Simultaneous learning of motion and appearance

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Tracking of objects with variable appearance

- **Tracking** - iterative estimation of object pose (e.g., human head).
- **Variable appearance** - the way how the object looks like in the camera changes due to illumination, non-rigid deformation, out-of-plane rotation, ...

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[Lucas-IJCV-1981] - Hard template update

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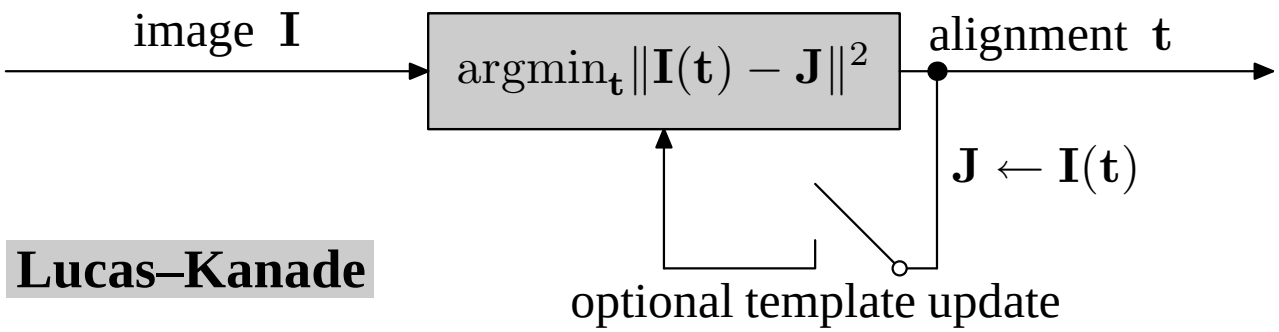
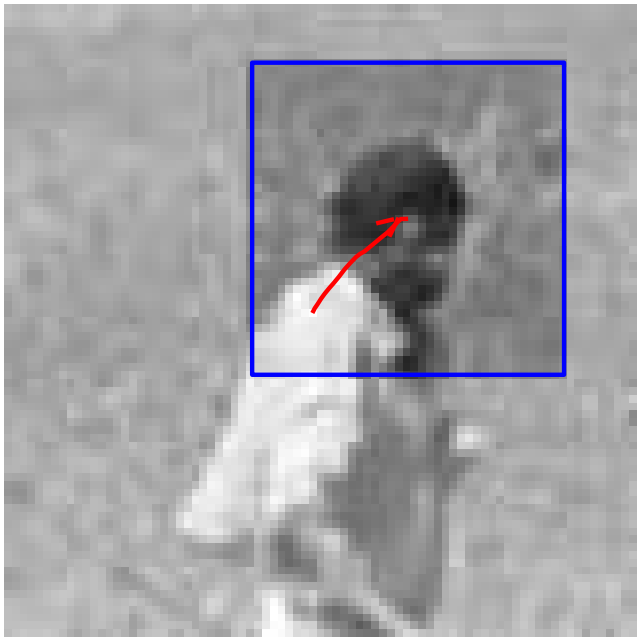
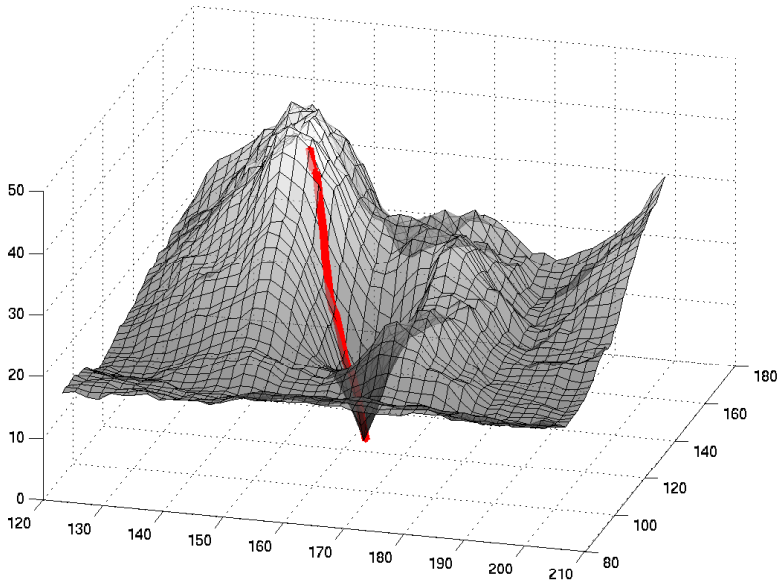


Lucas–Kanade





[Jurie-BMVC-2002] - learned motion and optional hard template update

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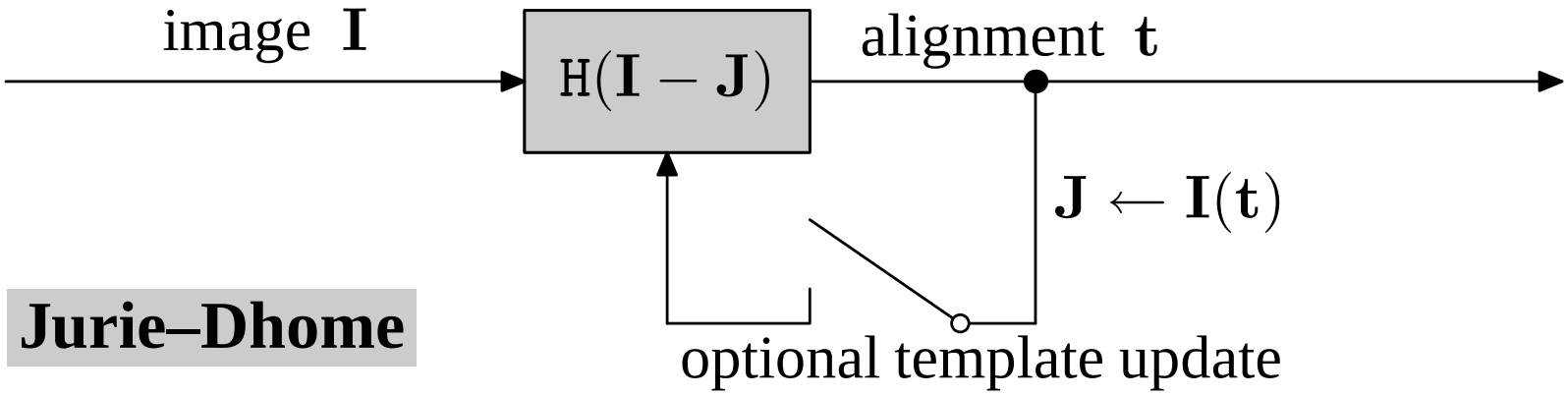

Jurie–Dhome

Learning alignment

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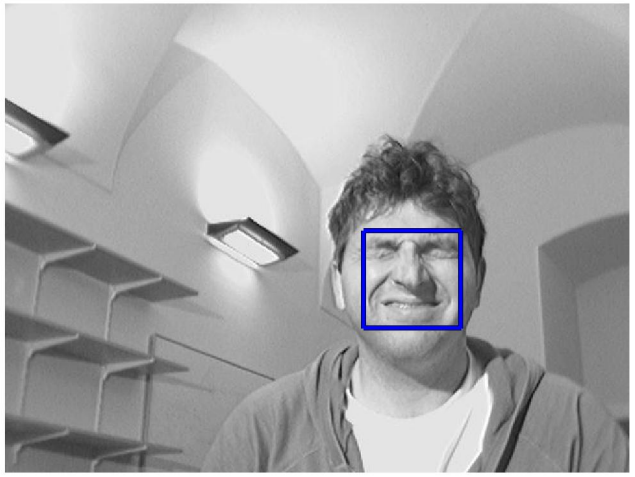

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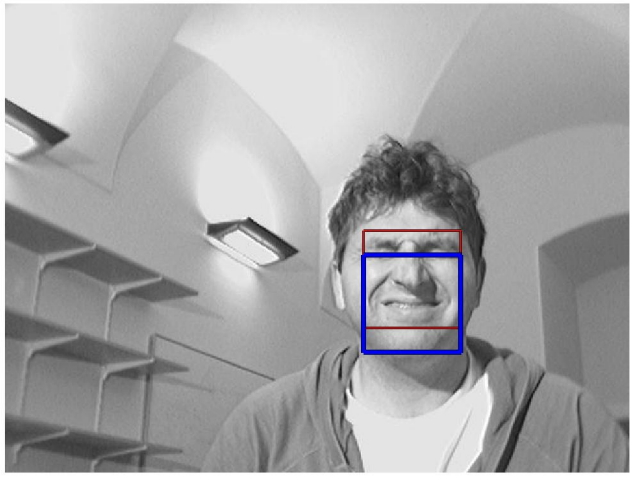

