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

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

The Resulting Equations for for the JPDAF

Assignment probabilities:

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

Actions of the targets:

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

Observations:

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

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.

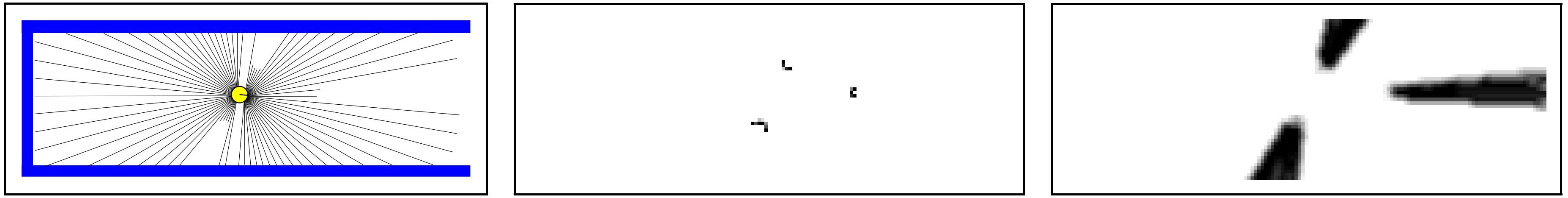
$$\hat{W}_i^k = (1 - \delta)\hat{W}_i^{k-1} + \delta W_i^k.$$

Tracking People with a Mobile Robot

We consider different aspects:

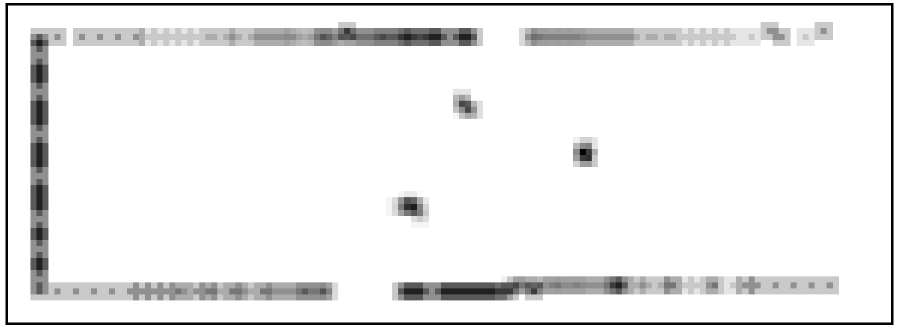
1. **local minima in the range scans**,
2. **differences** in the grid maps of **consecutive range scans**
3. **occluded areas** in range scans

