

Multiple Object Tracking Using Local PCA

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Motivation

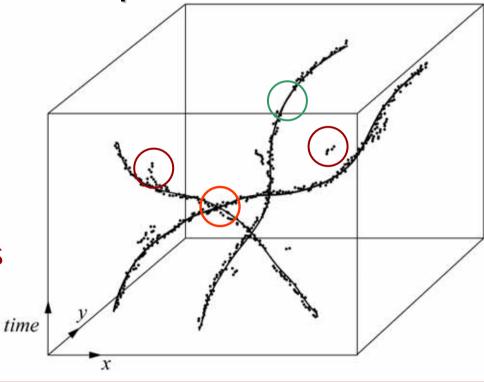
Task: tracking multiple objects in the space of observations

$$\mathbf{X}_i = {\{\mathbf{x}, t\}, 1 \le i \le N}$$

Desired output: consistent motion path

Complexity of tracking task:

- interacting objects
- missing observations
- clutter, noisy observations



Contents

- Introduction, related research
- Input data
- Trajectory segments by local PCA
- Trajectory segment linking
- Results and evaluation
- Conclusion

Related research

- JPDAF Tracker (Bar-Shalom1987)
 - Single stage approximation using fixed number of targets
 - Can not recover from failure

Data association following "deferred logic"

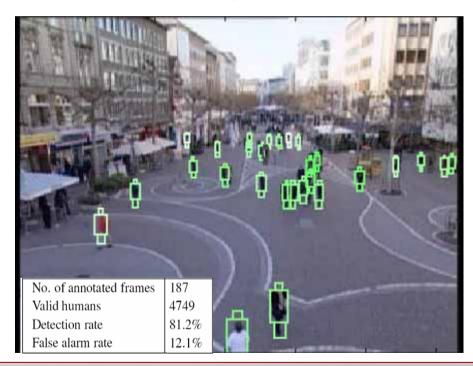
- Multiple Hypothesis Tracker (Reid1979)
 - Heuristics to overcome computational complexity: pruning, gating, N-scan back, k-best hypotheses
- Monte Carlo methods (Vermaak et. al 2003)
 - Promising performance in challenging scenarios

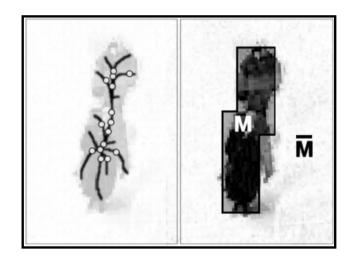


Input data: Motion-based human detection

■ Fast clustering of the difference image

- Mean Shift procedure using integral images.
- Model-based validation of hypothesized configurations:
 - Removing spurious detections
 - Occlusion handling





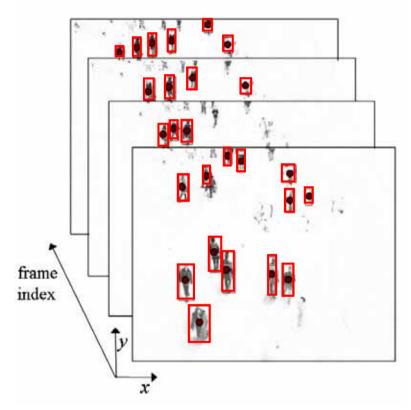
C. Beleznai, B. Frühstück and H. Bischof, "Tracking Multiple Humans using Fast Mean Shift Mode Seeking", PETS 2005 Workshop

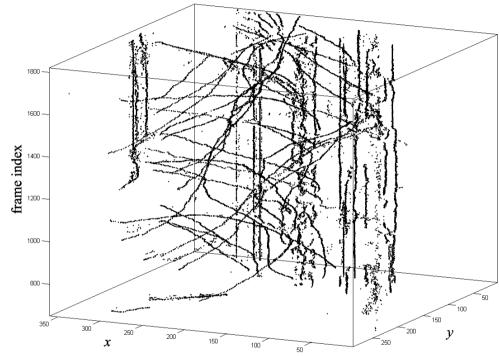
Related background I research

Detecting objects (humans) by difference image clustering

(C. Beleznai et al., ICIP 2004)

Spatio-temporal data points (observations)





Prior information:

