Persons Tracking with Gaussian Process Joint Particle Filtering

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Outline

- Keypoints
- Motivation
- Gaussian process and displacement experts
- Particle filters
- GPJPF tracking algorithm
- Floor sensor setting
- Tracking experiments
- Conclusions

Keypoints

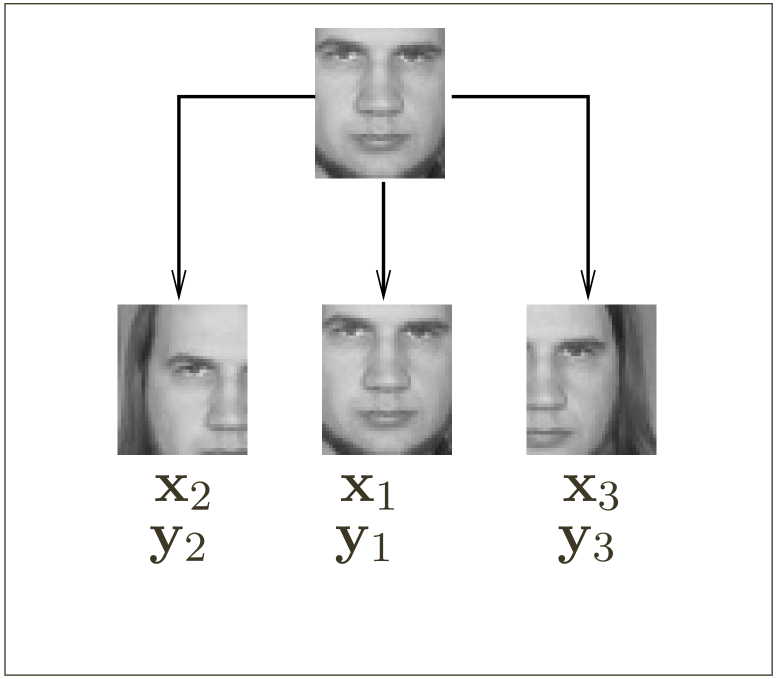
- Combining machine learning (Gaussian Process (GP)) and dynamical state-space modeling (Particle Filtering (PF)) for persons tracking
  - GP regression model trained on measurement data
  - Joint Particle Filter (JPF) with Markov Random Fields (MRF) is used to model multiple moving targets and their interaction
  - Gaussian Process Joint Particle Filtering (GPJPF): MRF and GP can be directly embedded on the JPF formulation
- Applying algorithm to persons tracking on a floor sensor
  - Floor matrix of pressure-sensitive binary switches is used

Motivation

- Why persons localization and tracking?
  - Ubiquitous computing: every-where context-aware computing systems need person localization and identification to provide personalized services
  - Location-aware monitoring: health care, eldery care, and surveillance
  - Floor sensors: can be embedded to the environment, transparent and natural localization
- Why machine learning?
  - Non-linear human motion, noisy and limited measurement data
- Why Sequential Monte Carlo?
  - Variable number of multiple targets, non-linear motion, target interaction

Tracking Methodology

- Gaussian Process Regression
  - Mapping from high dimensional input feature vector to continuous target $f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$
  - GP mean $m(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})]$
  - GP covariance $k(\mathbf{x}, \mathbf{x}') = \mathbb{E}[f(\mathbf{x}) - m(\mathbf{x})] - m(\mathbf{x}')$
- Learning displacement expert
  - Learning regressor to predict spatial displacement [1] $\mathbf{u}_t = \mathbf{u}_{t-1} + GP_\mu(\mathbf{x})$
  - Sampling from seed input examples $y \sim uniform(-\Delta, \Delta)$



[1] O. Williams, A. Blake, and R. Cipolla, “Sparse bayesian learning for efficient visual tracking,” *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, vol. 27, no. 8, pp. 1292–1304, 2005.

