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Safeguarding Privacy by Reliable Automatic Blurring of Faces in Mobile Mapping Images

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Overview

- Introduction
- Provided datasets
- Suggested approach
  - Scale-space location relation
  - Color-based removal of pedestrian-like detections
  - Soft blurring approach
- Results
- Conclusions and future work

Introduction

- Mobile mapping & remote sensing = fast growing industry
- Capturing data in the wild leads to privacy issues in crowded environments and questions on how to handle them
  - Avoiding pedestrians while capturing mobile mapping data is nearly impossible.
  - Manual blurring labor is expensive and time consuming
  - Datasets grow larger and larger every day up to millions of images a day
- Definitely need of a system that
  1. Automatically detects pedestrians in mobile mapping data
  2. Automatically ensures privacy safety through automated smooth blurring approach without manual intervention

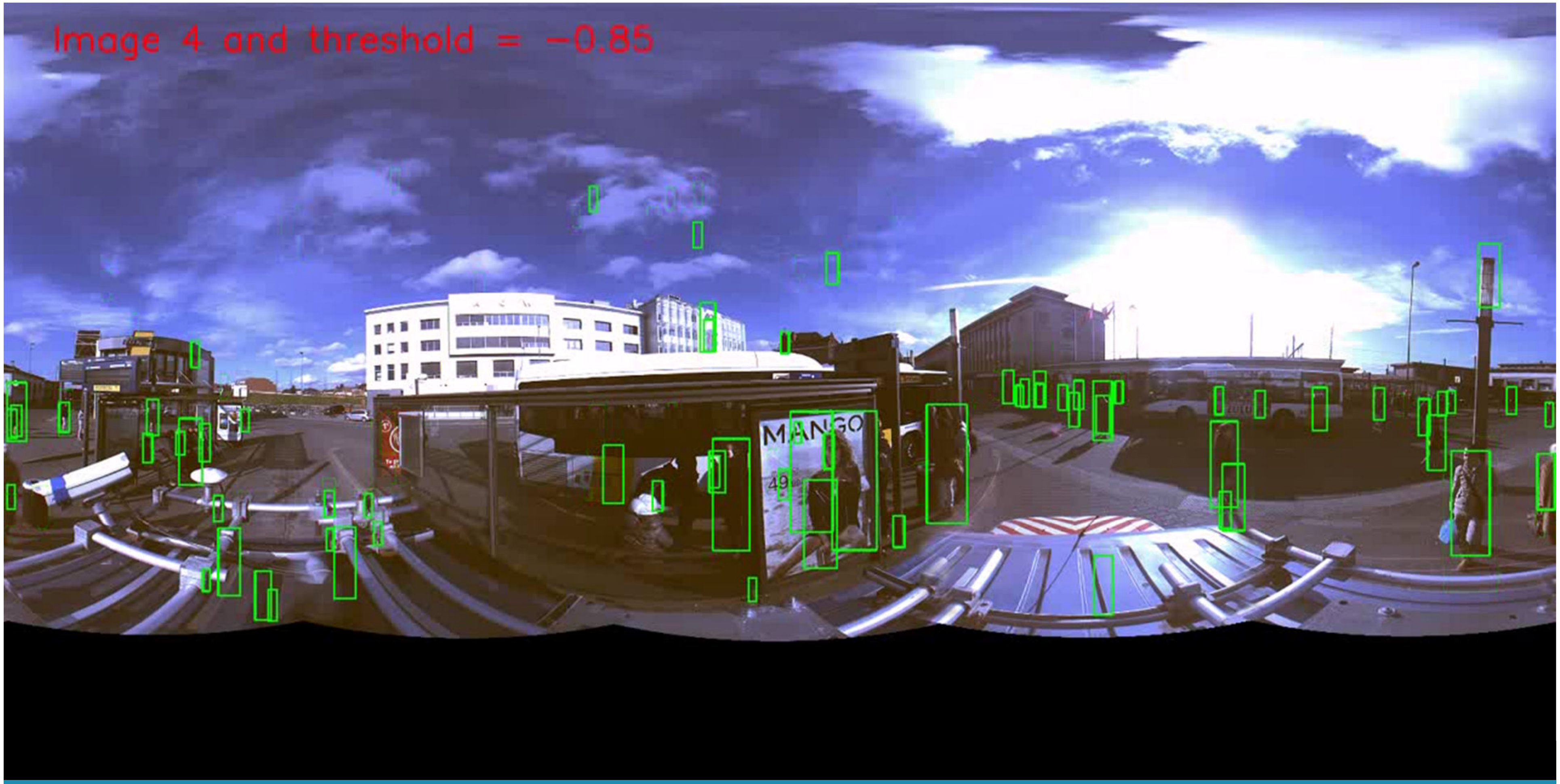
Introduction

- Challenge when using of the shelf pedestrian detectors
  - Setting the certainty threshold too sloppy
    - Ensure we find all pedestrians in the given image
    - However, increase in false positive detections
    - Too much privacy secure information is blurred
  - Setting the certainty threshold too strict
    - We will loose pedestrian detections
    - Privacy insecure data will be released into the public

- Our application focusses on capturing cycloramic mobile mapping data in crowded environments while
  1. Safeguarding the privacy of pedestrians
  2. Maintaining as much image information as possible