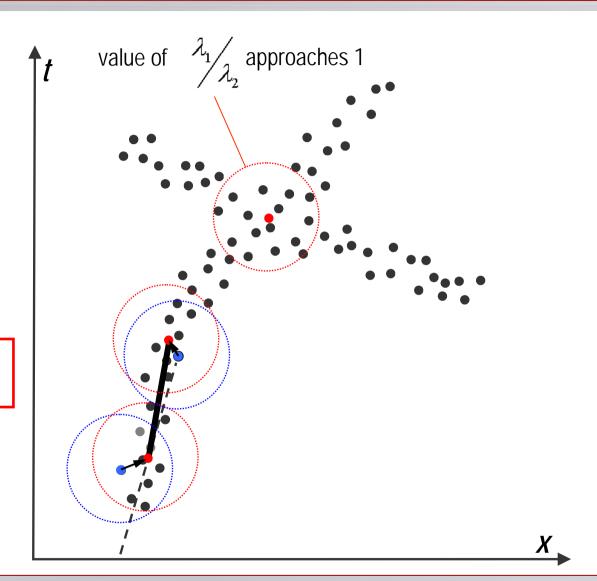
- object size model *H(x)*

- Motion of real-world objects is subjected to kinematic constraints
- Consequence: Observations at consecutive time instances are strongly correlated.



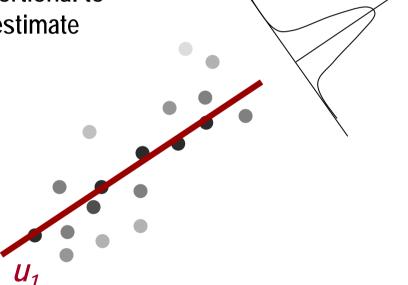
Tracking by local PCA

- (1) Selecting an initial point
- (2) Mean shift iterations to nearby mode
- (3) LPCA within the analysis window
- (4) Repeating from Step (2)
- (5) Computing local anisotropy measure
- (6) Stopping if:
 - no more data available
 - distribution shows no anisotropy



Motion model

- The first eigenvector u_1 can be interpreted as a velocity estimate
 - Simple update: $\mathbf{v}(t + \Delta) = \alpha_s \cdot \mathbf{v}(t) + (1 \alpha_s) \cdot \mathbf{u}_1$
 - Computing data weights inversely proportional to the distance between data and motion estimate
 - Applying weighted local PCA



Trajectory segment linking

K generated trajectory segments

$$\{T_i\}_{i=1..K}$$

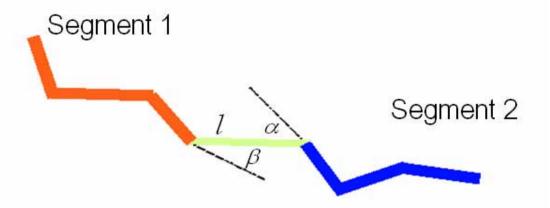
Constraints:

- temporal ordering
- spatio-temporal smoothness

$$C(L) = \frac{l(L)}{H(\mathbf{x}_c)} + \delta S(L)$$

l(L) – length of a link

S(L) – sum of angles: $(\alpha+\beta)$ / π

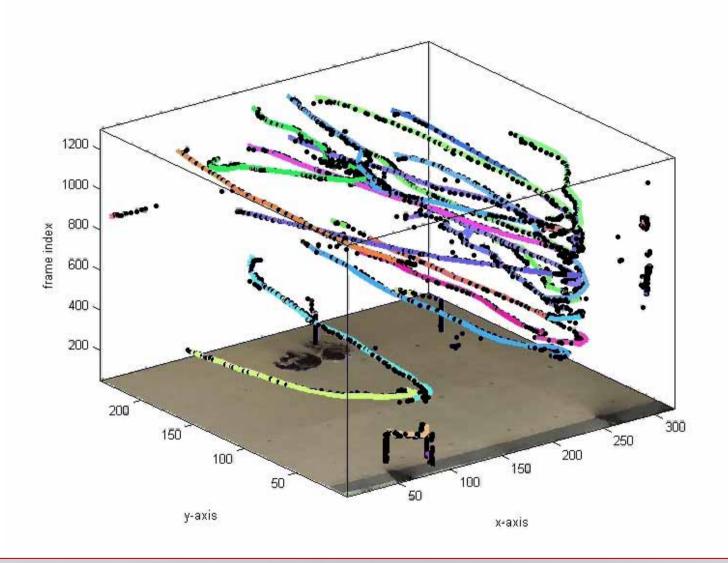


Greedy strategy to incrementally link segments (stopping criterion)