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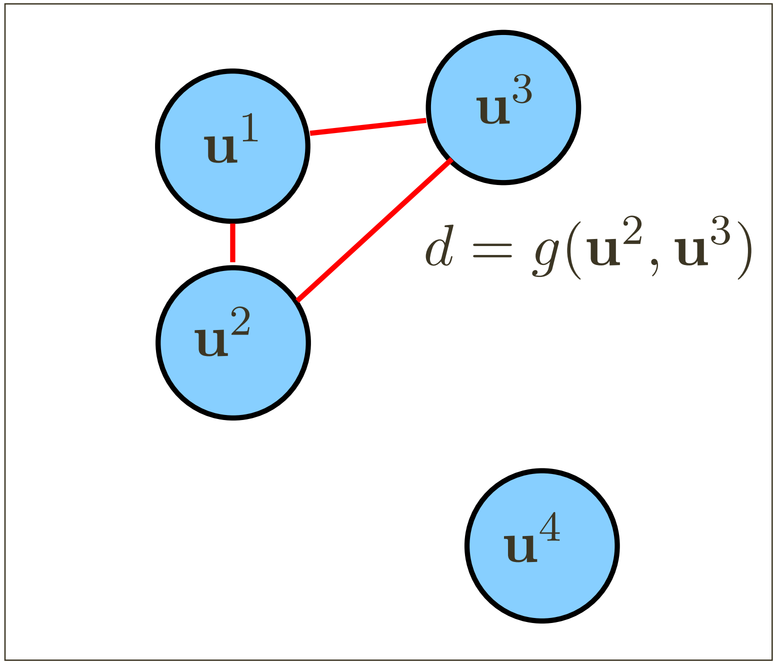
Tracking Methodology (cont.)

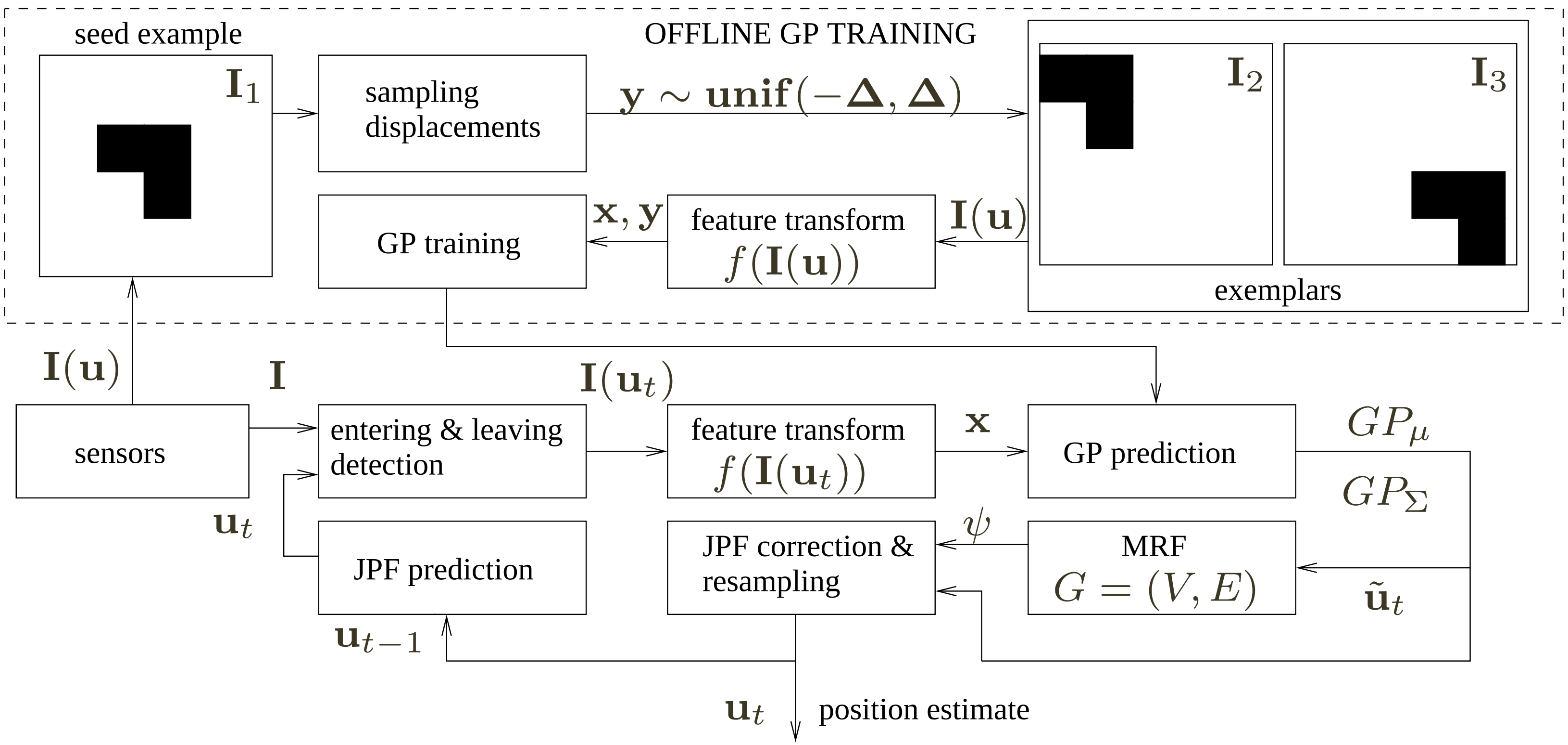
- Joint Particle Filter
  - Implements sequential Bayesian filtering for multiple targets
  - Each particle captures the state $\mathbf{u}$ of all the targets jointly
  - Sampling from the dynamic model $p(\mathbf{u}_t|\mathbf{u}_{t-1}) \propto \prod_i p(\mathbf{u}_t^i|\mathbf{u}_{t-1}^i)$
  - A factored likelihood model $p(\mathbf{z}_t|\mathbf{u}_t) \propto \prod_i p(\mathbf{z}_t^i|\mathbf{u}_t^i)$
  - Resampling $N_{eff} = \frac{1}{\sum_{k=1}^{N}(w_k)^2}$ (SIR Particle Filter)
- Markov Random Fields model for interaction $G = (V, E)$ $p(\mathbf{u}_t|\mathbf{u}_{t-1}) \propto \prod_{i=1}^{n} p(\mathbf{z}_t^i|\mathbf{u}_t^i) \prod_{i,j\in E} \psi(\mathbf{u}_t^i, \mathbf{u}_t^j)$
- Pairwise interaction potentials $\psi(\mathbf{u}^i, \mathbf{u}^j) \propto \exp(-g(\mathbf{u}^i, \mathbf{u}^j))$
- MRF is formed between targets close to each others