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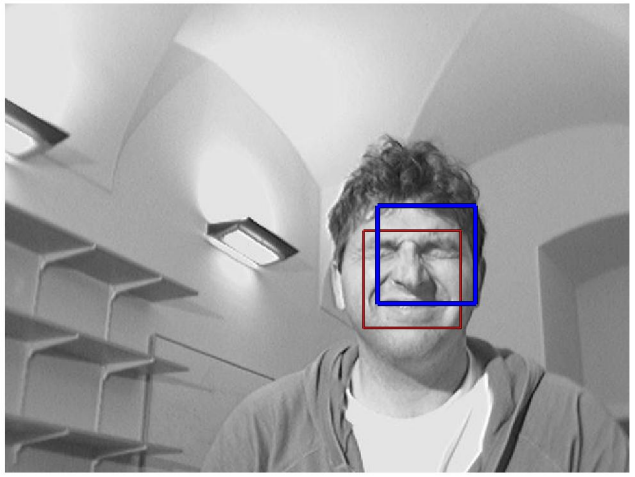

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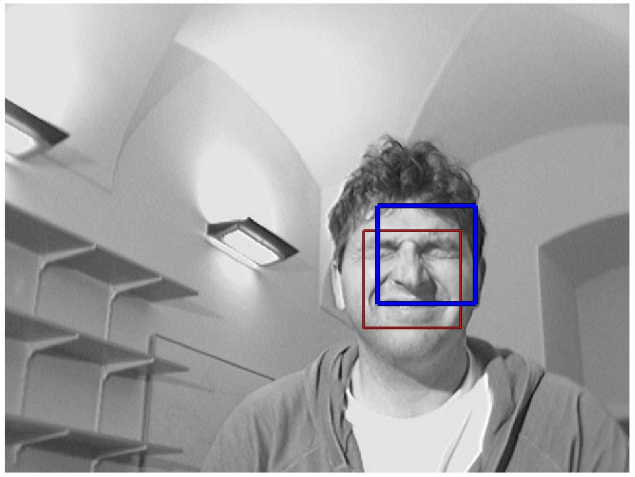

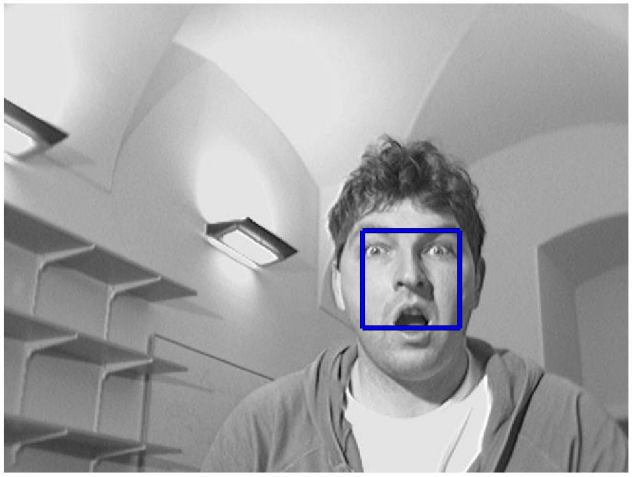

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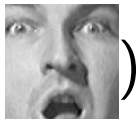
- $\varphi($  $) = (0,0)^\top$
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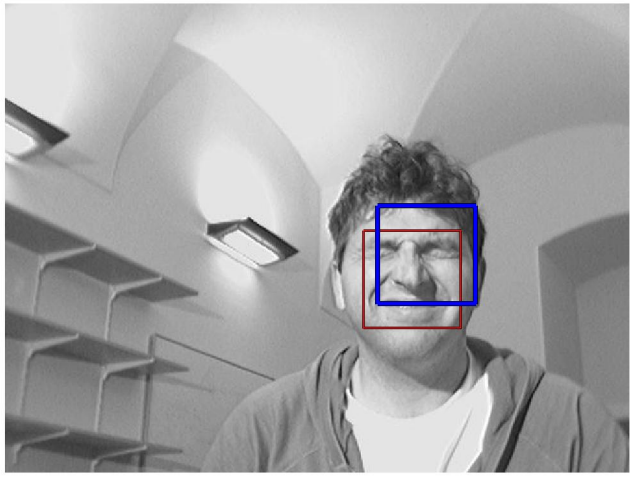

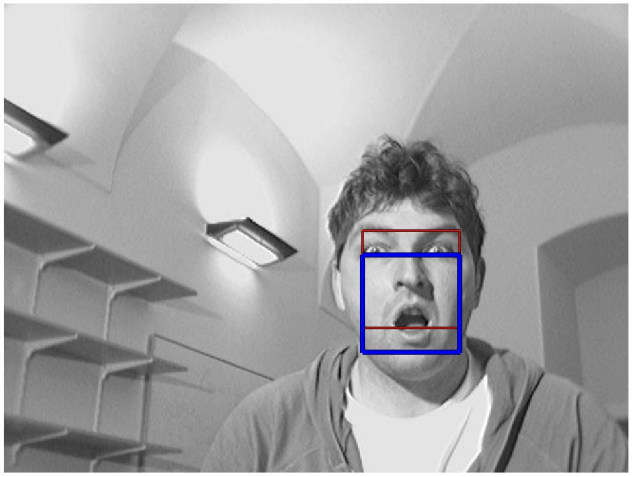

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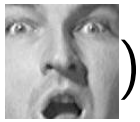
- $\varphi($  $) = (0,0)^\top$
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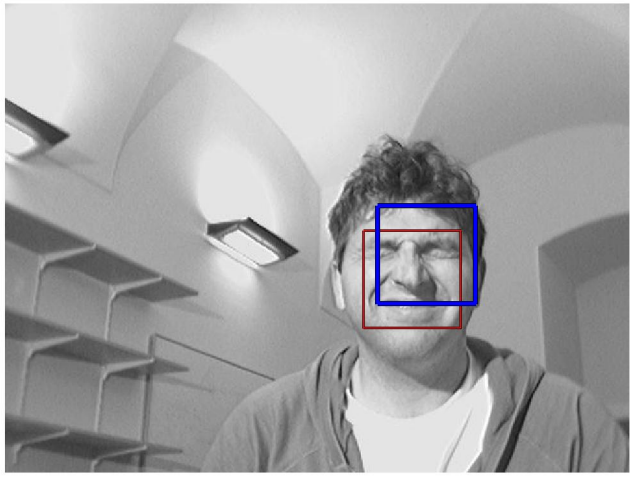

