \mathbf{x}_i^k)$$

The Resulting Equations for for the JPDAF

Assignment probabilities:

$$\beta_{ji} \quad = \quad \sum_{\theta \in \Theta_{ji}} \alpha \, \gamma^{(m_k - |\theta|)} \prod_{(j,i) \in \theta} p(\mathbf{z}_j(k) \mid \mathbf{x}_i^k)$$

Actions of the targets:

$$p(\mathbf{x}_i^k \mid \mathbf{Z}^{k-1}) \quad = \quad \int p(\mathbf{x}_i^k \mid \mathbf{x}_i^{k-1}, t) \, p(\mathbf{x}_i^{k-1} \mid \mathbf{Z}^{k-1}) \, d\mathbf{x}_i^{k-1}$$

Observations:

$$p(\mathbf{x}_i^k \mid \mathbf{Z}^k) \quad = \quad \alpha \sum_{j=0}^{m_k} \beta_{ji} p(\mathbf{z}_j(k) \mid \mathbf{x}_i^k) \, p(\mathbf{x}_i^k)$$

Remaining Problems

- How can we estimate the number of objects?
- How do we represent the underlying densities?
- How can we determine $p(\mathbf{x}_i^k \mid \mathbf{x}_i^{k-1}, t)$?
- How can we estimate $p(\mathbf{z}_j(k) \mid \mathbf{x}_i^k)$?

Sample-based JPDAFs (SJPDAFs)

Key idea: Represent $p(\mathbf{x}_i^k \mid \mathbf{Z}^k)$ by a set $\mathbf{S}_i^k$ of N weighted, random samples or *particles* $s_{i,n}^k (n = 1 \ldots N)$.

To compute β_{ji} we integrate over all samples:

$$p(\mathbf{z}_j(k) \mid \mathbf{x}_i^k) \quad = \quad \frac{1}{N} \sum_{n=1}^{N} p(\mathbf{z}_j(k) \mid x_{i,n}^k).$$

In the correction step we obtain the weights of the samples according to:

$$w_{i,n}^k = \alpha \sum_{j=0}^{m_k} \beta_{ji} p(\mathbf{z}_j(k) \mid x_{i,n}^k),$$

Estimating the Number of Objects

Idea: Use Bayesian filtering to estimate $P(N^k \mid \mathbf{M}^k)$ over the number of objects N^k:

$$P(N^k \mid \mathbf{M}^k) \quad = \quad \alpha \cdot P(m_k \mid N^k) \cdot \sum_n P(N^k \mid N^{k-1} = n) \cdot P(N^{k-1} = n \mid \mathbf{M}^{k-1})$$

We **initialize new filters** using a **uniform distribution**.

We **remove the filter** with the **lowest discounted average** $\hat{W}_i^k$ of the sum of the sample weights.

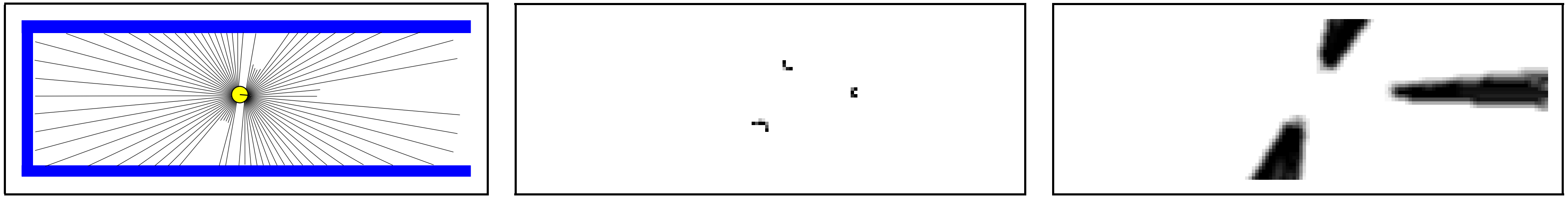
$$\hat{W}_i^k = (1-\delta)\hat{W}_i^{k-1} + \delta W_i^k.$$

Tracking People with a Mobile Robot

We consider different aspects:

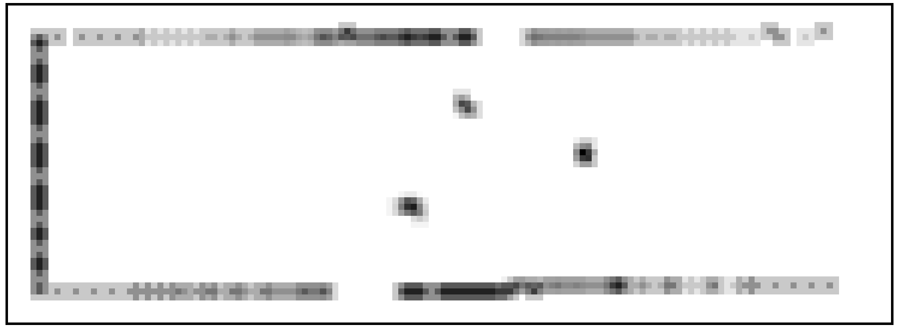
1. **local minima in the range scans**,
2. **differences** in the grid maps of **consecutive range scans**
3. **occluded areas** in range scans

All features are converted into **local grid maps**:

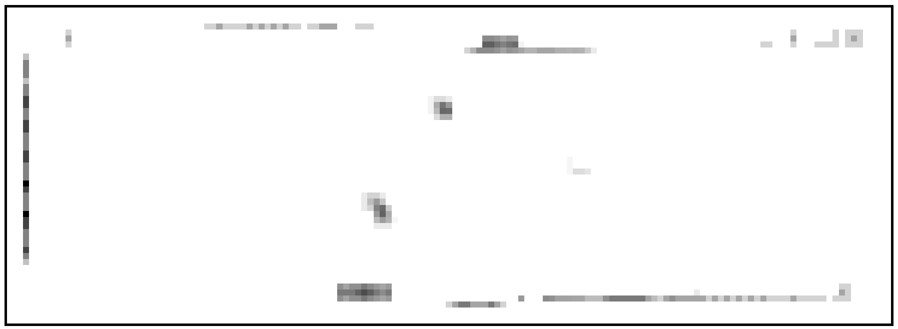


Integration with Differences between Consecutive Scans

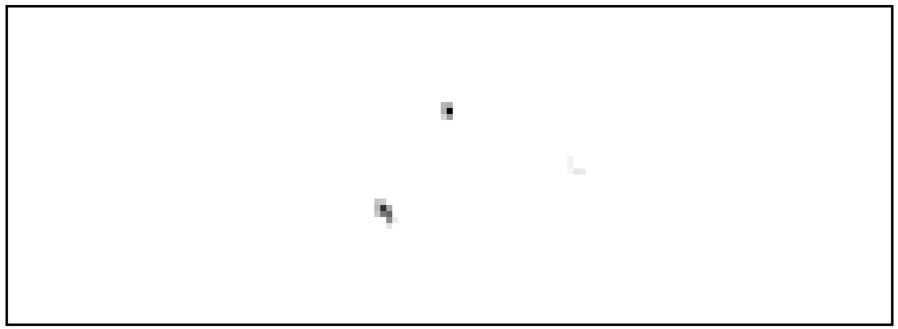
Map of previous scan



