

Detecting Nonexistent Pedestrians

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CVPR'17

Joint Workshop on Scene Understanding and LSUN Challenge

Hawaii Convention Center, Hawaii, July 26, 2017

Morning Session: Scene Understanding Workshop (SUNw'17)

Organizers: Bolei Zhou, Aditya Khosla, Jianxiong Xiao, James Hays

Afternoon Session: Large SUN Challenge (LSUN'17)

Organizers: Fisher Yu, Peter Kotschieder, Shuran Song, Ming Jiang, Yinda Zhang, Catherine Qi Zhao, Thomas Funkhouser, Jianxiong Xiao

Leaderboard for Our CVPR-2017 Workshop Challenge

The challenge is ended. We have received 63 submissions during that time period. Following is the final leader-board, where the parsing challenge is ranked by Mean IoU(%) and the pose challenge is ranked by PCK. We have omitted results without clear description.

Human Pose Challenge



Show entries

Search:

Ranking	Method	PCK	Details	Submit Time
1	NTHU-Pose	87.400	Details	2017-06-02 03:06:07
2	Pyramid Stream Network (Multi-Model)	82.100	Details	2017-06-03 08:03:30
3	BUPTMM-POSE	80.200	Details	2017-06-04 14:53:20
4	Hybrid Pose Matchine	77.200	Details	2017-06-04 13:38:59

Showing 1 to 4 of 4 entries

Previous

1

Next

Abbreviations

Detecting *nonexistent* pedestrians?



Urban Scene Understanding



What? Where? When? Why?



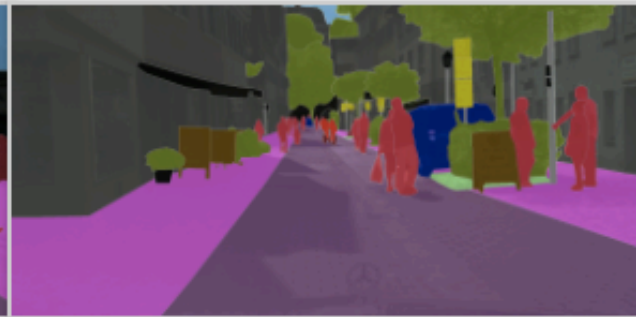
Stuttgart



Zurich



Ulm



Tübingen



Münster



Cologne



Bonn



Erfurt



Jena



Düsseldorf



Lindau



Weimar

CITYSCAPES Dataset

Detecting Nonexistent Pedestrians vs. Detecting Pedestrians

- Predict from context
- Where to look at to find people?

Problem Definition

To predict the presence probabilities of nonexistent pedestrians in a street scene

Input image



Probabilities map



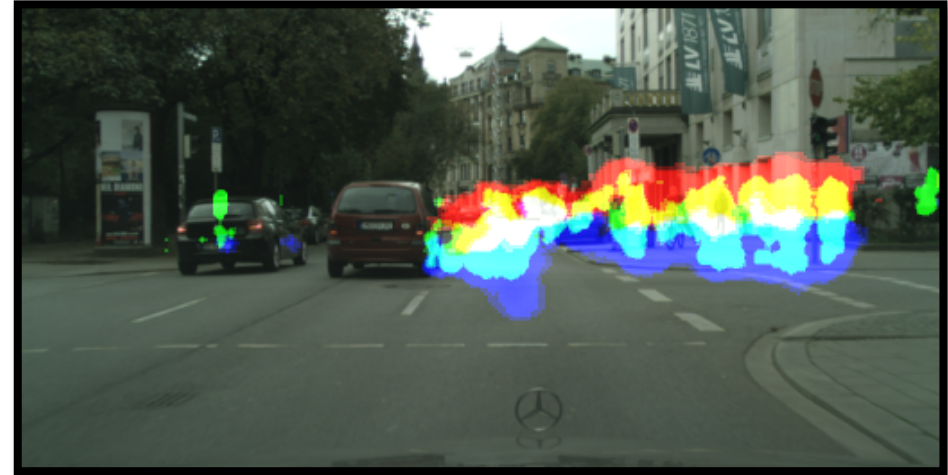
Synthetic image



Experimental Results



a. Input image



b. Predicted heat map



c. Pedestrians placed arbitrary



d. Pedestrians placed according to (b)

Pipeline

1. Generate training data

- Collection
- Pose estimation
- Inpainting
- Input / output

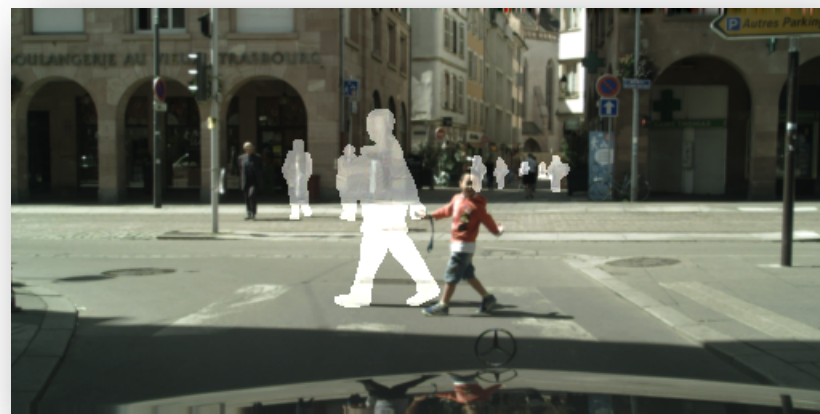
2. Train the network

- Adversarial learning

3. Synthesize images

- Pedestrian datasets
- Synthesis

Training Data



Generate Training Data – Collection

Dataset



M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, "The Cityscapes Dataset for Semantic Urban Scene Understanding," in *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. [Bibtex]

