Analyse eines Forschungsthemas

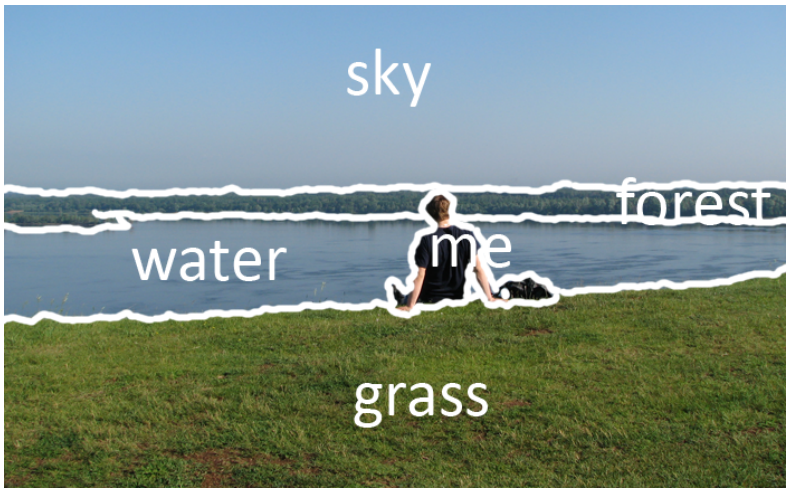
- 2 of 3 papers deal with pose estimation -

