HuPBA

Universitat de Barcelona

CVC Centre de Visió per Computador

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Learning To Segment Humans By Stacking Their Body Parts

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Outline

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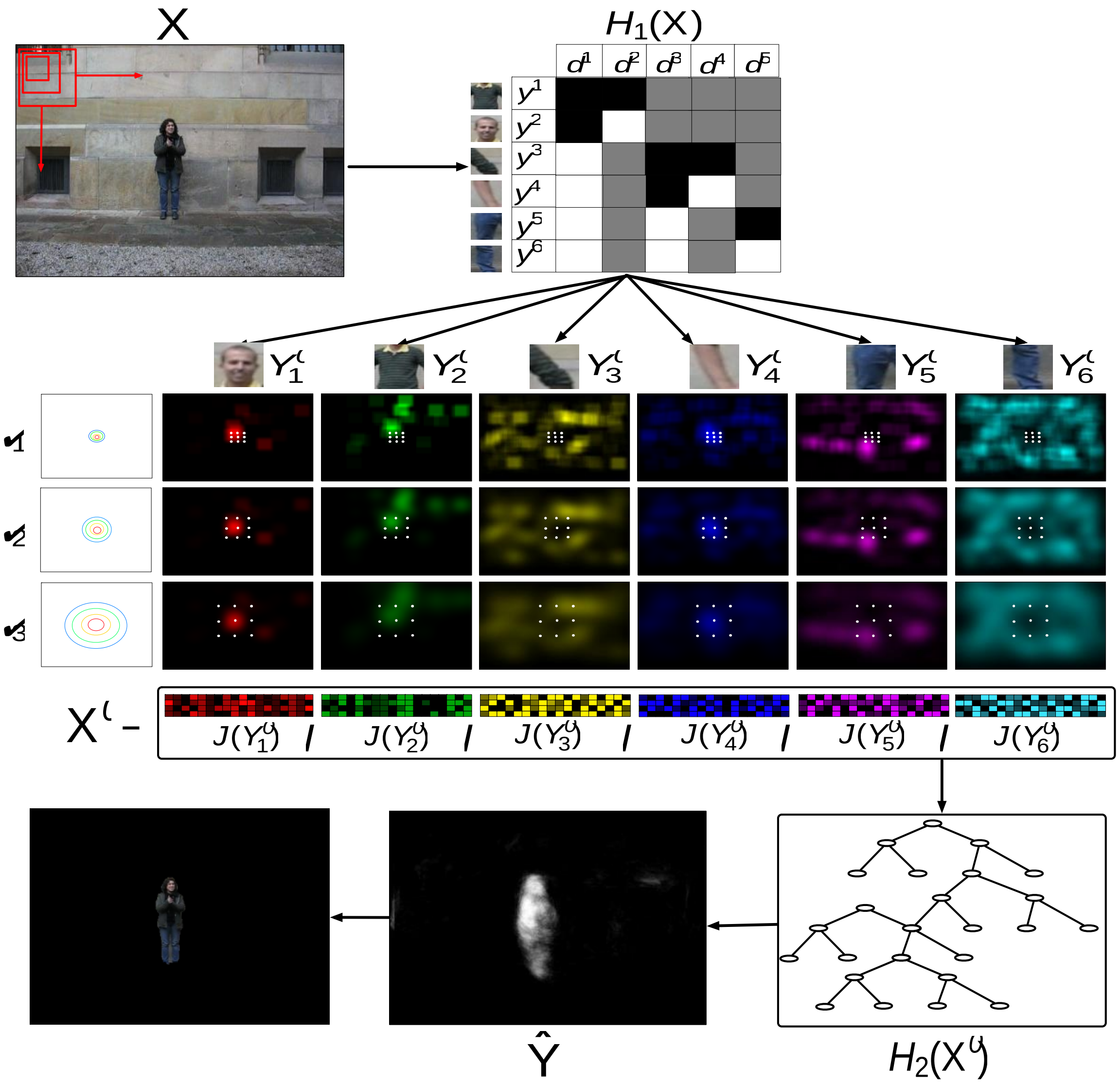
2. Methodology.
3. Results.
4. Conclusions.