Map of current scan



Difference map

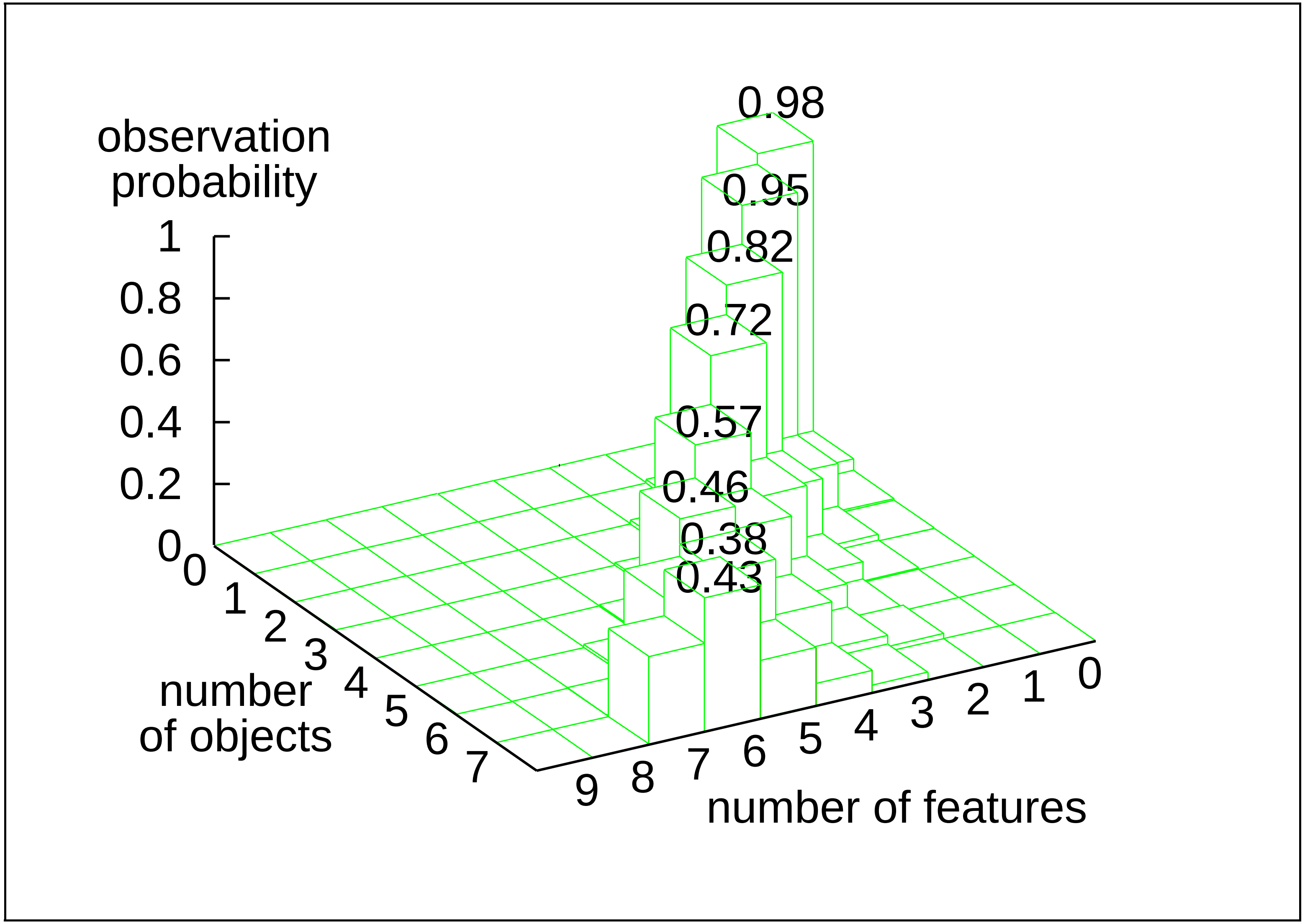


Map based on all features

The Motion Model

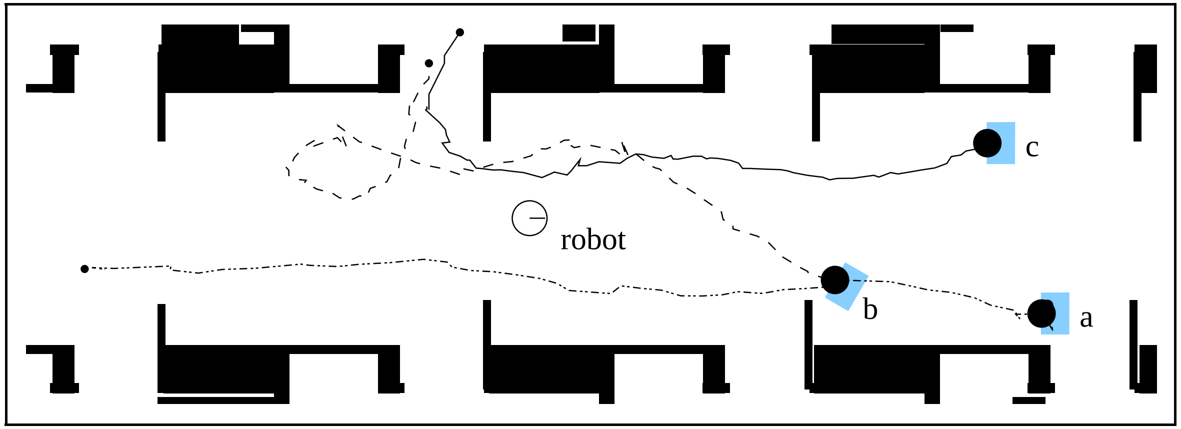
- Persons change their walking direction and walking speed according to Gaussian distributions.
- After a person stopped, he proceeds in an arbitrary direction.
- The walking speed lies between 0 and 150 m/sec.
- People don't walk through static objects.