Type of annotations



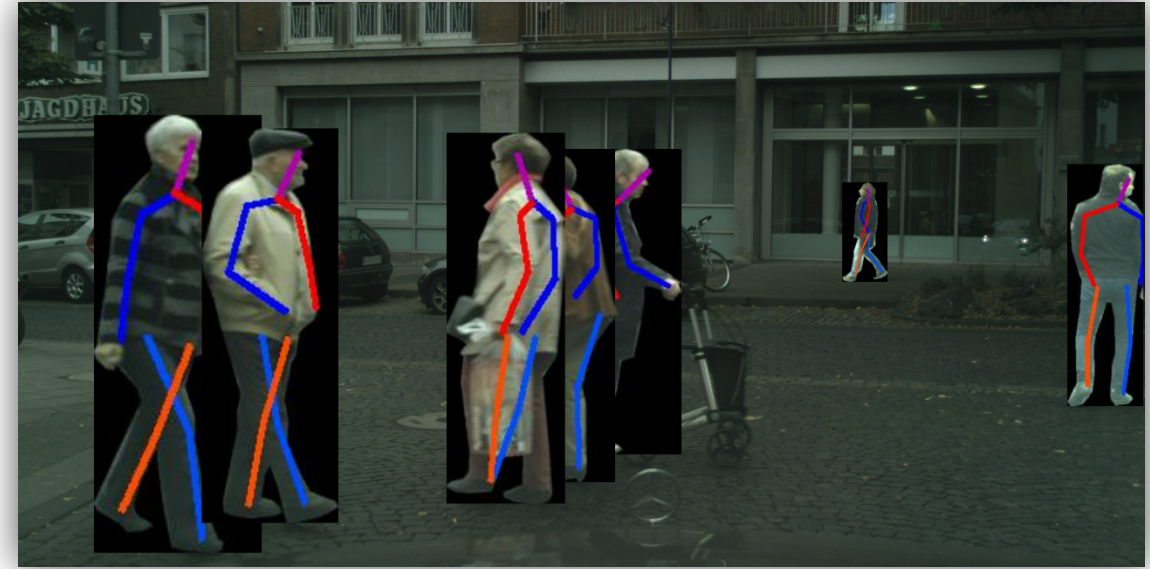
1024 x 2048



256 x 512



Generate Training Data – Pose Estimation



Generate Training Data - Inpainting



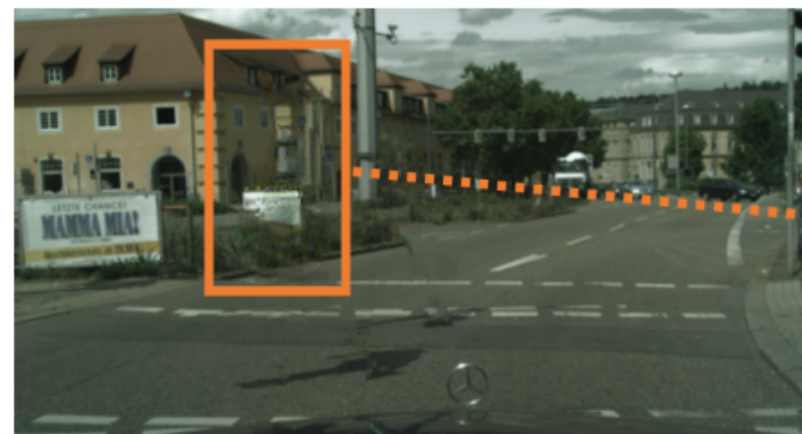
(a)



(b)



(c)



(d)

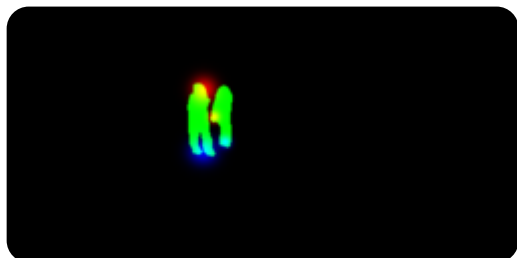
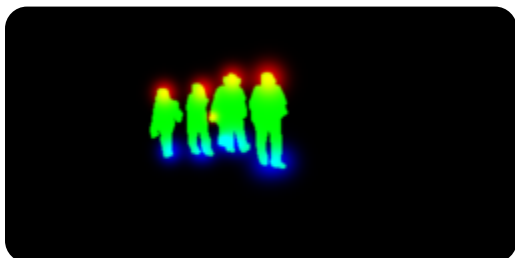


