Analyse eines Forschungsthemas

- 2 of 3 papers deal with pose estimation -

Josef Schulz

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Example Problems

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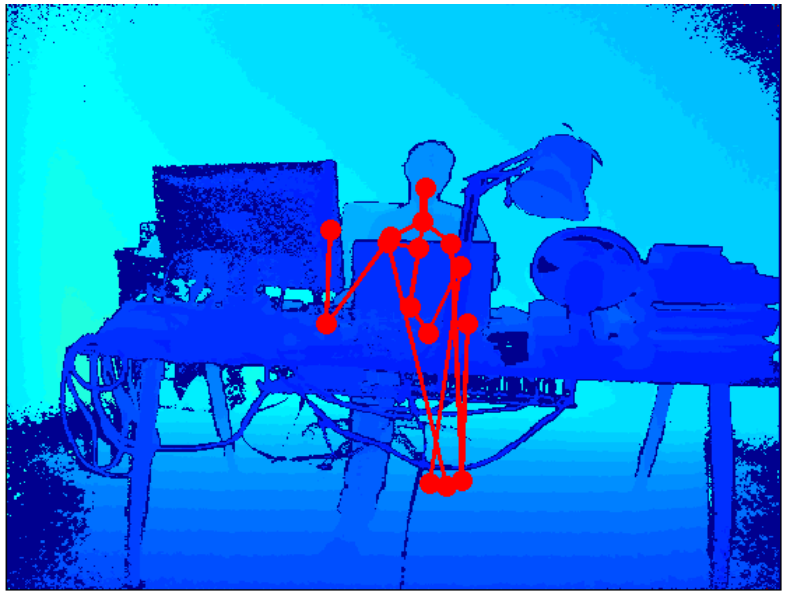
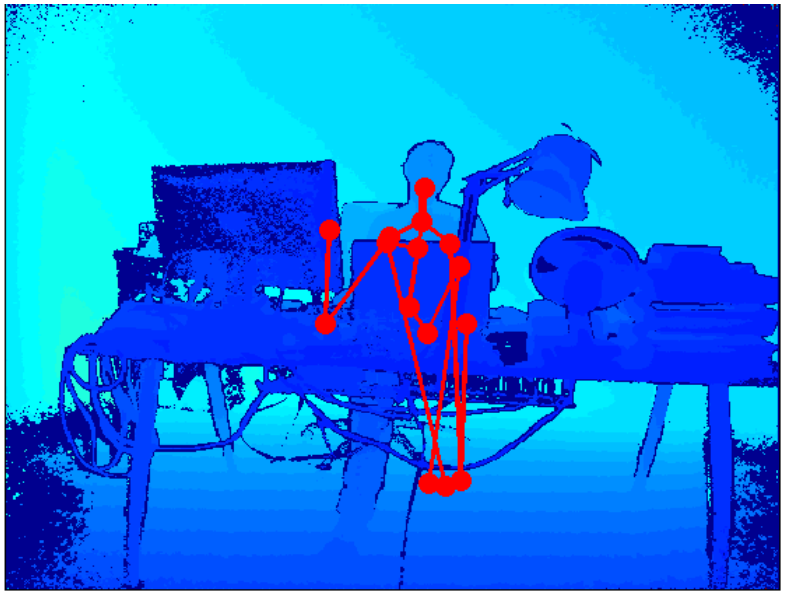
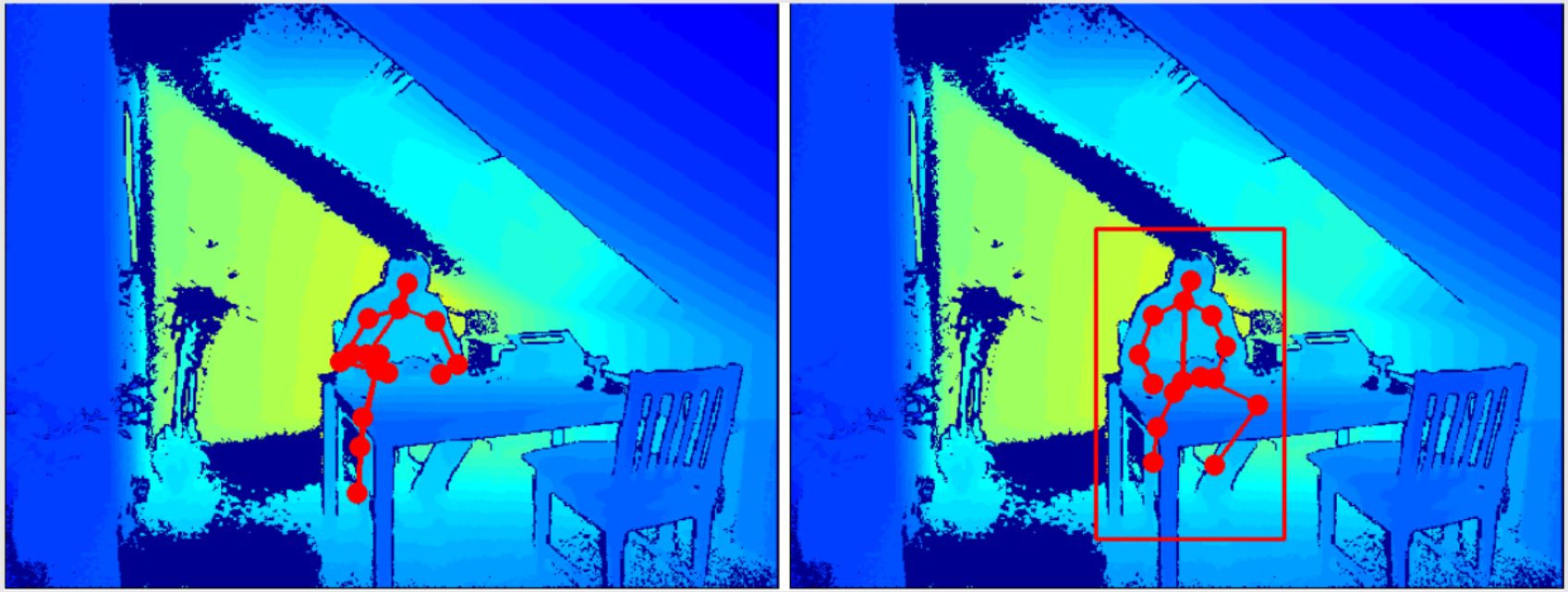