GPJPF

- Combining JPF with Gaussian process correction step
- GPJPF importance weight update with embedded GP and MRF

$$w_t = w_{t-1} \prod_{i=1}^{n} \mathcal{N}(\tilde{\mathbf{u}}_t^i; \mathbf{u}_t^i, GP_\Sigma^i(\mathbf{x})) \prod_{i,j \in E} \psi(\tilde{\mathbf{u}}_t^i, \tilde{\mathbf{u}}_t^j)$$



GPJPF (cont.)

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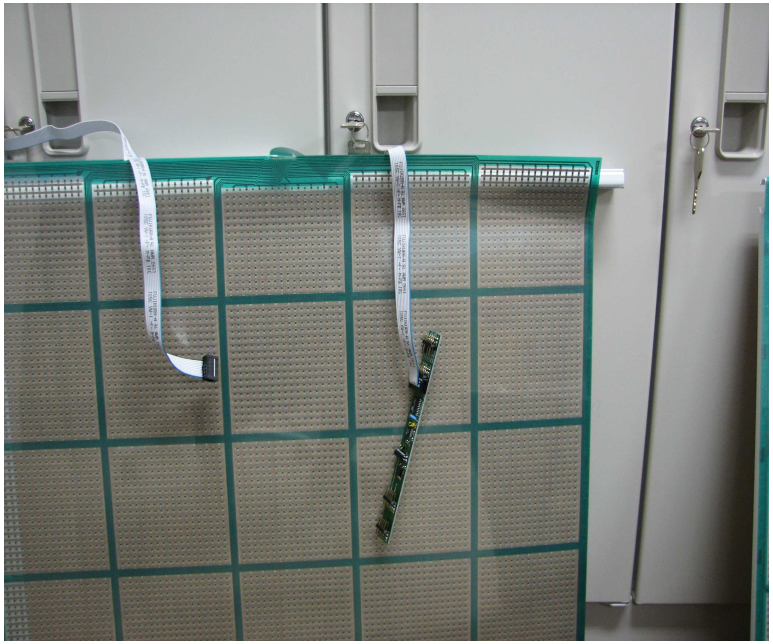
1. Initialization (N particles, M targets), $t = 0$:
for $i = 1$ to N **do**
  for $j = 1$ to M **do**
    Initialize particles $\mathbf{u}_0^{i,j} \sim p(\mathbf{u}_0^{i,j})$
    Initialize importance weights $w_i = 1/N$
  end for
end for
2. Sequential Bayesian Filtering
for $t = 1$ to $\ldots$ **do**
  2.1 Prediction Step
  for $i = 1$ to N **do**
    for $j = 1$ to M **do**
      Sample particles $\tilde{\mathbf{u}}_t^{i,j} \sim p(\mathbf{u}_t^{i,j} | \mathbf{u}_{t-1}^{i,j})$
    end for
  end for
  2.2 Target Entering/Leaving Detection (M targets, P candidates),
  2.3 GP-MRF -based Correction Step
  2.4 Output estimation
  for $j = 1$ to M **do**
    Estimate current state of each targets
    $E_j(g(\mathbf{u}_t^j)) = \sum_{k=1}^N w_k^i u_k^{i,j}$
  end for
  2.5 Resampling Step
  if $N_{eff} < threshold$ **then**
    Resample particles $\mathbf{u}_t^i$ from $\tilde{\mathbf{u}}_t^i$ according to the importance weights $\mathbf{w}_t^i$
    for $i = 1$ to N **do**
      Re-initialize weights $w_i = 1/N$
    end for
  else
    $\mathbf{u}_t \leftarrow \tilde{\mathbf{u}}_t$
  end if
end for

- GPJPF algorithm for a variable number of targets
- Entering sensor area (i.e., birth)
  $p(\mathbf{c}_t^i | \mathbf{x}_t) \approx \sum_{j=1}^n p(\mathbf{c}_t^i | \mathbf{x}_t^j)$
- Leaving sensor area (i.e., death)
  $p(\mathbf{x}_t | \mathbf{I}_t) \approx \sum_{i=1}^n p(\mathbf{x}_t^i | \mathbf{I}_t^i)$

GP-MRF -based Correction Step (M targets, N particles)
for $i = 1$ to N **do**
  for $j = 1$ to M **do**
    Calculate GP displacement $GP_\mu(\mathbf{u}_t^{i,j})$, $GP_\Sigma(\mathbf{u}_t^{i,j})$
    Correct estimate $\tilde{\mathbf{u}}_t^{i,j}$ using GP displacements
    Calculate likelihood score using GP
    Calculate interaction score using MRF
  end for
end for
for $i = 1$ to N **do**
  Evaluate importance weight w_t^i
end for
for $i = 1$ to N **do**
  Normalize weights $w_i = w_i / \sum_{k=1}^N w_k$
end for