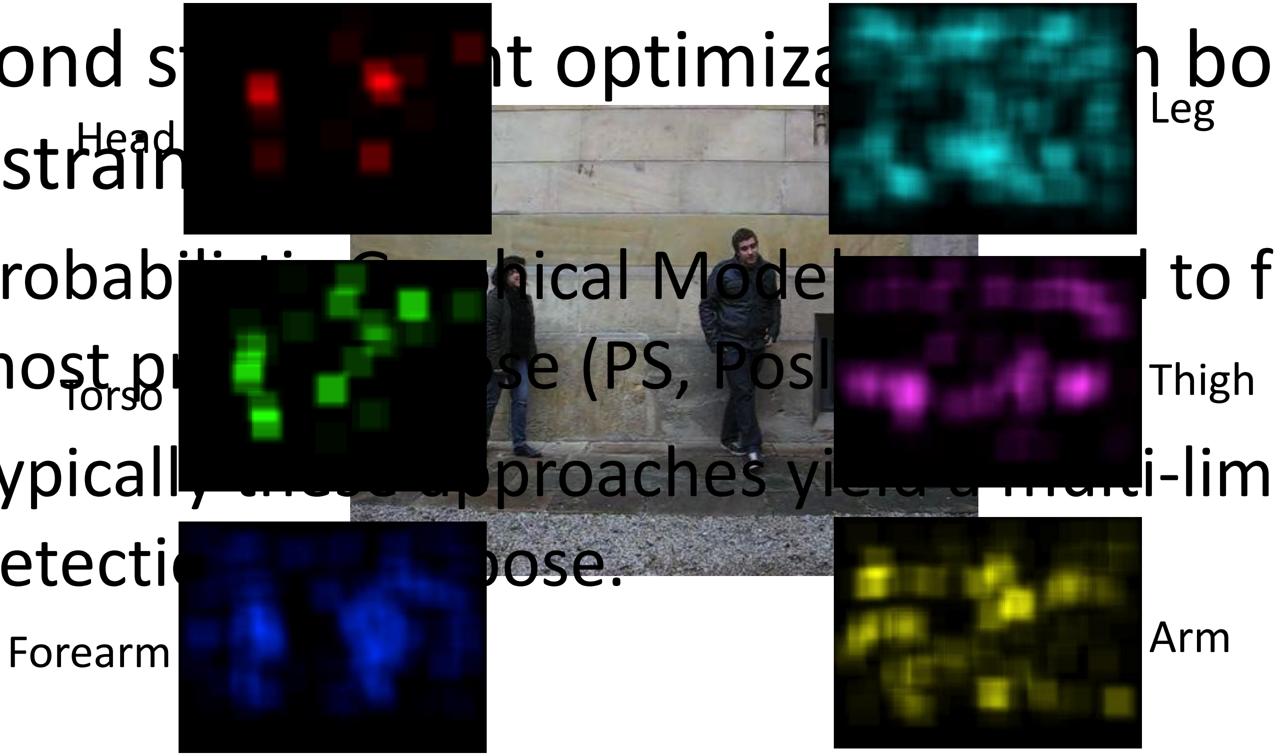
Segmenting humans in still images

- Problem:
  - **Segmenting the human** body (not the body-parts) in still **RGB images.**
  - **Several people** can appear portraying a **wide range of poses.**
- Approaches:
  - **One stage:**
    - Dalal & Triggs (HoG+SVM).
  - **Two stage**:
    - Andriluka, Roth & Schiele (Pictorial Structure)[1].
    - Bourdev, Maji, Brox & Malik (Poselets) [2].
    - Hernandez, Zlateva, Marinov, Reyes, Radeva, Dimov & Escalera (Graph Cuts) [3].

1. Andriluka, M., Roth, S., Schiele, B.: Pictorial structures revisited: People detection and articulated pose estimation. In: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. pp. 1014–1021. IEEE (2009)
2. Bourdev, L., Maji, S., Brox, T., Malik, J.: Detecting people using mutually consis- tent poselet activations. In: Computer Vision–ECCV 2010, pp. 168–181. Springer (2010)
3. 3Hernandez-Vela, A., Zlateva, N., Marinov, A., Reyes, M., Radeva, P., Dimov, D., Escalera, S.: Graph cuts optimization for multi-limb human segmentation in depth maps. In: CVPR. pp. 726–732 (2012)