Introduction

- The certainty threshold setting illustrated



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Provided datasets

- Research is based on 2 datasets, made publicly available
  - Dataset 1: calm urban area in the Netherlands
    - *4800 x 2400* pixel cycloramic images using *LadyBug 1* camera
    - *450* images under day-light conditions with *240* pedestrian annotations
  - Dataset 2: train and bus station in Belgium
    - *8000 x 4000* pixel cycloramic images using *LadyBug 2* camera
    - *45* images under day-light conditions with *1630* pedestrian annotations

  - Available at http://www.eavise.be/MobileMappingDataset

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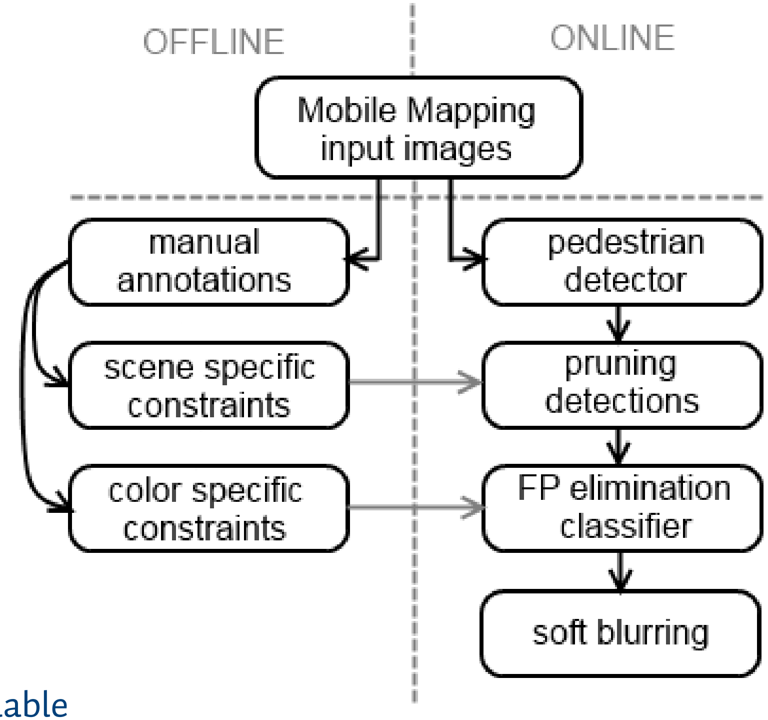
Suggested approach:
Overall approach



- Using of-the-shelf pedestrian detection algorithms
  - In our case, a cascaded LatentSVM4 pedestrian detector using a part based object detector [1]
  - Benefits
    - Highly interchangeable with other detectors
    - Non rigid model → different pose capturing
    - We have an optimized C++ implementation available

- **Offline** part
  - Preprocessing of the training data
  - Defining the scene constraints
  - Generating effective post processing filters countering FP detections

- **Online** part
  - Execute the pedestrian detector
  - Prune detections using constraints
  - Eliminate FP detections
  - Apply the soft blurring approach

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[1] De Smedt, F., Struyf, L., Beckers, S., Vennekens, J., De Samblanx, G., and Goedeme, T. (2012). Is the game worth the candle? Evaluation of OpenCL for object detection algorithm optimization. PECCS, pages 284–291.

