Automation of Pedestrian Tracking in a Crowded Situation

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Counting vs. Tracking

Counting

- Available only at selected point in the infrastructure
- People count is only a small fraction of the information contained in trajectory data sets

Tracking

- Trajectory = movement of pedestrians across the infrastructure over time
- offer much richer information for systematically comparing infrastructures

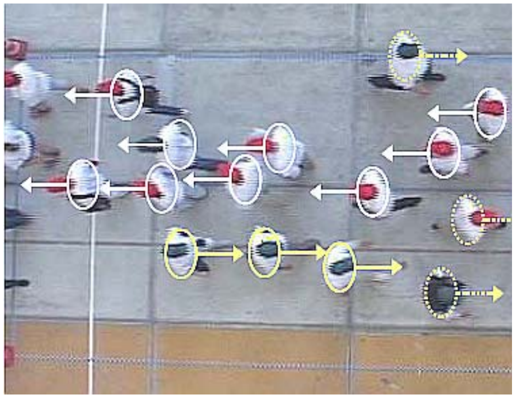
Tracking Applications

- Comparison of different configurations of infrastructures
- Calibration and validation of pedestrian simulations
- Anomaly detection (detect significant deviations from the typical situations)

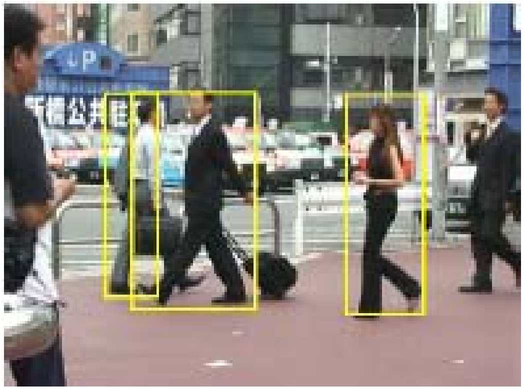
The need of automated tracking

- Microscopic pedestrian field requires large amount of trajectory data of individual pedestrian.
- Manual data collection: needs tremendous efforts and very time consuming.

Literatures on Detection/Tracking



Hoogendoorn & Daamen (2003)
Top view tracking



Leibe et al, Ober (2007)
Side view, detection only
(feet movement)

Kelly et al (2007)
Crowded, detection only,
stereo camera (disparity map)

- Most of the pedestrian detection & tracking techniques work with a few number of people or top view or side view.

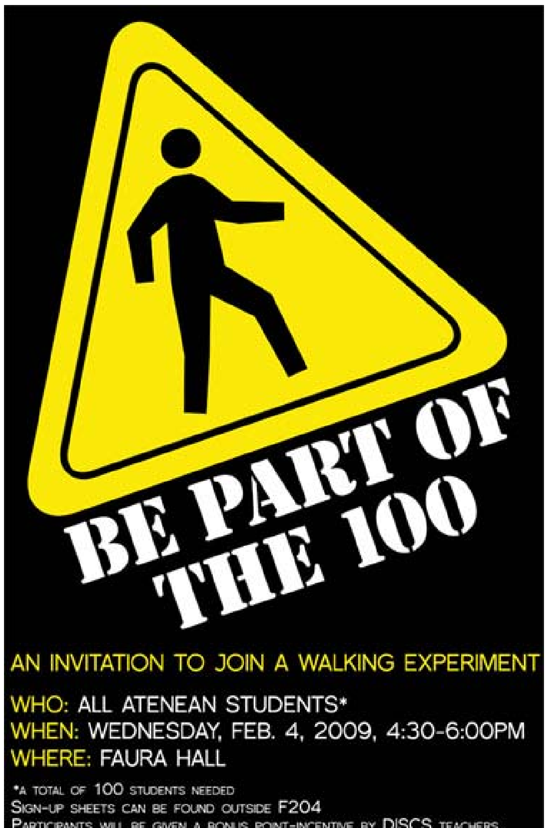
Problems in Multi-objects Tracking

- Occlusions: an object closer to the viewer masks or occludes an object further away from the viewer.

- Clutter: existence of noise and shadow interfere with the scene in a disorderly way

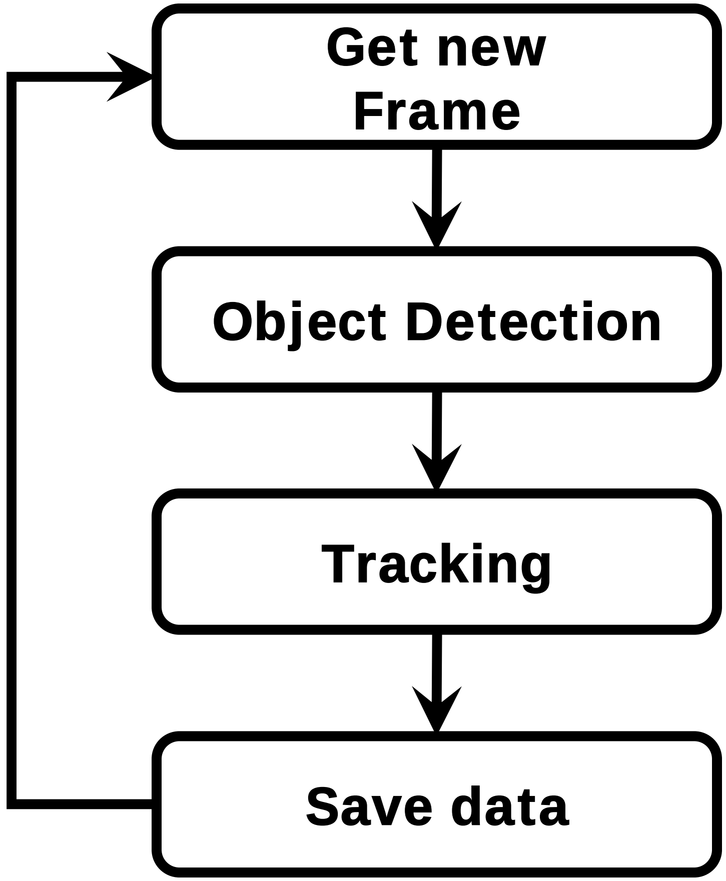
Motivation, Problem & Objective

Tracking pedestrian crowd under occlusions from an angular scene using a single camera