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

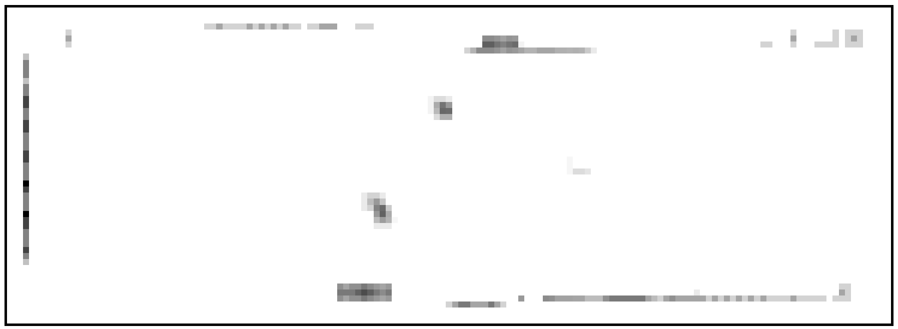


Integration with Differences between Consecutive Scans

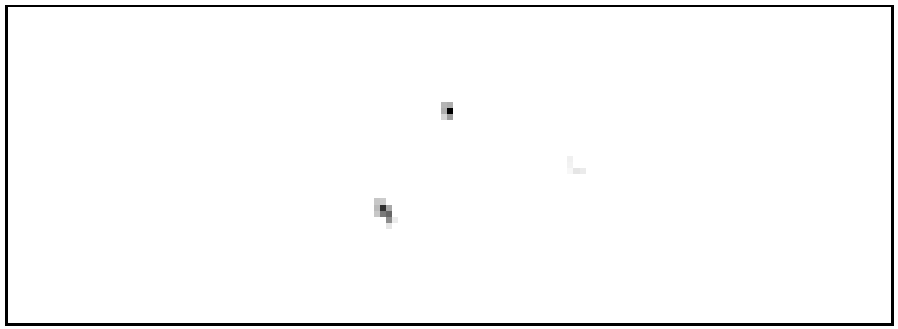
Map of previous scan



Map of current scan



Difference map

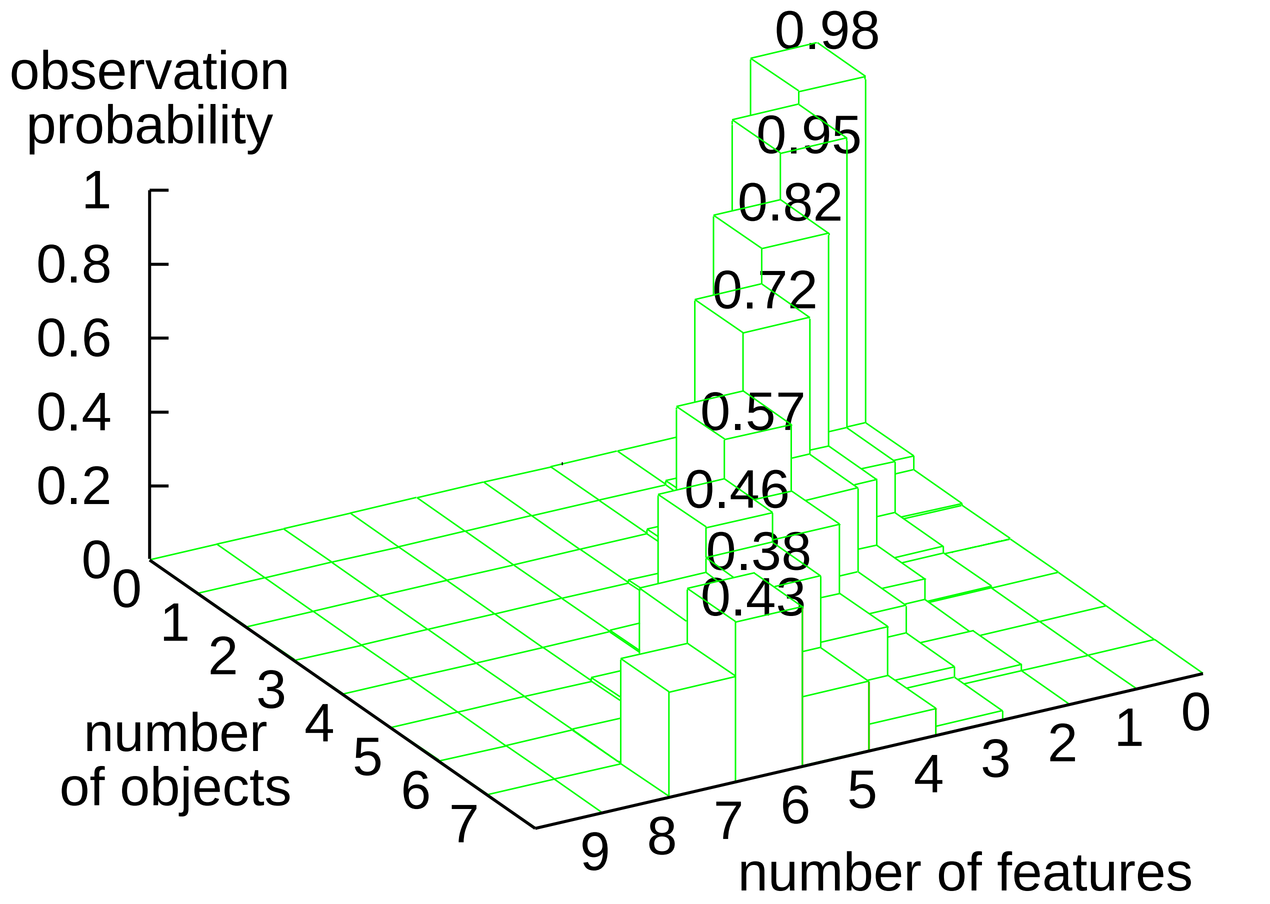


Map based on all features

The Motion Model

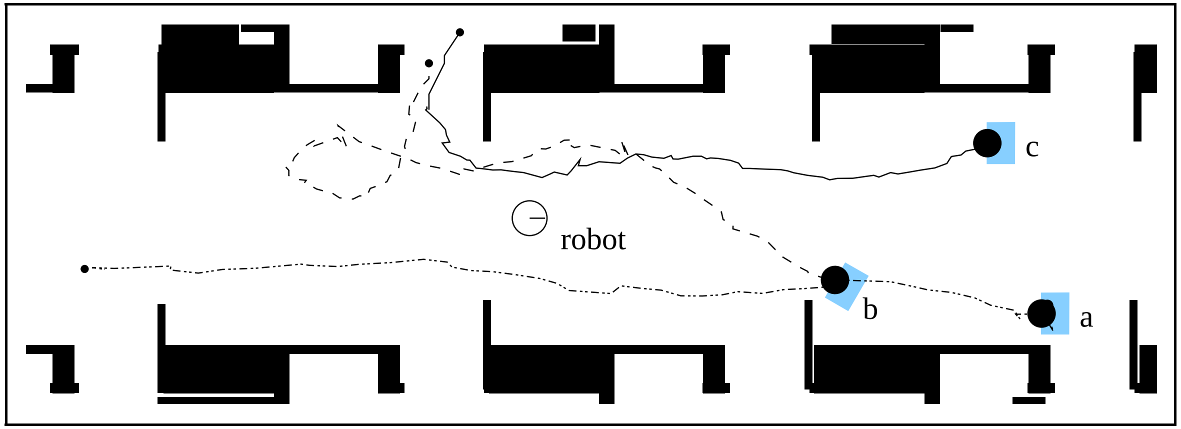