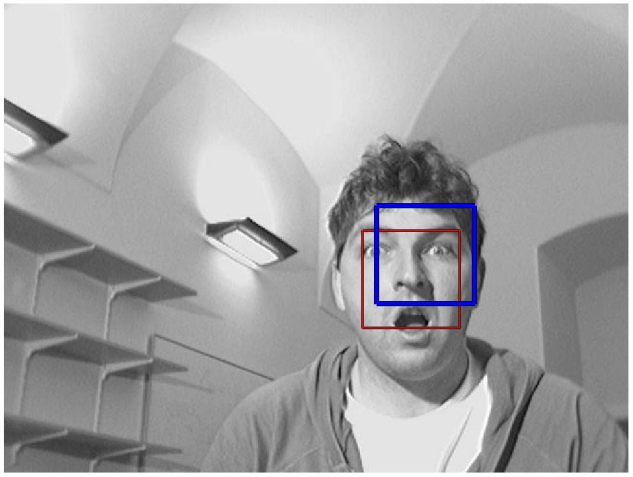

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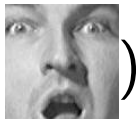
- $\varphi($  $) = (0,0)^\top$
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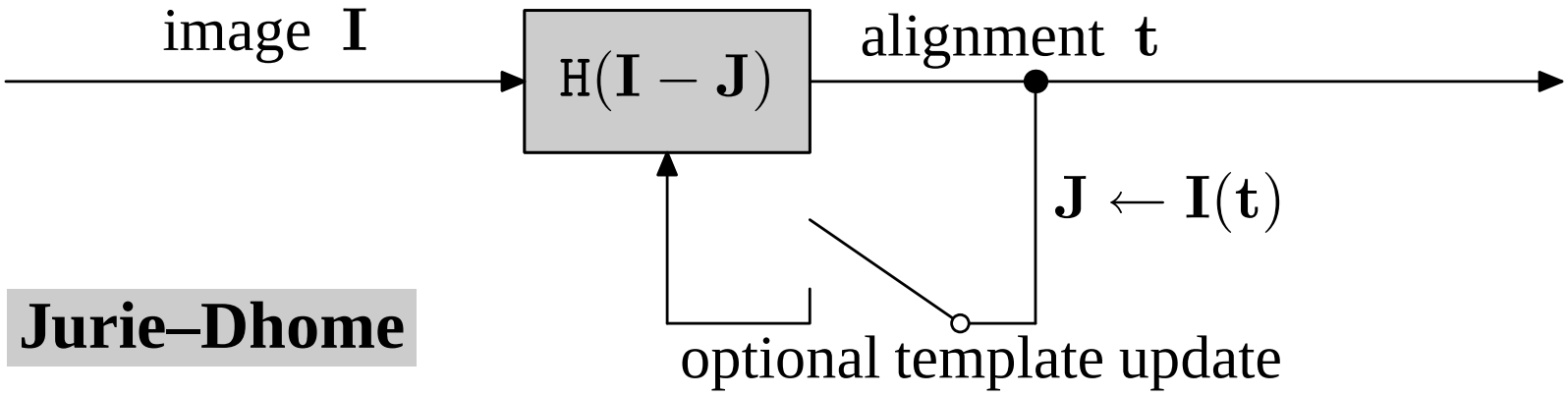

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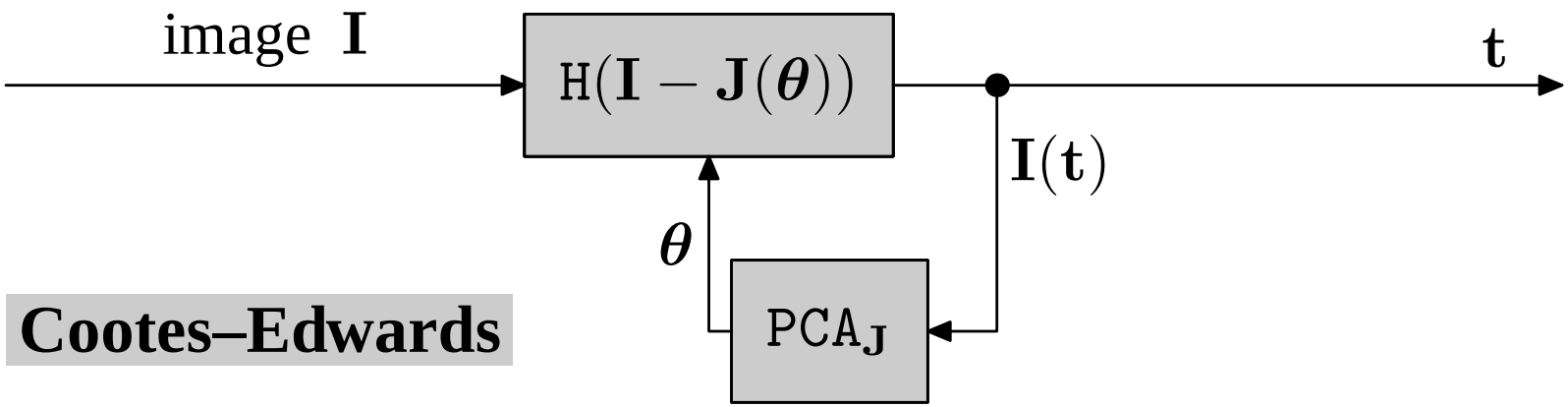

Cootes–Edwards

Learning appearance – our approach

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T.Svoboda
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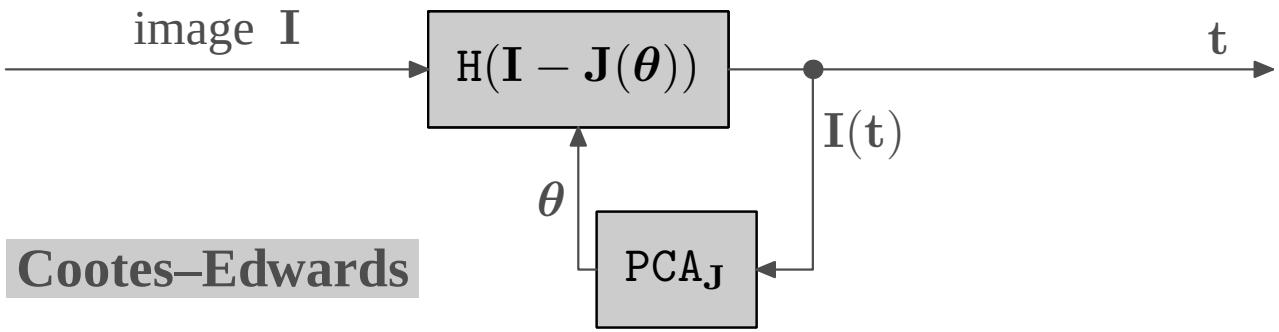

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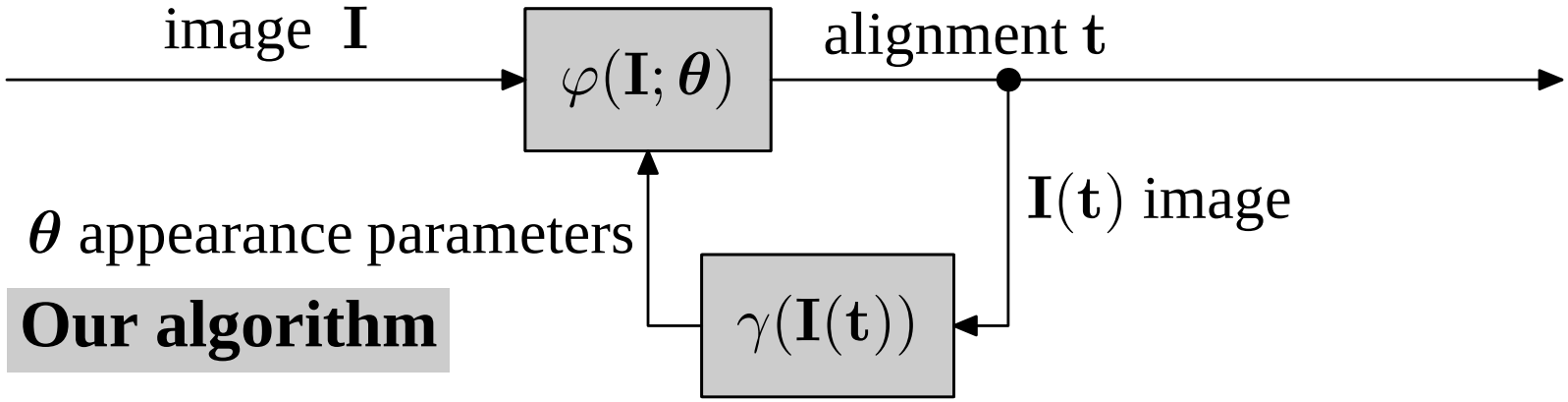

Our algorithm

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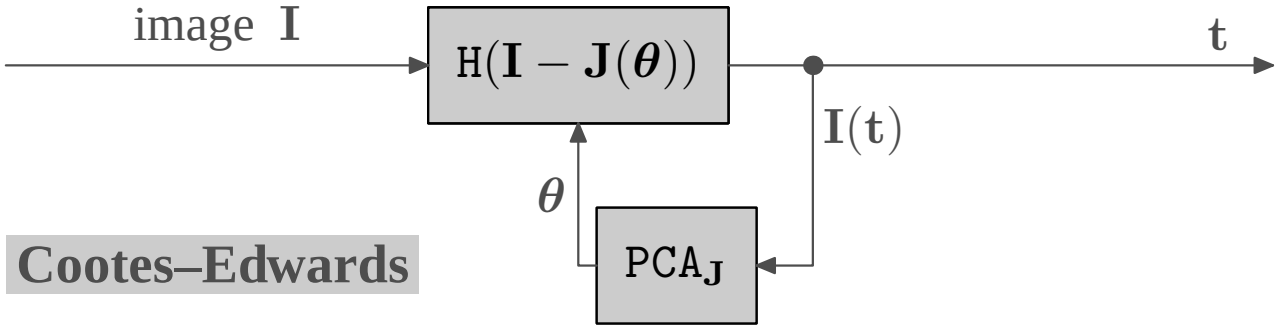