Walking Experiments

Flow chart



Detection

- Without prior information:
  - Create background image
  - Background substraction

- With prior information:
  - Pedestrians are wearing red hat
  - Color detection

Detection without prior information

- Background Image (Gaussian distribution)

$$\mu_t = \frac{t-1}{t}\mu_{t-1} + \frac{I_t}{t}$$

$$\sigma_t^2 = \alpha\sigma_{t-1}^2 + (1-\alpha)(I_t - \mu_t)^2$$

$$B_t = \mu_t + \eta\sigma_t$$

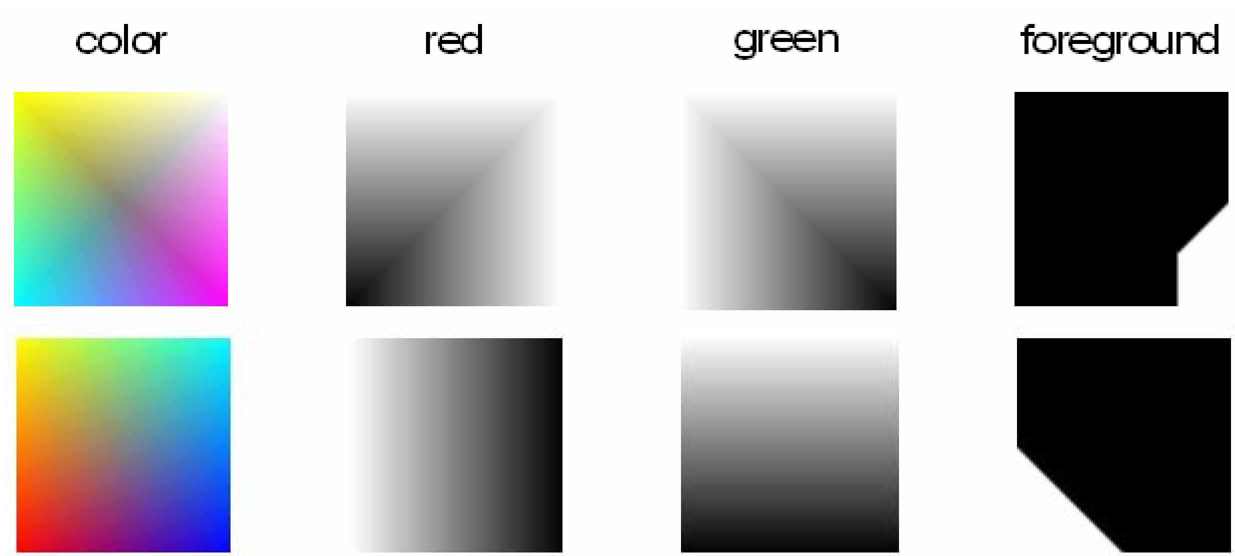
- Foreground from Background Substraction

$$F_t = (I_t - B_t) > \phi$$

Detection with prior information

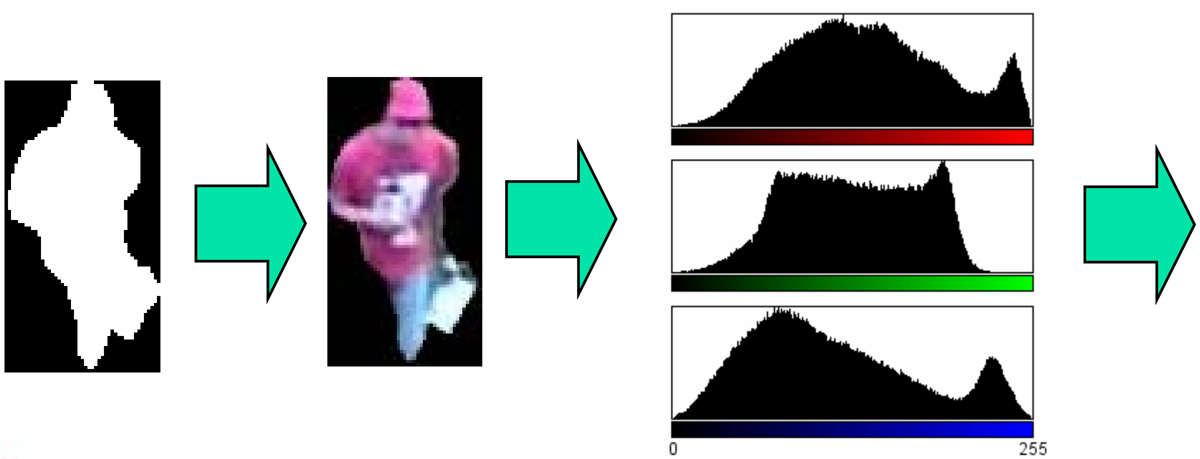
- No background modeling
- Red – (Green – Blue) channels ➔ preserve only red information

$$F_t = \left(r_t - g_t\right) > \phi$$



Pre & Post Processing

- Morphological image operations (dilate, open and close)
- Blobs ➔ features (centroid, histogram, area) ➔ derived features (entropy, distance, speed, angle)



490.500	496.500	490.500	496.500	2.82
102.864	500.136	102.864	500.136	18.97
379.500	500	379.500	500	7.65
458.786	504.071	458.786	504.071	11.65
388.250	504.250	388.250	504.250	7.65
110.250	505.500	110.250	505.500	7.07
142.300	506.300	142.300	506.300	9.07
471.700	505.800	471.700	505.800	11.07
123.500	506.500	123.500	506.500	2.82
116.500	507.500	116.500	507.500	2.82
378.500	508	378.500	508	4.24

Pedestrian Tracking

1. Features from color blobs
2. Finding possibility Matrix
3. Probability Tree
4. Tracking the blobs

Features from color blobs

- Distance

$$d_{ij} = \sqrt{\| \overline{X_{i,l}X_{j,h}} \|}$$

- Entropy Difference (sum of all colors)

$$E_c = -\sum \frac{H_c}{A_c} * \log\left(\frac{H_c}{A_c}\right) \Rightarrow \Delta E = \left| E_h - E_l \right|$$