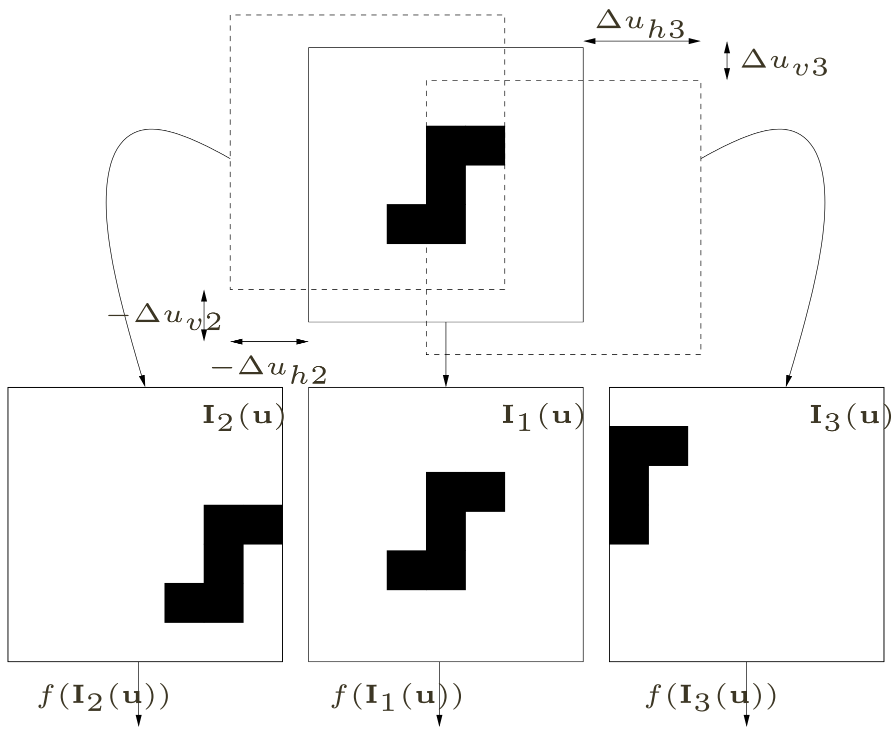
Floor Sensor Setting

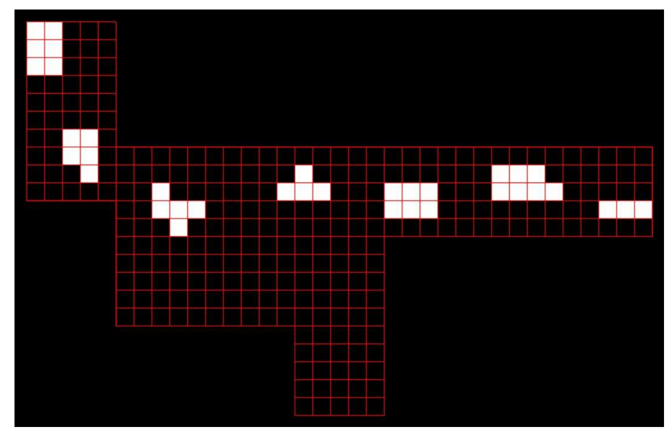


- “InfoFloor”
- Installed in Tokyo University of Agriculture and Technology
- 10cm x 10cm binary sensor tiles
- Each unit contains 25 tiles (size of 50cm x 50cm)
- Totally 300 binary switches
- Output sampling frequency 16Hz

Data Collection

- Dataset
  - 3 persons: 2 male and a female subjects wearing their own shoes
  - 70 walking sequence of different scenarios
- Training displacement expert
  - A single GP model trained with 50 displacement examples
  - Squared exponential kernel $k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp(-\frac{1}{2l^2}||\mathbf{x} - \mathbf{x}'||^2)$





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- Motion model
  - Stationary 1st-order Markov model

$$\mathbf{u}_t = \mathbf{F}\mathbf{u}_{t-1} + \epsilon$$

where

$$\mathbf{u}_t = [x_t \; y_t]^T, \mathbf{F} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\epsilon = [\epsilon_x, \epsilon_y]^T, \epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$$

- Measurement model

$$p(\mathbf{z}_t | \mathbf{u}_t) = \frac{1}{(2\pi)^{d/2}\sqrt{|GP_\Sigma|}} \exp[-\frac{1}{2}(GP_\mu^T GP_\Sigma^{-1} GP_\mu)]$$

Persons Tracking Experiments

- Tracking of 2 simultaneuosly walking persons
- Comparison of different PF-based algorithms
- Independent Particle Filter (IPF) [1], Gaussian Process Independent Particle Filter (GPIPF), Mixture Particle Filter (MPF) [2], Gaussian Process Mixture Particle Filter (GPMPF), Joint Particle Filter (JPF) [3], Gaussian Process Joint Particle Filter (GPJPF)

		Sequence failures (%)	Frame failures (%)			
Method	Samples	Total	Position	Identity	Number	Total
IPF [1]	50/target	57.14	15.18	6.00	7.18	16.58
GPIPF	25/target	52.86	13.65	5.10	6.92	15.28
MPF [2]	50/target	12.38	0.37	0.37	0.87	1.11
GPMPF	25/target	8.57	0.21	0.25	0.28	0.48
JPF [3]	100	9.05	**0.04**	**0.00**	0.47	0.51
GPJPF	50	**3.81**	0.09	**0.00**	**0.06**	**0.12**

- GP variants outperforms their counter parts and GPJPF performs best

[1] A. Doucet, N. de Freitas, and N. Gordon, Eds., *Sequential Monte Carlo Methods in Practice*, Springer Verlag, 2001.