Generate Training Data – Input / Output

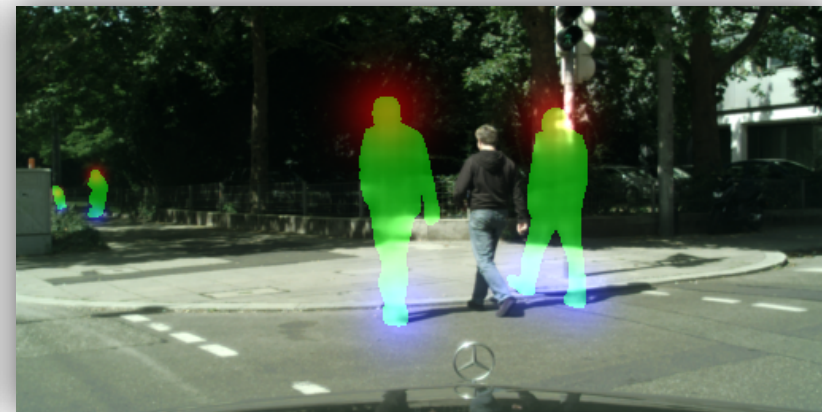
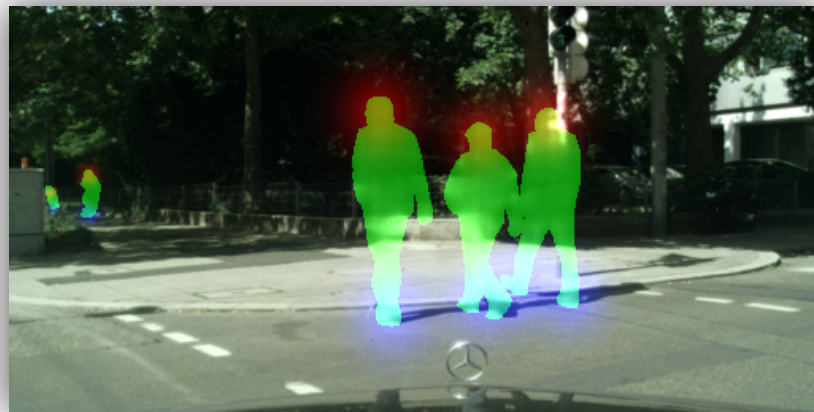
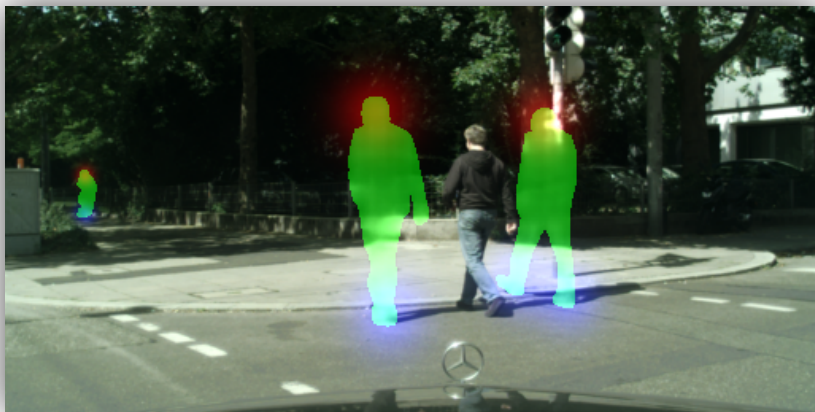
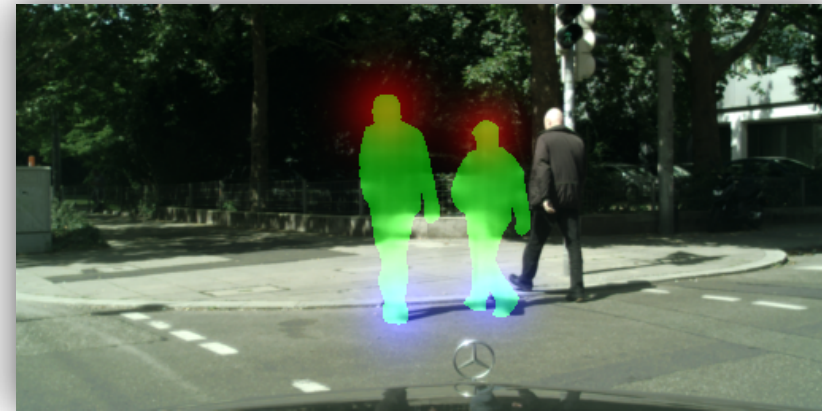
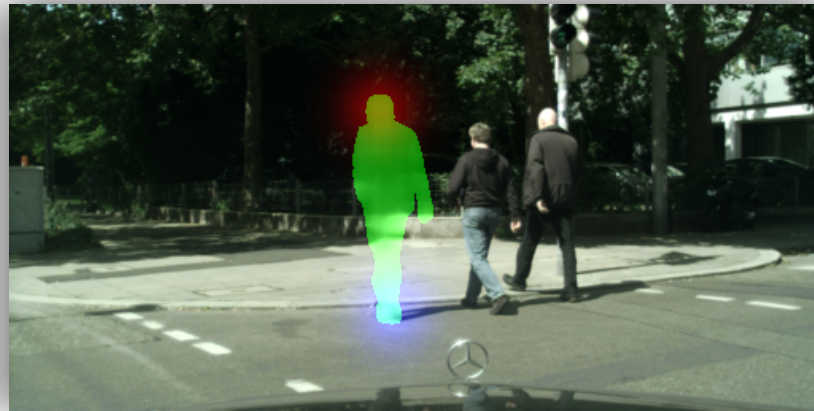
image



heatmap



More Examples



Pipeline

1. Generate training data

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- Inpainting
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2. **Train the network**