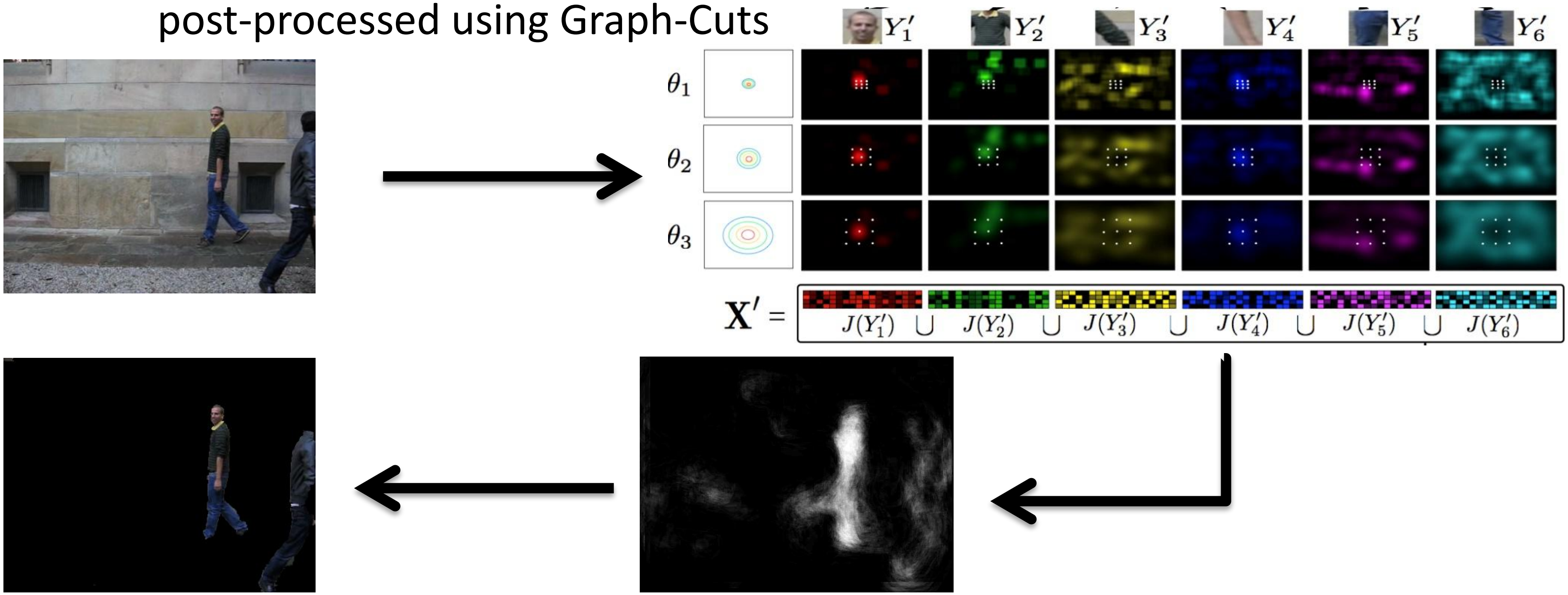
Two-Stage approach for human (multi-limb) segmentation

- First stage (body-part detection)
  - Use “unexpensive” classifiers to learn body parts: SVM, Adaboost, Cascading Classifiers, etc.
  - A large/noisy set of candidate parts is obtained.
- Second s t optimiza n body constrain
  - Probabi hical Mode l to find the most p se (PS, Posl
  - Typicall proaches yi i-limb detecti ose.



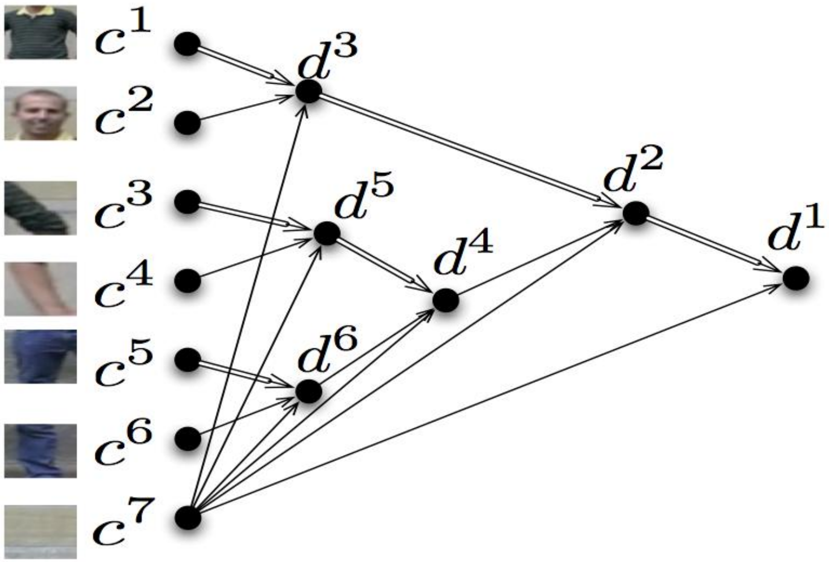
Segmenting humans by stacking body-parts

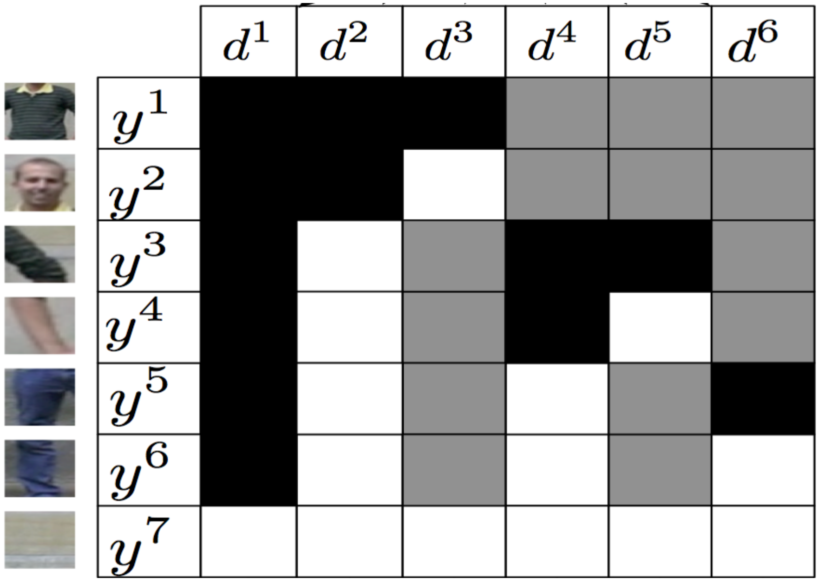
- **Our goal**
  - **Improve the binary segmentation** of the human body in RGB images by **learning context-aware features**.
- **Our proposal**
  - Define a **two stage** scheme where an extended feature set is learned.
  - Use the **Multi-Scale Stacked Sequential Learning** framework (MSSL) to build the extended feature set.
  - Obtain a prior **pixel-wise binary classification** of the image which is post-processed using Graph-Cuts