[2] J. Vermaak, A. Doucet, and P. Pérez, "Maintaining multi-modality through mixture tracking," in *9th IEEE International Conference on Computer Vision (ICCV)*, 2003.

[3] Z. Khan, T. Balch, and F. Dellaert, "MCMC-based particle filtering for tracking a variable number of interacting targets," *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, vol. 27, pp. 1805–1918, 2005.

Persons Tracking Experiments (cont.)

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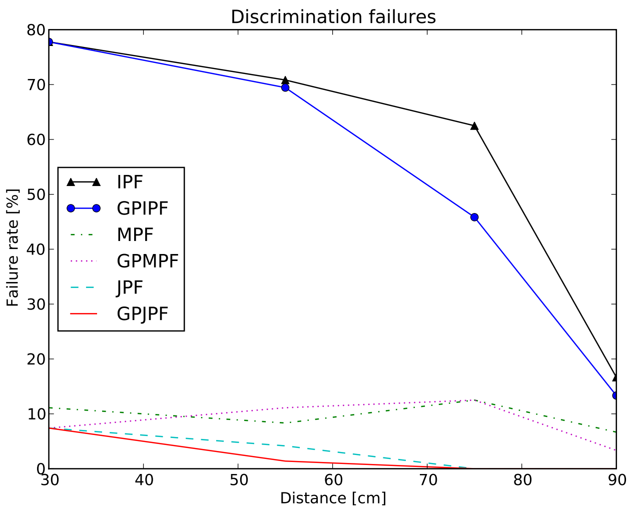
Discrimination accuracy

	Tracking failures (%)			
Method	30-55cm	55-75cm	75-90cm	90-120cm
IPF	77.8	70.8	62.5	16.7
GPIPF	77.8	69.4	45.8	13.3
MPF	11.1	8.3	12.5	6.7
GPMPF	7.4	11.1	12.5	3.3
JPF	**7.4**	4.2	**0.0**	**0.0**
GPJPF	**7.4**	**1.4**	**0.0**	**0.0**



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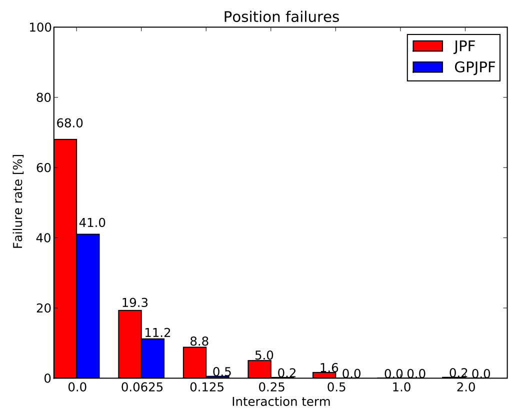
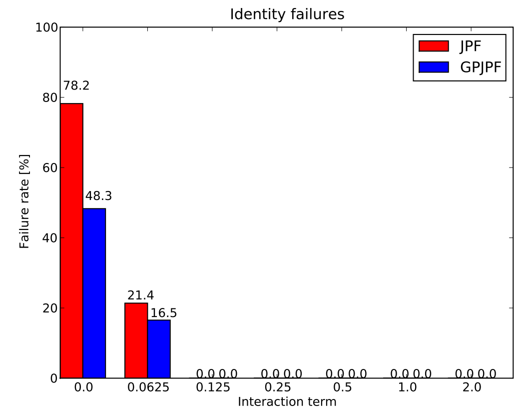
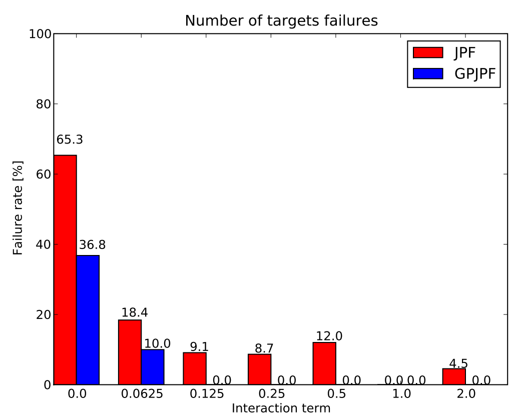
Influences of the MRF Model