- **Adversarial learning**

3. Synthesize images

- Pedestrian datasets
- Synthesis

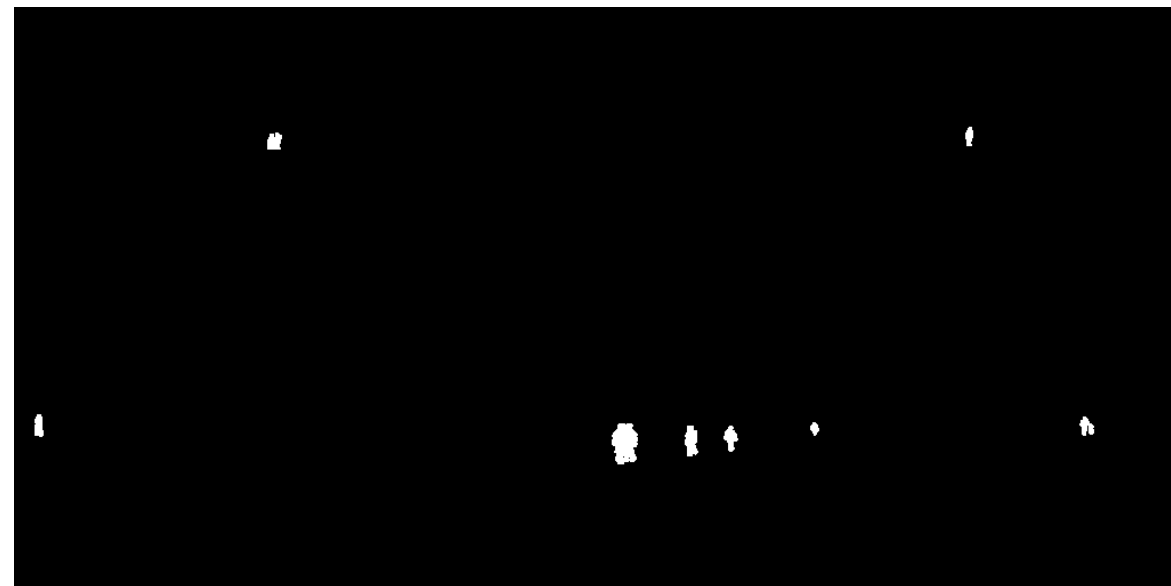
Task



pedestrian pixel ratio > 5%

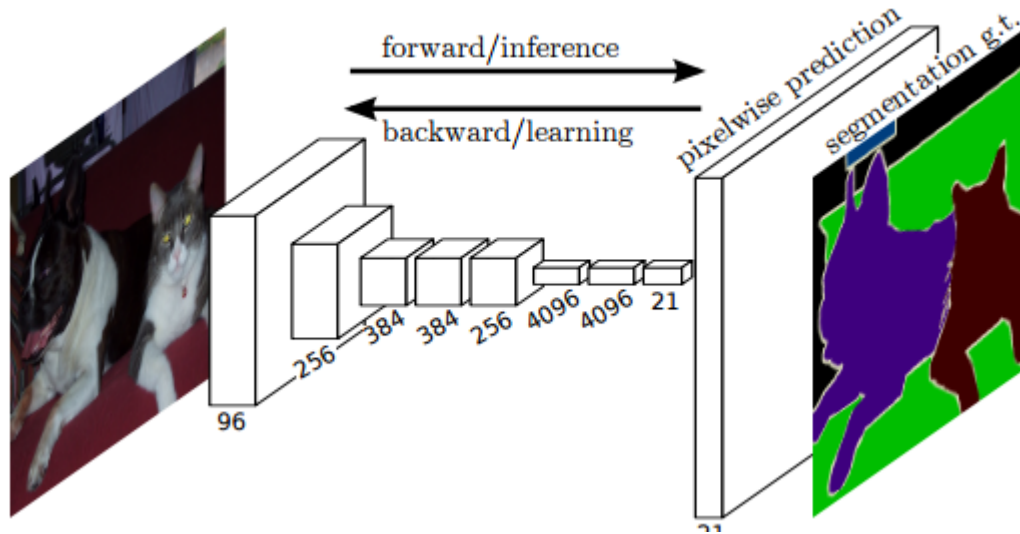


pedestrian pixel ratio <= 5%

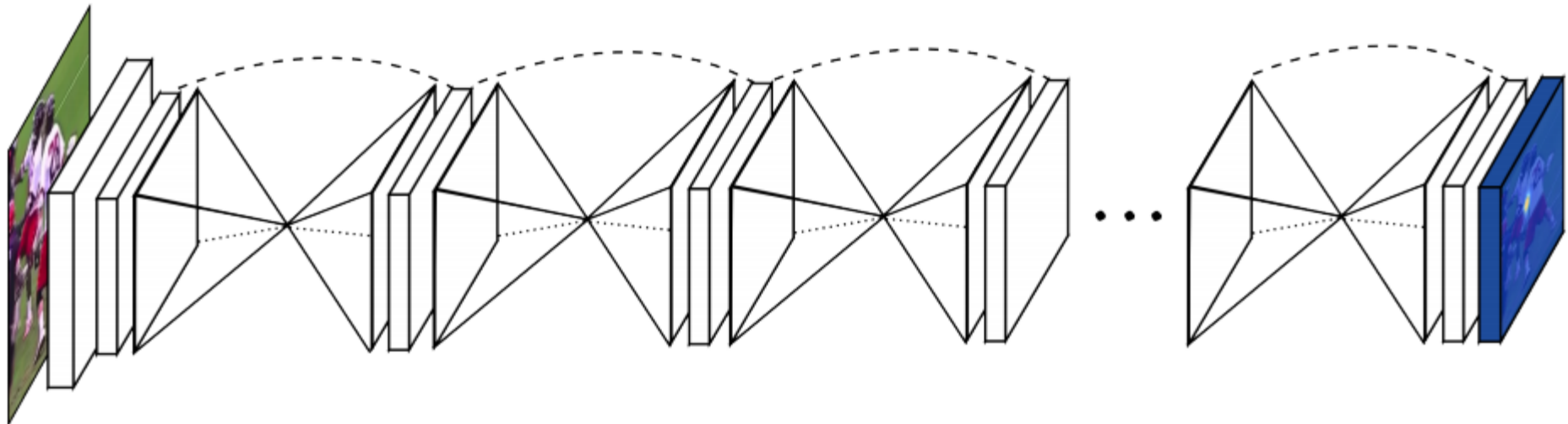


Network

- FCN



- Stacked Hourglass



Adversarial Learning

- **GAN**

- DCGAN
- WGAN
- WGAN improved

- **Using adversarial loss is popular**

- Image-to-Image Translation with Conditional Adversarial Networks (CVPR2017)
- Adversarial PoseNet: A Structure-aware Convolutional Network for Human Pose Estimation
- SalGAN: Visual Saliency Prediction with Generative Adversarial Networks (CVPR2017 workshop)

And more...

- **Image Inpainting**

- Context Encoders: Feature Learning by Inpainting (CVPR2016)
- Generative face completion (CVPR2017)
- Globally and Locally Consistent Image Completion (SIGGRAPH 2017)

- **Super-Resolution**

- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

- **Object Detection**

- A-Fast-RCNN: Hard Positive Generation via Adversary for Object Detection (CVPR2017)

- **Video Prediction**

- Generating Videos with Scene Dynamics (NIPS2016)