Josef Schulz

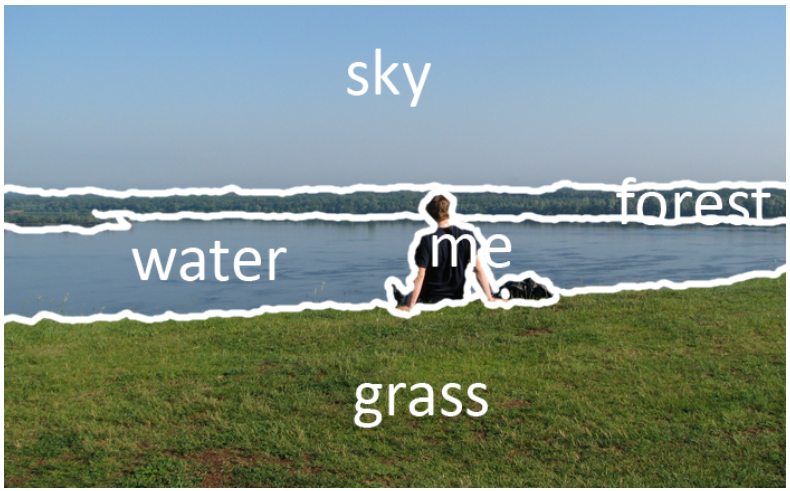
April 18, 2016

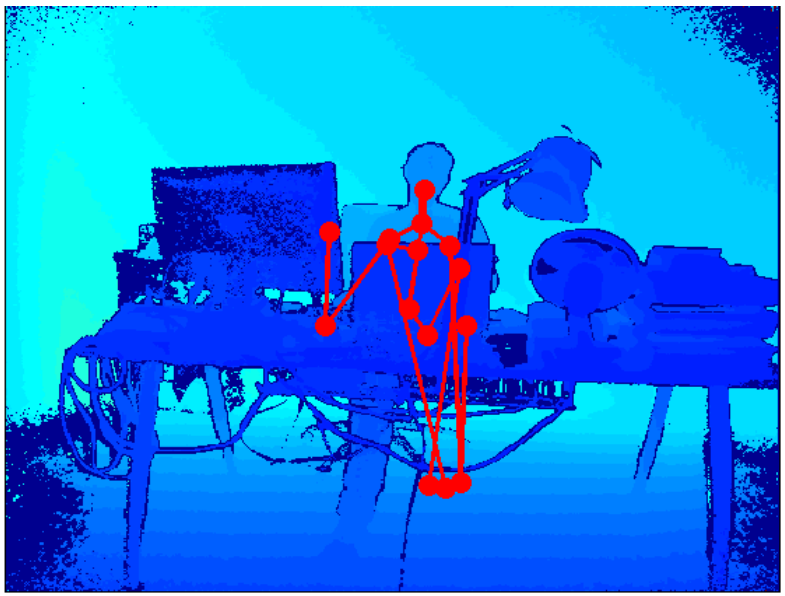
Example Problems

Example Problems

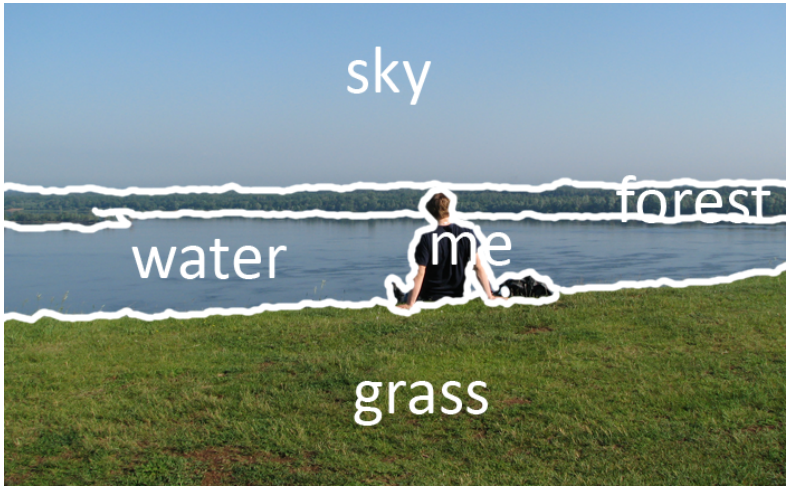


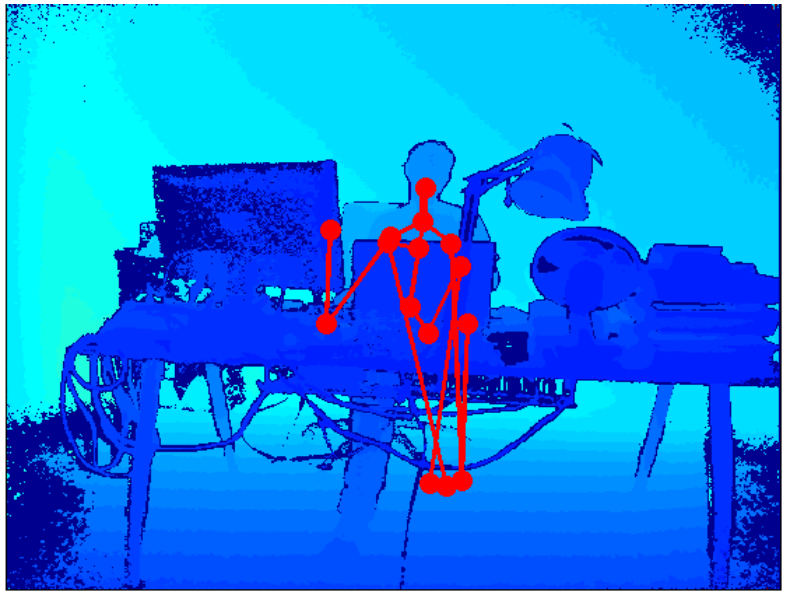