Example Problems



Content

A Semantic Occlusion Model For Human Pose Estimation



Input : single Depth-Image

Output : estimated poses of all parts

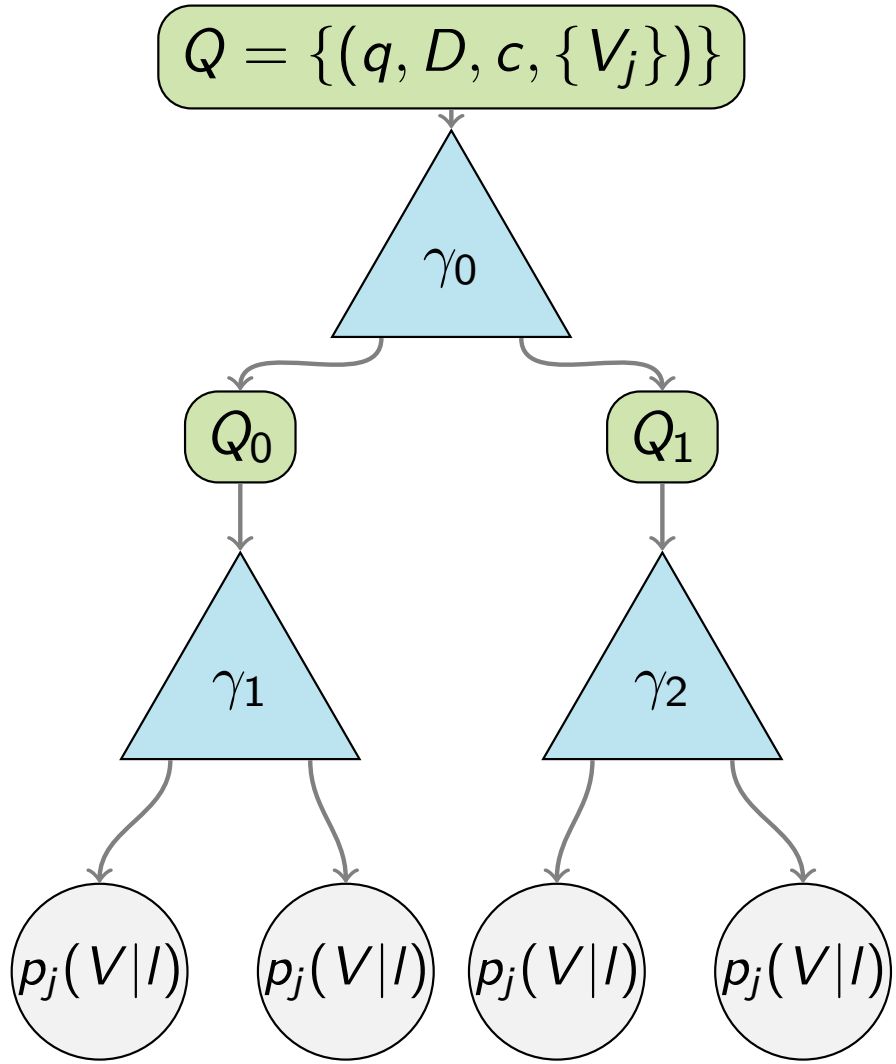
Regression Forest

Training Set

$$Q = \{(q, D, c, \{V_j\}), ...\}$$

- q pixel location
- D reference depth image
- c class label corresponding to limbs
- $\{V_j\}$ is set of vectors:

$$V_j = q_j - q$$



Slit Node

$$\gamma = (u, v, \tau)$$

$$\Phi_\gamma(q, D) \mapsto \{0, 1\}$$

$$\Phi_\gamma(q, D) = \begin{cases} 1 & \text{if } D(q + \frac{u}{D(q)}) - D(q + \frac{v}{D(q)}) > \tau \\ 0 & \text{else} \end{cases}$$

u, v - offset vectors

τ - threshold

$D(q)$ - depth value

Evaluating The Splitting Functions Information Gain

$$\Phi^* = \arg\max_{\Phi} g(\Phi)$$

$$g(\Phi) = H(Q) - \sum_{s \in \{0,1\}} \frac{|Q_s(\Phi)|}{|Q|} H(Q_s(\Phi))$$

$$H(Q) = -\sum_{c} p(c|Q) \log(p(c|Q))$$

$H(Q)$ - Shannon entropy

$g(\Phi)$ - information gain

Leaf Node

$$p_j(V|l) \propto \sum_{k \in K} w_{ljk} \cdot \exp(-\| \frac{V - V_{ljk}}{b} \|_2^2)$$

K - cluster

w_{ljk} - is determined by offset vectors ended in the cluster k, support

V_{ljk} - cluster center

Pose Estimation

$$p_j(x|D) \propto \sum_{(x_j,w_j)\in X_j} w_j \cdot \exp(-\| \frac{x - x_j}{b_j} \|_2^2)$$

$$X_j = \{(x_j, w_j)\}$$

x_j - absolute joint position, $x_j = q + V_{ljk}$

w_j - confidence value, $w_j = w_{ljk} \cdot D^2(q)$

the clusters with the highest summed weights w_j are used for prediction.

Occlusion Aware Regression Forests

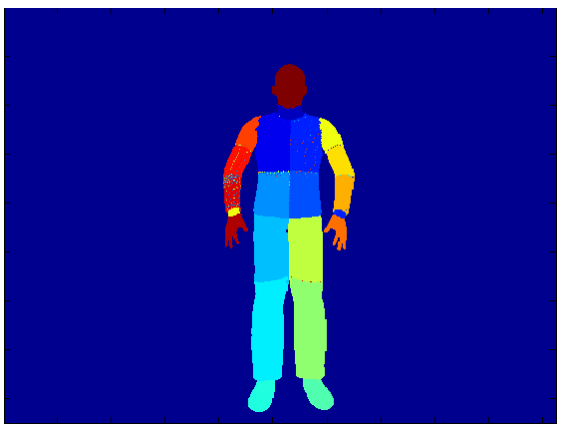
$$Q = Q \cup \{(q_{occ}, D, C_{occ}, \{v_{jocc}\})\}$$