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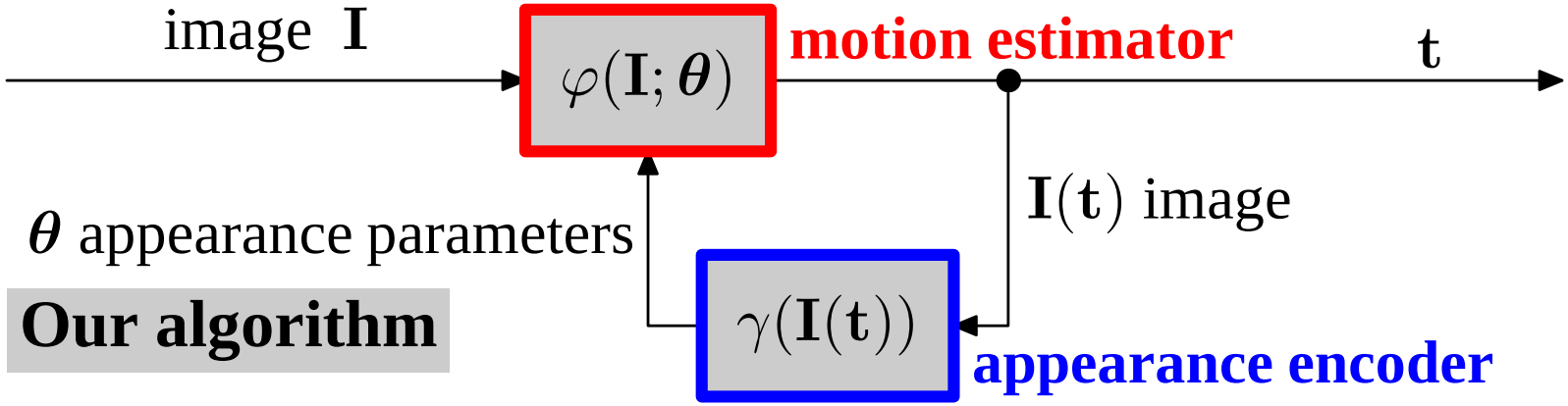

Our algorithm

Learning the appearance encoder γ

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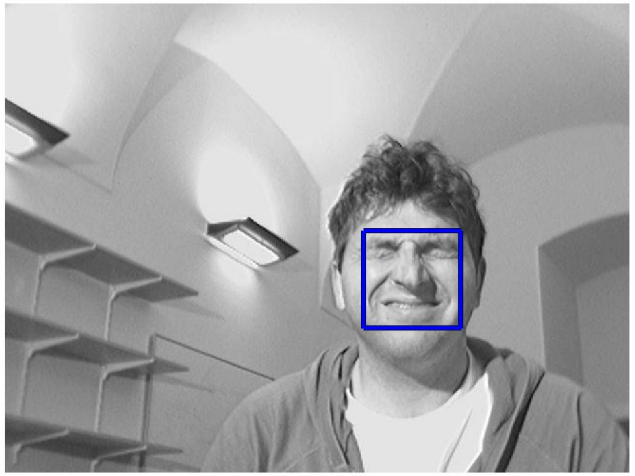
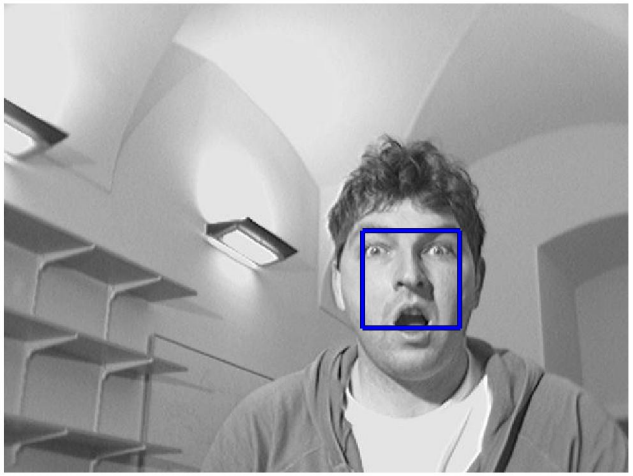
- Current appearance encoded in low-dim parameters.





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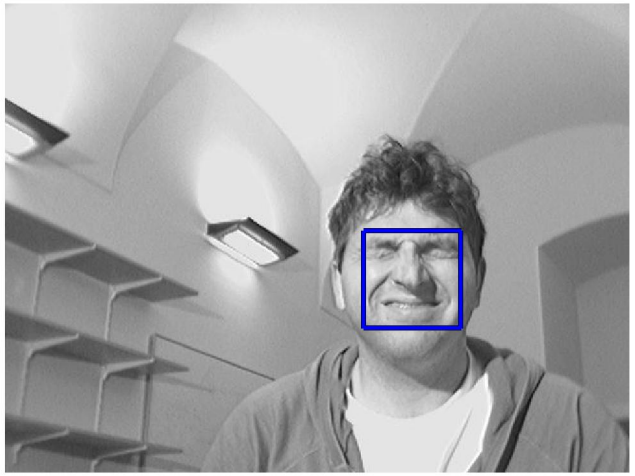

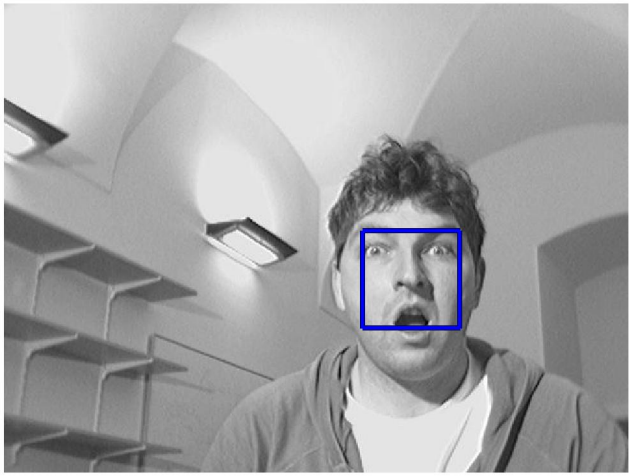

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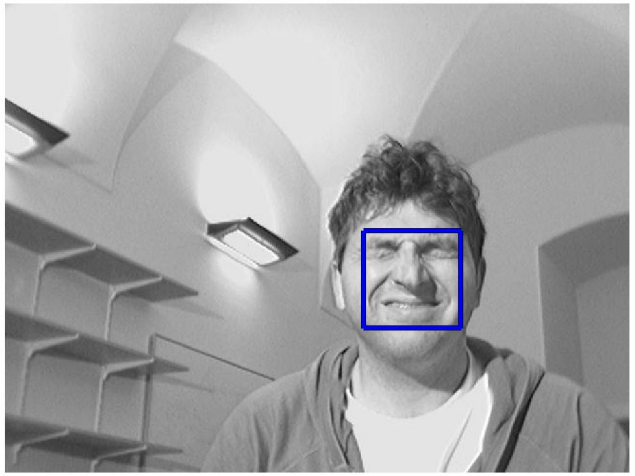

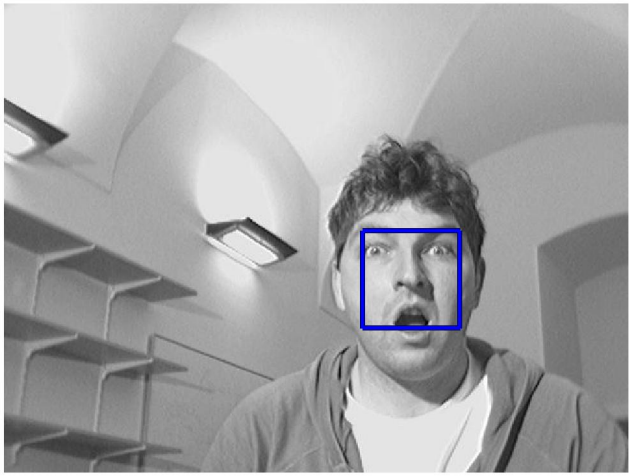

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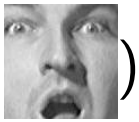
- $\gamma($  $) = \boldsymbol{\theta}_2$

