

# HOLISTIC, INSTANCE-LEVEL HUMAN PARSING

## INTRODUCTION

Instance-level human parsing = category-level part segmentation + distinction between instances

A holistic solution to instance-level part segmentation is one which readily produces:

- Instance-level human segmentation
- Semantic part segmentation 11.

In contrast to existing instance segmentation methods [1], our approach segments humans at multiple granularities in a single forward pass through our network.

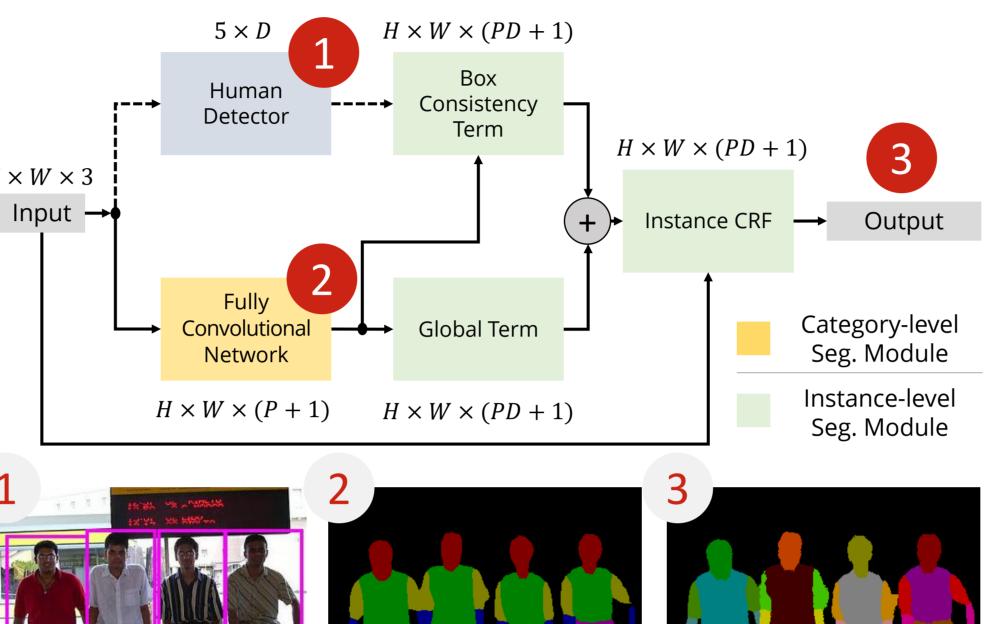
#### NETWORK OVERVIEW

Category-level Segmentation Module	<ul> <li>Semantically segments body parts</li> </ul>	resulting backgro The <b>b</b> oundir
Human Detector	<ul> <li>Localises humans with bounding boxes and scores</li> </ul>	The <b>glo</b> equal like
Instance-level Segmentation Module	<ul> <li>Converts category-level unary potential to instance-level</li> <li>Encourages visual and spatial consistency</li> </ul>	We for E(V =

[1] J Dai, et al. Instance-aware semantic segmentation via multi-task network cascades. In CVPR, 2016 [2] P Krahenbuhl and V Koltun. Efficient Inference in fully connected CRFs with Gaussian edge potentials. In *NIPS*, 2011 [3] B Hariharan et al. Simultaneous detection and segmentation. In ECCV, 2014.

[4] Y Chen, et al. Multi-instance object segmentation with occlusion handling. In CVPR, 2015 [6] A Arnab, et al. Bottom-up instance segmentation with deep higher order crfs. In BMVC, 2016

 $H \times W \times 3$ 





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Figure 1. Overview of our proposed end-to-end network (given detections), containing a category-level segmentation module, a human detector, and an instance-level segmentation module. All modules are fully differentiable.

## INSTANCE SEG. MODULE

The category-level seg. module assigns each pixel to one of the P body parts. Each of the D detections defines a possible human instance, sulting in a label space of  $\{1, 2, ..., D\} \times \{1, 2, ..., P\} \cup \{(0,0)\}$ , including ckground (0,0). A label of (i, j) denotes part j of human i.

he **box consistency term**  $\psi_{Box}$  encourages pixels inside a human ounding box  $B_i$  to associate with the *i*-th human detection:

$$\psi_{Box}\left(V_k = (i,j)\right) = \begin{cases} s_i Q_k(j), & k \in B_i \\ 0, & \text{otherwise} \end{cases}$$

he **global term**  $\psi_{Global}$  handles poor detection localisation by assuming ual likelihood for a pixel to belong to any of the detected humans:

$$\psi_{Global}(V_k = (i,j)) = Q_k(j)$$

/e formulate a **Dense CRF** [2] over these V variables:

$$= \boldsymbol{v}) = -\sum_{i}^{N} \ln(w_1 \psi_{Box}(v_i) + w_2 \psi_{Global}(v_i) + \varepsilon) + \sum_{i < j}^{N} \psi_{Pairwise}(v_i, v_j)$$

We evaluate our instance-level *part* segmentation method on the Pascal Person-Parts (PPP) Dataset and obtain state-of-the-art results using Multi-task Network Cascades (MNC) [1] as a strong baseline.

The  $AP^r$  metric [3] is used to compare to other methods. A prediction is only considered correct if it has an intersection over union (IoU) with a ground truth instance above a certain threshold.

#### Method

MNC<sup>[1]</sup> Ours, piecewise, k Ours, piecewise Ours, end-to-end

Table 1. Comparison of  $AP^r$  for instance-level part segmentation on PPP val. set

Converting our output to **instance-level** human segmentation only involves mapping the predicted label (i, j) to i. We compare to other instance segmentation methods on the human category of the VOC12 val. set, and also achieve state-of-the-art performance.

#### Method

SDS [3] Chen *et al.* [4] PFN [5] Arnab *et al.* [6] R2-IOS [7] Arnab et al. [8] Ours, piecewise Ours, end-to-end

Table 2. Comparison of AP<sup>r</sup> for instance-level human segmentation on VOC12 val. set



### RESULTS

$$AP_{\rm vol}^r = \sum_{i=1}^9 AP_{i/10}^r$$

IoU threshold			
0.6	0.7	$AP_{vol}^{r}$	
8 28.1	19.3	36.7	
28.9	17.5	36.7	
29.7	18.7	37.4	
5 30.4	19.1	38.4	
	0.6 8 28.1 7 28.9 7 29.7	0.60.7328.1 <b>19.3</b> 728.917.5729.718.7	

	$AP_{nol}^r$				
0.5	0.6	0.7	0.8	0.9	APvol
47.8	31.8	15.7	3.3	0.1	-
48.3	35.6	22.6	6.5	0.6	-
48.4	38.0	26.5	16.5	5.9	41.3
58.6	52.6	41.1	30.4	10.7	51.8
60.4	51.2	33.2	-	-	-
65.6	58.0	46.7	33.0	14.6	57.4
64.0	59.8	51.0	38.3	20.1	57.2
70.2	63.1	54.1	41.0	19.6	61.0

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