Y'_1
Y'_2
Y'_3
Y'_4
Y'_5
Y'_6
θ_1
θ_2
θ_3
$\mathbf{X}' = J(Y'_1) \cup J(Y'_2) \cup J(Y'_3) \cup J(Y'_4) \cup J(Y'_5) \cup J(Y'_6)$

Stage One (H_1): Soft Body Parts Detectors and Error-Correcting Output Codes (TR)

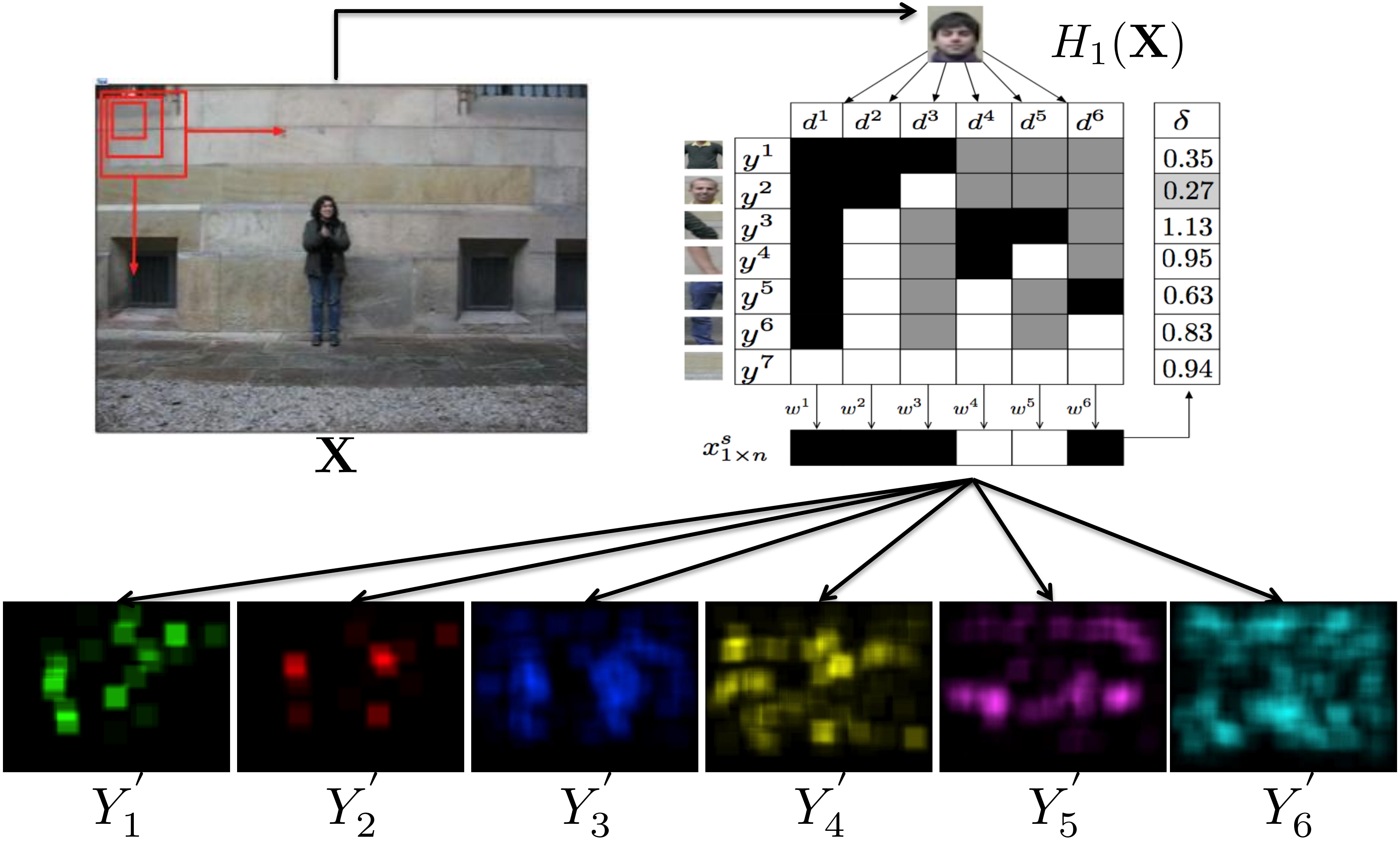
- Multi-class body-part detection based on **Error-Correcting Output Codes** (ECOC) and Soft Body Part Detectors (Cascading classifiers+Adaboost).
- **Problem-dependent coding** for body-part learning, where difficult dichotomies have few classes.
- Each d^i denotes a **dichotomy** (binary body part classification problem), that is coded within the ECOC coding matrix.