Semantic Segmentation using Adversarial Networks

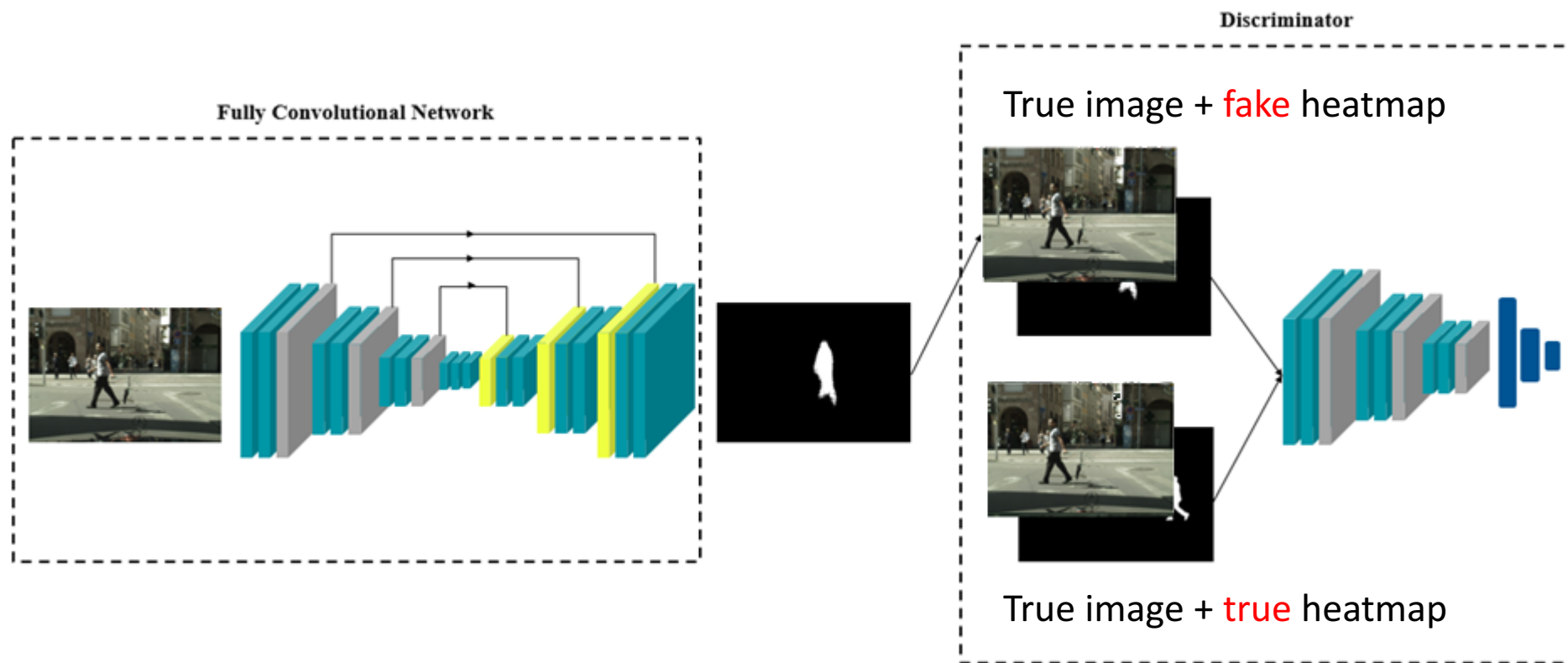
Reference:

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Soumith Chintala
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Ours:



Experiments - Validation

To evaluate the performance of these methods on predicting heatmaps, we use the recall rate as the metric. It is formulated as follows:

$$\frac{1}{N} \sum_{i=1}^N \frac{\text{area}(l_i \cap h_i)}{\text{area}(l_i)}$$

where N is the number of images in validation set. $\text{Area}(l_i \cap h_i)$ is the overlap between ground truth heatmap l_i and predicted heatmap h_i .

FCN	Hourglass	FCN+D
0.86	0.88	0.89

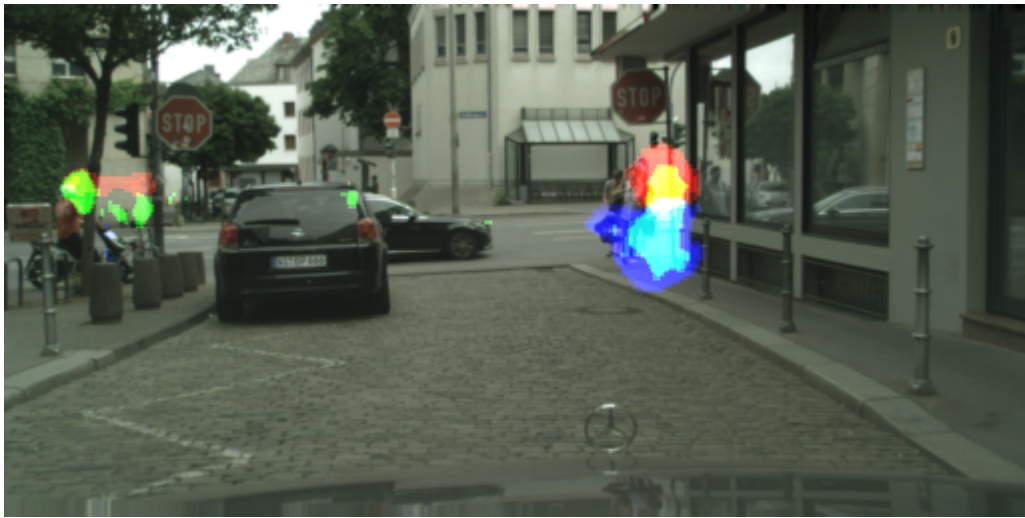
Experiments – Test

1. Sidewalks, safety islands, and bus stops are often assigned with high probabilities of pedestrian presence, even if the scene is void of pedestrians.
2. The timing is right: The *phantom* pedestrians is inclined to cross the street when there is no car.
3. People tend to form groups.
4. Depth and perspective are correct: The `sizes' of high-response areas in the heatmap are in accordance with the depth and vanishing point.