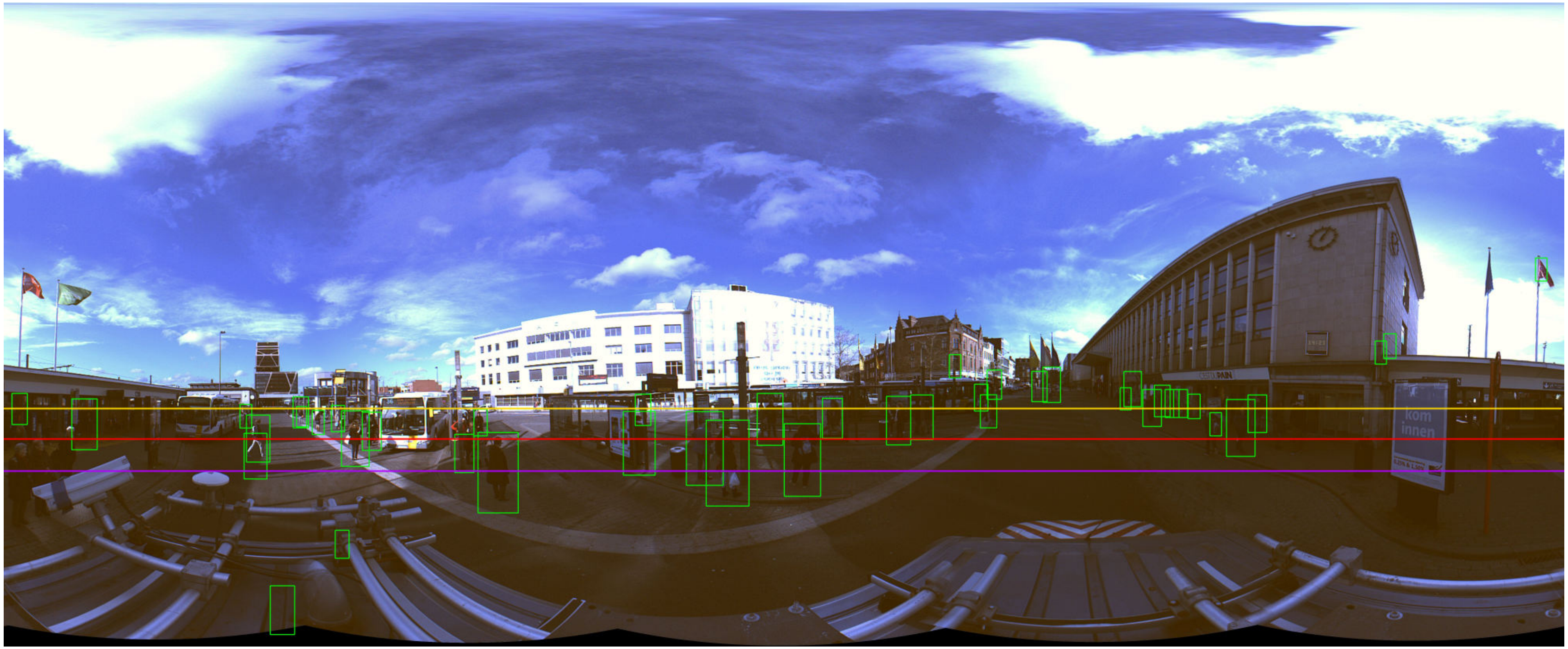
Suggested approach:
Scale-space location relation

- From the small set of manually labelled scene specific input images we derive a scale-space location relation
    - Based on the *ground plane assumption* concept = due to fixed position of the camera in relation to the ground plane, each pedestrian has a fixed scale position relation in the resulting 360 degree cycloramic image
    - For any given horizontal line in the image, we can state that all pedestrians on that line will have the same average height, of course keeping in mind that we have a natural height variance within pedestrians

- From this idea we modelled a scale-space location relation
    - Ideal for pruning FP detections from a detector with a more sloppy threshold
    - Remove regions where pedestrian detections are not possible