Example Problems





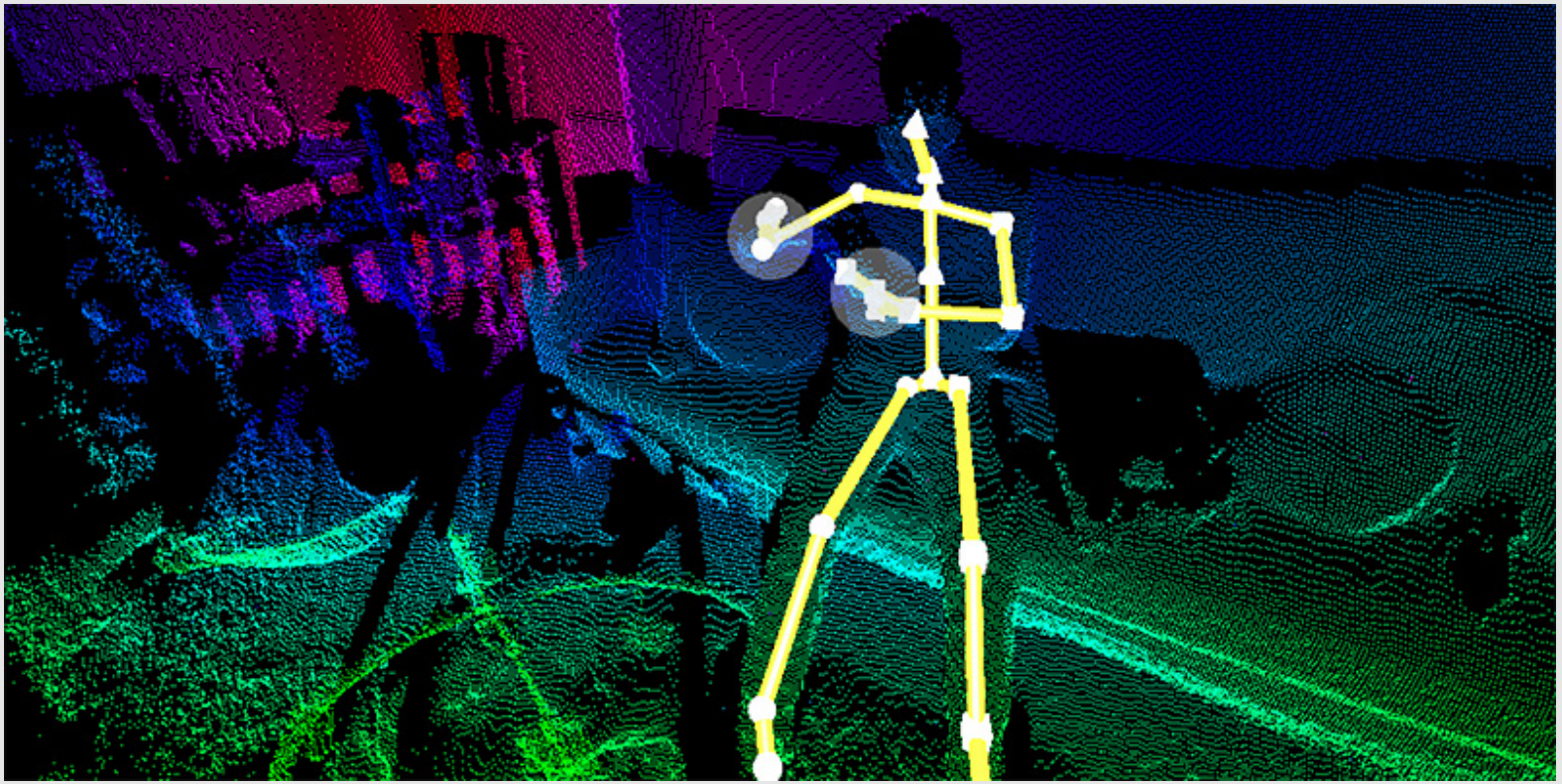
Example Problems





Content

A Semantic Occlusion Model For Human Pose Estimation



Input : single Depth-Image

Output : estimated poses of all parts