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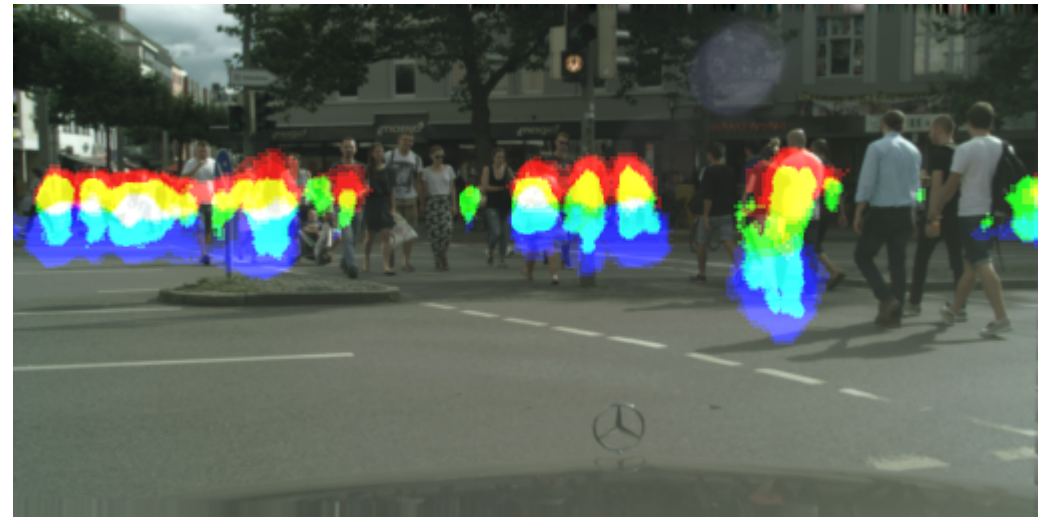
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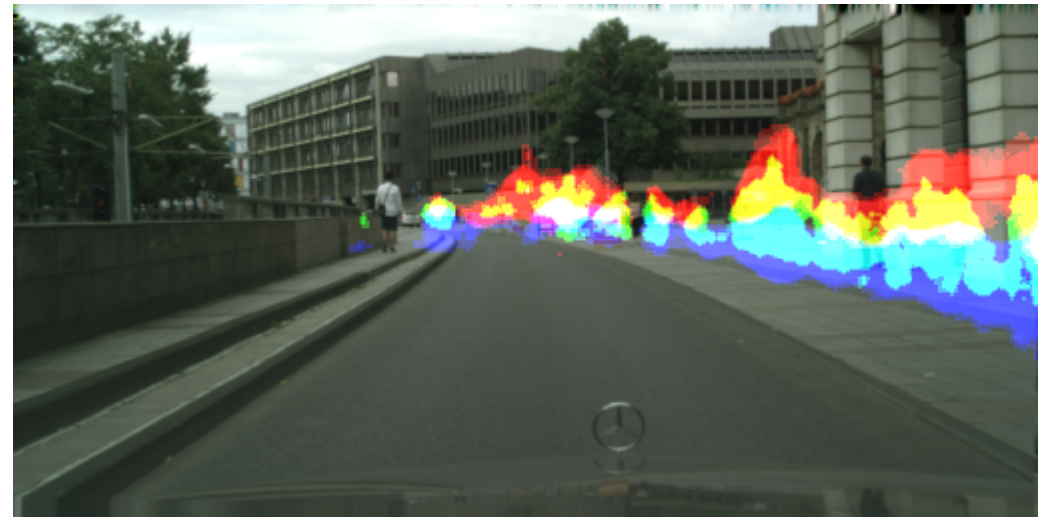
3. People tend to form groups.



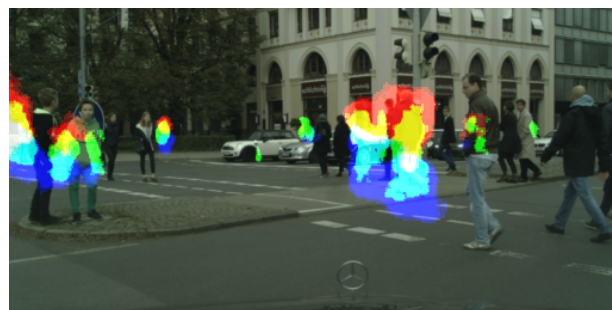
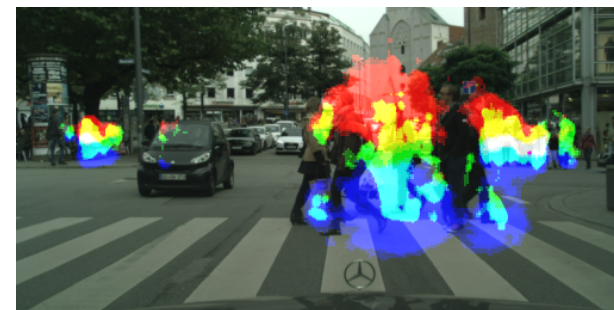
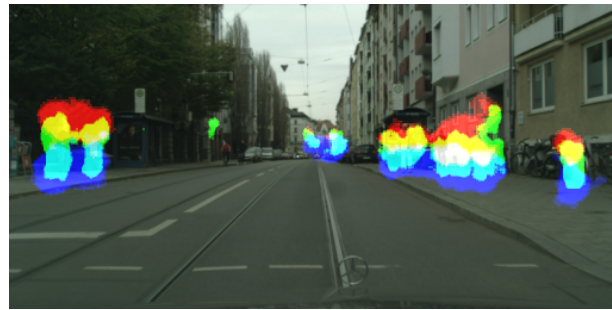
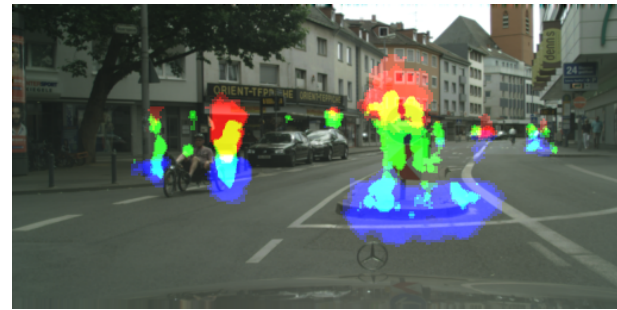
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More Results



Pipeline

1. Prepare training data

- Collection
- Pose estimation
- Inpainting
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2. Train the network

- Adversarial learning

3. **Synthesize images**

- **Pedestrian datasets**
- **Synthesis**

Pedestrian Datasets

- Images collected from *Cityscapes* and *PedCut*
- Categorized by height, width, aspect ratio...