Suggested approach:
Scale-space location relation

AveragePurple > AverageSizeRed > AverageSizeYellow



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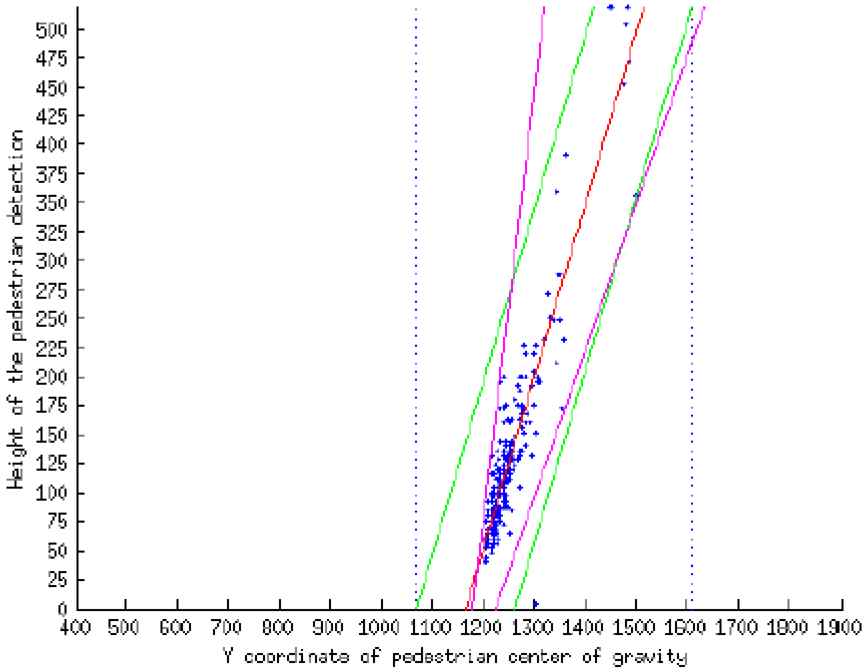
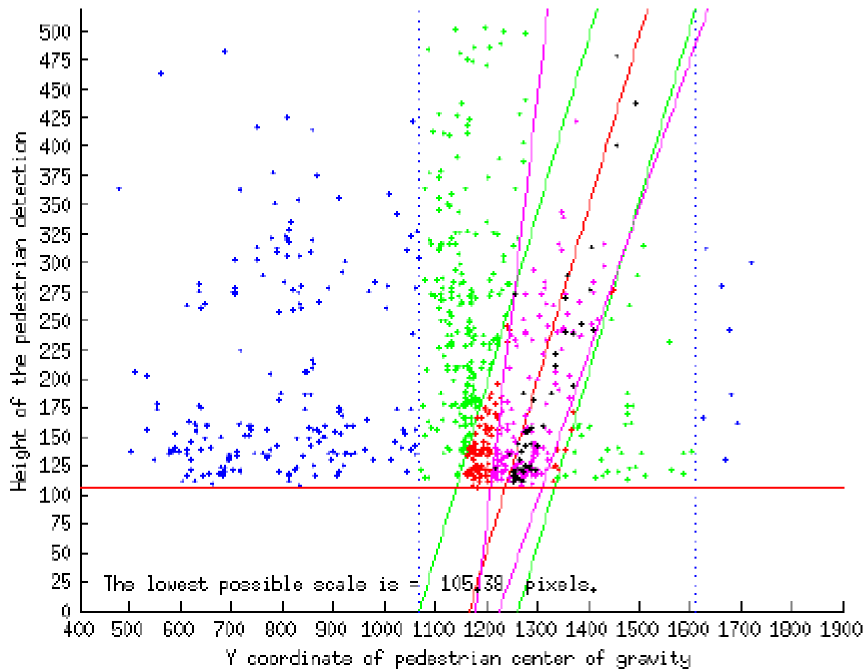
Suggested approach:

Scale-space location relation



(a) Ground truth annotations with general and narrow bounds



(d) Score Threshold and smallest detection size

Initial border = [-3σ,+3σ]

Manually defined tighter border

Unrealistic pedestrian regions

Pink dots → filtered detections with sloppy threshold to ensure a FN rate close to 0%

Black dots = certainty threshold > 0

Suggested approach:
Color-based removal of pedestrian like detections

- Pedestrian detectors tend to fail at pedestrian-like objects/structures inside the image
  - The feature representation of these objects is very similar to pedestrians
  - Suggestion to use small Naïve Bayes post filters based on color information to remove these unwanted detections
  - Fast, easy to train, simple filters!