Learning the tracker $\varphi(\mathbf{I};\boldsymbol{\theta})$

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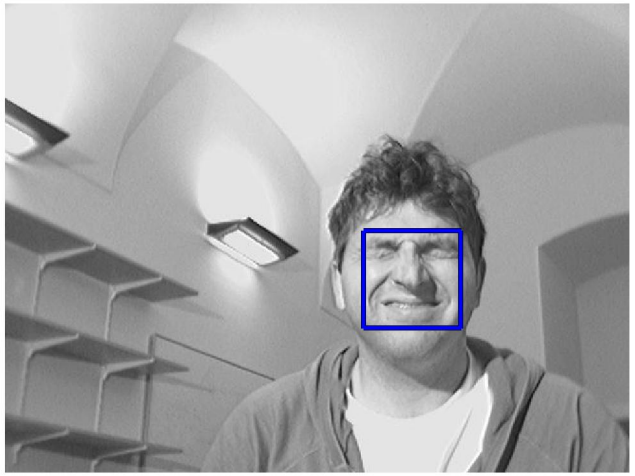

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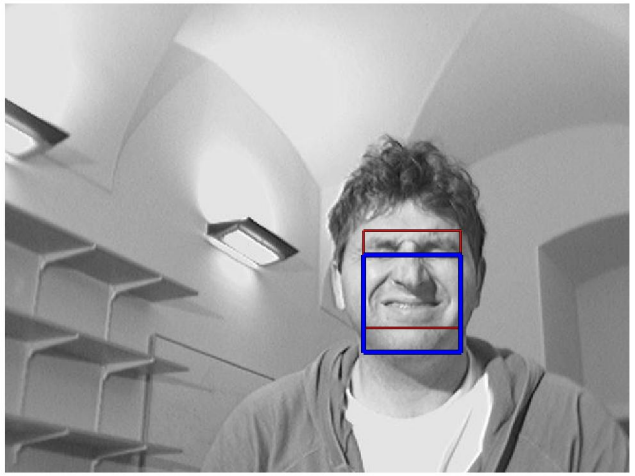

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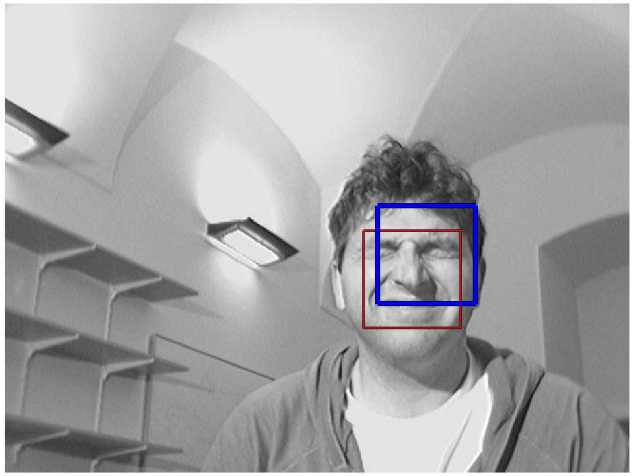

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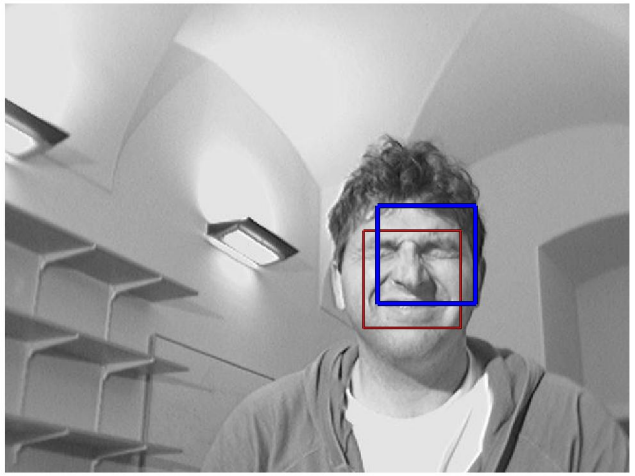

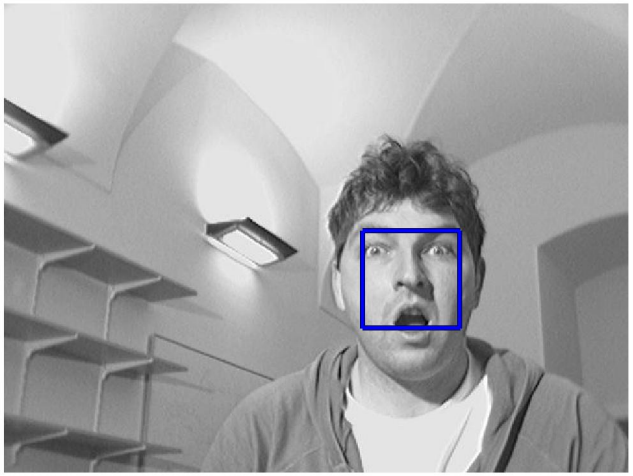

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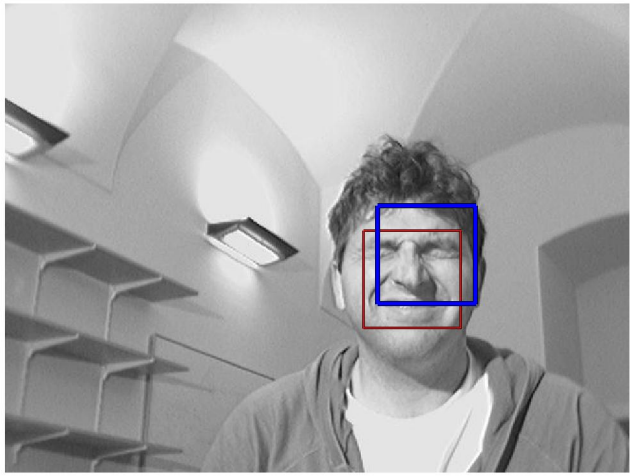

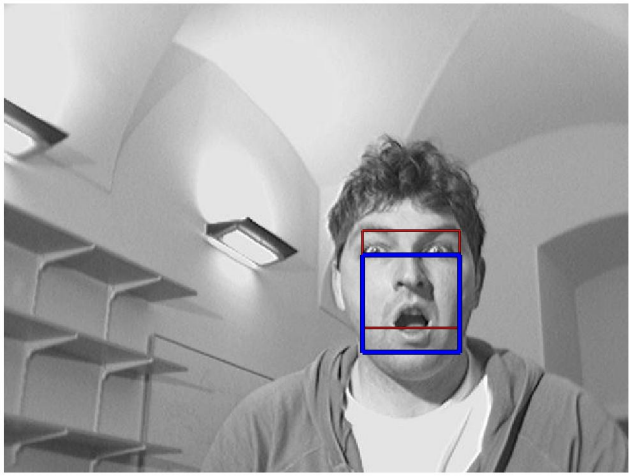

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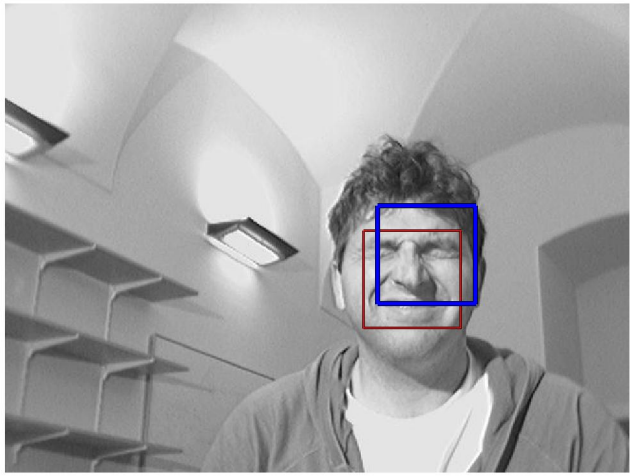

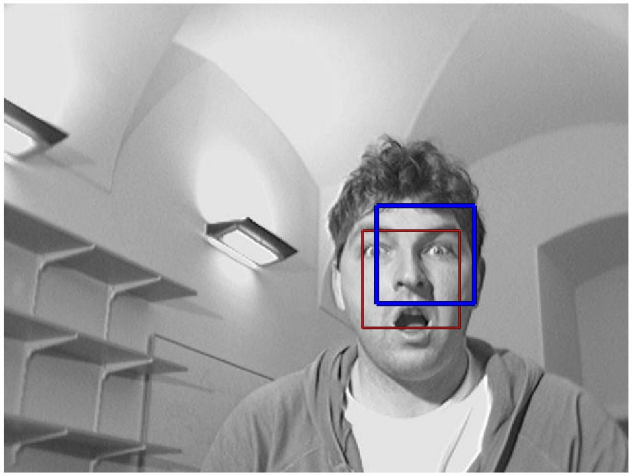

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Simultaneous learning of φ and γ

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- **Learning = minimization of the least-squares error**

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Linear mapping

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- $\gamma(\mathbf{J}) : \boldsymbol{\theta} = \mathtt{G}\mathbf{J}$
- $\varphi(\mathbf{I}, \boldsymbol{\theta}) : \mathbf{t} = (\mathtt{H}_0 + \theta_1 \mathtt{H}_1 + \cdots + \theta_n \mathtt{H}_n)\mathbf{I}$
- Criterion is sum of squares of bilinear functions.