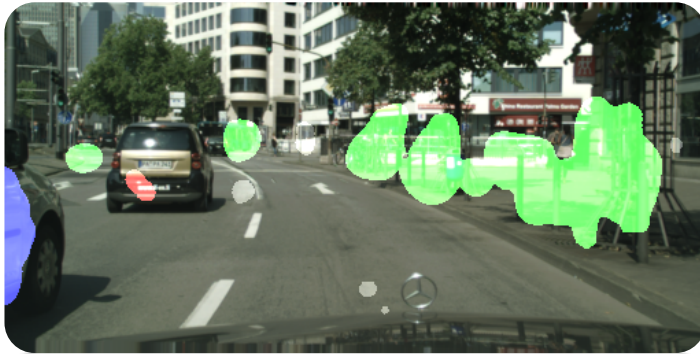
Synthesis Pipeline - Basic



a. Input image



b. Predicted probability map (raw)

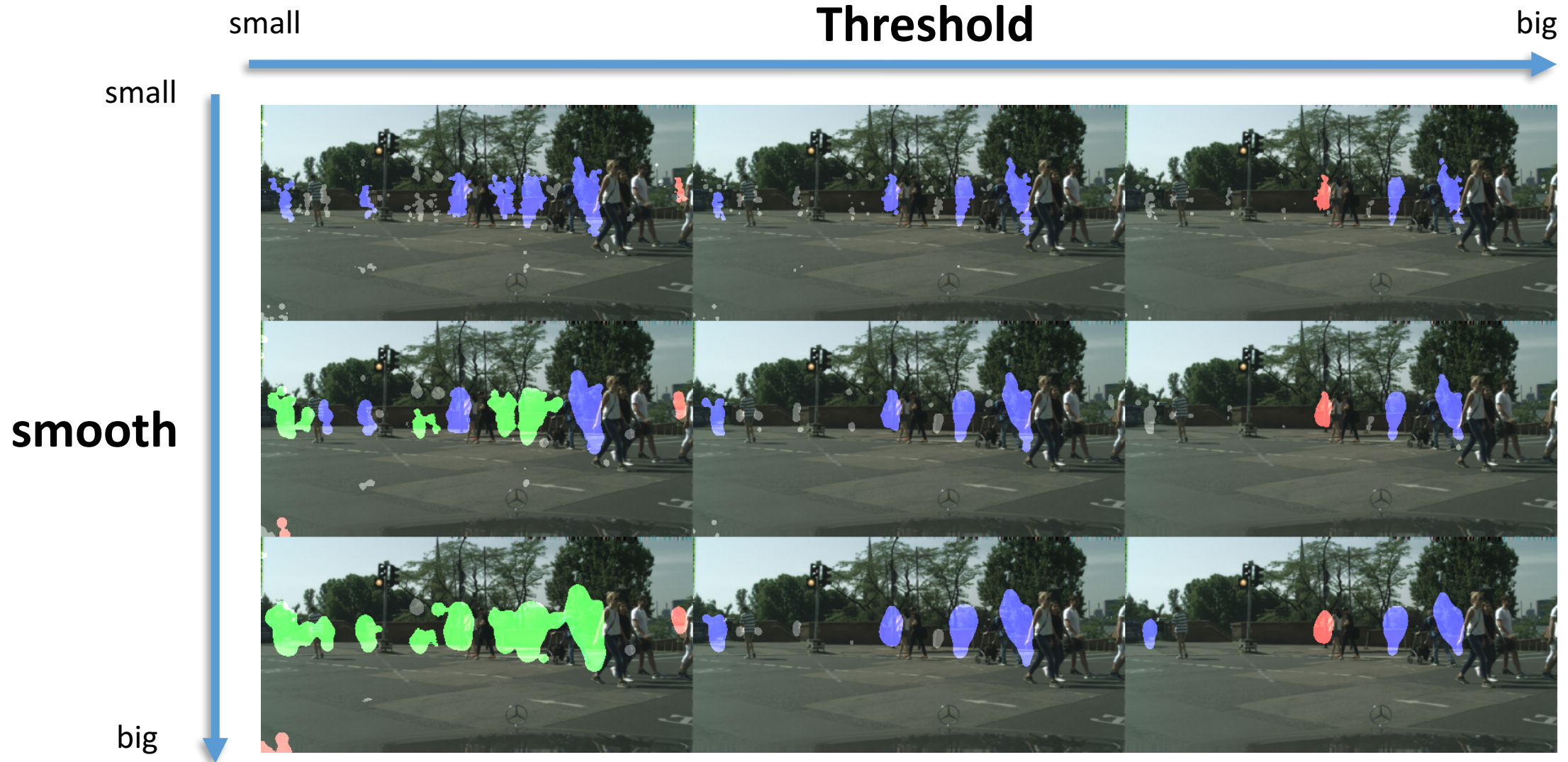


c. (b) with post processing



d. Synthesized according to (c)