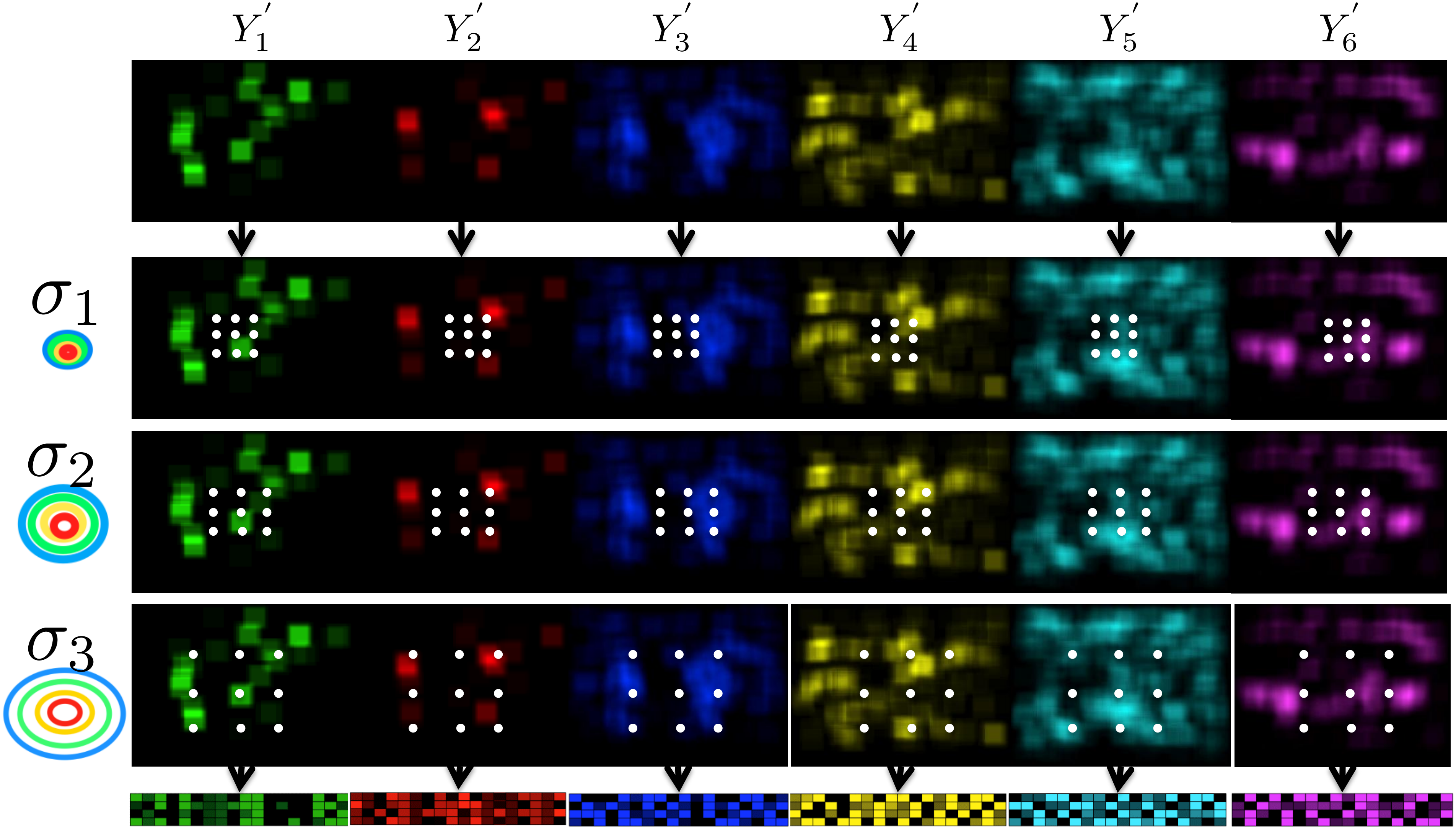
	d^1	d^2	d^3	d^4	d^5	d^6
y^1	■	■	■	▨	▨	▨
y^2	■	■	□	▨	▨	▨
y^3	■	□	▨	■	■	▨
y^4	■	□	▨	■	□	▨
y^5	■	□	▨	□	▨	■
y^6	■	□	▨	□	▨	□
y^7	□	□	□	□	□	□

