

The chains model for detecting parts by their context

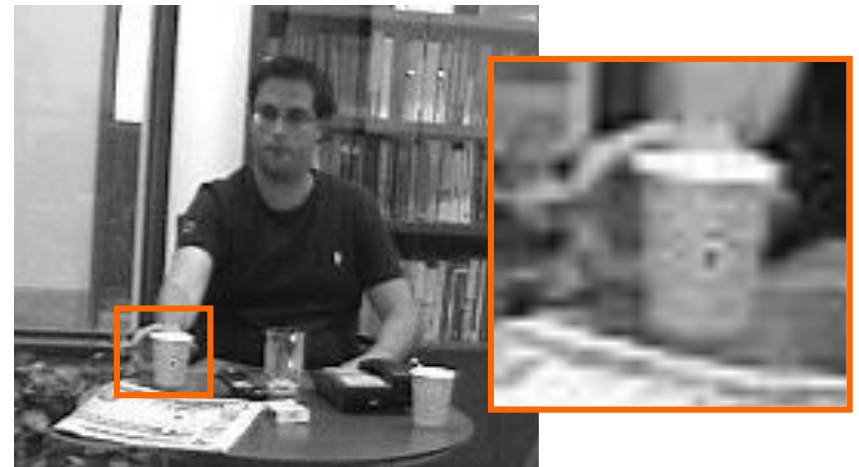
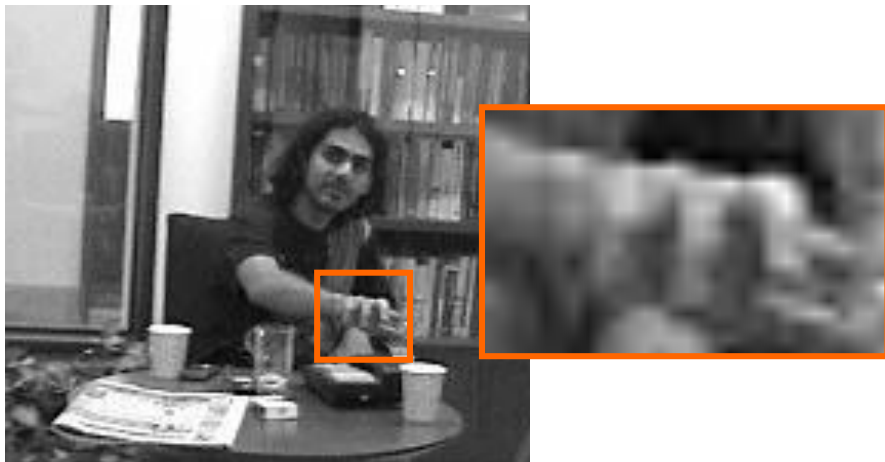
Leonid Karlinsky, Michael
Dinerstein, Daniel Harari, and
Shimon Ullman



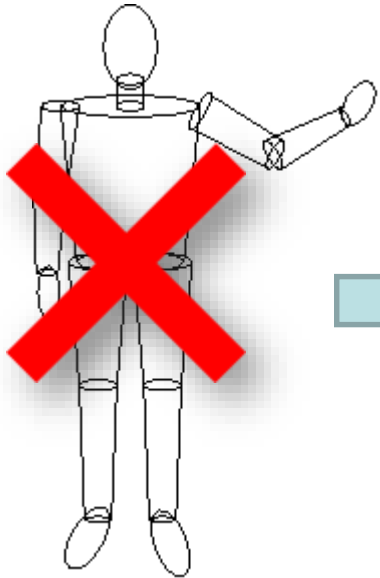
Goals & Intuition

- Detects a “**difficult**” part by **extending** from an “**easy**” reference part
- Detect by **marginalizing** over **chains** of intermediate features