- Persons change their walking direction and walking speed according to Gaussian distributions.
- After a person stopped, he proceeds in an arbitrary direction.
- The walking speed lies between 0 and 150 m/sec.
- People don’t walk through static objects.

Estimating the Number of People

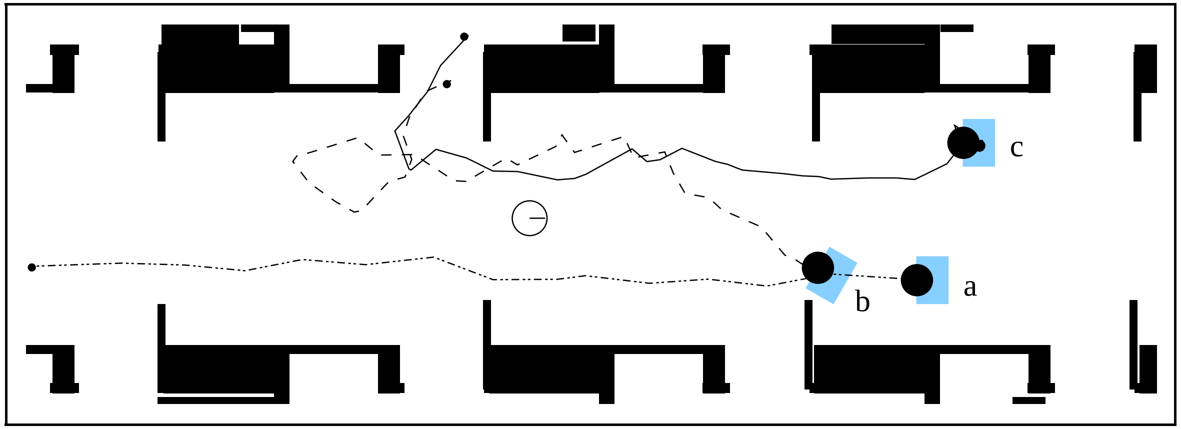


Application Result

Ground truth:

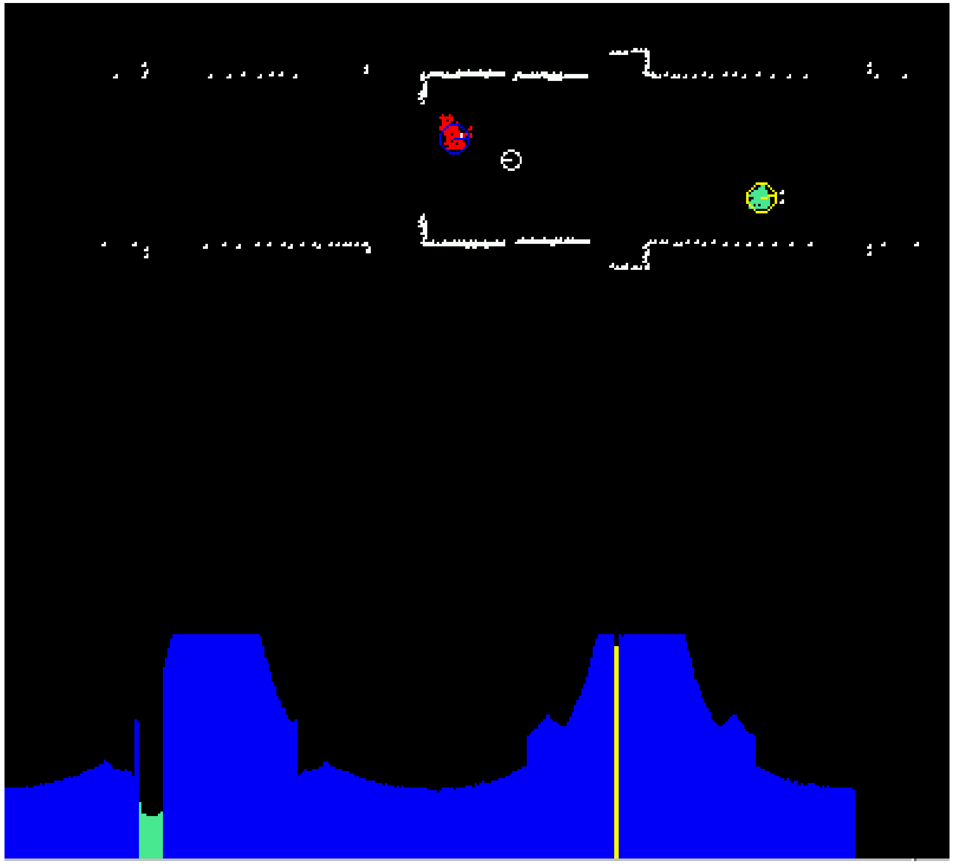


Estimated trajectory:



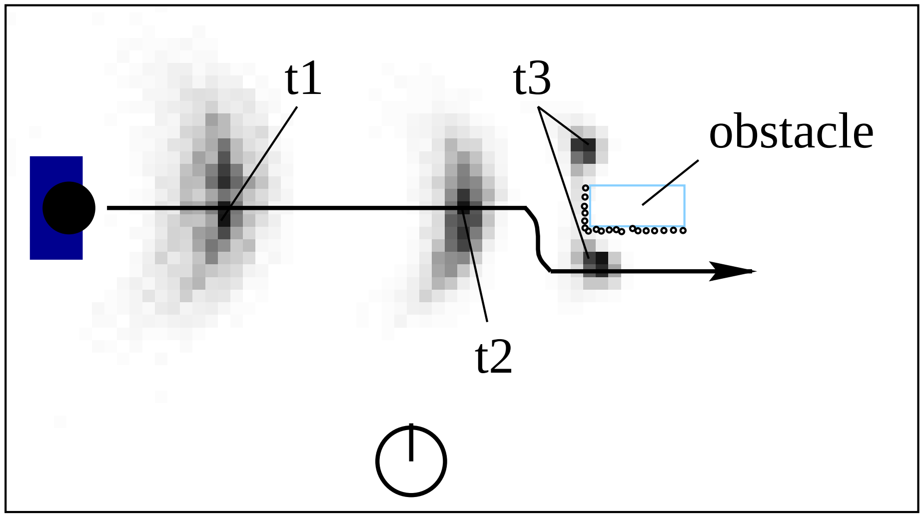
Average displacement 19cm, maximum displacement 37cm

Animations (1)