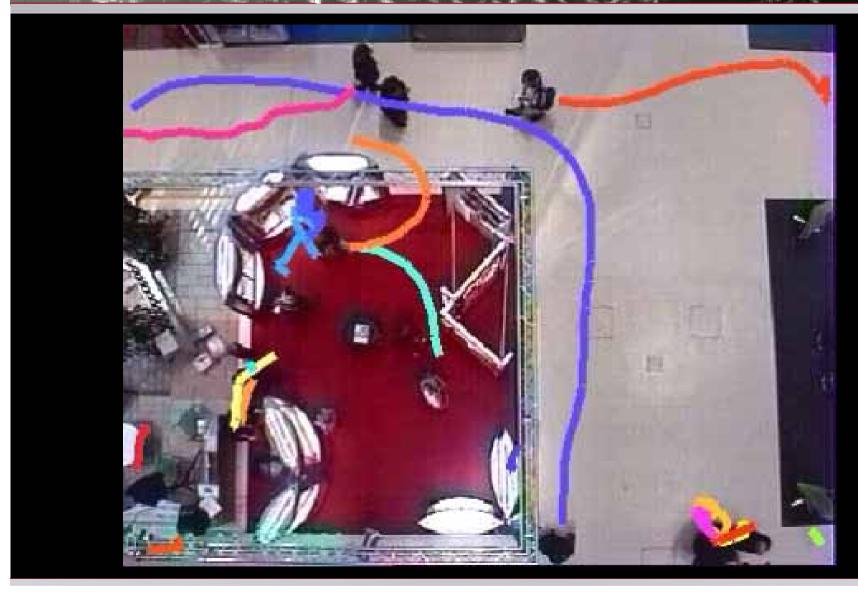
Results – Sequence 1



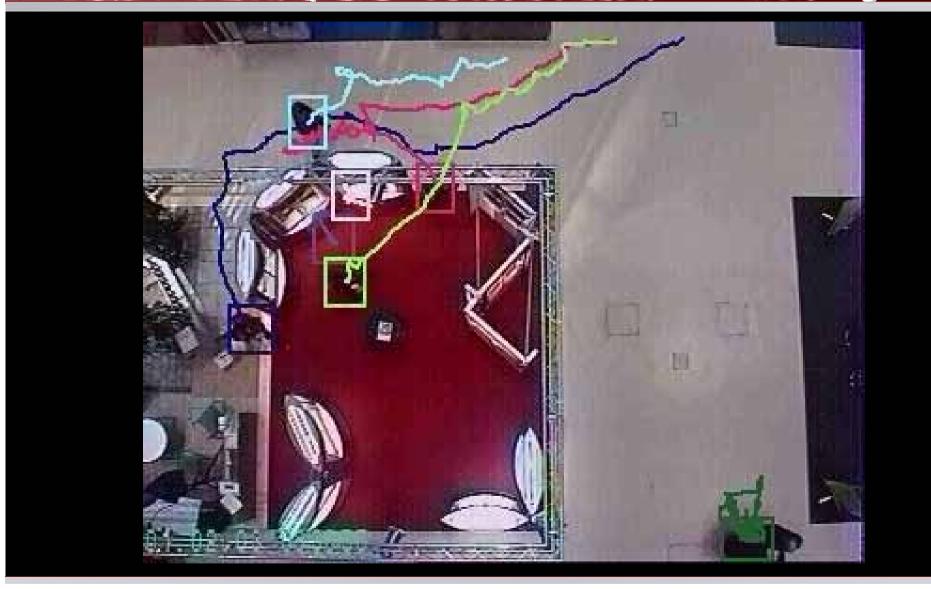
Results - Sequence 1



Results - Sequence 2



Results - Sequence 2 - frame-to-frame tracking

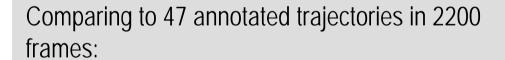


Results – Evaluation of tracking performance

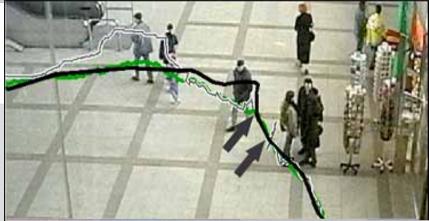
Norm. spatial deviation between ground truth and measurement: $D(j) = \frac{\left|\mathbf{x}_{j}^{m} - \mathbf{x}_{j}^{0}\right|}{H(\mathbf{x}_{j}^{0})}$

Comparing to 42 annotated trajectories in 1013 frames:

Tracking method	# of detected trajectories	Avg. norm. dev.
LPCA	62	0.19
Frame-to-frame	93	0.3



Tracking method	# of detected trajectories	Avg. norm. dev.
LPCA	89	0.11
Frame-to-frame	129	0.18





Conclusions

- A simple and novel tracking approach.
- Two passes:
 - (1) LPCA-based trajectory segment generation,
 - (2) Trajectory segment linking.
- Tracker produces stable results at a low computational demand.
- Possible improvements:
 - (1) combining forward and backward tracking,
 - (2) hierarchical grouping of local trajectory estimates,
 - (3) embedding complementary tracking mechanisms