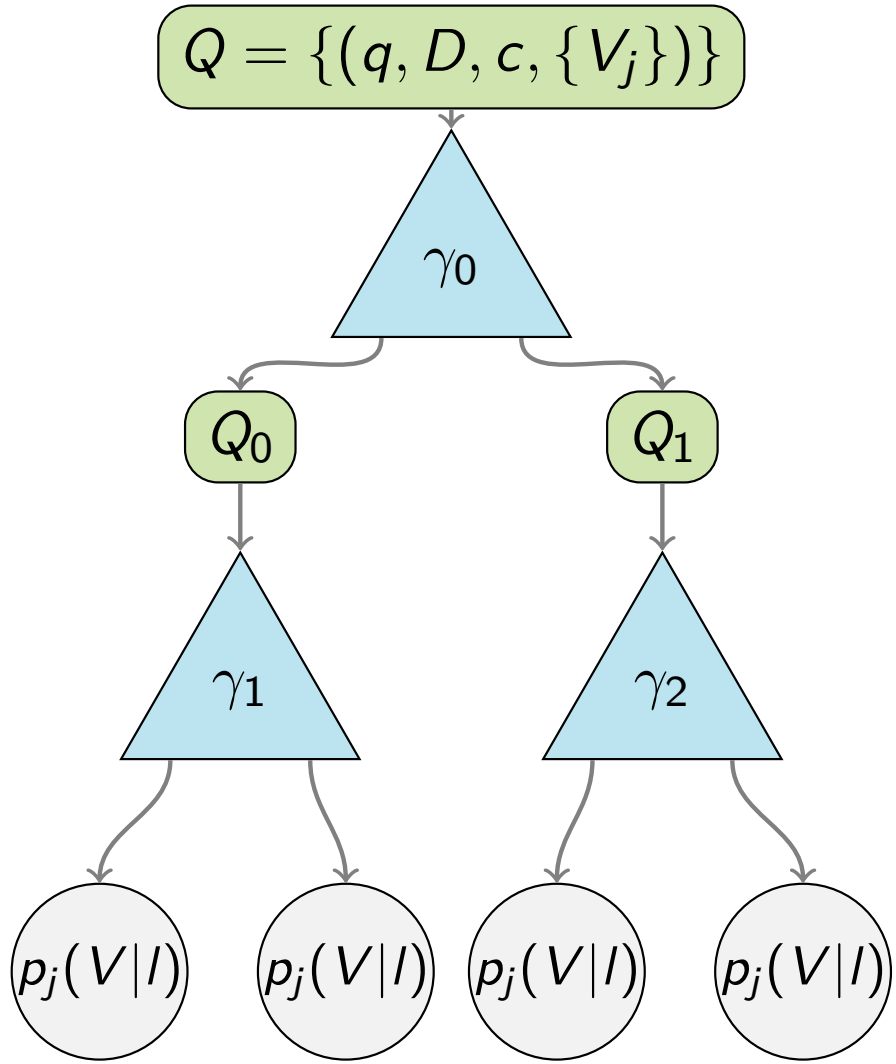
Regression Forest

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

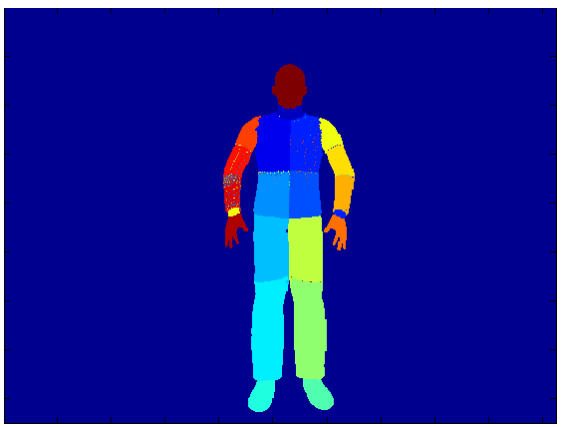
$$Q = Q \cup \{(q_{occ}, D, C_{occ}, \{v_{jocc}\})\}$$