Estimating the Number of People

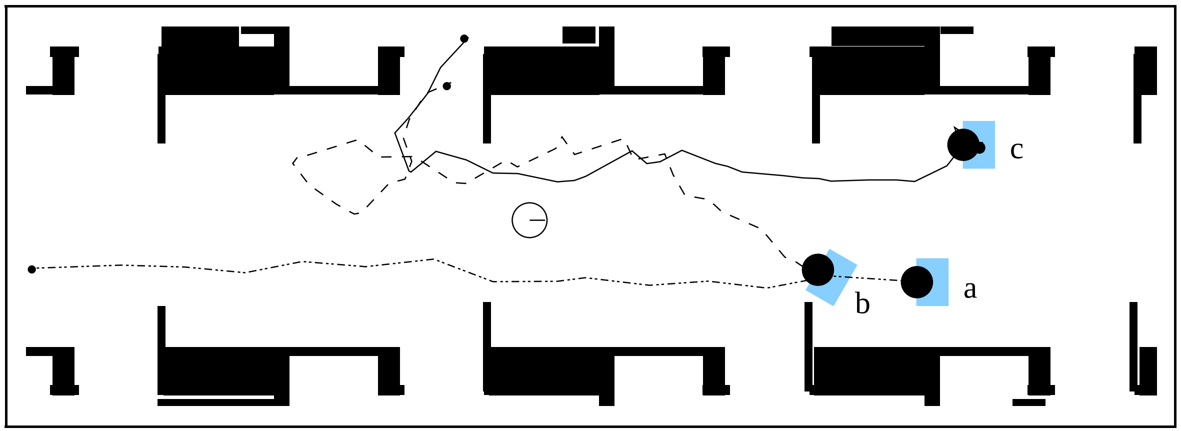


Application Result

Ground truth:

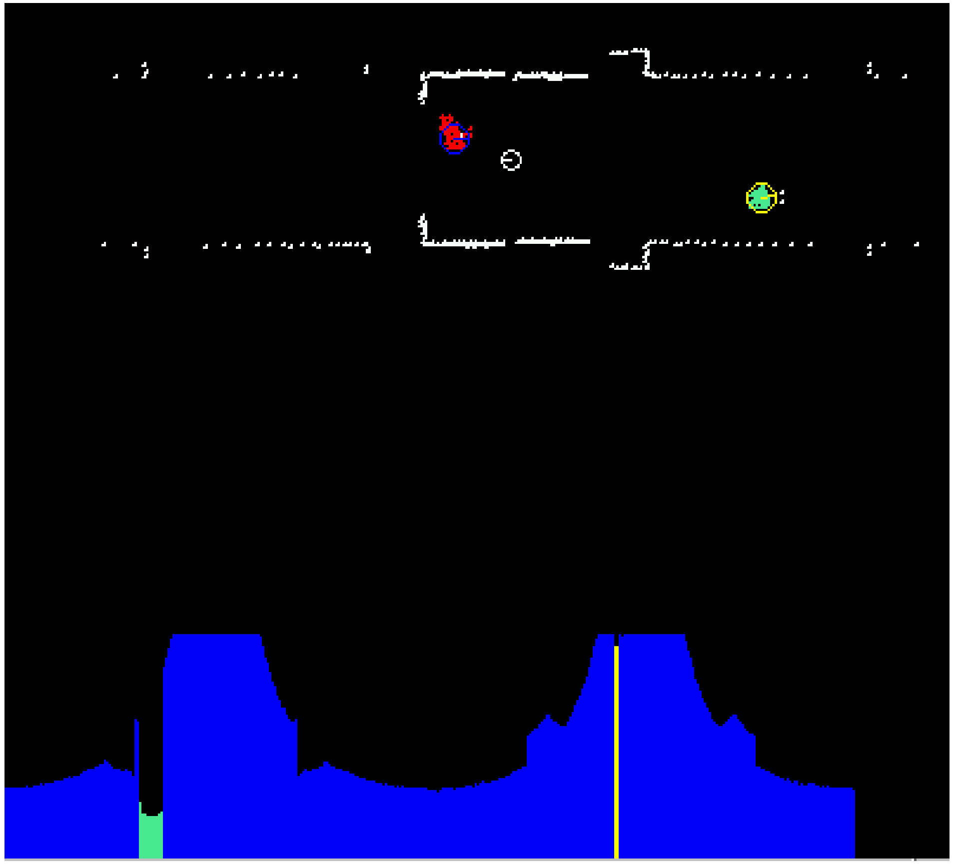


Estimated trajectory:



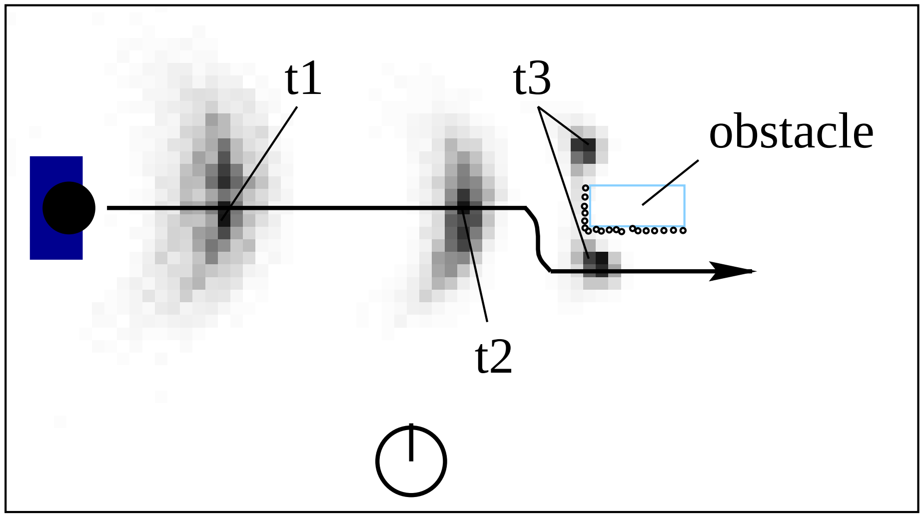
Average displacement 19cm, maximum displacement 37cm

Animations (1)

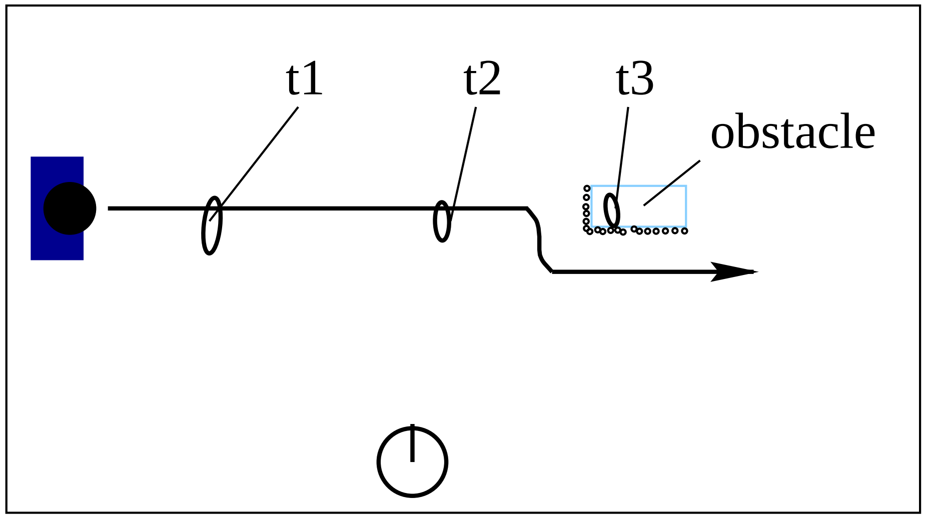


Animations (2)