- Movement Angle

$$\theta = w_1\left(1 - \frac{\overline{X_{i,t-2}X_{j,t-1}X_{j,t-1}X_{k,t}}}{\| \overline{X_{i,t-2}X_{j,t-1}} \| \| \overline{X_{j,t-1}X_{k,t}} \|}\right)$$

Chetverikov and Verestoy (1998)

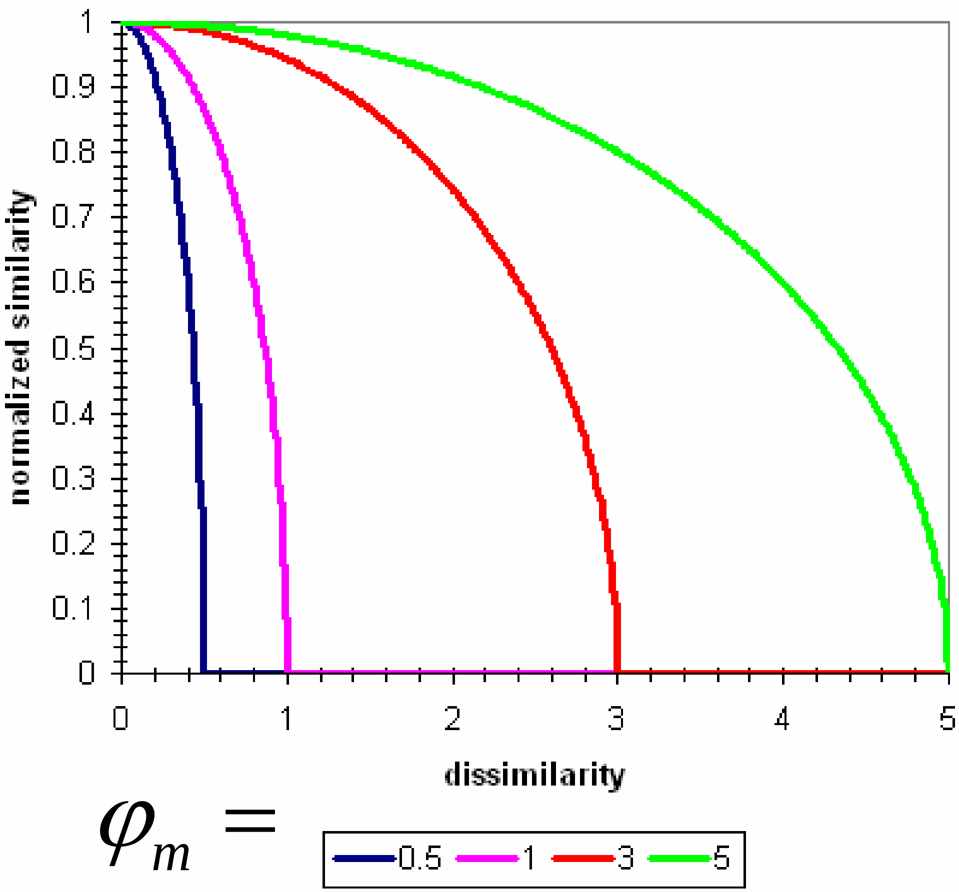
- Speed Difference

$$\Delta v = w_2\left(1 - 2\frac{\sqrt{\| \overline{X_{i,t-2}X_{j,t-1}} \| \| \overline{X_{j,t-1}X_{k,t}} \|}}{\| \overline{X_{i,t-2}X_{j,t-1}} \| + \| \overline{X_{j,t-1}X_{k,t}} \|}\right)$$

Normalization of features

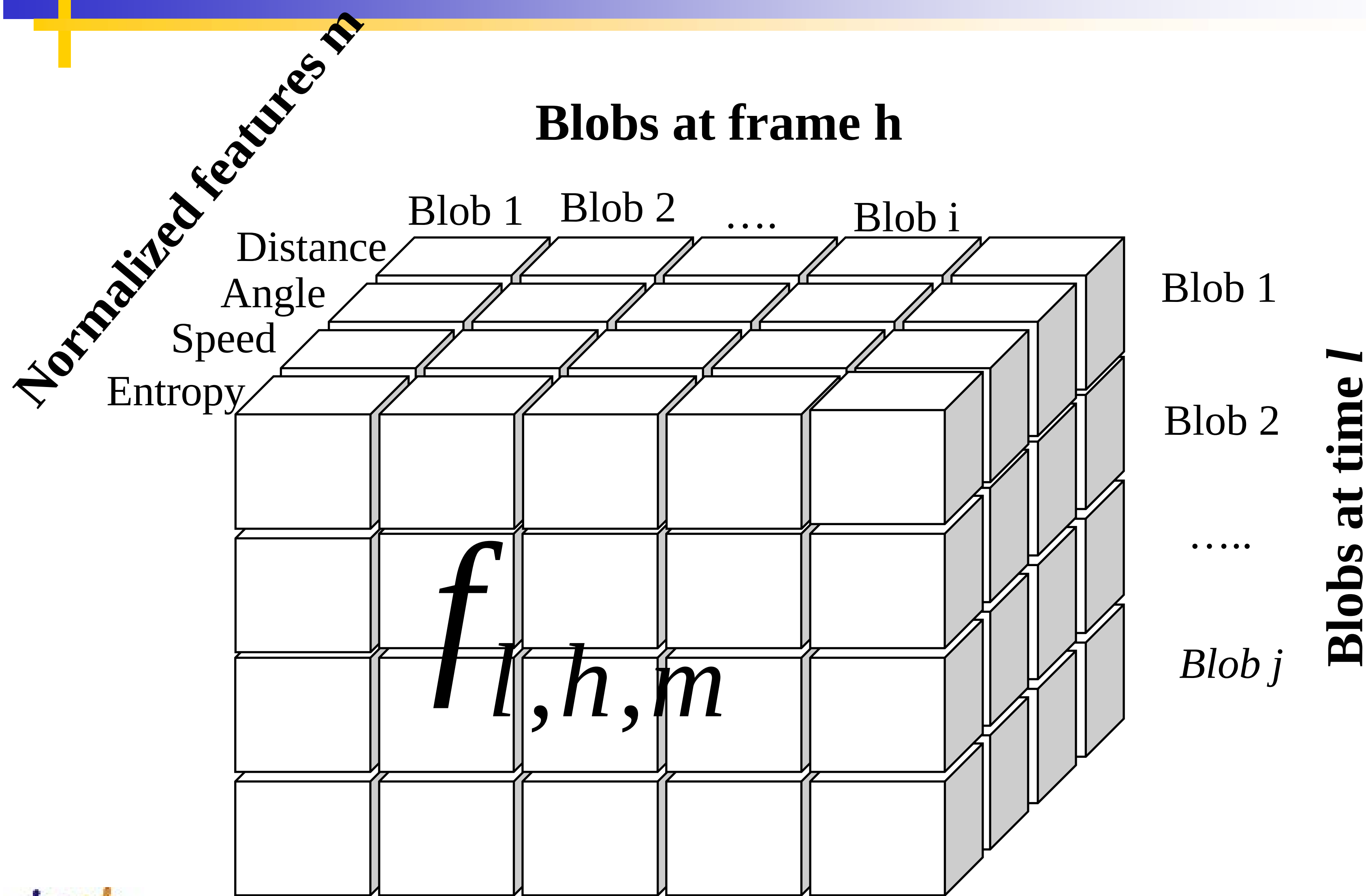
- Feature Normalization (dissimilarity ➔ similarity)