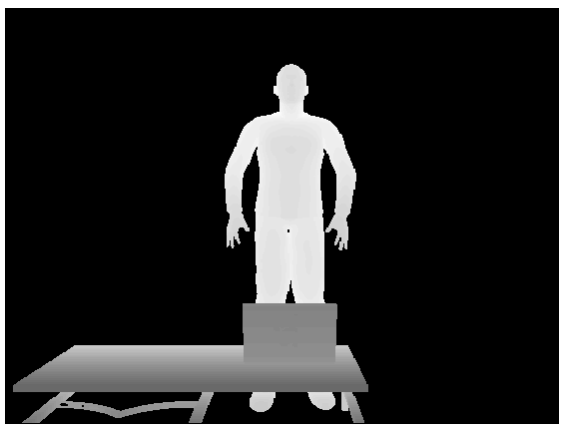
without Semantics

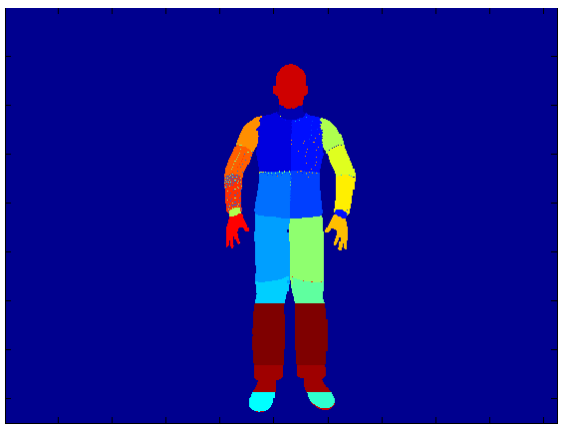
$$C_{occ} = \{c_{occ}\}$$

with Semantics

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







Training Data

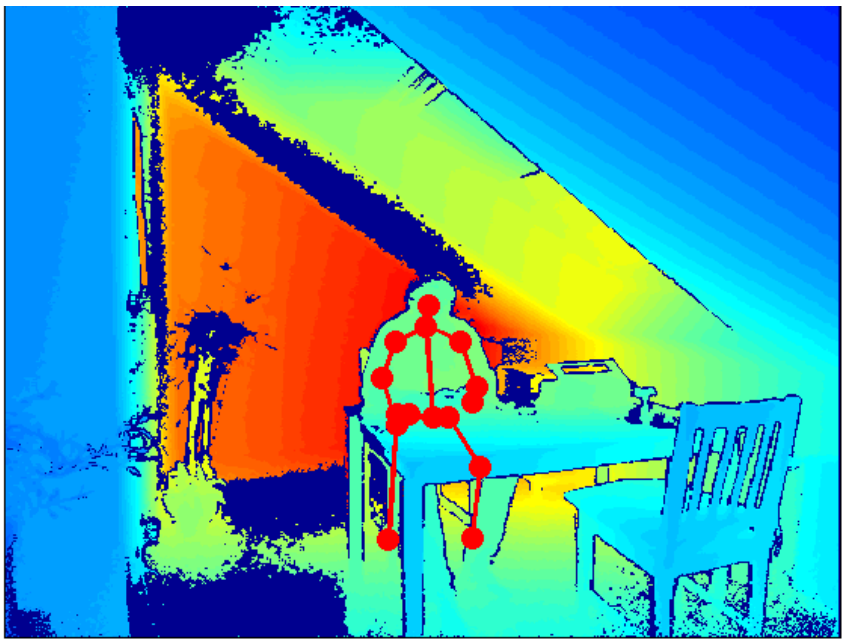
Synthetic Data (552 images)

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

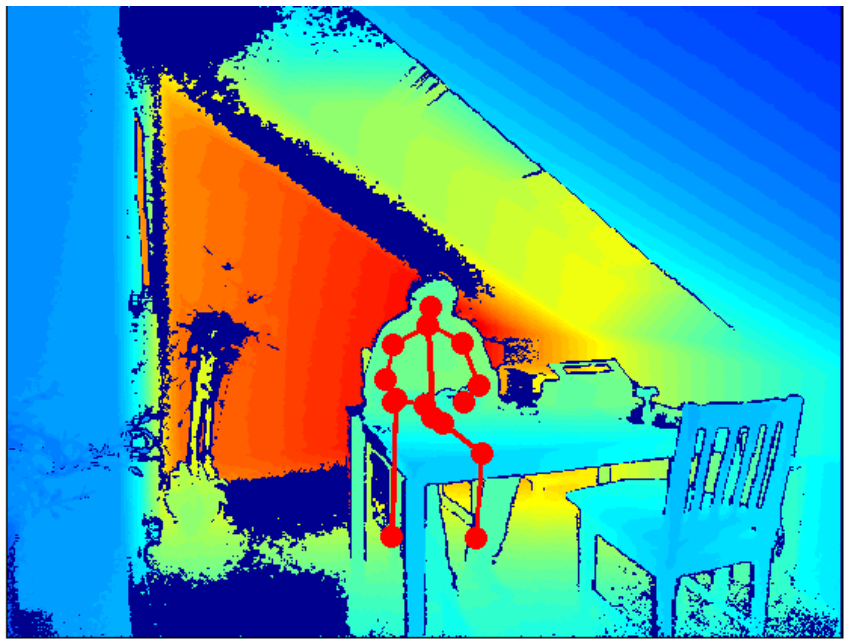
Real Data (552 images)