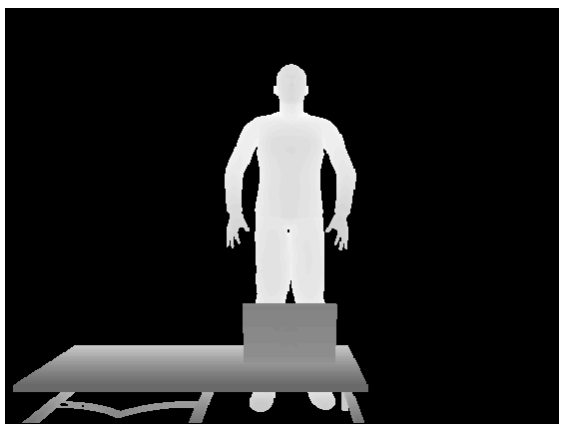
without Semantics

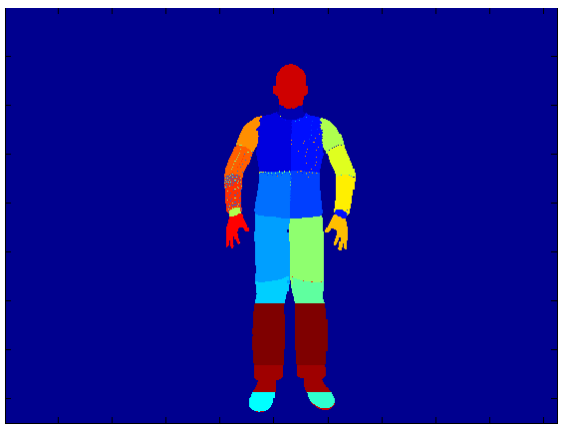
$$C_{occ} = \{c_{occ}\}$$

with Semantics

$$C_{occ} = \{c_{obj1}, c_{obj2}, ...\}$$







Training Data

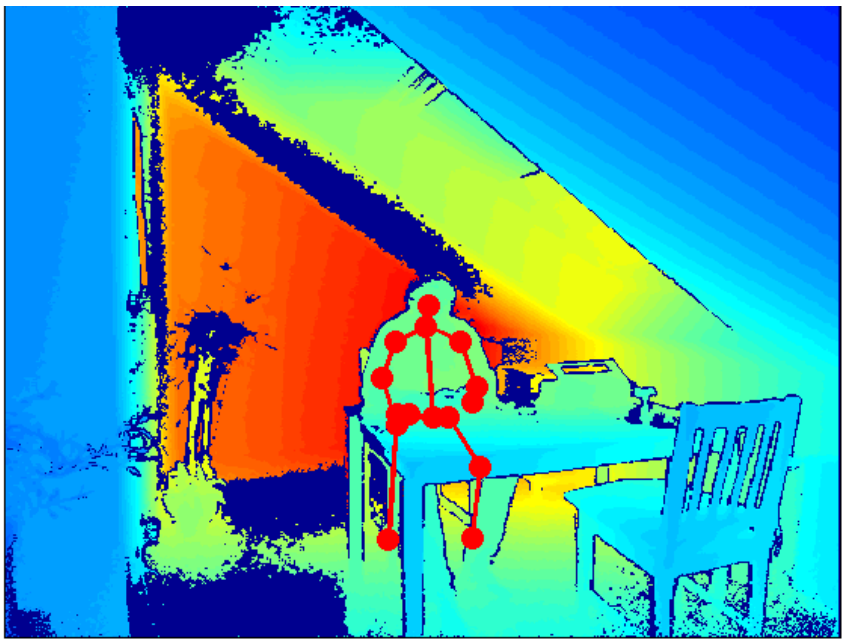
Synthetic Data (552 images)

- Human Poses from CMU-Database [10]
- body part labels for each pixel

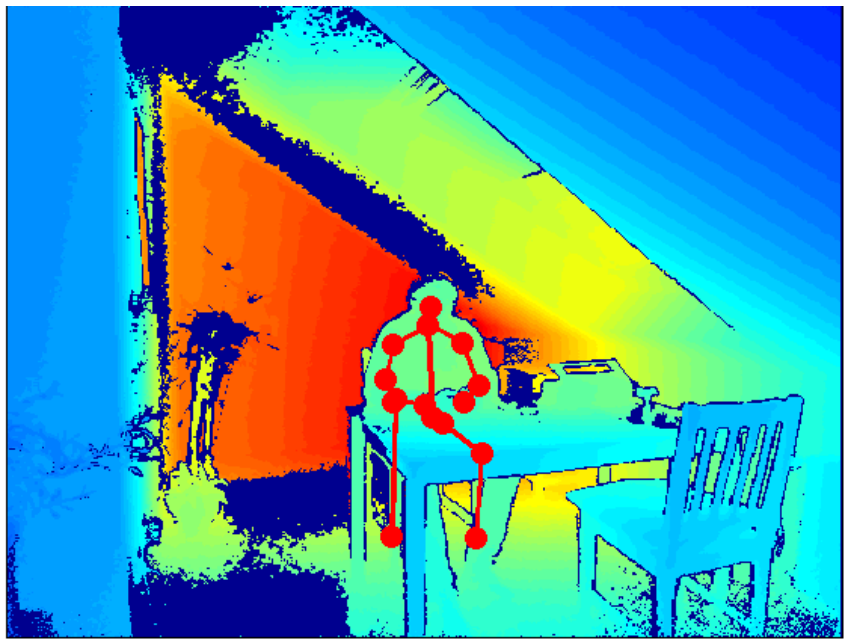
Real Data (552 images)

- Kinect2 SDK, all fails are discarded

With And Without Semantics

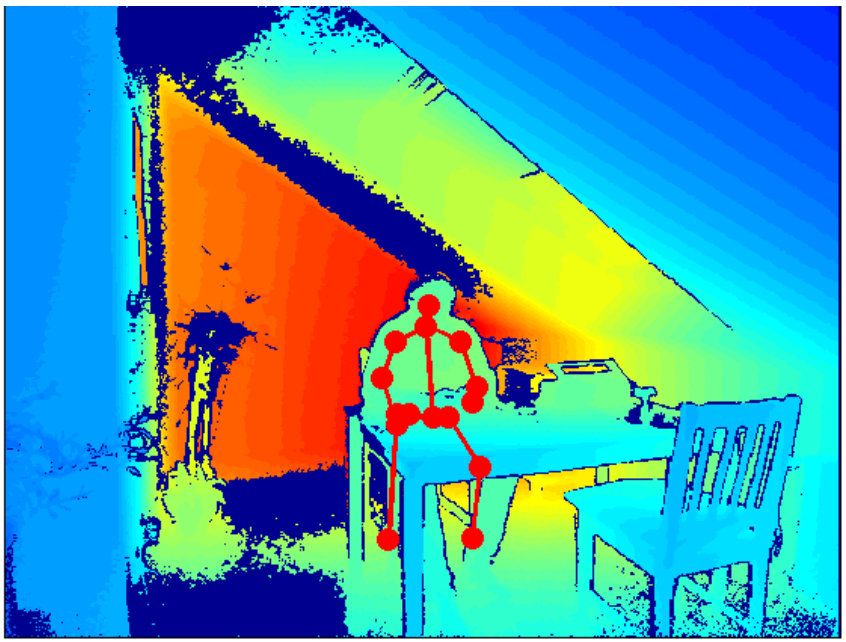


with semantics

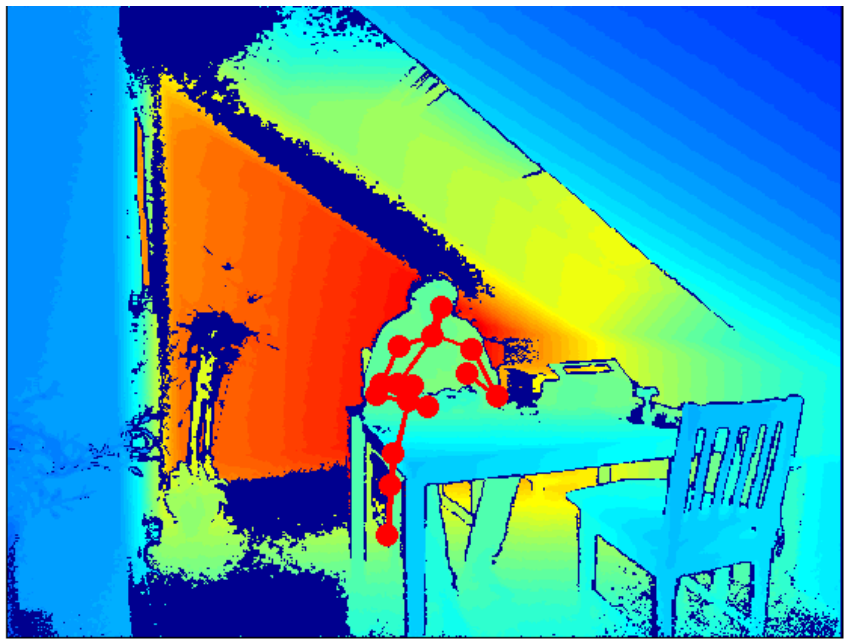


without semantics

OARF vs. Kinect2 SDK



OARF with semantics



Kinect2 SDK

Results

	Occluded Joints	Non Occluded Joints	All Joints
OARF W/O	32.60	55.50	50.66
OARF W	35.77	56.01	51.72
Kinect2 SDK	18.13	66.36	56.94

in %

Real + Synthetic Data

Occlusion Patterns for Object Class Detection

Input : Single RGB-Image

Output : Object-Bounding-Boxes

Deformable Models Approch

- Consider each object as a deformed version of a template
- Compact representation