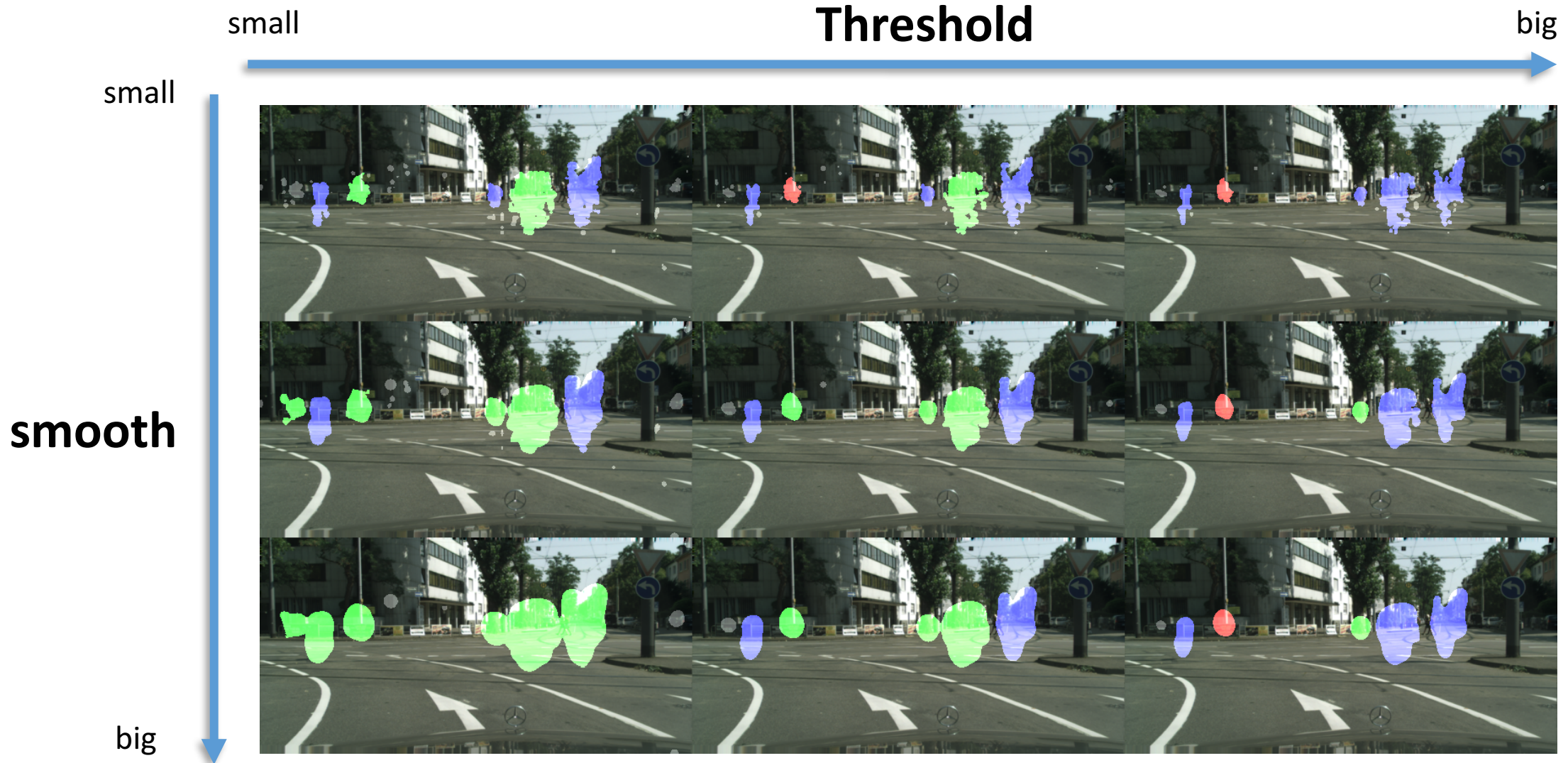
Hyperparameters



Hyperparameters



Hyperparameters

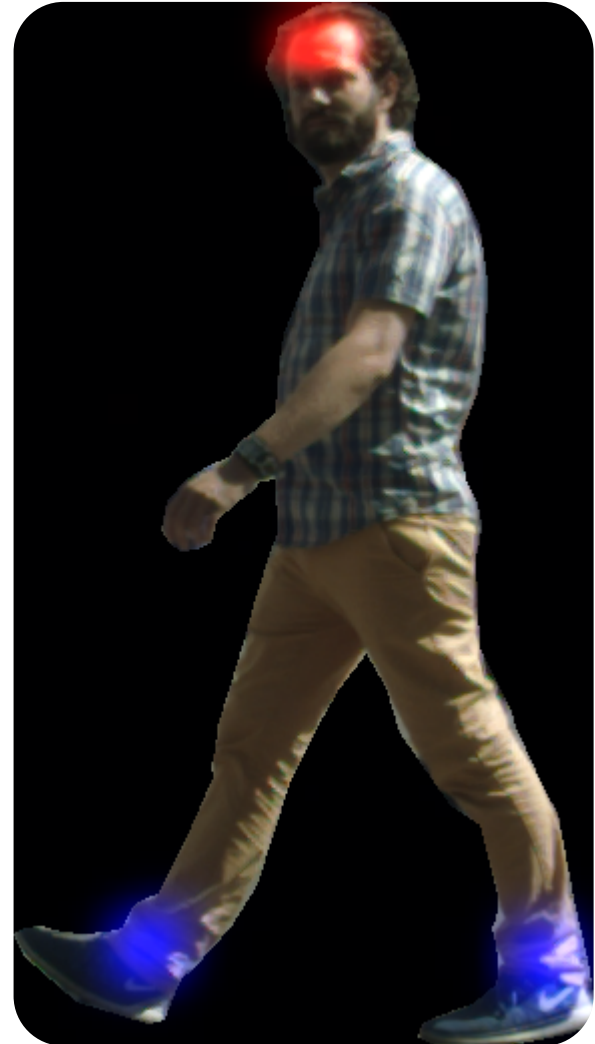


Hyperparameters



Synthesis Pipeline - Advanced

- Find pedestrians with the most similar pose!

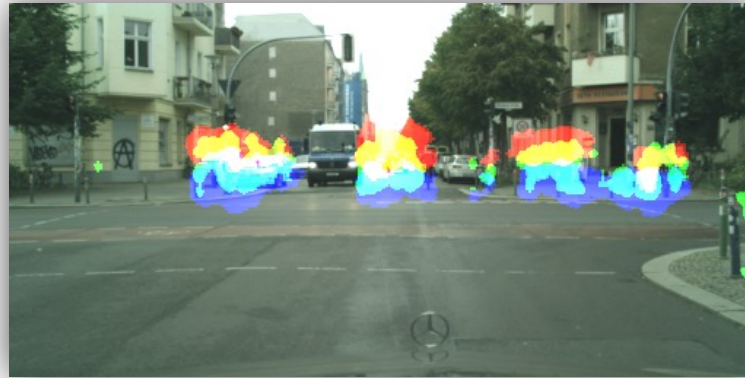


More Results

Image



Probability map



Synthetic output



More Results

Image



Probability map



Synthetic output



More Results

Image

Probability map

Synthetic output



Thanks