Stage One (H_1): Soft Body Parts Detectors and Error-Correcting Output Codes (TR)


$H_1(\mathbf{X})$
$\mathbf{X}$
w^1 w^2 w^3 w^4 w^5 w^6
$x^s_{1\times n}$
Y'_1 Y'_2 Y'_3 Y'_4 Y'_5 Y'_6

	d^1	d^2	d^3	d^4	d^5	d^6	δ
y^1	■	■	■	▨	▨	▨	0.35
y^2	■	■	□	▨	▨	▨	0.27
y^3	■	□	▨	■	■	▨	1.13
y^4	■	□	▨	■	□	▨	0.95
y^5	■	□	▨	□	▨	■	0.63
y^6	■	□	▨	□	▨	□	0.83
y^7	□	□	□	□	□	□	0.94
$x^s_{1\times n}$	■	■	■	□	□	■	

Stage Two: Fusing Limb Likelihood Maps Using MSSL (TR)

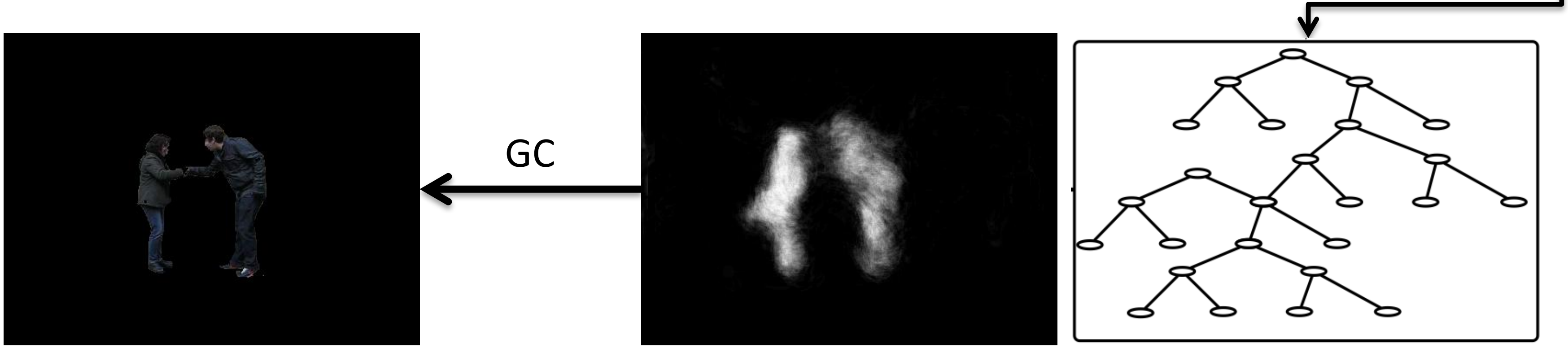


$$\mathbf{X}' = J(Y_1') \cup J(Y_2') \cup J(Y_3') \cup J(Y_4') \cup J(Y_5') \cup J(Y_6') \in \mathbb{R}^{\#N \times \#S \times \#Y}$$

Stage Two: Fusing Limb Likelihood Maps Using MSSL (TR & TE)

- The **extended feature set** $\mathbf{X}'$ encodes for each sampled pixel a concatenation of the **probability of neighbouring pixels** to belong to a certain **body part**.
- Then we use a **Random Forest** classifier $H_2(\mathbf{X}')$ to learn the **pixel-wise classification problem** (person vs. background), which output is then optimized by means of Graph Cuts.

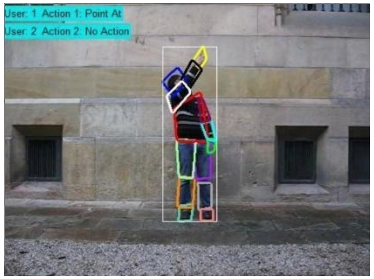
$$\mathbf{X}' = \boxed{J(Y_1') \;\cup\; J(Y_2') \;\cup\; J(Y_3') \;\cup\; J(Y_4') \;\cup\; J(Y_5') \;\cup\; J(Y_6')}$$

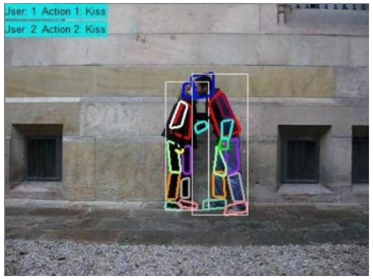


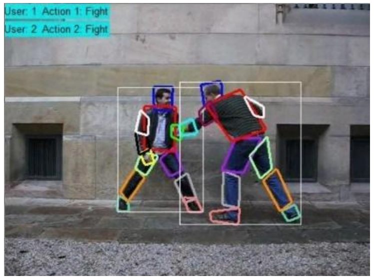
$H_2(\mathbf{X}')$

Experimental Settings I

- **Dataset:**
  - We used **HuPBA 8k+ dataset** which contains more than **8000 labeled** images at pixel precision, including more than **120000 manually labeled samples** of 14 different limbs.
  - We reduced the number of limbs from the 14 available in the dataset to 6: **head, torso, forearms, arms, thighs and legs**.