Figure 5: Example of the need of an extra filter for traffic signs still passing the post-processing steps.

(a) (b) (c) (d) (e)

Figure 7: Naive Bayes Features: (a) original (b) CMY(K) (c) C response (d) M response (e) Y response.

(a) Positive training set

(b) Negative training set

(c) Test set + Classification result (green = sign / red = pedestrian)

Figure 6: Positive, negative training and test set for traffic sign filtering.

Suggested approach:
Soft blurring approach

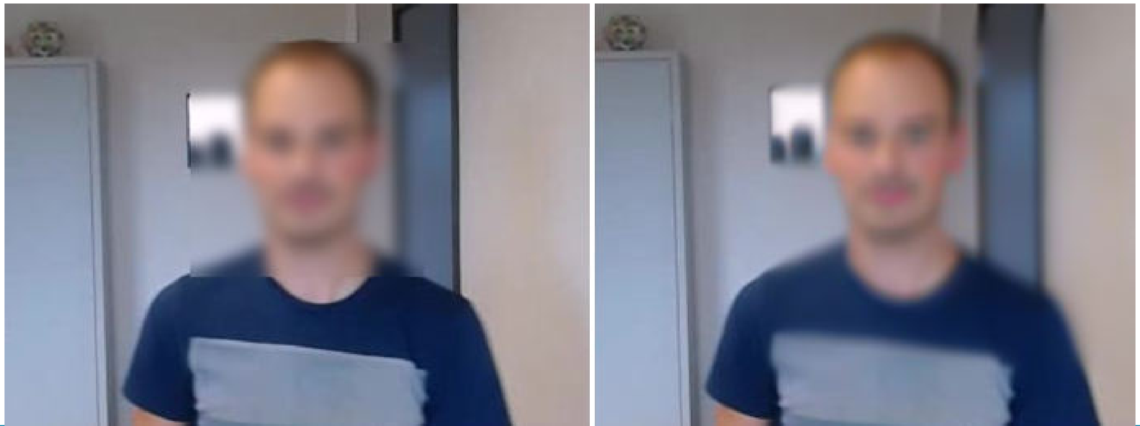
- Most privacy blurring approaches use a standard Gaussian blurring filter on a region of interest.
  - *Downside*: existence of very prominent edge artifacts which cannot be removed
  - *Preferable*: blurring filter that is soft on the edges and hard in the center

- Solution: apply a convolution with an adaptable Gaussian kernel, with a sigma in relation to the normalized pixel distance to the center of the region of interest.

$$\Psi = 1 - \frac{d(center_{detection}, position)}{r} \quad (1)$$

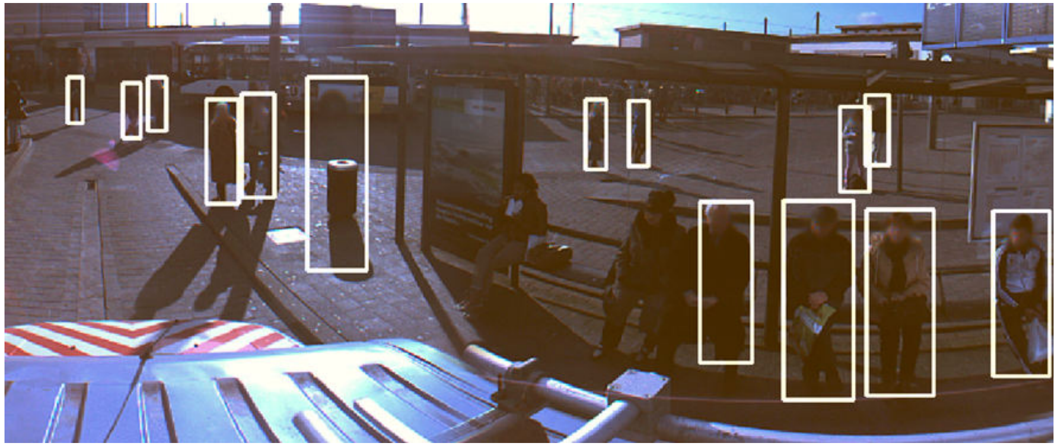
$$\Delta = \frac{area(pedestrian)}{area(image)} \quad (2)$$

$$\sigma_{kernel} = 0.1 + (\Delta\Psi^2) \quad (3)$$



Suggested approach:
Soft blurring approach

- Option to do both face & pedestrian blurring as desired by the user, using the retrieved region of interest of the pedestrian detector