$$f_{l,h,m} = \sqrt{1-(\delta_{l,h,m}/\varphi_m)^2}$$



$\varphi_m =$

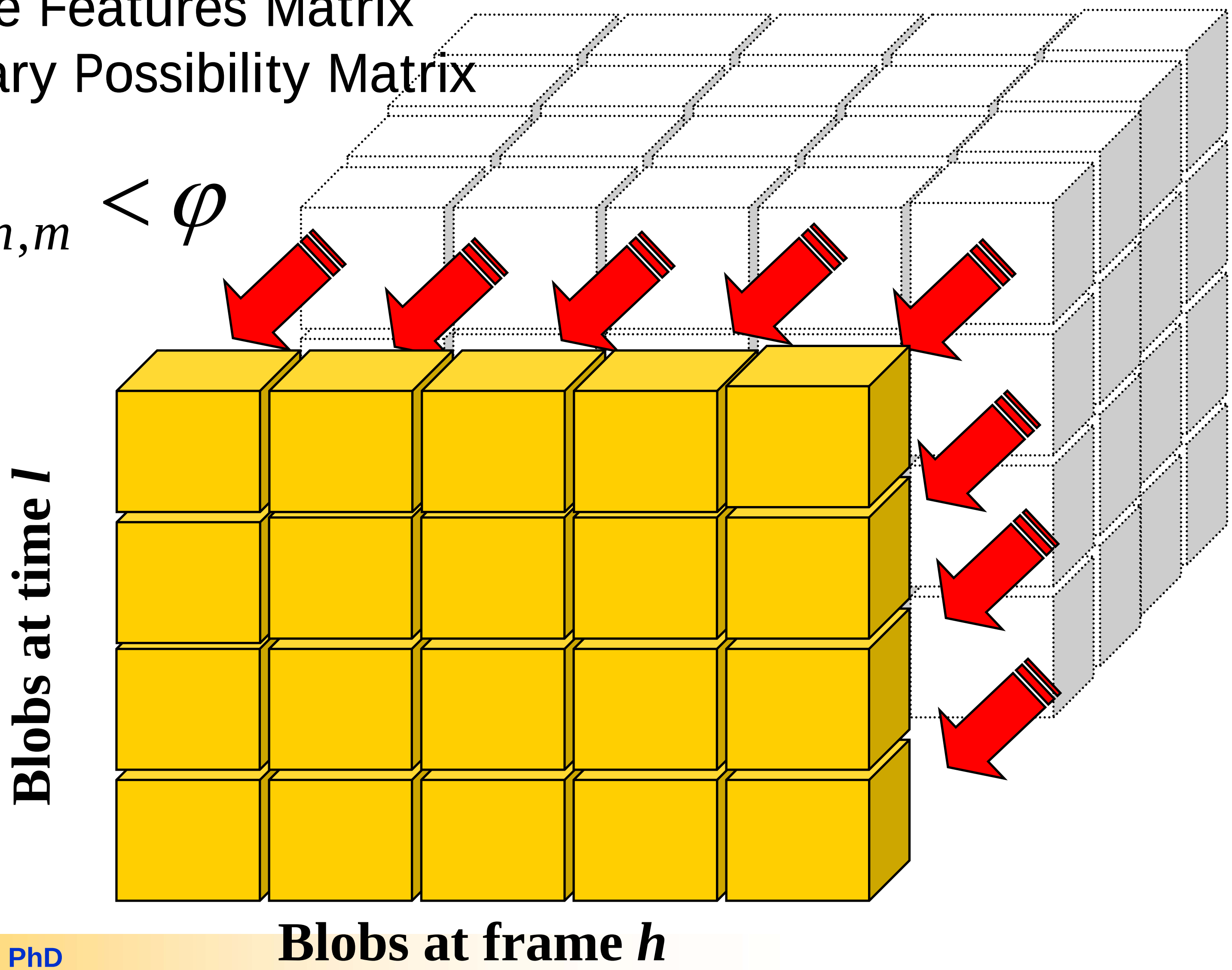
Multidimensional Features Matrix



Possibility Matrix

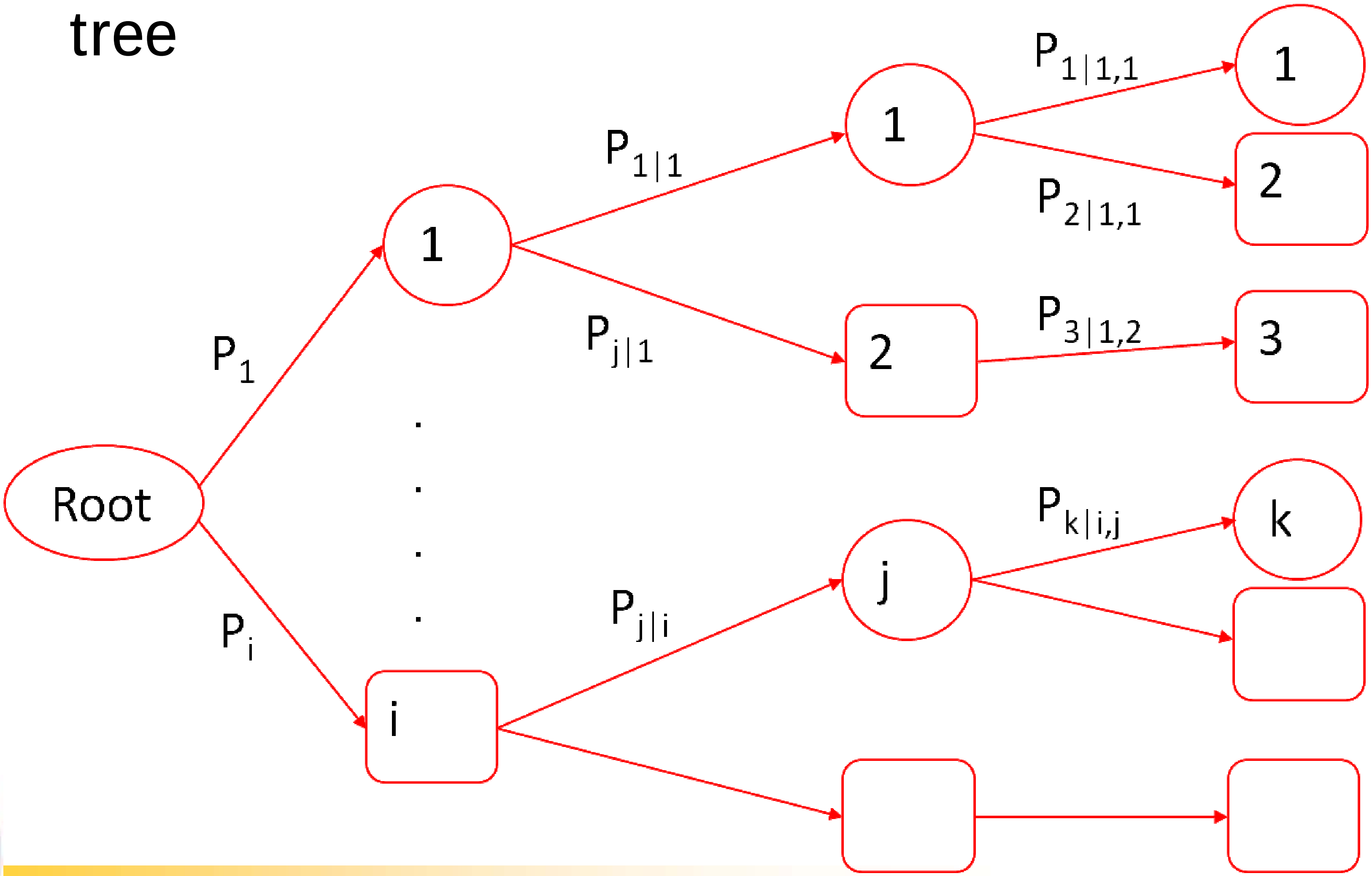
- Flatten the Features Matrix
- Make Binary Possibility Matrix

$$\sum_m \omega_m f_{l,h,m} < \varphi$$



Probability Tree

- Possibility matrix ➔ Structure of Probability tree



Calculate Bayesian probability

- Conditional probabilities

$$P_{k|i,j} = \frac{\sum_m \omega_m f_{j,k,m}}{\sum_j \sum_k \sum_m \omega_m f_{j,k,m}}$$

- Prior Probabilities

$$P_{i|j} = \frac{\sum_m \omega_m f_{i,j,m}}{\sum_i \sum_j \sum_m \omega_m f_{i,j,m}}$$

$$P_{i|j,k} = \frac{P_{j|i} P_{k|i,j} P_i}{\sum_i \sum_j \sum_k P_{j|i} P_{k|i,j} P_i}$$