- Kinect2 SDK, all fails are discarded

With And Without Semantics

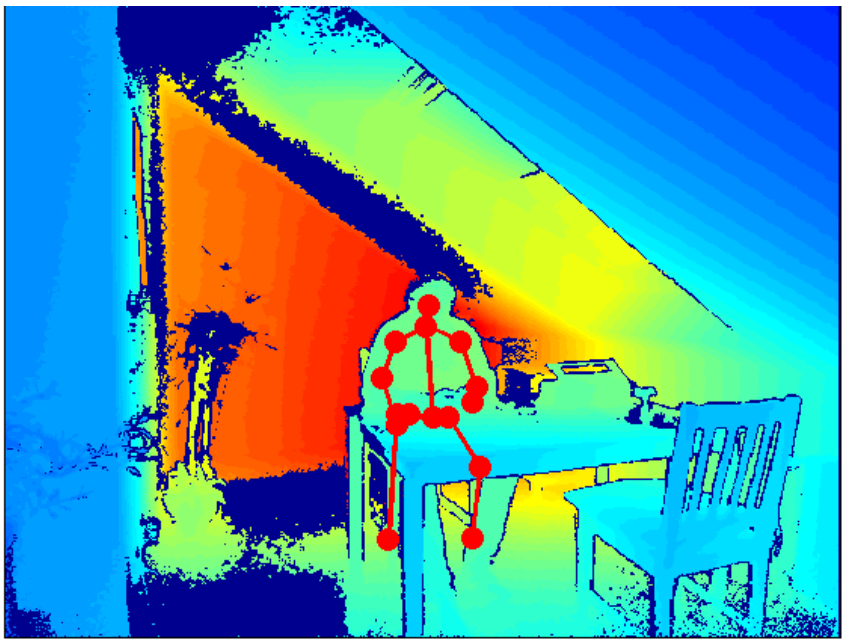


with semantics

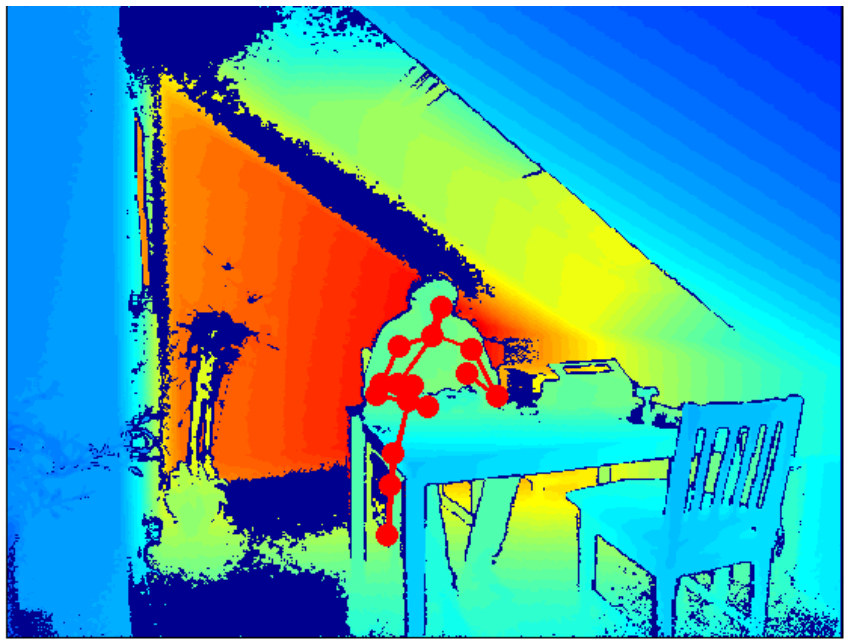


without semantics

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

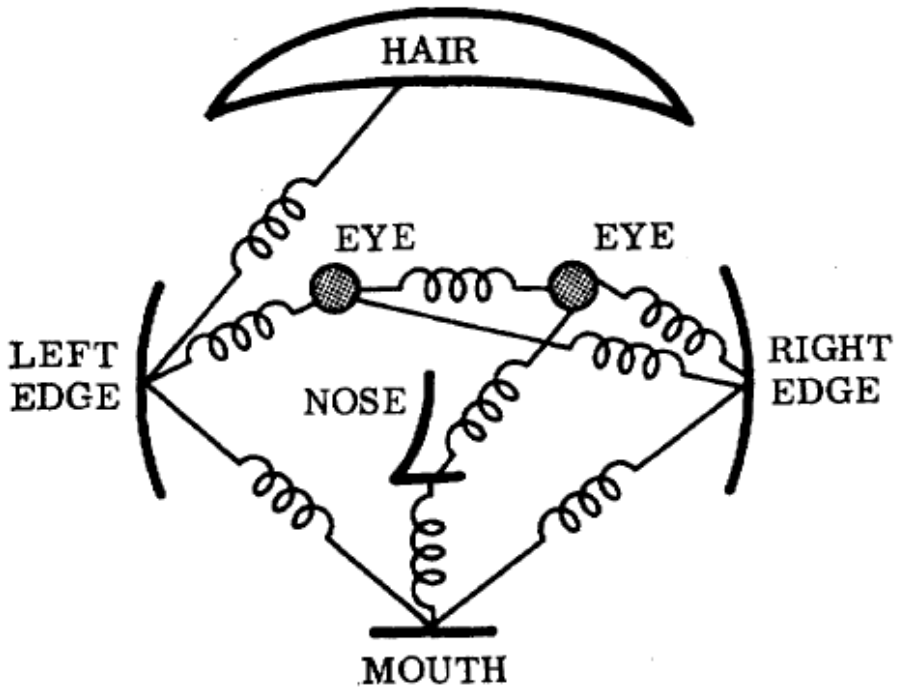


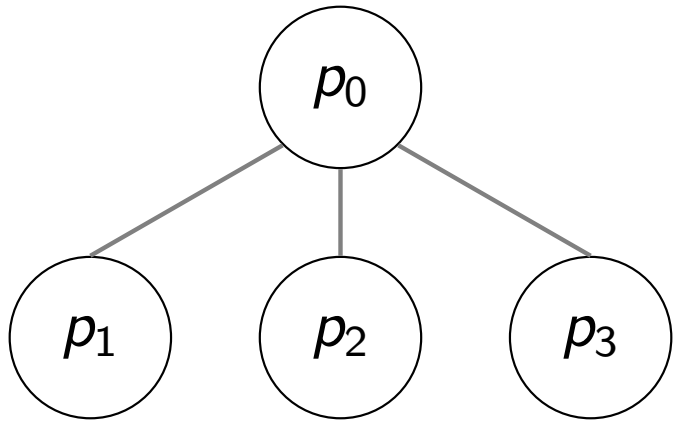
Figure : Pictorial Structure Model [9]

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)