- Result
  - Only privacy unsafe data is blurred out and the artefacts generated from that are visually pleasing
  - Other relevant areas of information are kept

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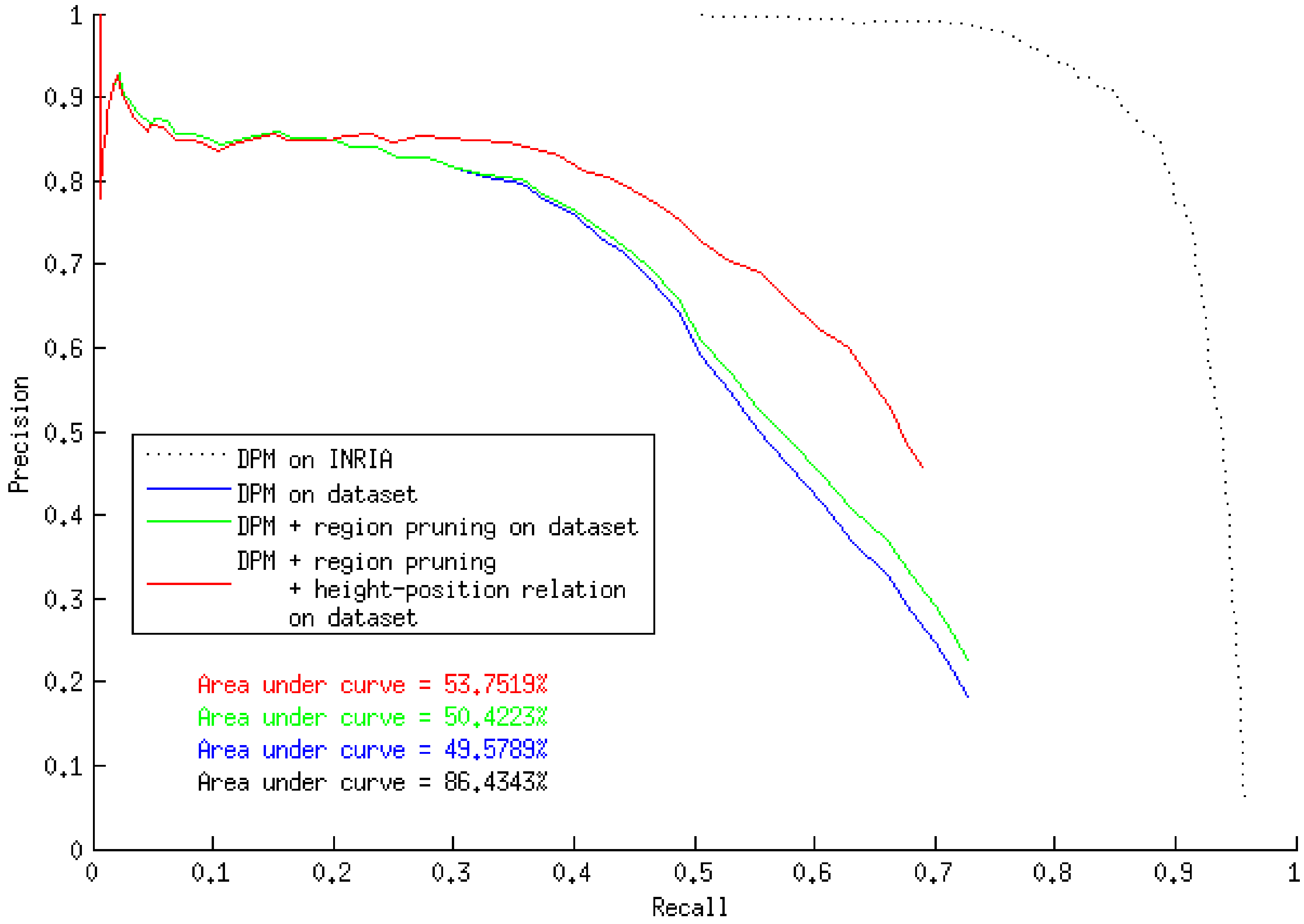
Results:

Efficiency of the detector using scene constraints



Results:

The complete pruning pipeline

- Clear visual reduction of undesired detections / false positives using both the scale-space location relation and the valid region pruning.