- Update the posterior

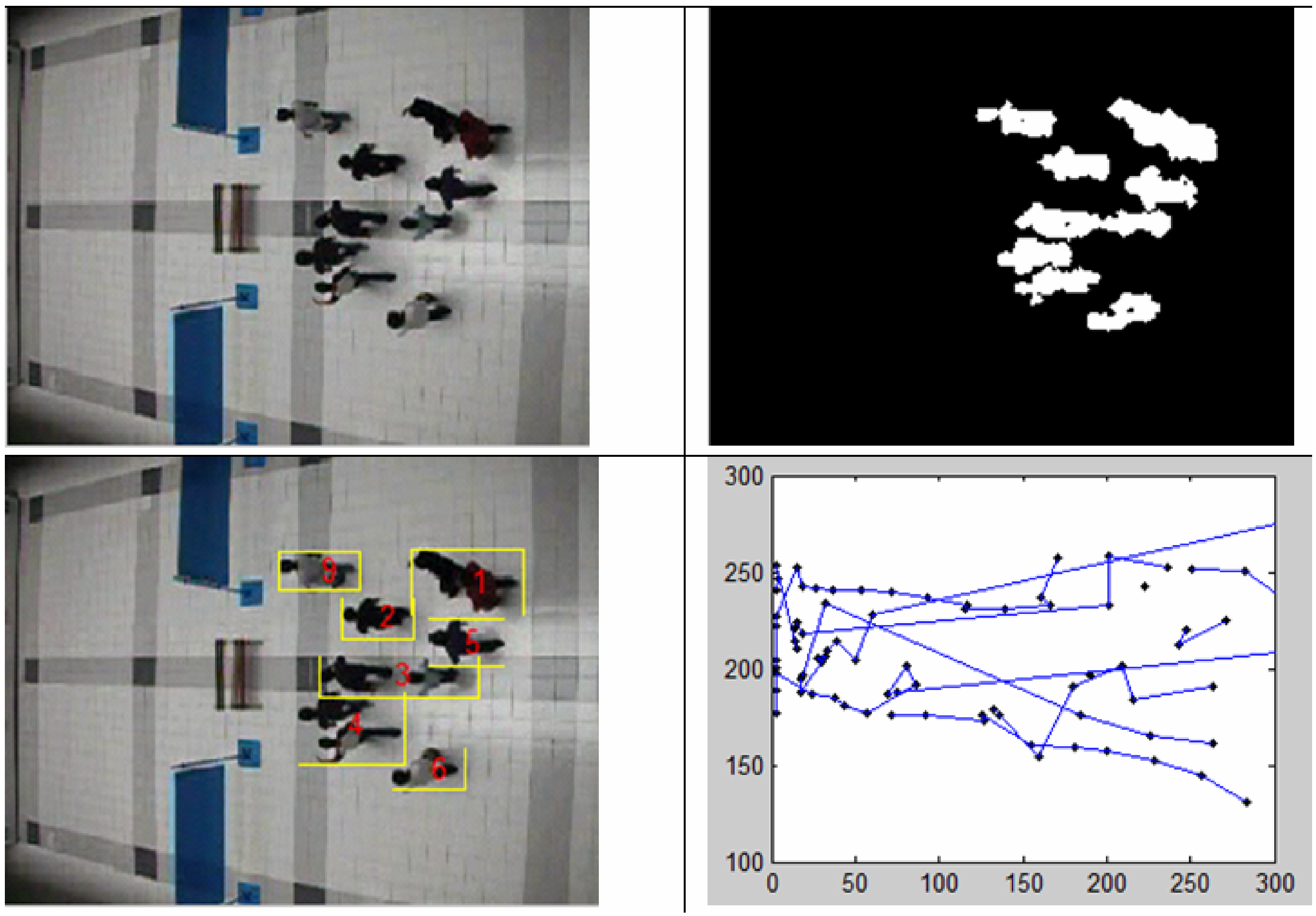
$$P_i \leftarrow P_j = \sum_i P_{j|i}$$

Track blobs

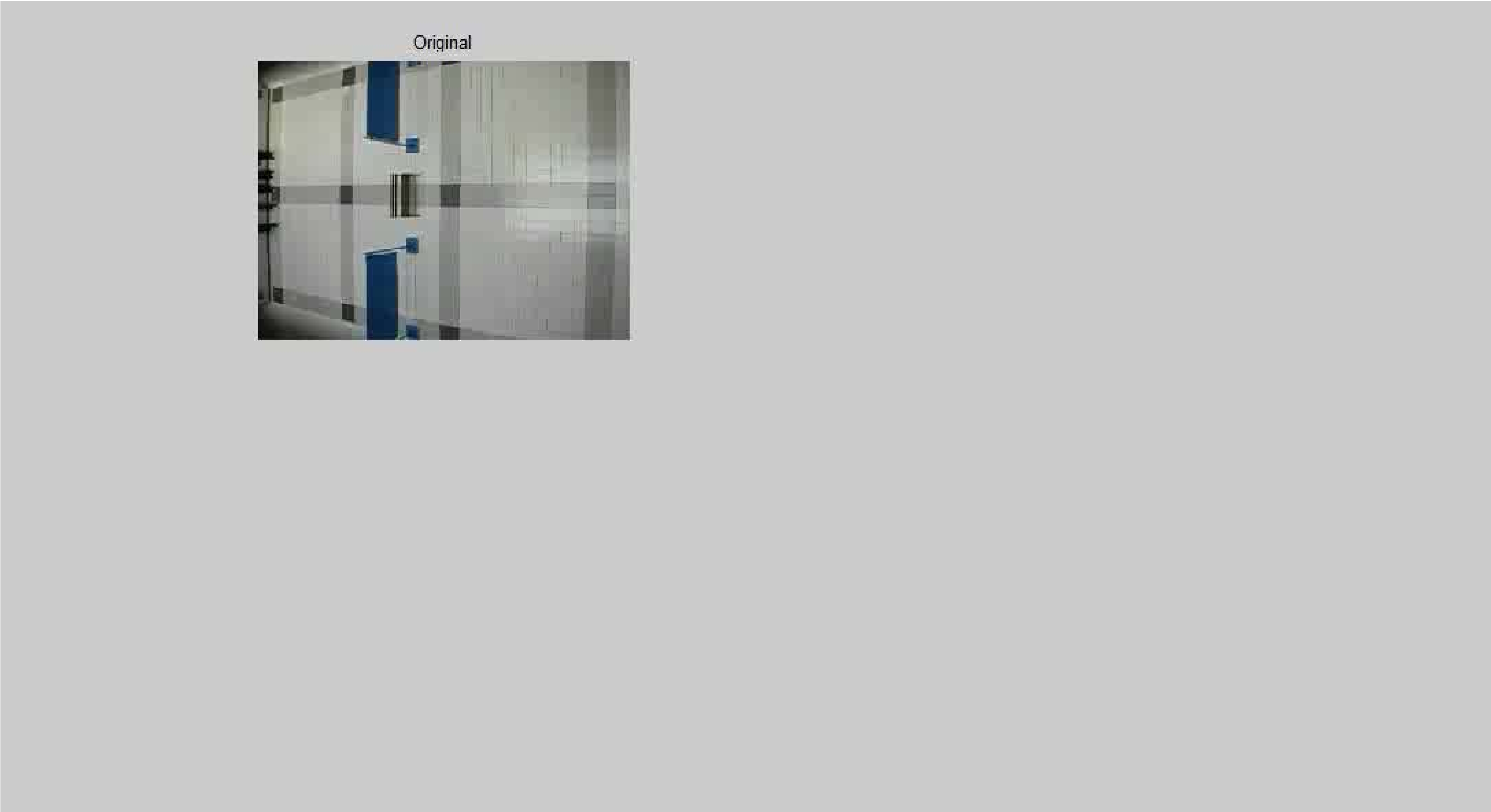
- First we find the maximum posterior probability in possibility matrix.
- Once we found match blob, then we make the row and the column of the matched blob into to zero. The procedure is repeated until the possibility matrix becomes a zero matrix.