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Algorithm: iterative minimization of criterion $e(\varphi, \gamma)$

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φ – motion (geometry mapping), γ – appearance mapping

color encodes criterion value $e(\varphi, \gamma)$

- Iterative minimization:
  - initialization $\gamma^0 = \mathrm{rand}$
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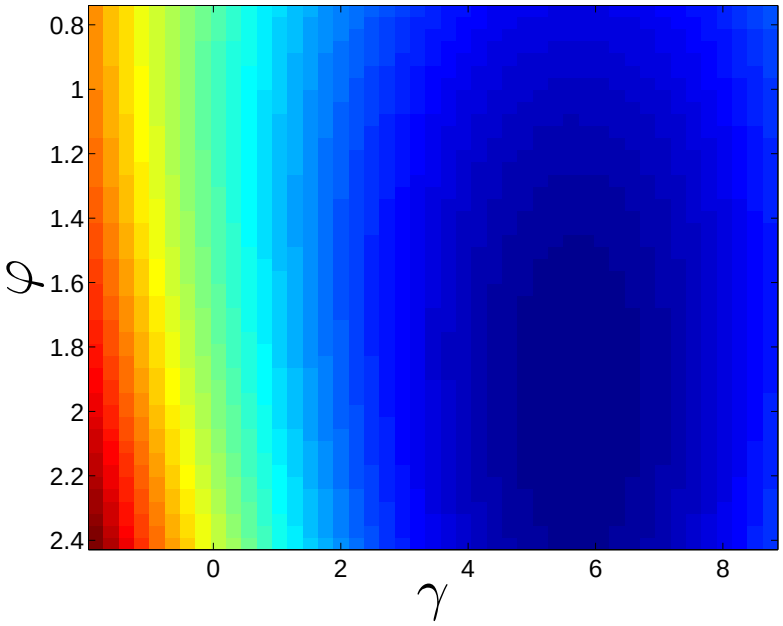

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T.Svoboda
J.Matas

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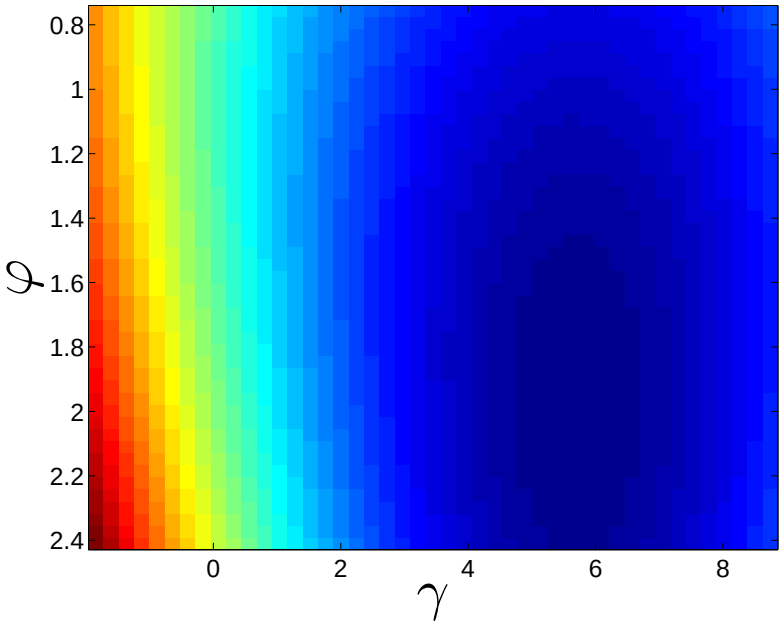

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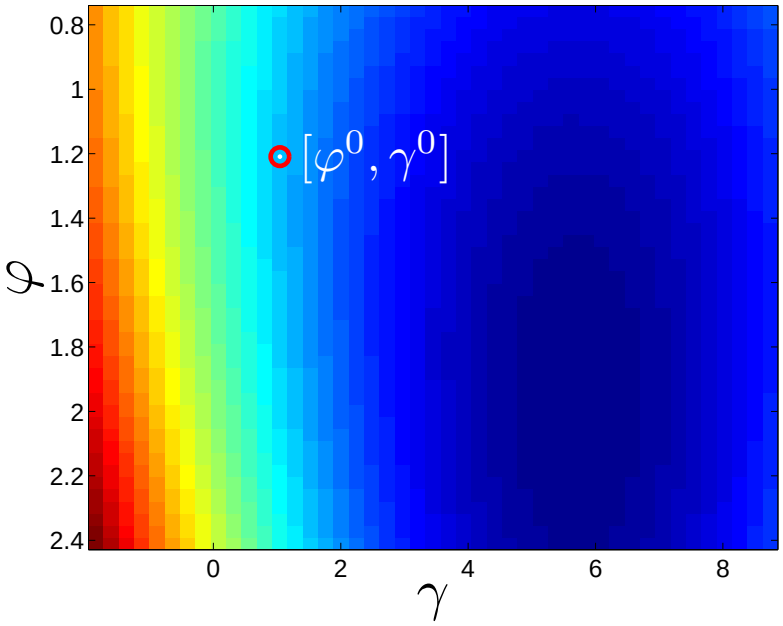

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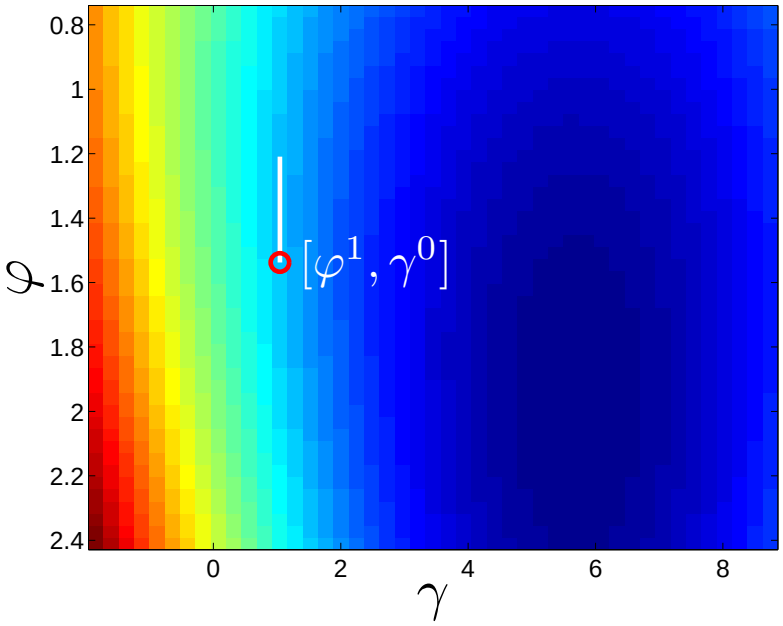

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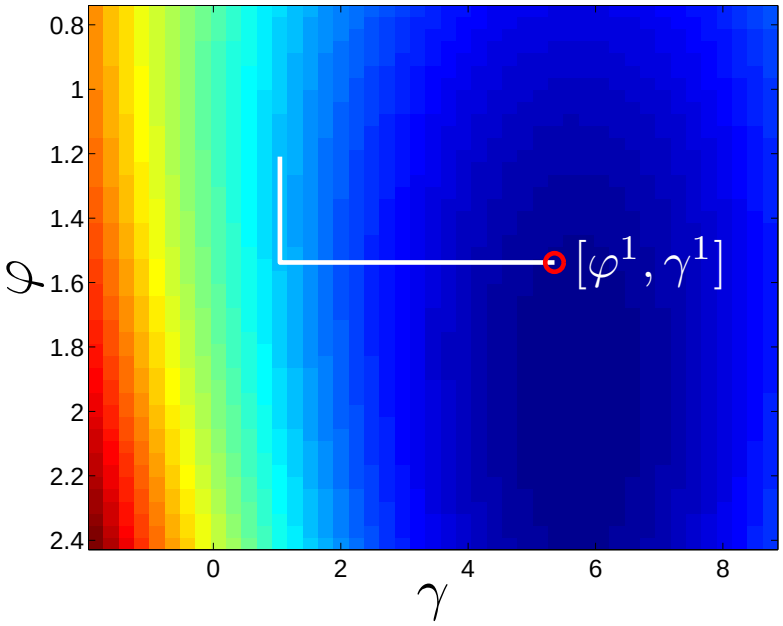