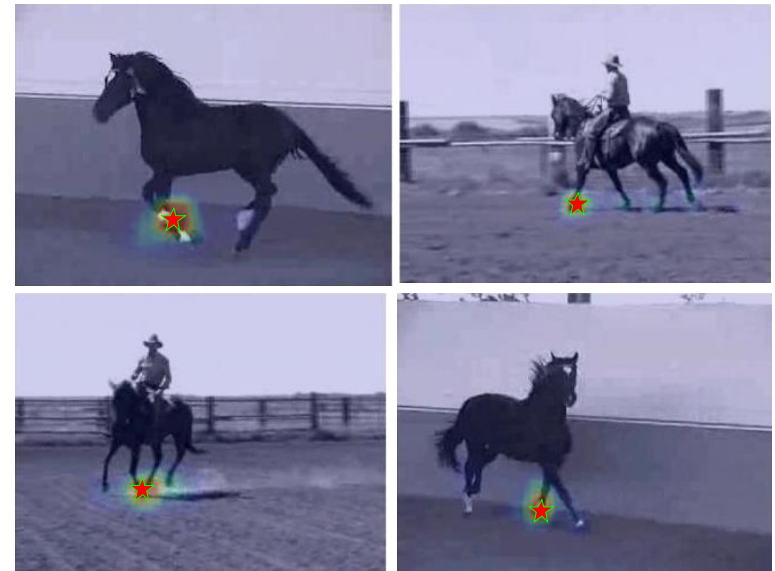
Use the face to disambiguate the hand



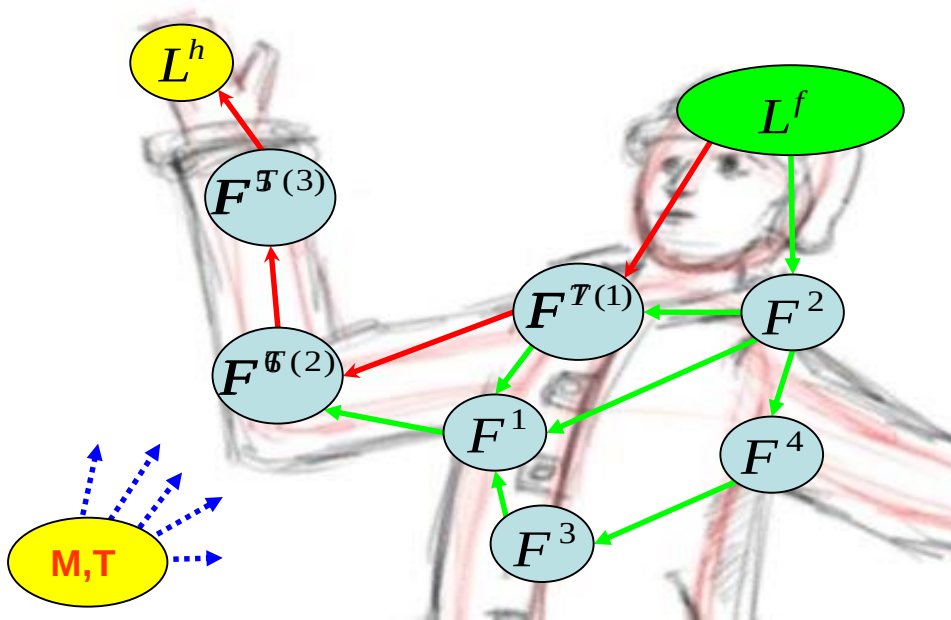
Examples & Generality



Same approach
for any parts of
any object!



The chains model



Chains model

Exact inference:

- Done over all **simple**
- Exhaustive search

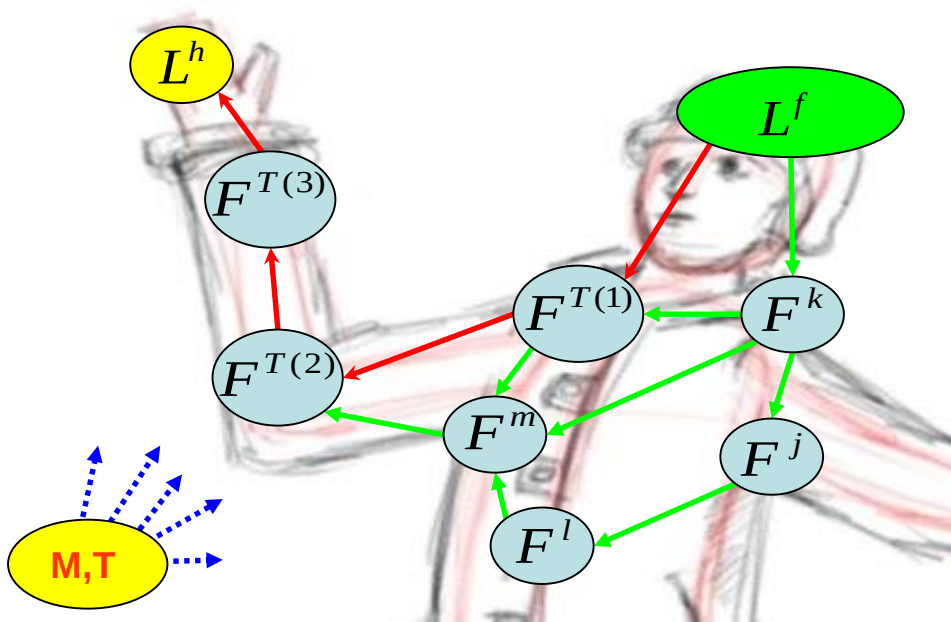
Approximate inference:

- Sample the **all** probability (that it is an ∞ length)
- Can be easily supported by feature multiplication

$$P_{CH}(M, T, L^h, L^f, \{F^i\}) = P(M, T) \cdot P(L^f) \cdot \prod_{i \notin T} P_{obj+bg}(F^i)$$

$$P_{obj}(L^h | F^{T(M)}) \cdot \left[\prod_{m=1}^{M-1} P_{obj}(F^{T(m+1)} | F^{T(m)}) \right] \cdot P_{obj}(F^{T(1)} | L^f)$$

Inference



Chains model

$$\sum_{M,T} P_{CH} (M, T, L^h, L^f, \{F^i\}) \approx$$

$$\underbrace{[\dots d_i \dots]}_D \cdot \sum_M \underbrace{\begin{bmatrix} \dots \\ \dots a_{ij} \dots \\ \dots \end{bmatrix}}_C^M \cdot \underbrace{\begin{bmatrix} \dots \\ s_j \\ \dots \end{bmatrix}}_S$$

voting probabilities = $D = \left\langle d_i = P_{obj} (L^h | F^i) \right\rangle$

Entry i-j is the marginal over all chains between F^i and F^j = C

object vs. background likelihood ratios = $S = \left\langle s_j = \frac{P_{obj} (F^j | L^f)}{P_{obj+bg} (F^j)} \right\rangle$

Training & probability estimation

Training:

- Get example images with detected reference part and target part marked by single point.

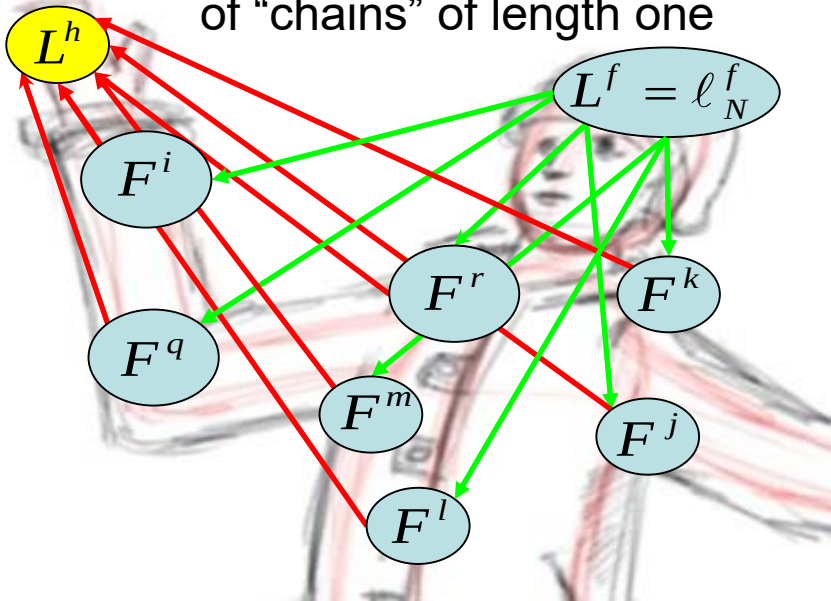
Non-parametric probability estimation in a nutshell:

- Store training image features and pairs of nearby features* in an efficient ANN search structures (KD-trees)
- Compute the estimated probability by approximate KDE
- E.g.: $P_{obj}(F^i, F^j)$ - search for K nearest neighbors of $[SIFT^i, SIFT^j, x^i - x^j]$, compute $P_{obj}(F^i, F^j) \approx \sum_{k=1}^K \exp\left(-\frac{d_k^2}{2\sigma^2}\right)$

