A resource allocation framework for adaptive selection of point matching strategies for visual tracking

ISPS – 7th of May 2013

Quentin De Neyer – UCL/ICTEAM

Outline of the presentation

- Active tracking with PTZ cameras
- Target registration with point matching
- Aggregation of observations for motion estimation
- Selection of points for matching
- Cost-reliability framework
- Discussion

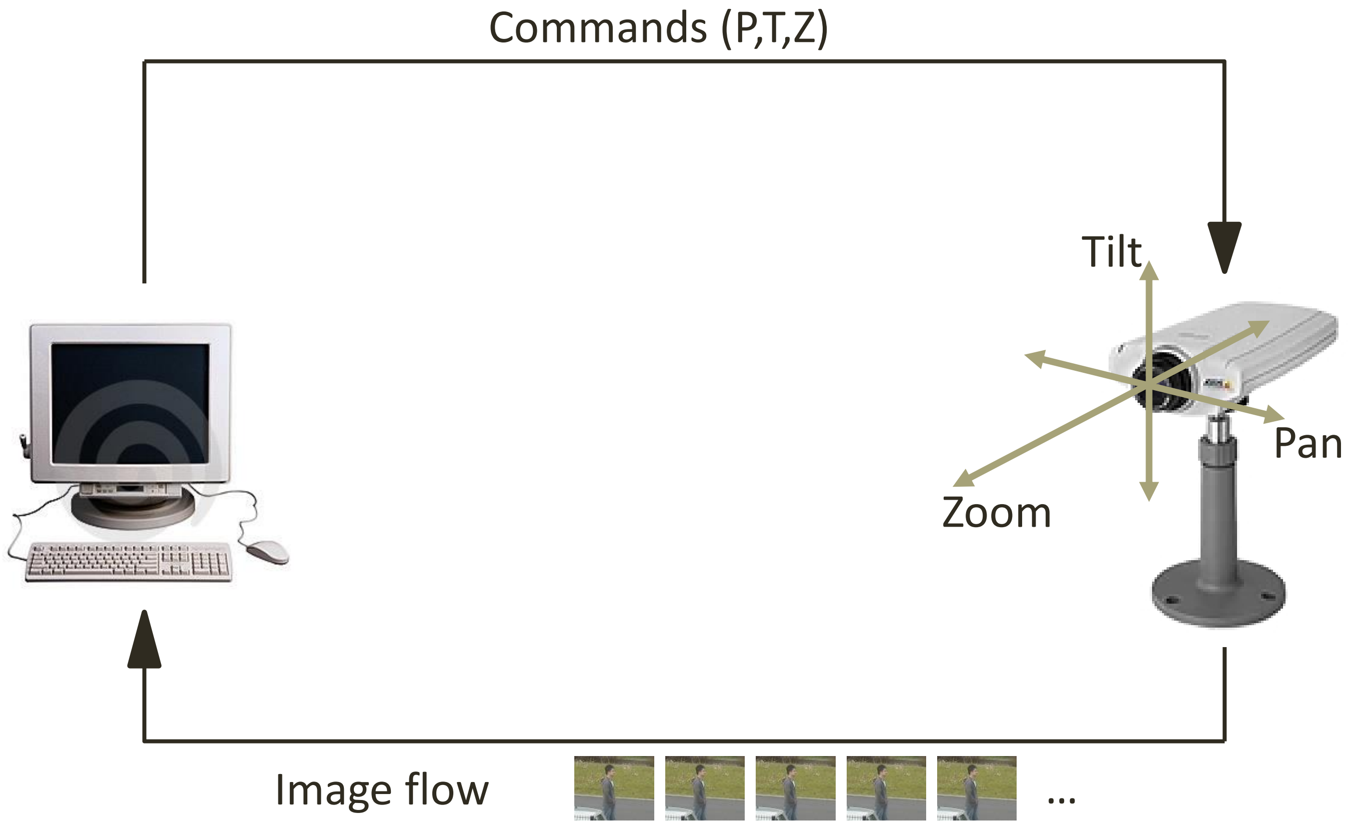
Visual tracking applications

- Active tracking useful for:

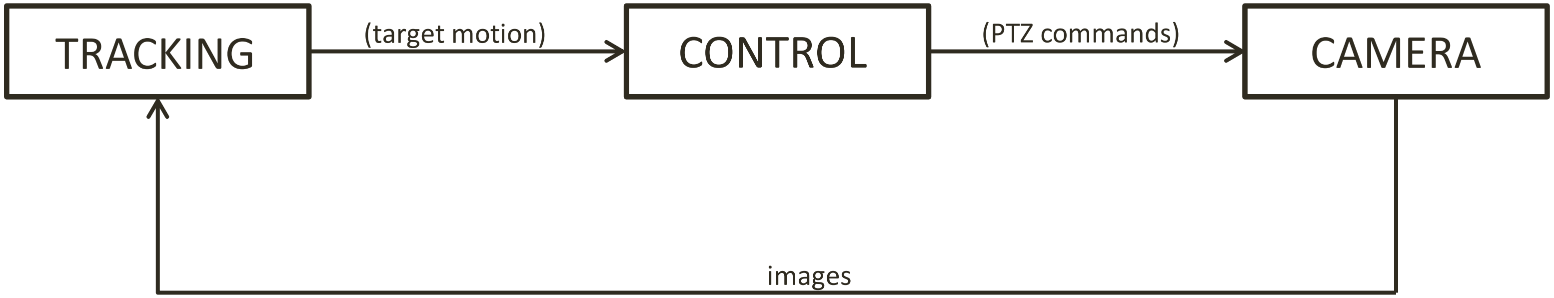
video surveillance

automatic production

Control of a Pan Tilt Zoom (PTZ) camera

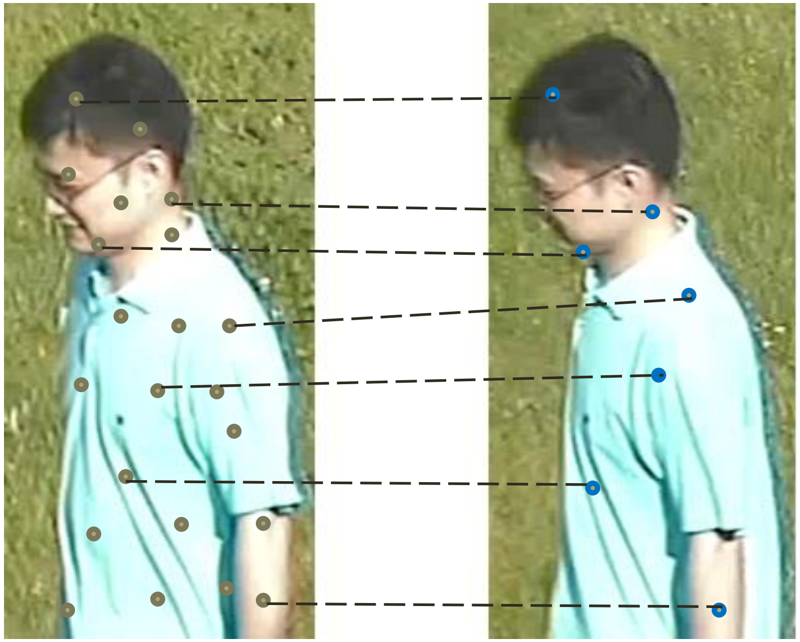


Control of a Pan Tilt Zoom (PTZ) camera



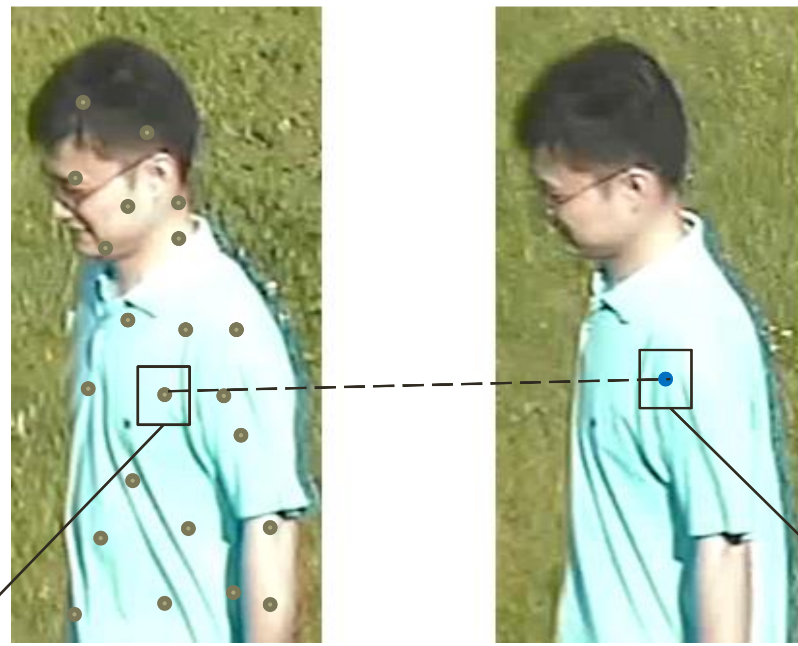
Point matching for target registration

- Challenge: Find displacement d of a target between two frames
- Technique:
  - model target with set of points
  - match points to find d