- **Methods:**
  - SBP-ECOC (H_1) + MSSL-RF (H_2) + Graph cut.
  - SBP-ECOC (H_1) + MSSL-RF (H_2) + GMM-Graph cut (Grabcut).
  - SBP-ECOC (H_1) + Graph Cut.
  - SBP-ECOC (H_1) + GMM-Graph Cut (Grabcut).

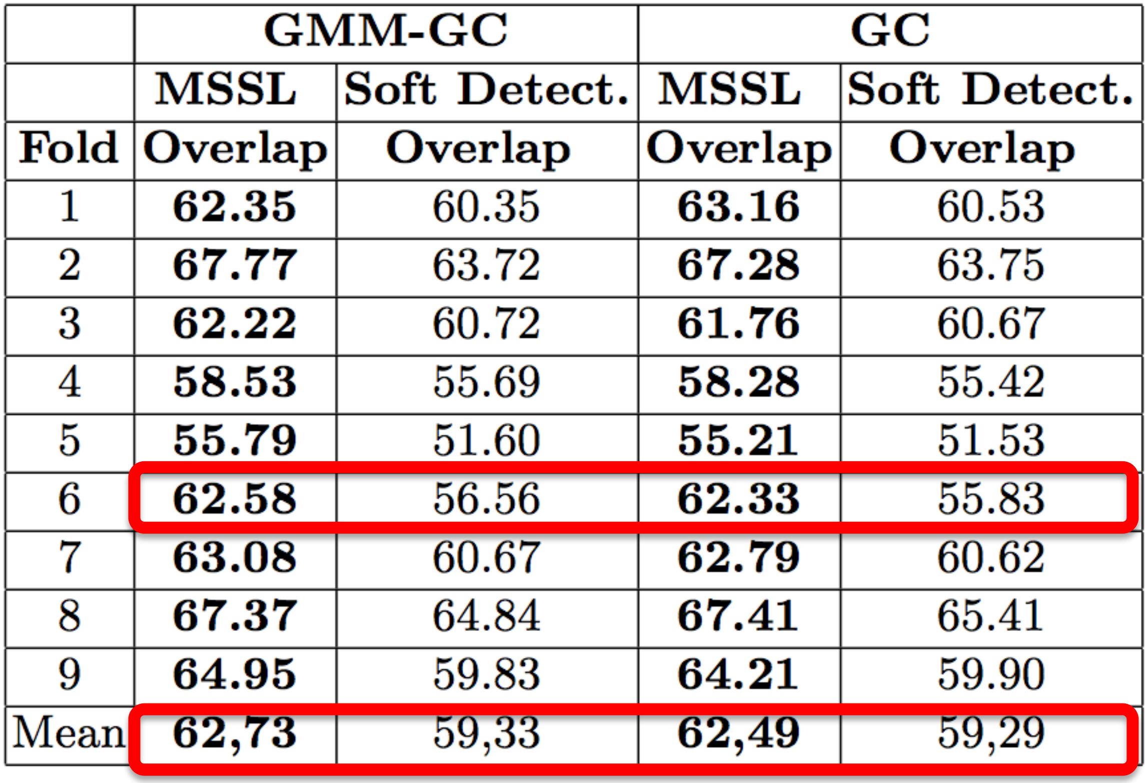
Experimental Settings II

- **Settings:**
  - We used the standard **Cascade of Classifiers** based on **AdaBoost and Haar-like features** as our body part multi-class classifier H_1, forcing a 0.99 false positive rate during 8 stages.
  - In the second stage, we performed **3-scale Gaussian decomposition** with $\sigma \in [8, 16, 32]$ for each body part.
  - We used a **Random Forest with 50 decision trees**, as H_2 classifier.
  - In a post-processing stage**, binary Graph Cuts with a GMM color modeling** (we experimentally set 3 components) were applied.
- **Validation Protocol:**
  - We used **9-fold cross-validation (leave one sequence out)**.
  - We used the **Jaccard Index of overlapping** as our results measurement.