Comparison to Standard JPDAFs



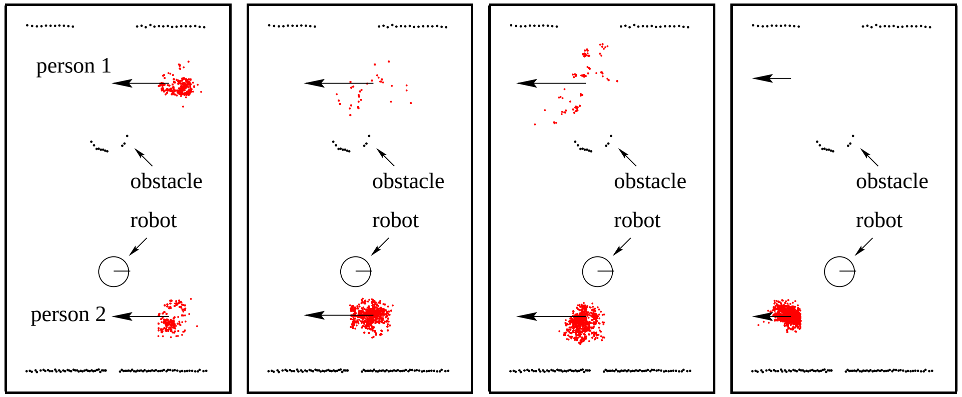
SJPDAF



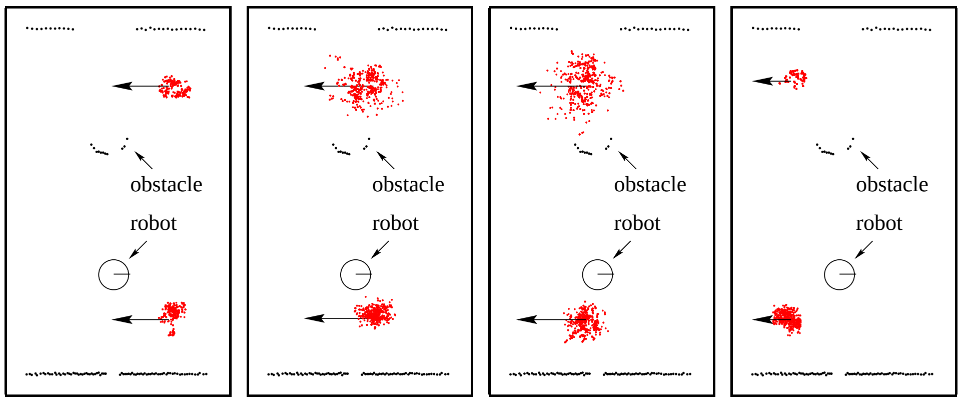
JPDAF using Gaussians

Comparison to a Standard Particle Filter

Standard particle filter:



SJPDAF:



Conclusions

- SJPDAFs are a robust means to keep track of multiple moving targets
- Our approach can represent multi-modal densities and still is able to efficiently track several persons.
- Our approach additionally is able to estimate the number of objects.
- The SJPDAF has been applied successfully to laser-based people tracking.
- SJPDAFs outperform other techniques developed so far.

References

- Y. Bar-Shalom and T.E. Fortmann. Tracking and Data Association. Mathematics in Science and Engineering. Academic Press, 1988.
- I.J. Cox. A review of statistical data association techniques for motion correspondence. International Journal of Computer Vision, 10(1):53 66, 1993.
- I.J. Cox and S.L. Hingorani. An efficient implementation of reids multiple hypothesis tracking algorithm and its evaluation for the purpose of visual tracking. In IEEE Transactions on PAMI, volume 18, pages 138 150. February 1996.
- N.J. Gordon. A hybrid bootstrap filter for target tracking in clutter. In IEEE Transactions on Aerospace and Electronic Systems, volume 33, pages 353 358. January 1997.
- D. Schulz, W. Burgard, D. Fox and A.B. Cremers. Tracking Multiple Moving Targets with a Mobile Robot using Particle Filters and Statistical Data Association. ICRA 2001.