Matching metric

- Comparison of two points using **matching metric**:
  - Point descriptor (e.g. patch of pixel luminance)
  - Distance metric (e.g. SoAD)



$v_{ref} = (x_0, x_1, \ldots, x_n) \longrightarrow dist(x,y) = \sum_{i=0}^{n} |x_i - y_i| \longleftarrow v_{candidate} = (y_0, y_1, \ldots, y_n)$

Matching metric and distance map

- Comparison of two points -> similarity measure
- Matching reference point in search window -> distance map

Aggregation of distance maps

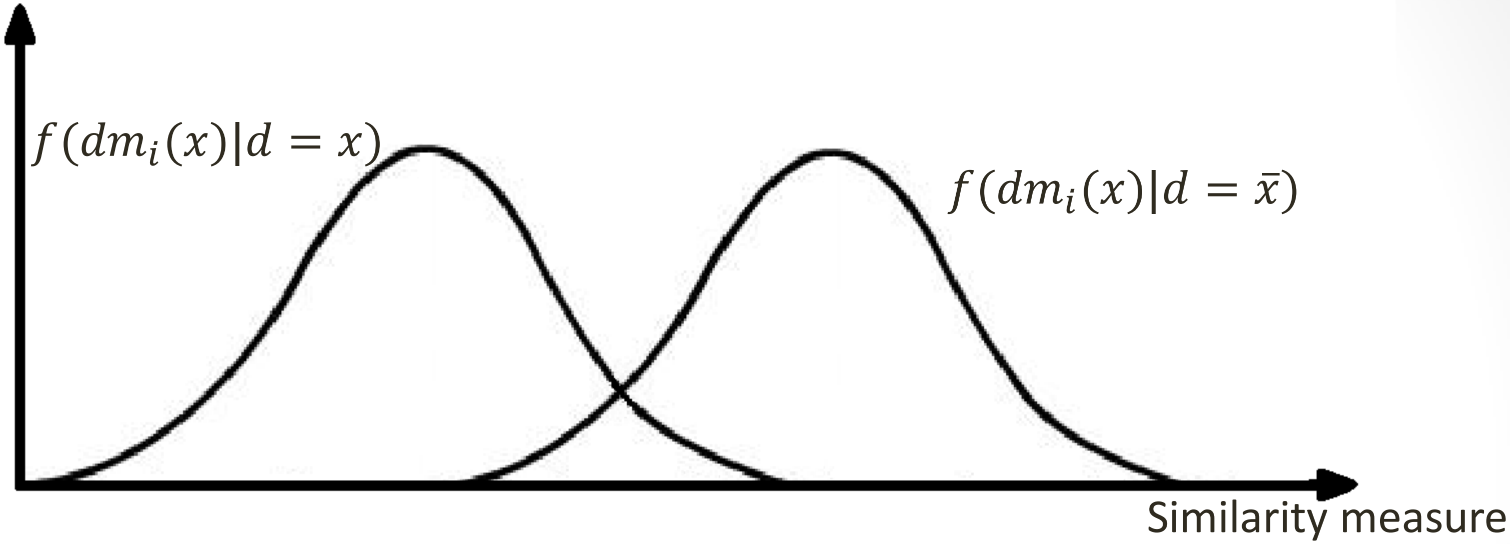
- Given a set of N distance maps, what is the most probable displacement?

$$\hat{X} = \underset{x \in \{X, \bar{X}\}}{\operatorname{argmax}} P(d = x | dm_i(X), dm_i(\bar{X})_{|i=1\ldots n})$$

- Using conditional independency of observations:

$$= \underset{x \in \{X, \bar{X}\}}{\operatorname{argmax}} \prod_{i=1}^{N} \frac{f(dm_i(x)|d = x)}{f(dm_i(x)|d = \bar{x})}$$

Aggregation of distance maps



- After few developements, the most probable displacement is:

$$\hat{X} = \underset{x \in \{X, \bar{X}\}}{\operatorname{argmin}} \sum_{i=1}^{N} \frac{\mu(D_i)}{\sigma^2(D_i)} dm_i(x)$$