$$J = \frac{A \cap B}{A \cup B}$$

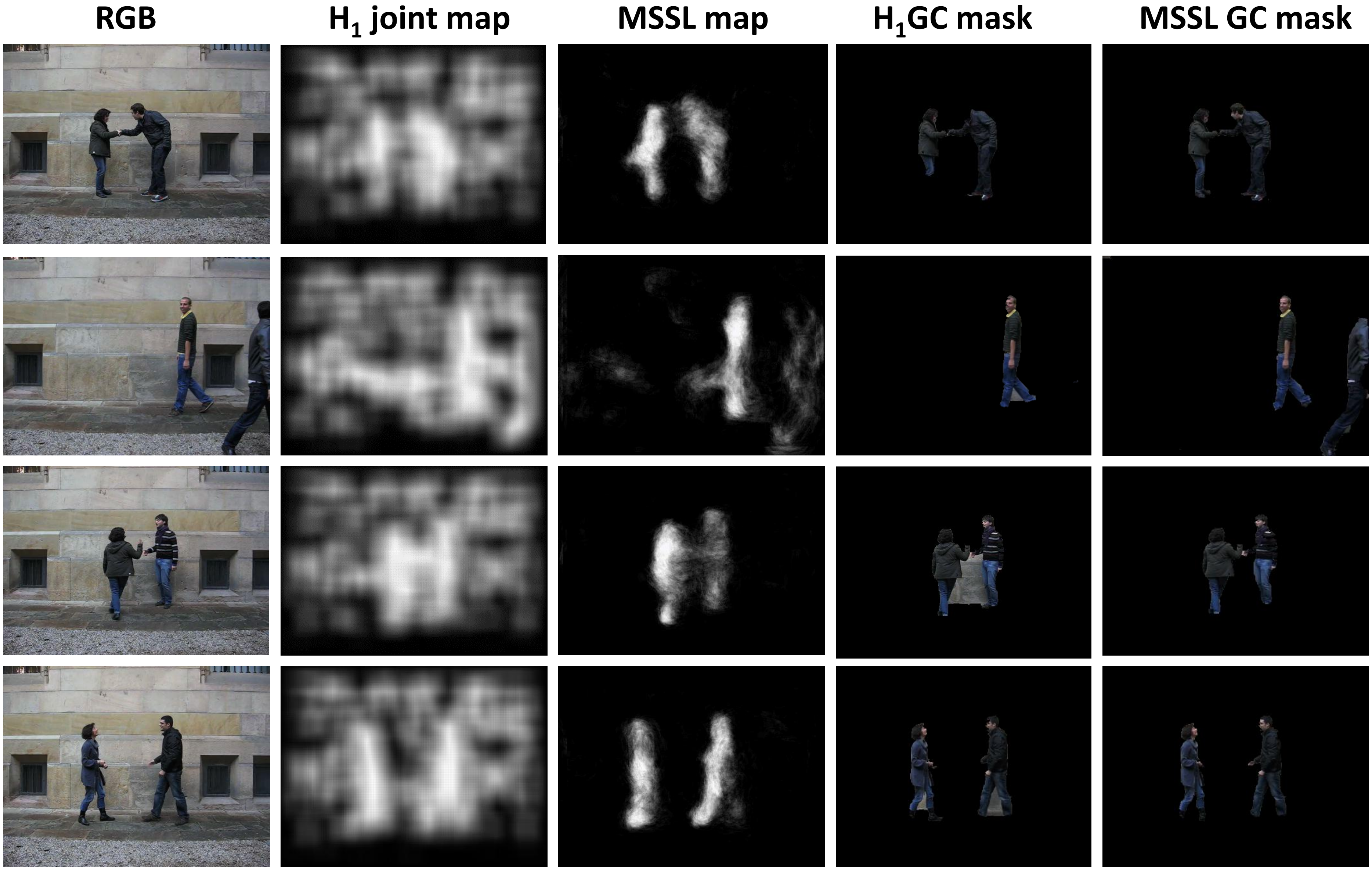
Quantitive Results

- When applying MSSL we find a consistent **improve in overlap of at least 3% in mean**.
- For certain folds the **improvements reach 5%**.



	GMM-GC		GC	
	MSSL	Soft Detect.	MSSL	Soft Detect.
Fold	Overlap	Overlap	Overlap	Overlap
1	**62.35**	60.35	**63.16**	60.53
2	**67.77**	63.72	**67.28**	63.75
3	**62.22**	60.72	**61.76**	60.67
4	**58.53**	55.69	**58.28**	55.42
5	**55.79**	51.60	**55.21**	51.53
6	**62.58**	56.56	**62.33**	55.83
7	**63.08**	60.67	**62.79**	60.62
8	**67.37**	64.84	**67.41**	65.41
9	**64.95**	59.83	**64.21**	59.90
Mean	**62,73**	59,33	**62,49**	59,29

Qualitative Results



Conclusions & Future Work

- We presented a **two-stage scheme based on the MSSL** framework for the **segmentation of the human body** in still images.
- **MSSL encodes extended feature** set using **contextual information** of human limbs.
- Our proposal was tested on a large dataset obtaining **significant segmentation improvement** over baseline methodologies.
- We are currently **extending the MSSL framework to the multi-limb case**, in which two multi-class classifiers will be concatenated to obtain a **body-aware segmentation**.

THANK YOU!

QUESTIONS?

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