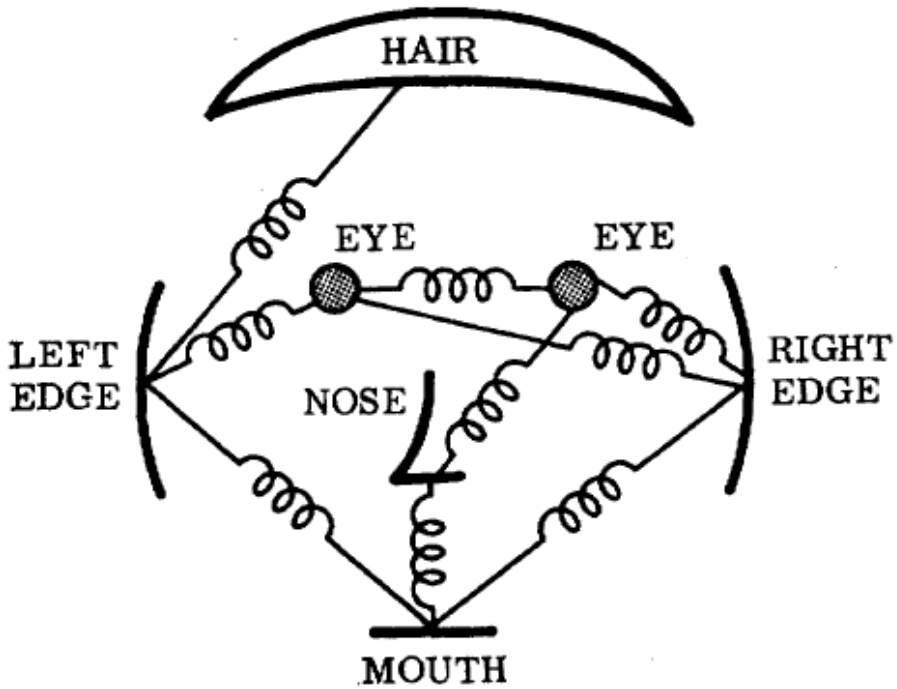


Figure : Pictorial Structure Model [9]

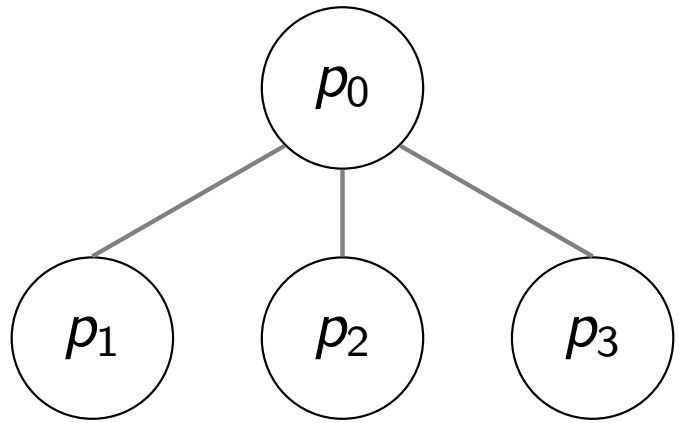
Matching model to image involves joint optimization of part locations "stretch and fit"

Model

Model is represented by a Graph

- $p = \{p_0, ..., p_M\}$ are the parts
- p_i is parameterized through their bounding box (l_i, r_i, t_i, b_i)

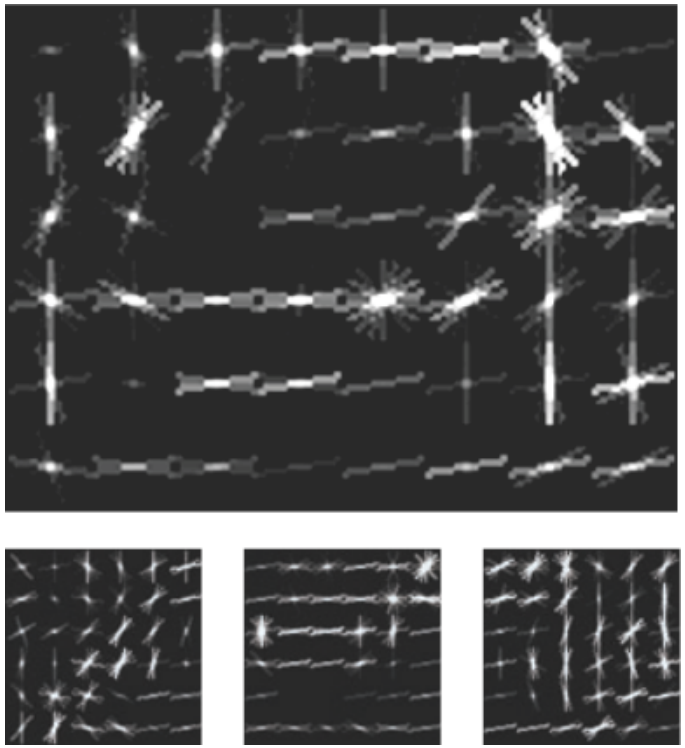
E_c - is the Energy function



$$E_c(p; I) = \underbrace{\sum_{i=0}^{M} \langle v_i^c, \Phi(p_i; I) \rangle}_{\text{placing cost}} + \underbrace{\sum_{i=1}^{M} \langle w_i^c, \Phi(p_0, p_i) \rangle}_{\text{deformation cost}}$$

Filter

- images with bounding boxes
- histograms of oriented gradients (HOG) for placement
- twice the resolution for every level
- Gaussians for deformation



KITTI Data Set

KITTI contains 7481 images

	#objects	#occluded objects	%
Car	28521	15231	53.4
Pedest.	4445	1805	40.6
Cycles	1612	772	44.5

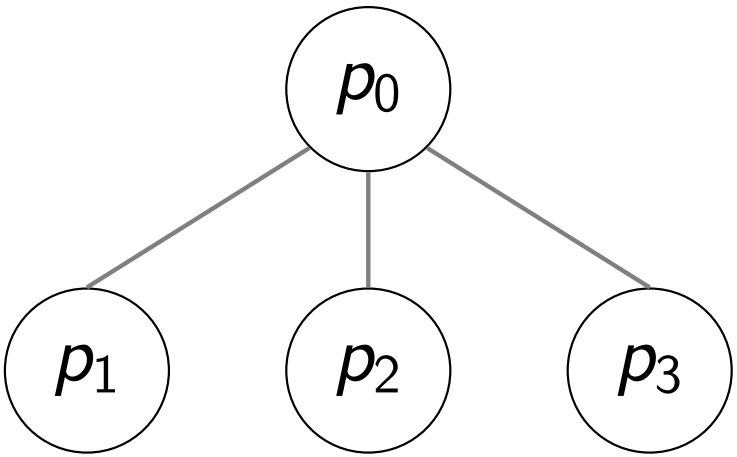
Parts:

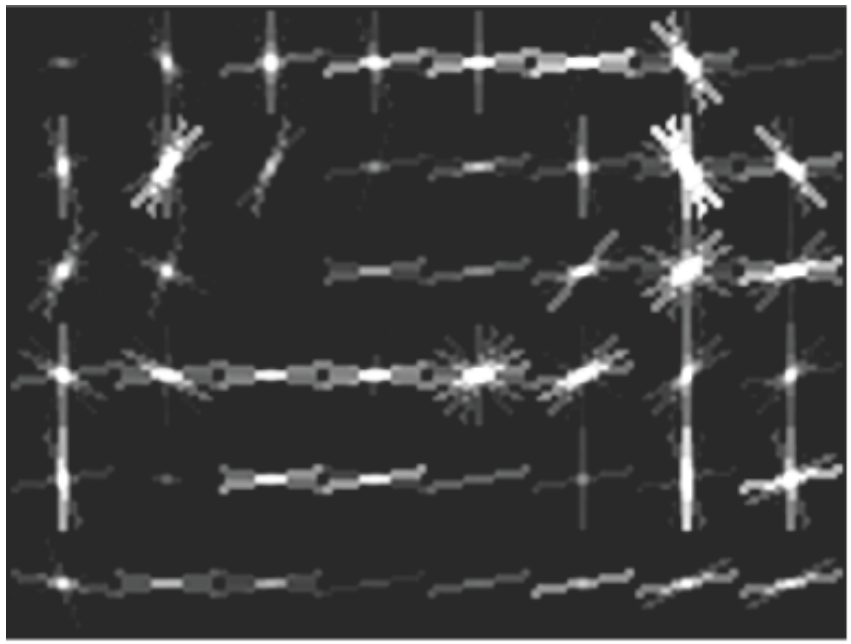
visible 6

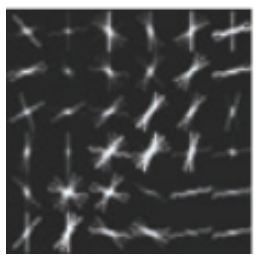
occluded $16 - 15$

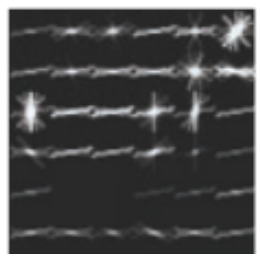
OC-DPM

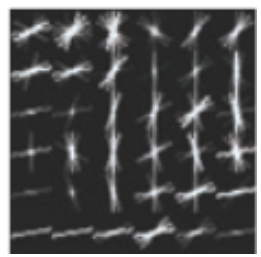
$$C = \{1, ..., C_{visible}\} \cup C_{invisble}$$







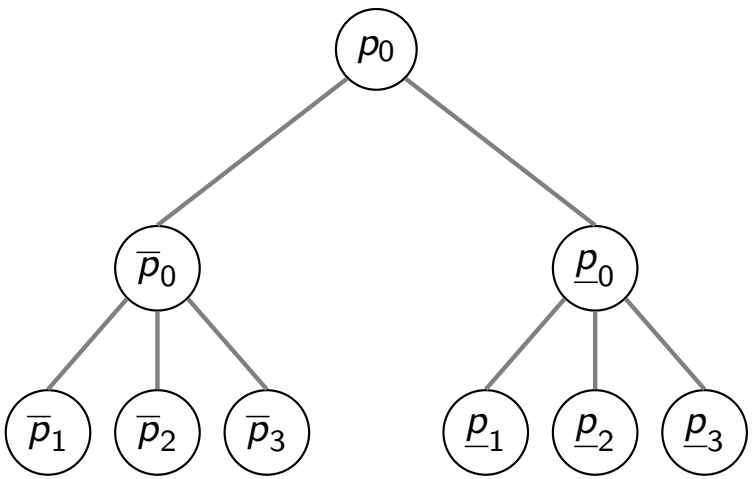


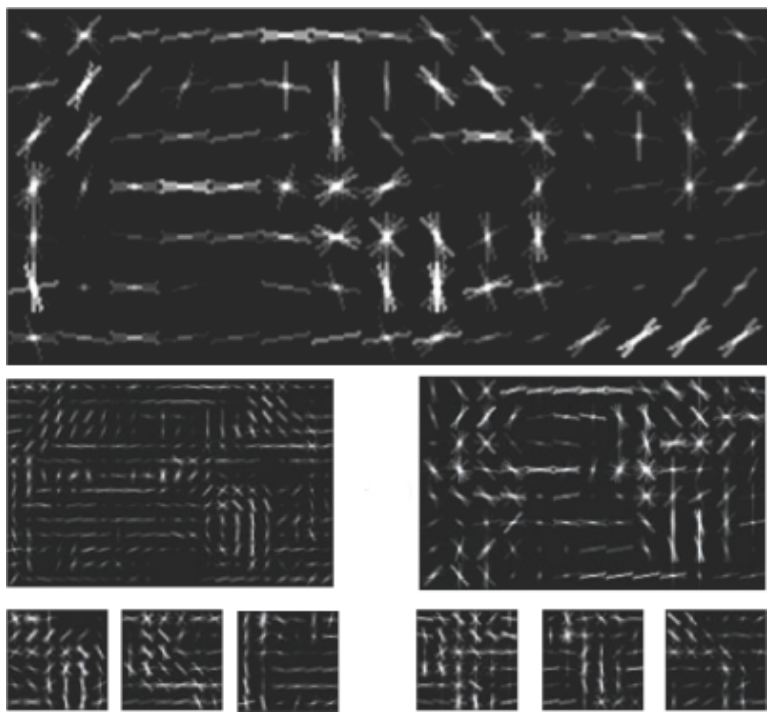


- like standart dpm
- trained with occlusion
- C are components

SYM-DPM

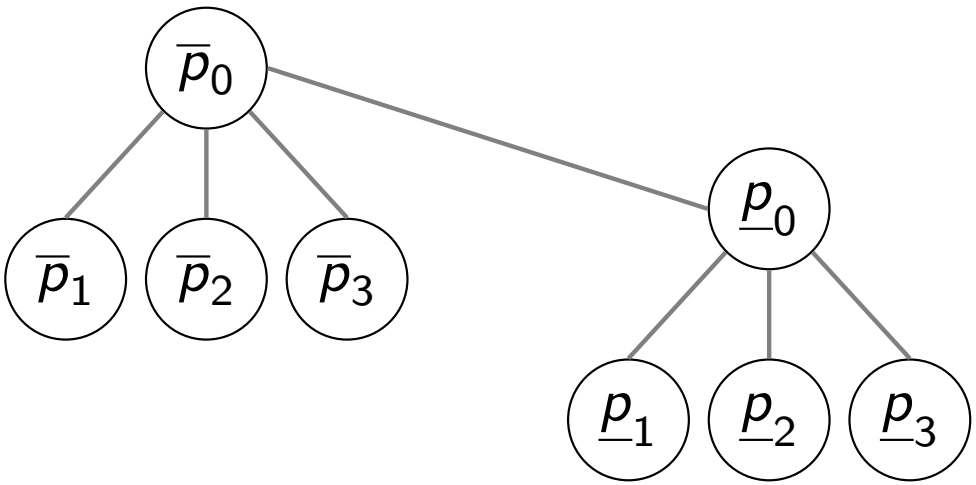
$$E'_c(p; I) = \langle v^c, \Phi(p_0; I)\rangle + \langle \overline{w}^c, \Phi(p_0, \overline{p}_0)\rangle + \langle \underline{w}^c, \Phi(p_0, \underline{p}_0)\rangle$$
$$+ E_c(\overline{p}_0; I) + E_c(\underline{p}_0; I)$$