Point selection

- Goal: minimize probability of wrong decision

$$\boldsymbol{m}^* = \operatorname*{argmax}_{\boldsymbol{m}\in\mathcal{M}^N} \sum_{i=1}^{N} \frac{\mu_{ik}^2}{\sigma_{ik}^2} = \operatorname*{argmax}_{\boldsymbol{m}\in\mathcal{M}^N} \sum_{i=1}^{N} r_{ik}$$

reliability criterion to optimize ← r_{ik}

- Extension to the complete distance map:

$$\boldsymbol{m}^* = \operatorname*{argmax}_{\boldsymbol{m}\in\mathcal{M}^N} \min_{j} \sum_{i=1}^{N} r_{ikj}$$

Cost-reliability framework

- Goal: find optimal matching metric assignment to minimize probability of error under complexity constraint

$$\boldsymbol{m}^* = \underset{\boldsymbol{m} \in \mathcal{M}^N}{\operatorname{argmax}} \min_j \sum_{i=1}^{N} r_{ikj}$$

$$\sum_{i=1}^{N} c_{ik} < C$$

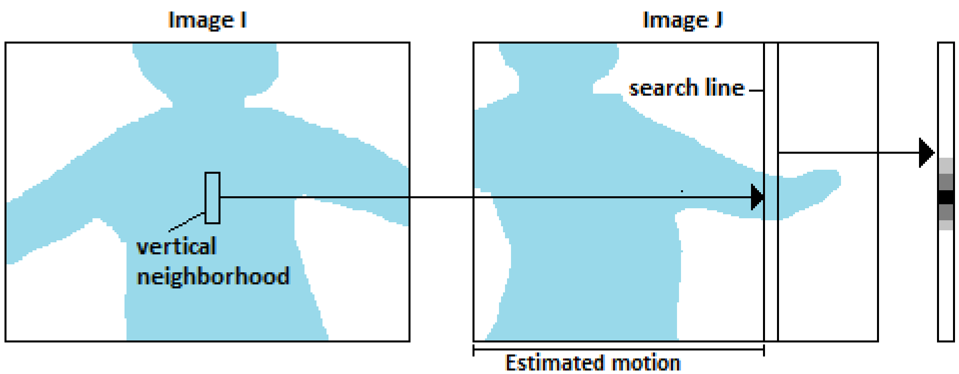
Cost-reliability framework

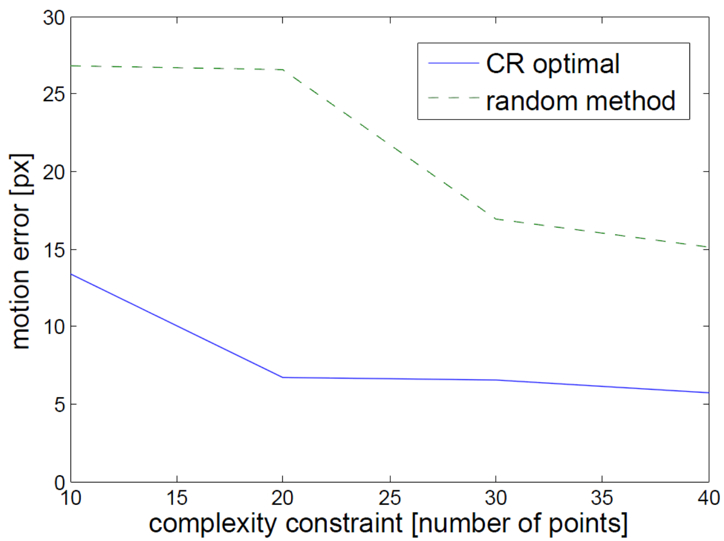
- The cost-reliability optimization scheme
  - Selects the (number of) points to match
  - Selects a matching metric for each point
- The optimal solution:
  - Generates a set of complementary distance maps
  - Selects more points able to disambiguate ambiguous regions
- The framework can be used with:
  - Costly but discriminating matching metrics
  - Cheap and poorly discriminating matching metrics
  - A combination of these

The weaker the better?

- Previous tests suggested that (numerous) weaker matching strategies are the most robust (to be confirmed)
- The displacement model does not require exact point to point correpondances
- Every point helps rejecting wrong displacement hypothese

Tests with basic matching metrics





Future works

- Test framework with extreme cases of complexity (low and high)
- Embed the point matching process into active tracking
- Work on higher level challenges of tracking (occlusion and deformation handling, motion blur, illumination changes, etc.)

C'est fini