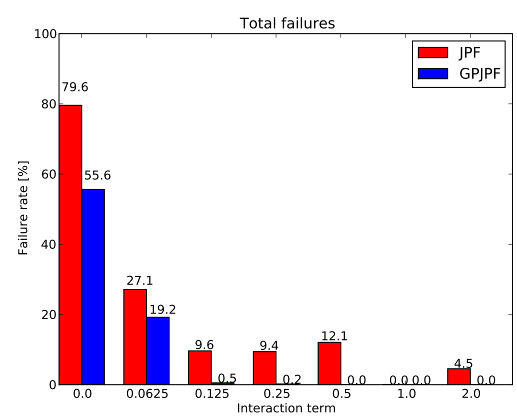
(a) Position failures.



(b) Identity failures.



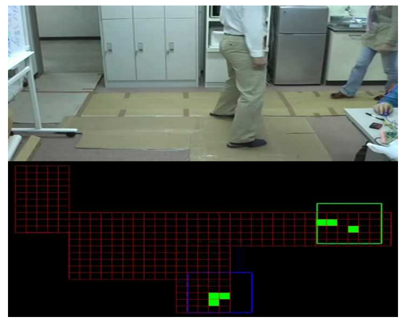
(c) Number of targets failures.



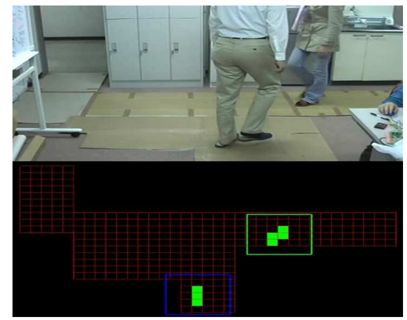
(d) Total failures.

Persons Tracking Experiments (cont.)

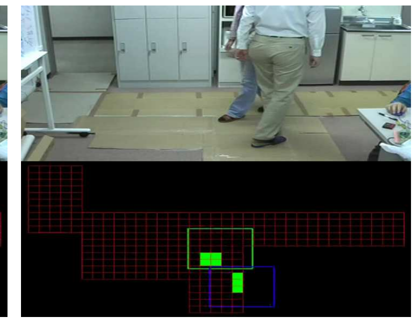
- Demonstration video



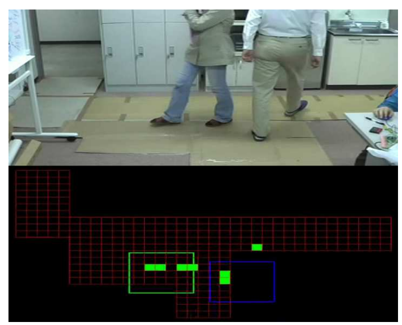
(a) Frame 385.



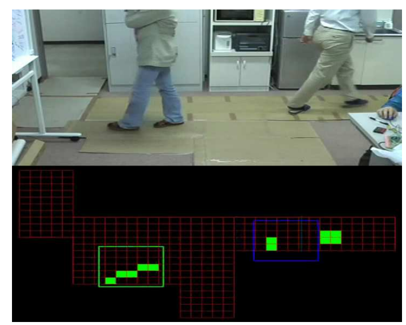
(b) Frame 410.



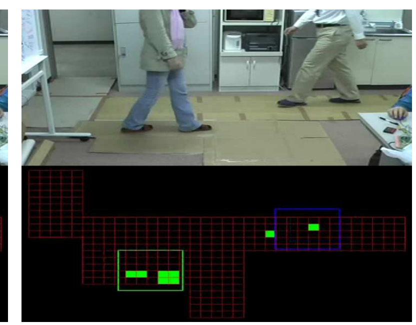
(c) Frame 434.



(d) Frame 445.



(e) Frame 462.



(f) Frame 522.

- Can be download from: `http://www.ee.oulu.fi/~jaska`

Conclusions and future work

- Conclusions
  - We have proposed an algorithm for multiple person tracking
  - A novel algorithm which combines GPR and JPF
  - Applied to sensor floor based position tracking
  - Interesting approach to ubiquitous and context-aware computing

Thank You!