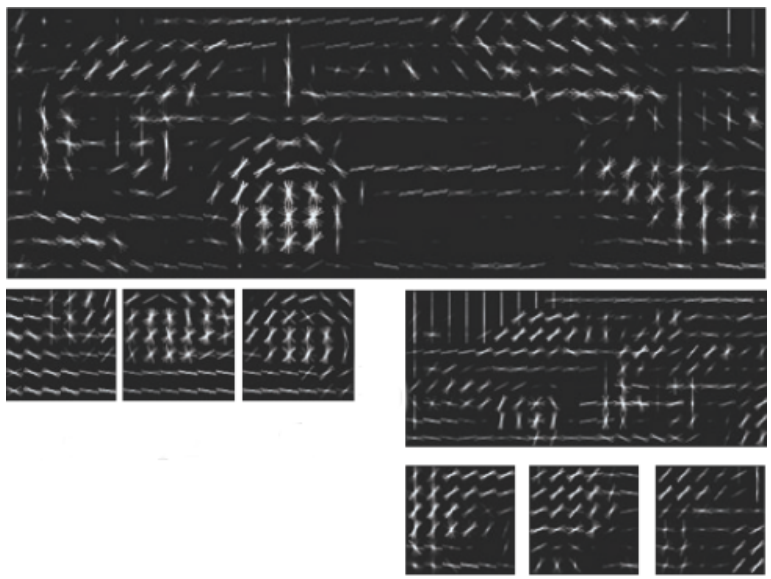




- one root part
- occluder $\overline{p}_0$ root part
- occludee $\underline{p}_0$ root part

ASYM-DPM





- occluder left, occludee right
- tree structure
- no extra terms

Mining Trainingsdata

Feature Space:

i occluder left/right of occludee

ii orientation of occluder/occludee

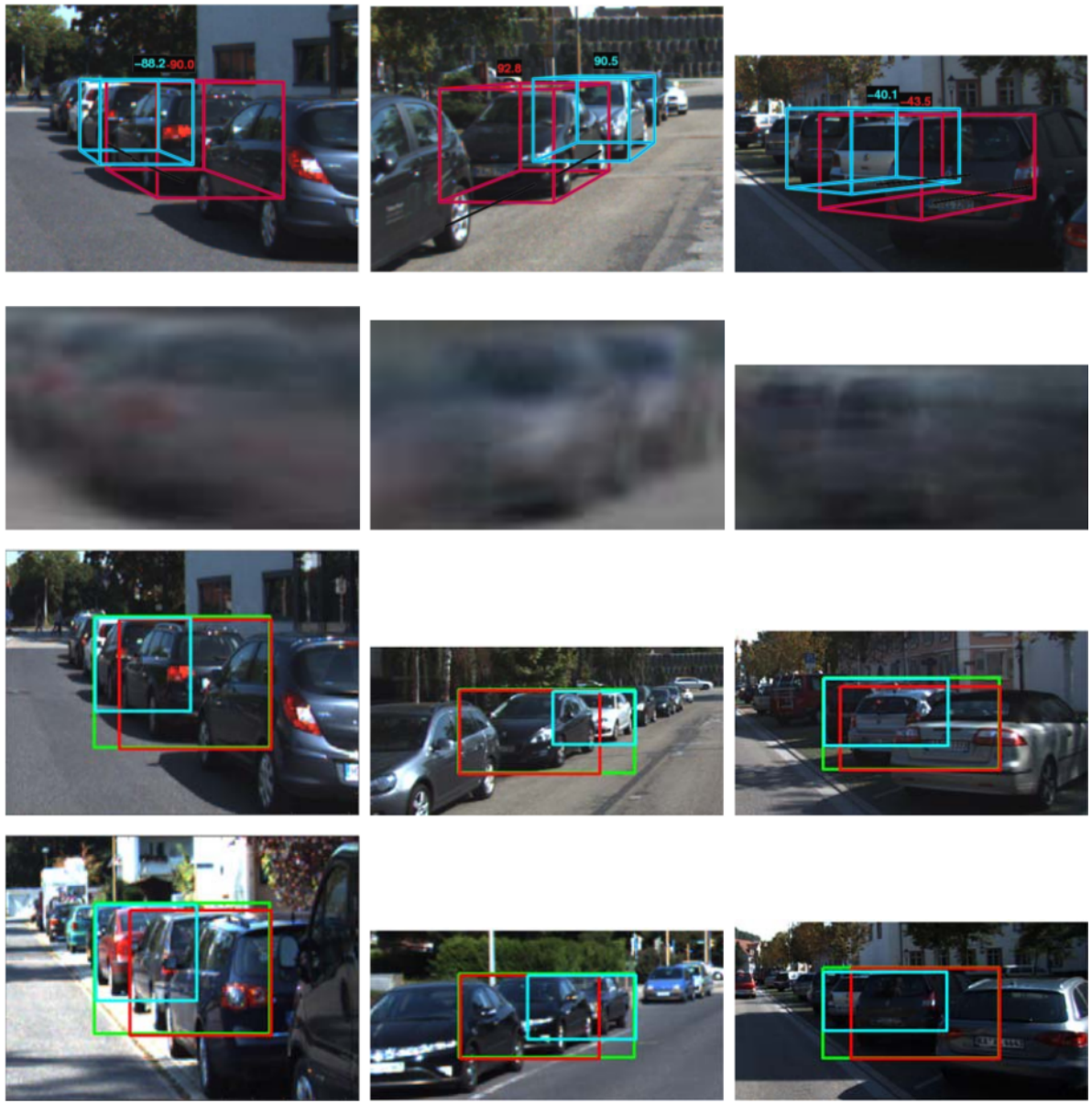
iii occluder is/is not occluded

iv degree of occlusion of occludee

Rule-based clustering

- repeatly splitting the training data
- according to the viewing angle of the occluder