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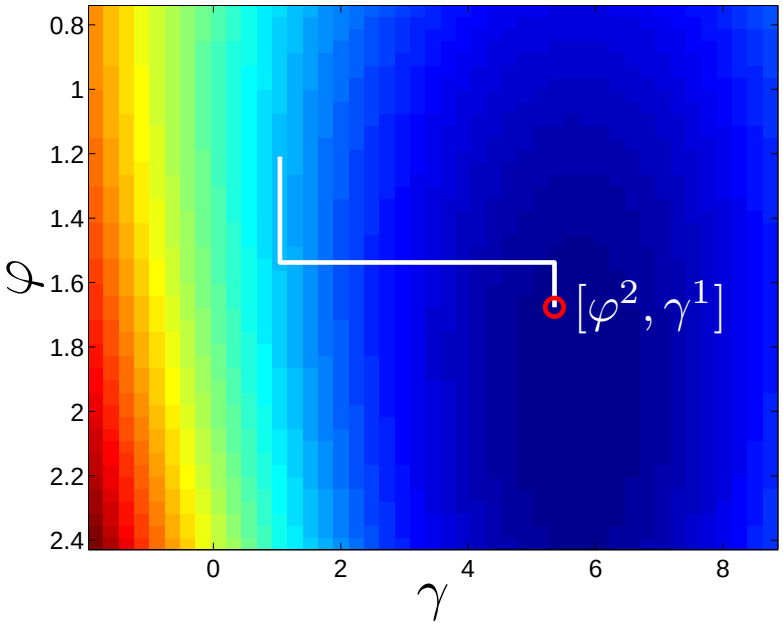

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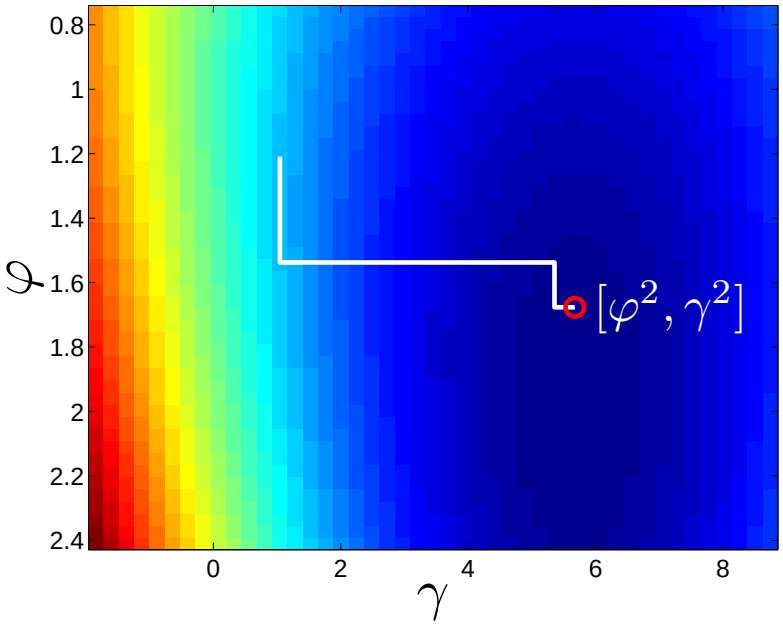

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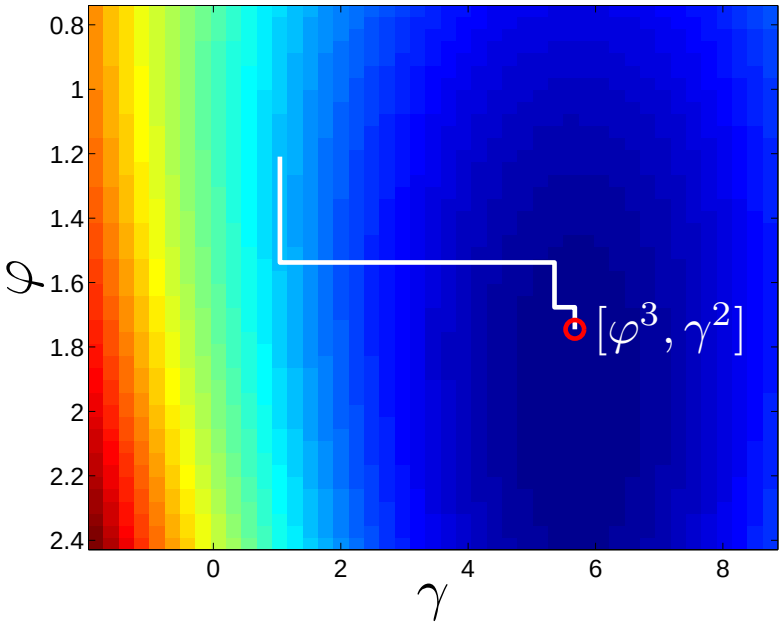

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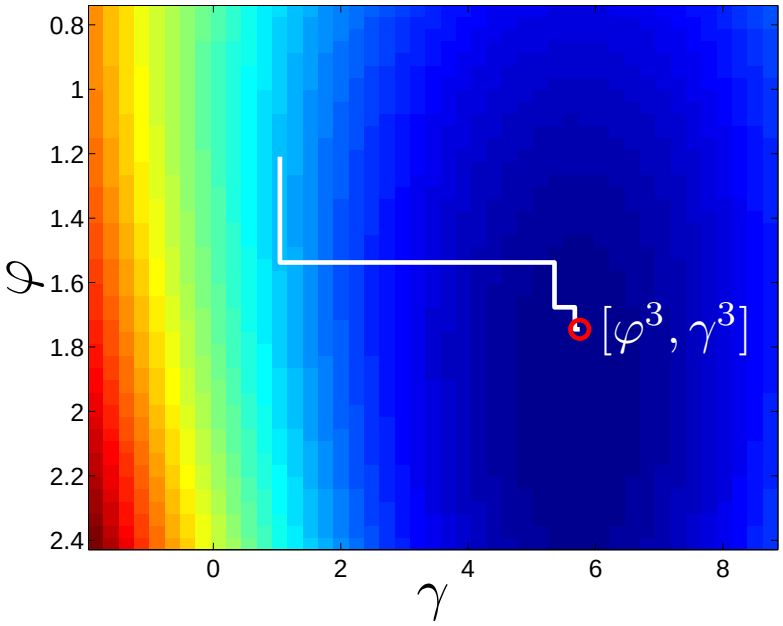

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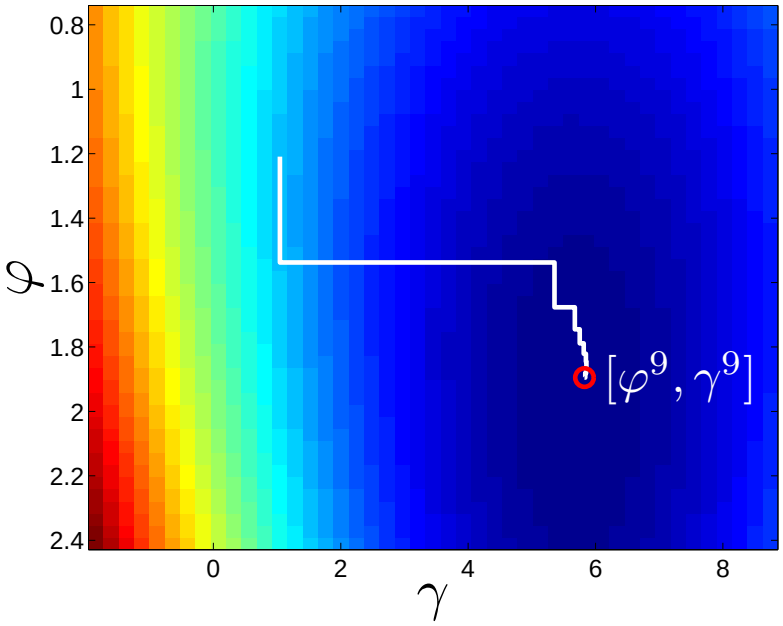