Results:

- Tracking without prior information



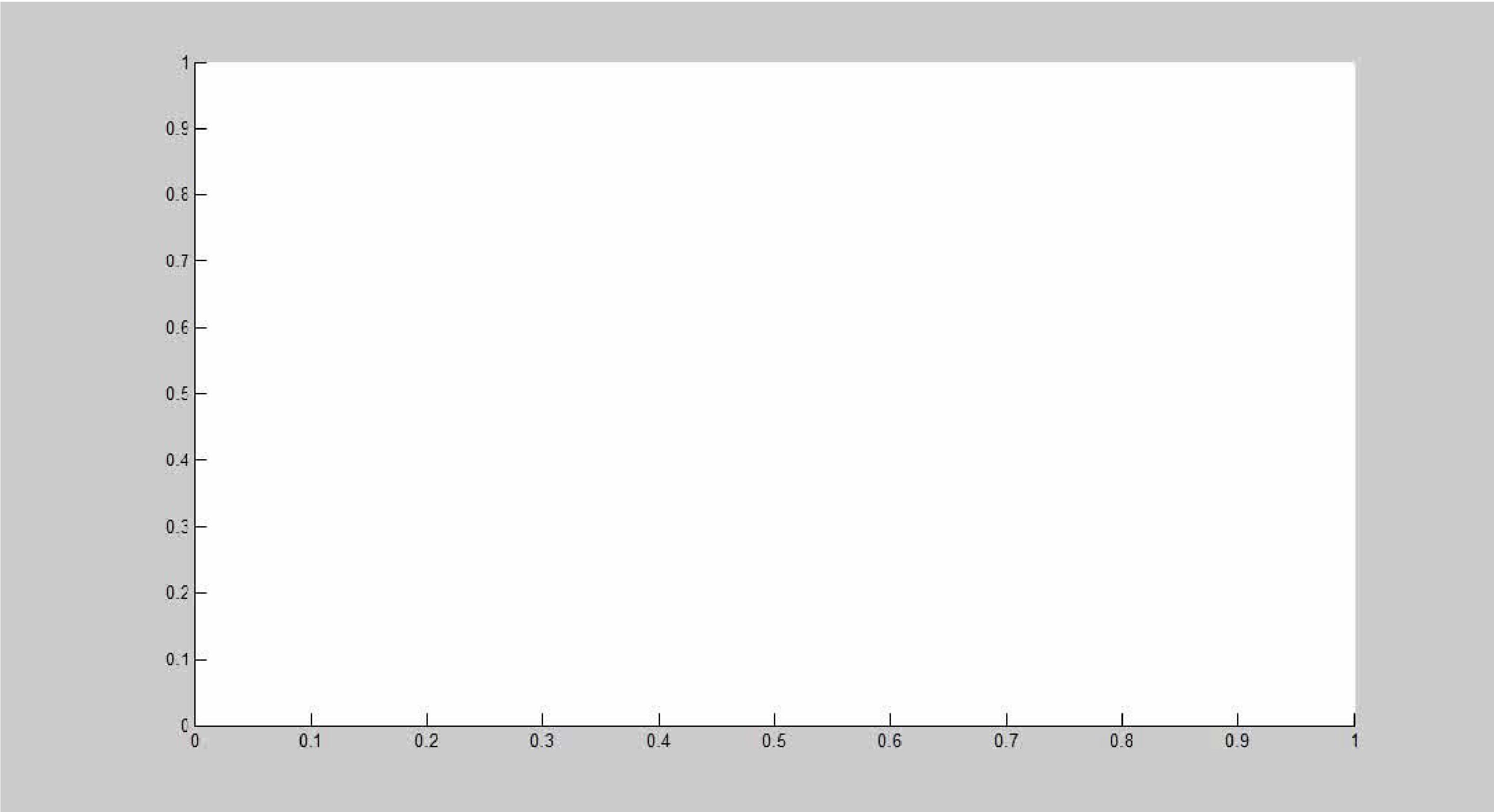
Videos



Results

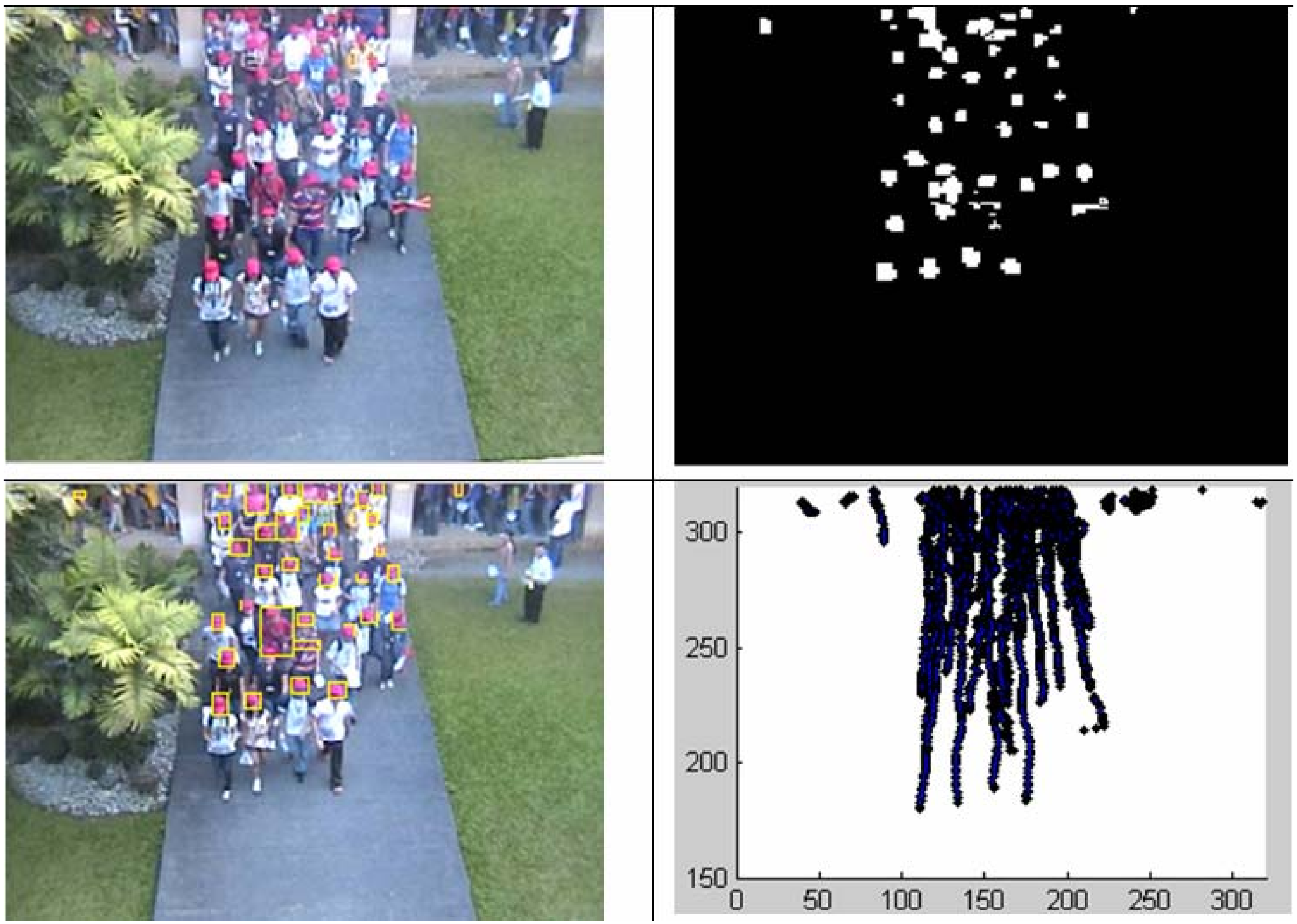
Original

Results

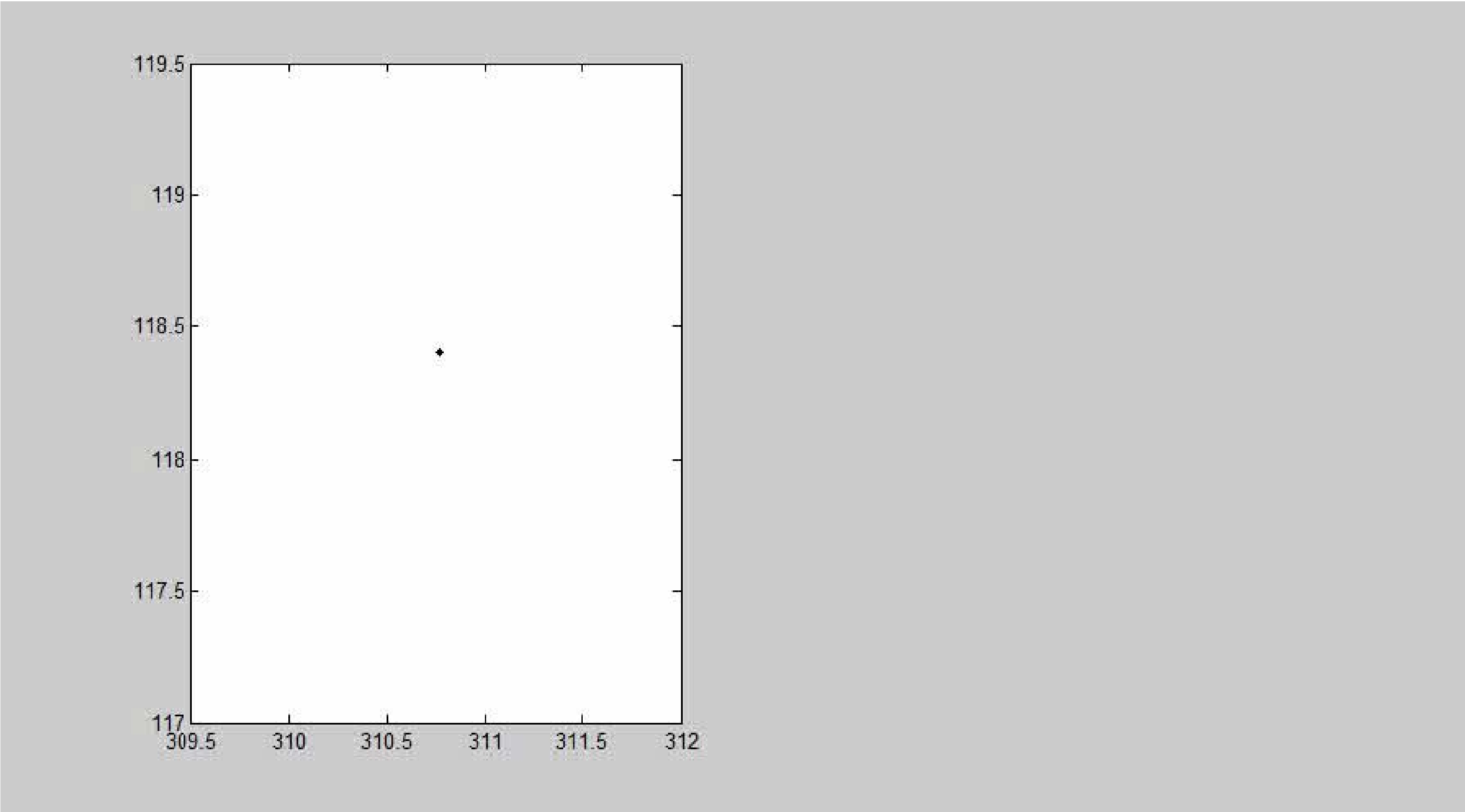


Results:

- Tracking with prior information



Results



Compared to ground truth data

Accuracy over time	Without prior information	With prior information
Normal scene	83%	Not applicable
Crowded scene	40%	94%

Our algorithm was able to find lost pedestrian even after 10 frames of occlusion

Conclusion

- Comparing two option of detections
- New algorithm to calculate the probability of tracking system using Bayesian Update in a probability tree