Mining Trainingsdata



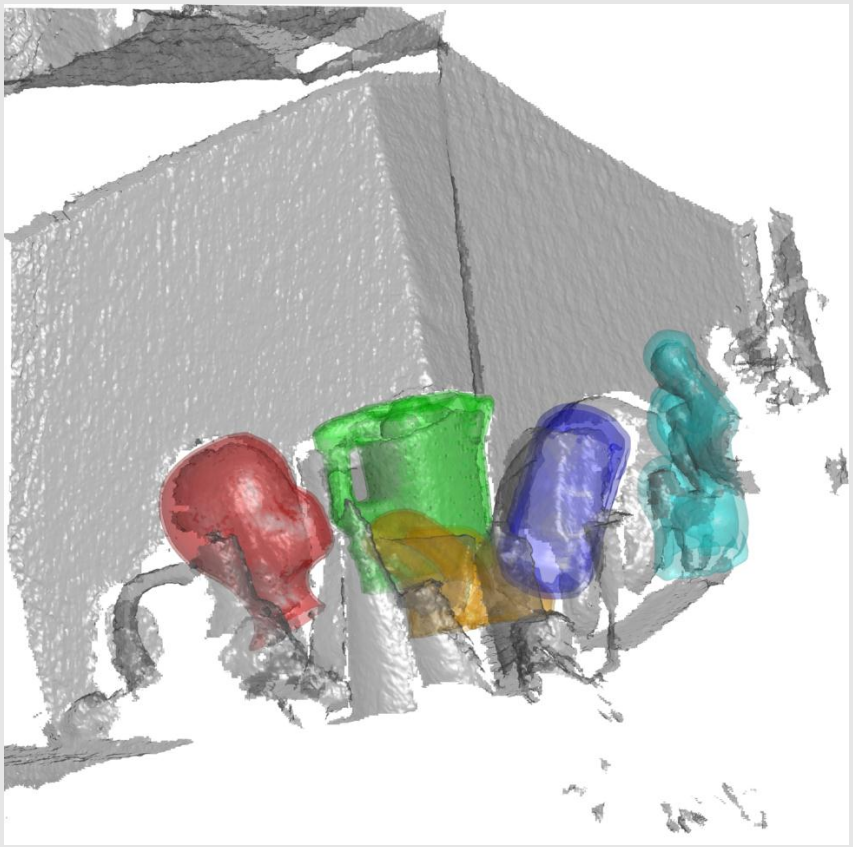
Results

OC-DPM DPM

	DPM	OC-DPM	SYM-DPM	ASYM-DPM
full dataset	62.8	64.4	53.7	52.3
Pedestrian	36.2	37.2	31.4	29.4

in %

Robust Instance Recognition in Presence of Occlusion and Clutter



Input : 5-10 consecutive frames as one Pointcloud

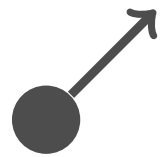
Output : 6D-Object-Pose

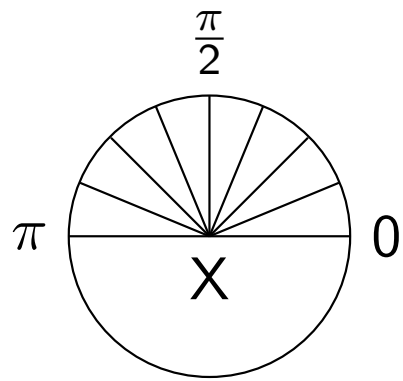
Intoduction

- object shape is invariant to changes in illumination or texture
- Kinect sensors generates cheap depth data
- it is easy to synthesize pointcloud data

Edgelet

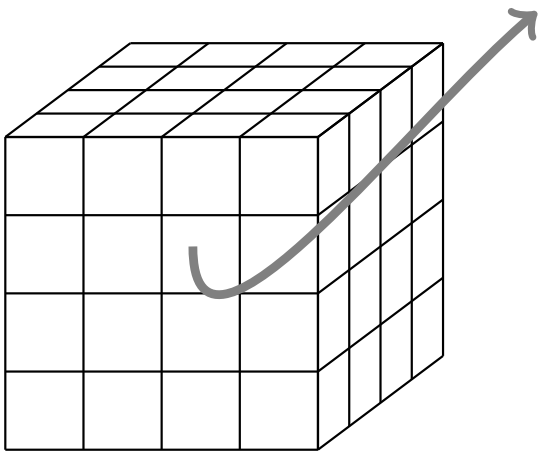
- N points per Pointcloud j
- FOR ALL $i \in \{1, ..., N\}$
  - calc λ_1 and λ_2
  - $r = \frac{\lambda_1}{\lambda_2}$
  - $r \rightarrow$ curvatureMap
- hysteresisThesholding(curvatureMap);
- nonmaximalSuppression(curvatureMap);
- hysteresisThesholding(depthMap);
- projectToPointcloud(curvatureMap, depthMap);
- RANSAC line fitting
- orientation to 8 bins// (direction%π)





Feature Vector

$w \times h \times d$



Voxel v

1	2	...	8

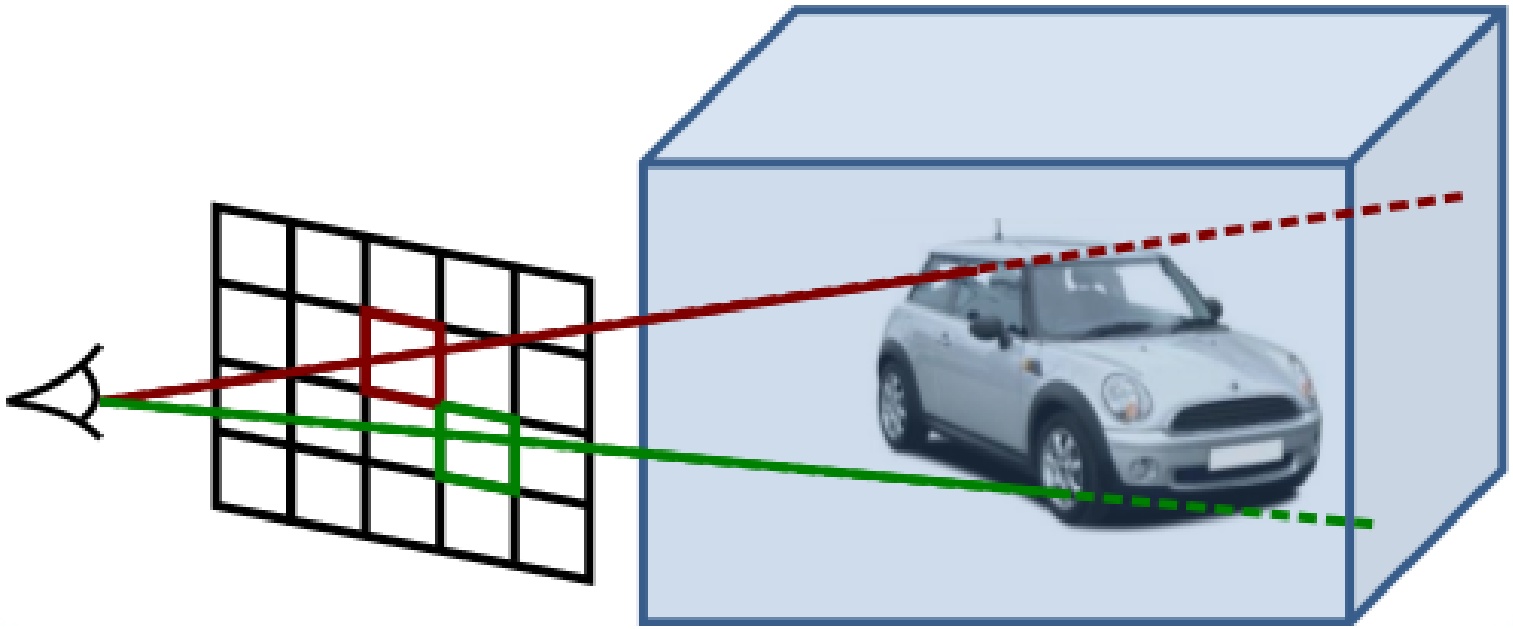
$$x_i^v = \begin{cases} 1 & \text{if } i \text{ is dominant} \\ 0 & \text{else } i\text{is not dominant} \end{cases}$$

$x^v = -1$ if v is not visible

The resulting feature vector is the concatenation of all voxels:

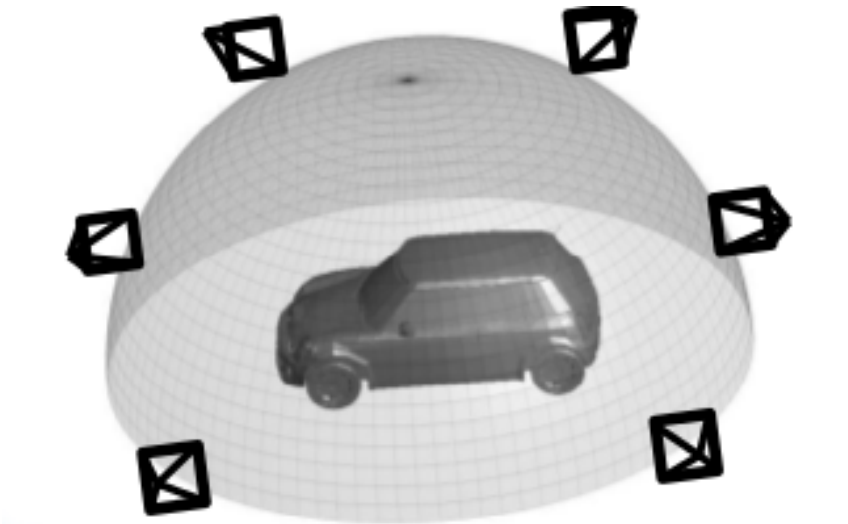
$$w \times h \times d \times 8$$

Box Model For Occluder



- occluder are rectangular
- occluders are restricted to start from the ground plane

Soft Label Random Forest



- 16 pose classes
- $+1$ class $= \begin{cases} 1 & \text{if bg} \\ 0 & \text{else} \end{cases}$
- $d_j^i = \|I - R_j^i\|_F$

$$l_j^i = \exp(-{d_j^i}^2), i \in \{1, ..., 16\}$$

$$\text{IF fg THEN } 1 = \sum_{i=1}^{16} l_j^i \text{ ELSE } 0$$

Occlusion Queries

$$x_j \in \{-1, 0, 1\}$$

(> -1) - visible versus occluded voxel

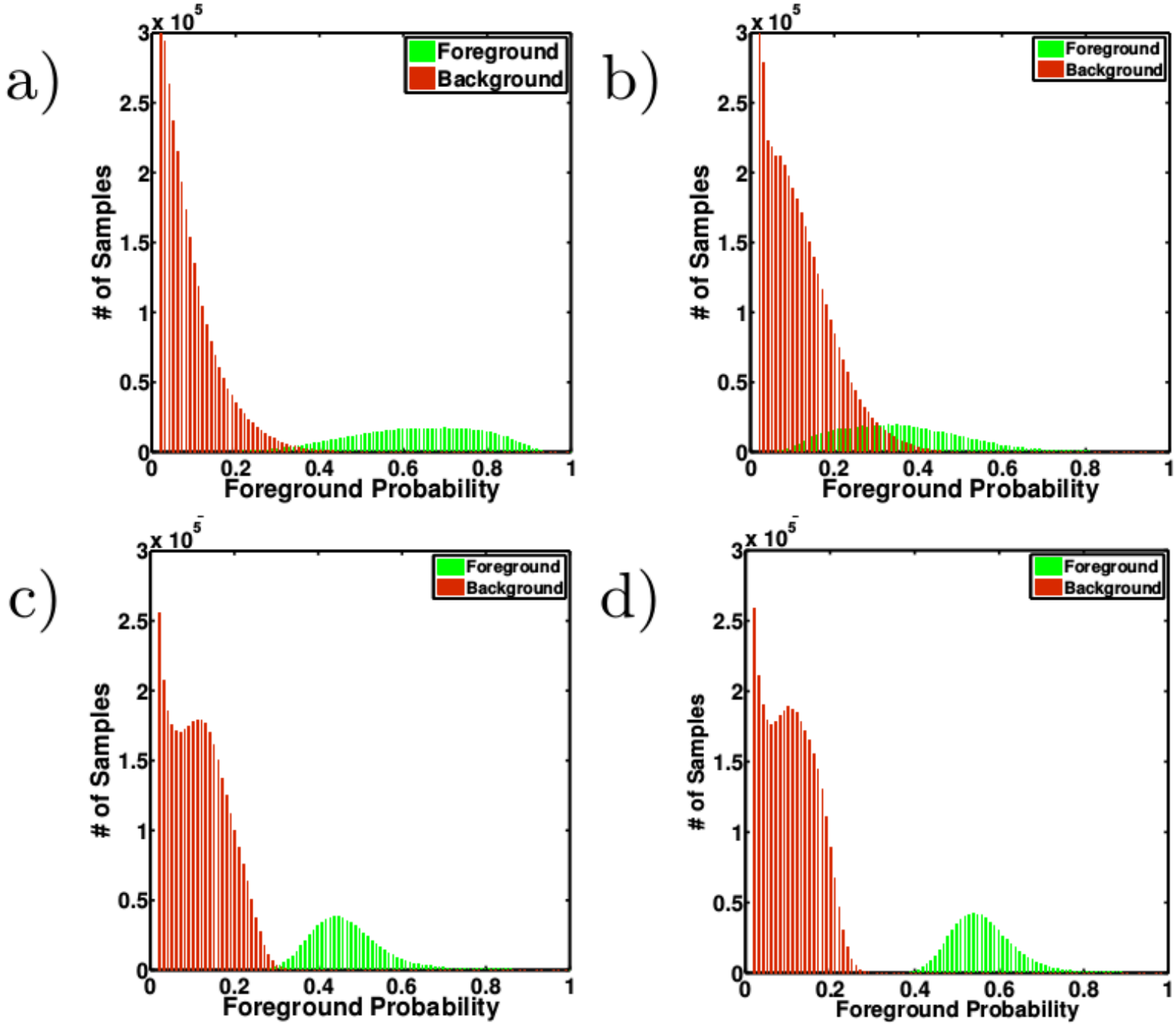
(> 0) - dominant or not visible voxel

- split questions in the topmost nodes ($\approx 5 - 10$) are restricted to the second type

training scheme for sLRF

Input: $X = \{x_j, l_j\}$, (≈ 27000) examples
Output: Learnt sLRF classifier

1. $X_s \subset X$, $|X_s| = |X|/20$
2. Train sLRF with X_s, compute p_{fg} with X
3. add borderline positive (low p_{fg}) and borderline negativ (high p_{fg})
4. add confusing samples
5. compute d_L for all positive samples, add samples with high d_L
6. repeat 2-5 till p_{fg} for all positive data is greater than p_{fg} for all negative data.


a)
b)
c)
d)
x 10^5
Foreground
Background
# of Samples
Foreground Probability
0
0.2
0.4
0.6
0.8
1
0.5
1.5
2
2.5
3

Results

	D-DPM	LineMod	S-Iterative (Edges)	S-Iterative (Occlusion)
L	40.50	30.15	70.70	81.89
L+P	23.72	13.17	52.62	62.11

Robustness Against Occlusion - Conclusion

- semantic (scene understanding)
- mixture models
- multiple representation for one object class
- good feature representation
- training with occlusion

Discussion

?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