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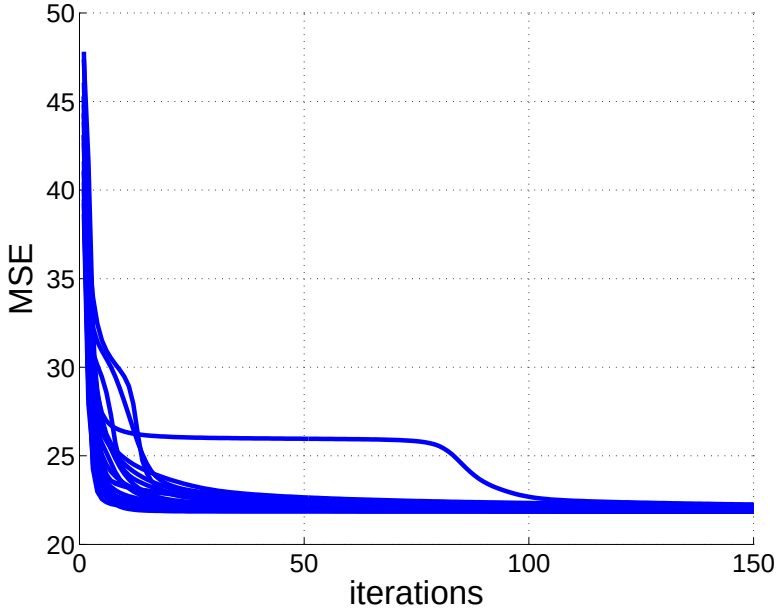

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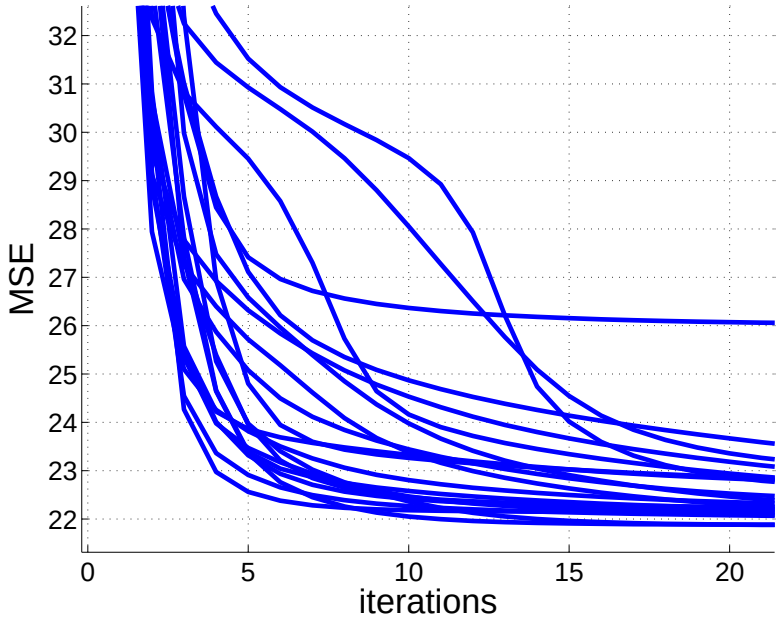

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Experiments - videos I

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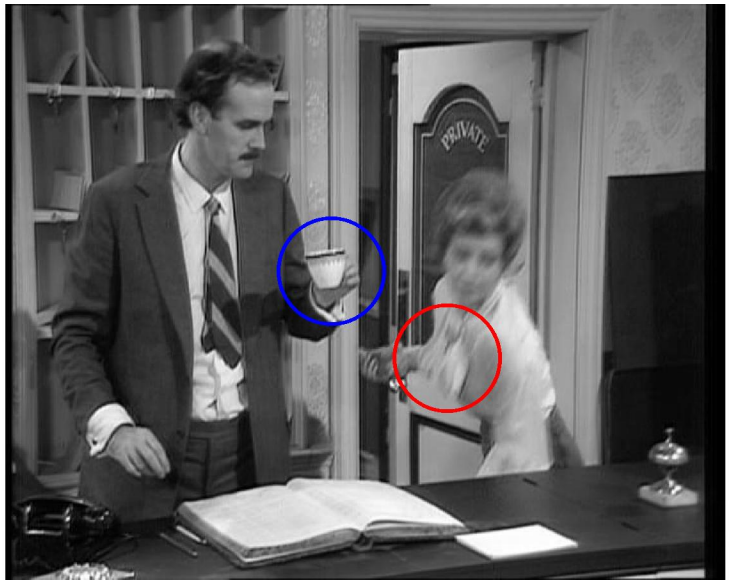
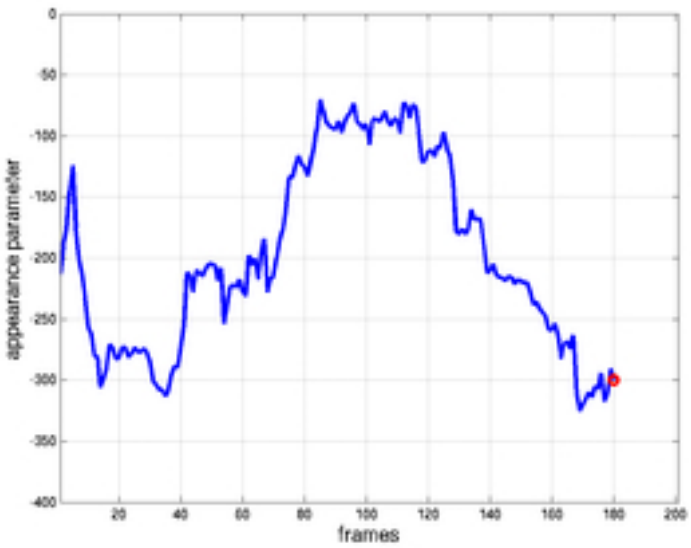
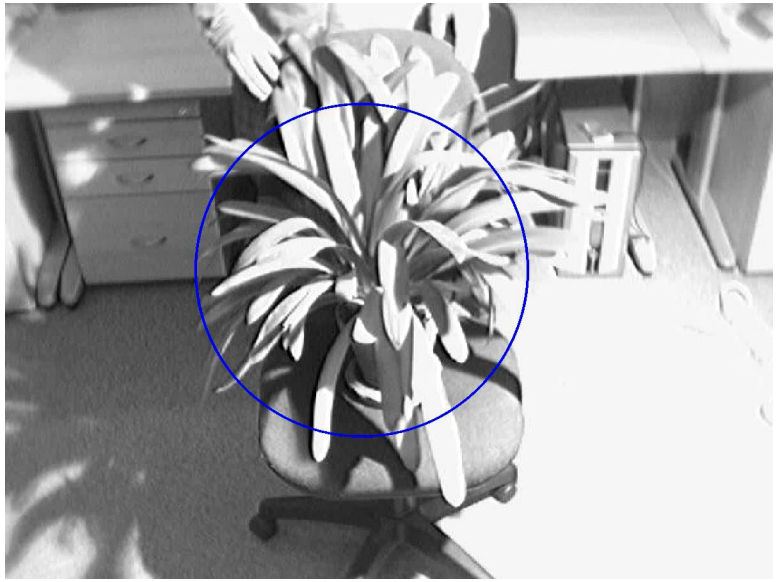




Experiments - videos II

K.Zimmermann
T.Svoboda
J.Matas



Experiments - Quantitative evaluation

K.Zimmermann
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- Comparison of tracking error and computation cost of appearance sensitive and simple tracker.

Object	Appearance sensitive				Simple		
	$\text{Error}_{\text{train}}$	$\text{Error}_{\text{test}}$	C	m	$\text{Error}_{\text{train}}$	$\text{Error}_{\text{test}}$	C_s
CUP	5.1	5.3	605	1	7.2	X	1352
BASIL	4.9	5.0	605	1	7.0	7.8	1352
SIBIL	4.9	7.4	605	1	7.0	X	1352
HEAD 1	2.7	3.4	1859	2	6.4	8.0	1922
HEAD 2	5.0	5.5	1248	2	7.5	8.5	1300
HEAD 2	4.3	4.5	1716	3	7.3	8.2	1860
FLOWER	3.3	3.6	2873	5	4.0	4.3	3362

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Conclusions

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- Simultaneous learning motion and appearance.
- Possible extension to sequential estimation as shown in [Zimmermann-PAMI-2008].
- Significant improvement in accuracy, robustness and computational cost w.r.t. appearance insensitive tracker.

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