* use a feature selection strategy (see paper)
to reduce the number of features and pairs

Chains & Stars

Star model – a special case of “chains” of length one



star result

Limitations of the star model:

1. Far away features do not contribute.
2. Features contribute to detection without testing for connectivity with the reference part.

$$P_{STAR}(L^h, L^f, \{F_i\}) = P(L^h) \cdot P(L^f) \cdot \prod_i [\alpha \cdot P_{obj}(F_i | L^h, L^f) + (1 - \alpha) \cdot P_{obj+bg}(F_i | L^f)]$$

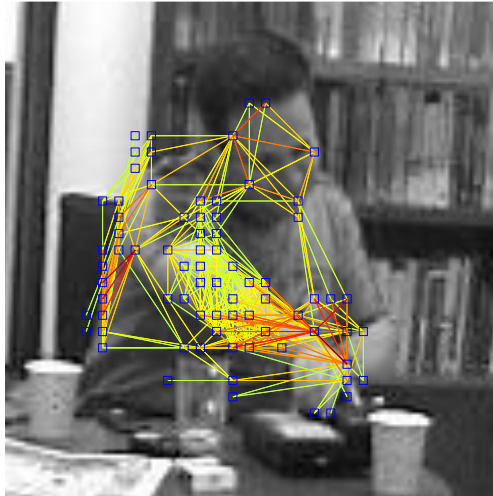
chains result

chains graph



Feature graph examples

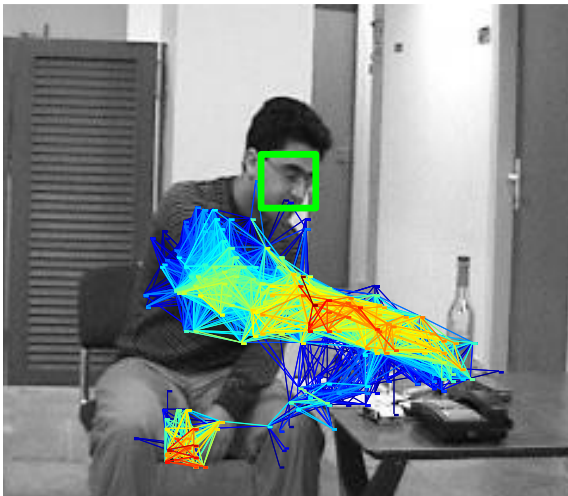
chains graph



chains result



chains graph

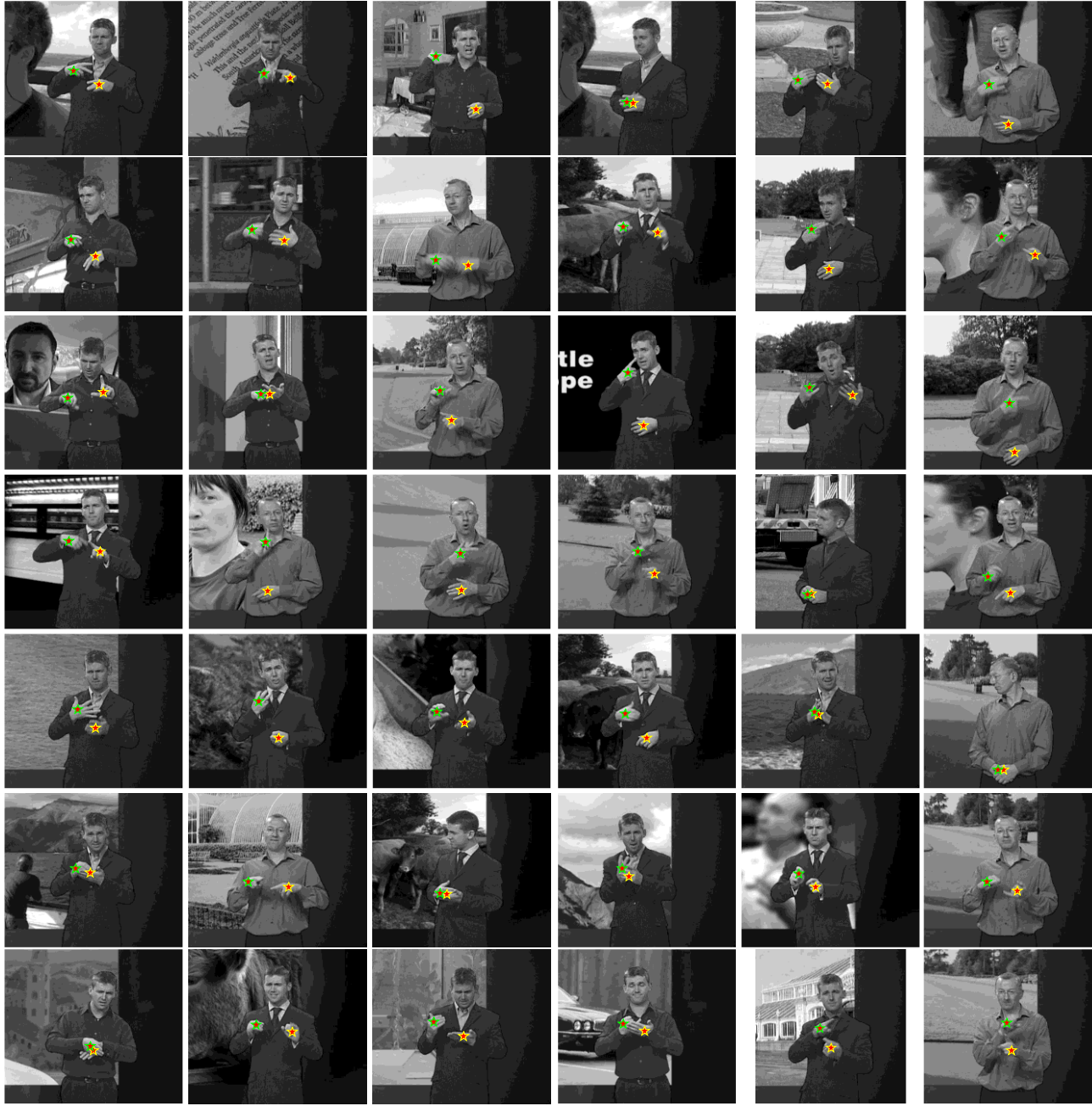


chains result



Results

Buehler et al 2008 – sign language dataset



Training:

600 frames of a news sequence

Testing:

195 frames from 5 other sequences

Our result:
84.9% detection

Best in the literature:

79% [Kumar et al, 2009]
(avg. over 6 body parts)

Ferrari et al 2008 - Buffy dataset



Training:
movies shot
in our lab

Testing:
308 frames
/ 3 episodes

Our result:
47% detection

Best in the literature:
46.1% [Andriluka et al, 2009]



Person cross generalization scenario (86.9%)

***Chains Model:
Person Cross
Generalization Scenario
PCG Dataset***

Self trained scenario (87%)

***Chains Model:
Self-Trained Scenario
ST Dataset***

Full generalization scenario (73.2%)

***Chains Model:
Full Generalization
Scenario
ST Dataset***

Buehler et al. 2008 – BBC news dataset (96.8%)

Best in the literature: 95.6% [Buehler et al, 2008]



UIUC cars dataset



Training:

550 positive /
500 neg.

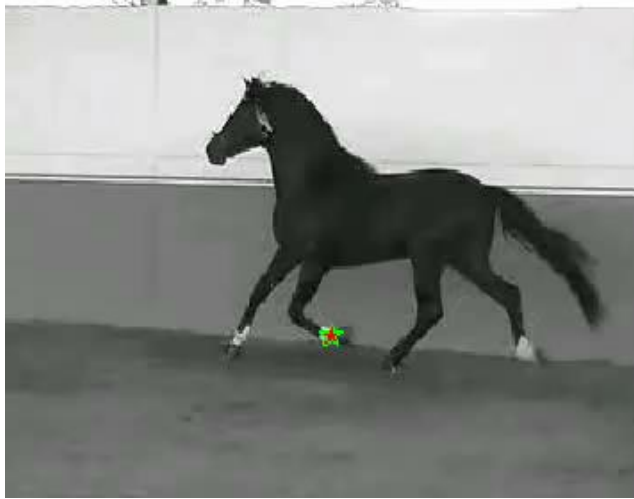
Testing:

200 cars in
170 images

Our result:
99.5% detection

Best in the literature:

99.9% [Mutch &
Lowe, 2006]



Same approach
(same params)
← works for other
object types
(out of the box)



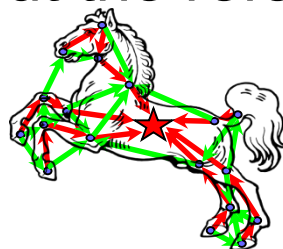
Our result:

63.1% - 1st max only

90.3% - 1st & 2nd max

Summary:

- A single non-parametric model for any object
- Detect difficult parts extending from the 'easy' parts
- Near features vote directly, far features vote through chains
- Can be used without the reference part and for full objects



[detailed numerical results...](#)

The End

	Chains				Star			
Scenario + Dataset	1 max	2 max	3 max	4 max	1 max	2 max	3 max	4 max
self trained (ST)	87	93.9	95.2	95.9	46.9	65	75.7	81.2
self trained (Horse)	63.1	90.3	93.4	94.6	50.2	61.6	68	74
person cross-generalization (PCG)	86.9	93.5	95.4	96.1	57.9	74.1	81.9	85.5
full generalization (ST)	73.2	86.6	90	92.2	37.6	52	66.9	74.7

	Chains				[Buehler et al., 2008]	[Kumar et al., 2009]	[Ferrari et al., 2008]	[Andriluka et al., 2009]
Setting	1 max	2 max	3 max	4 max	1 max	1 max	1 max	1 max
BBC news	96.8	99	99.5	99.6	95.6	86.37 ¹	-	-
5 signers	84.9	92.8	95.4	96.7	-	78.95 ¹	-	-
Buffy	47	53.9	56.7	59.3	-	39.2 ¹	56 ¹	46.1

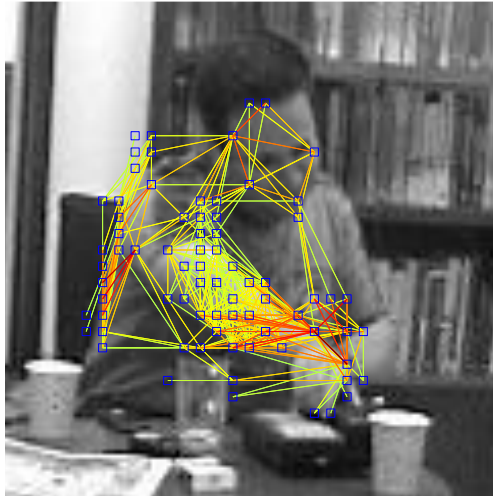
1 – average on 6 upper body parts
all except Andriluka et al. and us use tracking
all except us use color

Methods	Precision-Recall at EER - cars
Mutch and Lowe, 2006	99.9%
Leibe et al, 2008	97.5%
Lampert et al, 2008	98.5%
Gall and Lempitsky, 2009	98.5%
<i>chains model (trained on UIUC)</i>	99.5%
<i>chains model (trained on Caltech-101 cars)</i>	93.4%

Methods	Precision-Recall at EER - horses
Shotton et al, 2008	95.7%
Gall and Lempitsky, 2009	93.9%
<i>chains model</i>	97.5 ± 1%

Feature graph examples

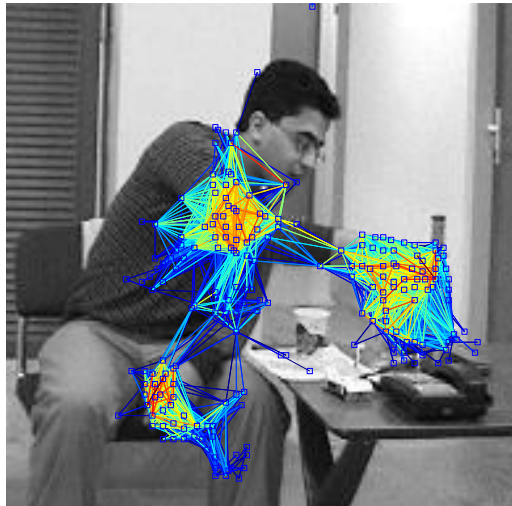
chains graph*



chains result



chains graph*



chains result



* weights — shown in logarithmic color scale