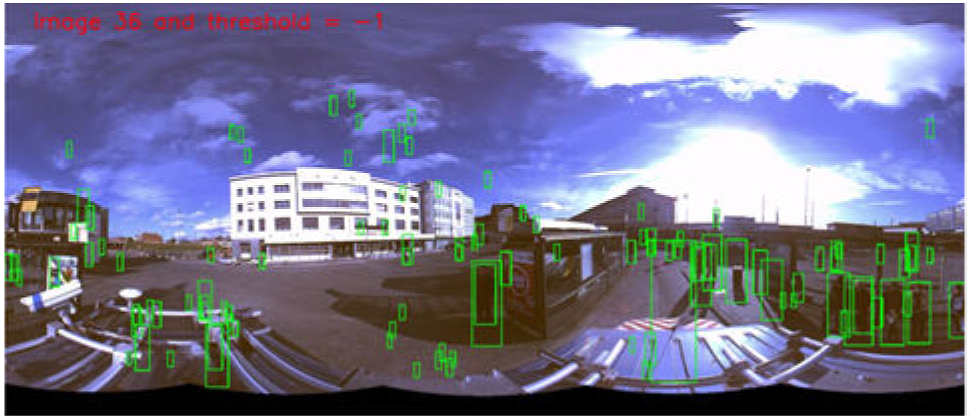
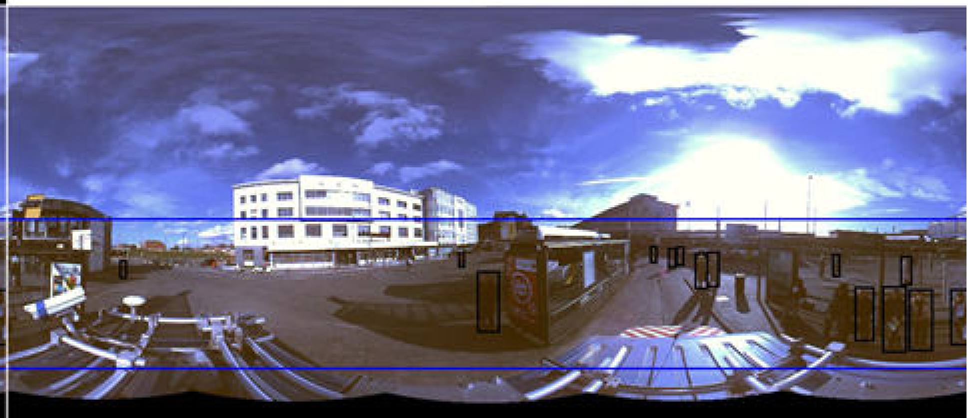


Table 1: Comparison of TP, FP and FN values after each post-processing step for first dataset. To obtain a clear benefit of applying these techniques, we ran the original DPM detector at a score threshold of -1 like in the visual results shown in Figure 13.

	#TP	#FP	#FN
DPM orig.	928	4159	349
After pruning	928	3182	349
After height-position	852	1015	384



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Conclusions

- The overall approach is mainly generated to improve the detection output of any available of-the-shelf pedestrian detector on any given dataset without retraining the complete model specific to that dataset

- By combining this of-the-shelf pedestrian detector, running at a sloppy threshold, with efficient pruning and post-processing filters, based on application specific constraints, we greatly improve the quality of the pedestrian detectors

- The quality improvement can be achieved by only using a small set of situation specific object annotations, efficiently reducing the manual effort

- We proposed an elegant soft blurring filter for privacy masking reasons

Future work

- We have an offline processing pipeline, so we do not have any time constraints
- Efficiently reducing the calculation time is still a big challenge
  - We suggest to integrate our scale-space relation during detection time, instead of using it as post-processing
  - Enable to do the processing online, during the capture of the data, and thus removing privacy issues completely
- We assume a ground plane assumption valid for our application
  - People standing on a balcony, sitting on a bench or driving a bike do not follow our scale-space relation
  - We suggest importing specific filter relations for each of these cases

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Thank you for your attention!

Any questions?

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