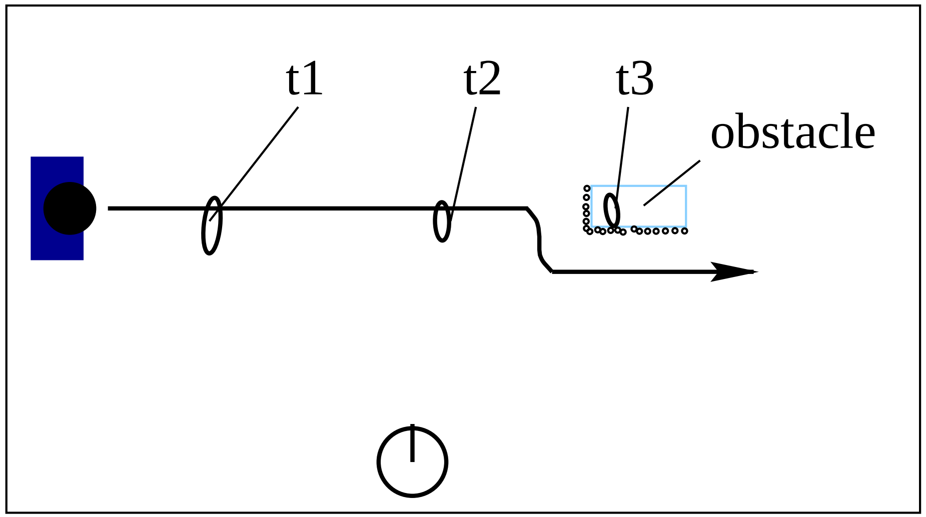


Animations (2)

Comparison to Standard JPDAFs



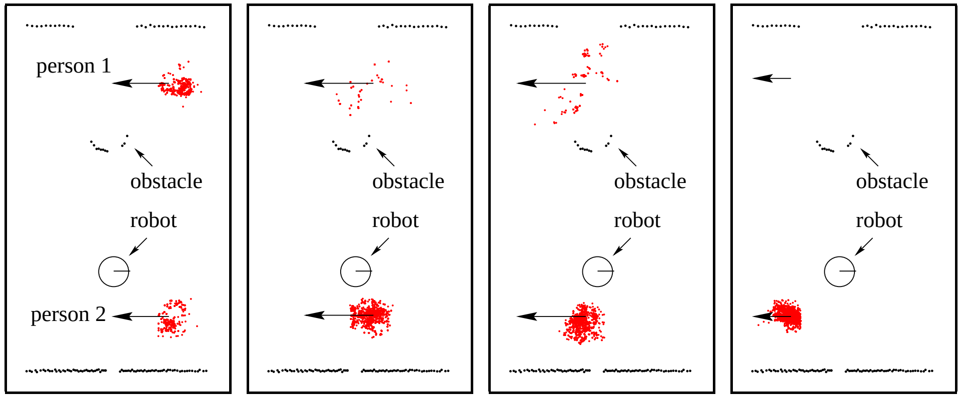
SJPDAF



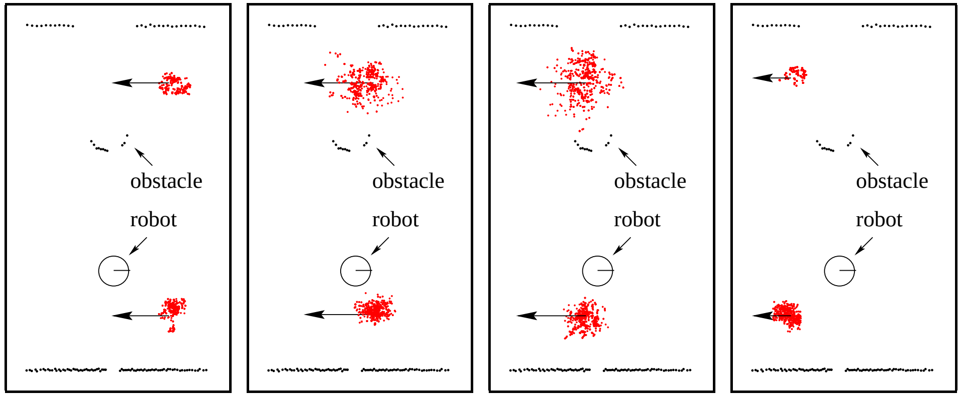
JPDAF using Gaussians

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

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