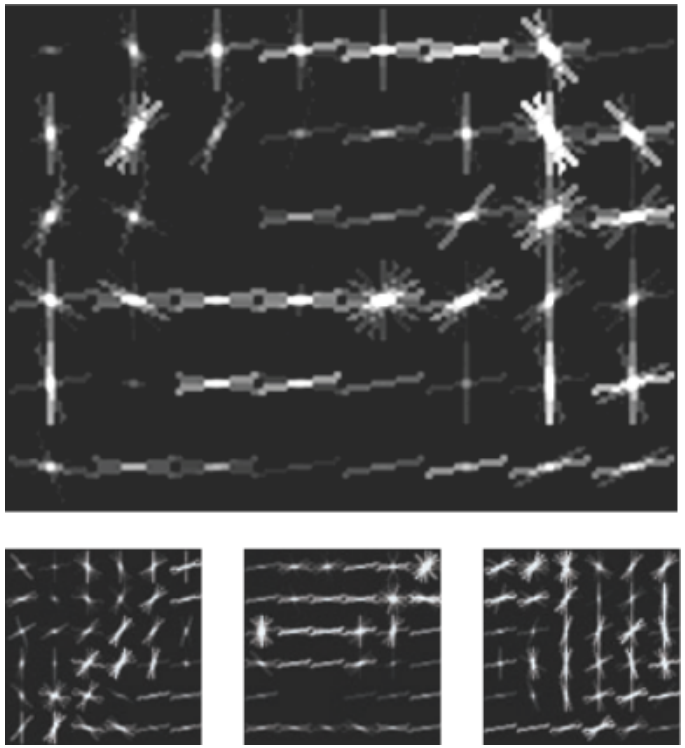


$$E_c(p; I) = \sum_{i=0}^{M} \langle v_i^c, \Phi(p_i; I) \rangle + \sum_{i=1}^{M} \langle w_i^c, \Phi(p_0, p_i) \rangle$$

E_c - is the Energy function

Filter

- images with bounding boxes
- Histograms of Oriented Gradients (HOG) as filter
- Gaussians as displacement filter



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

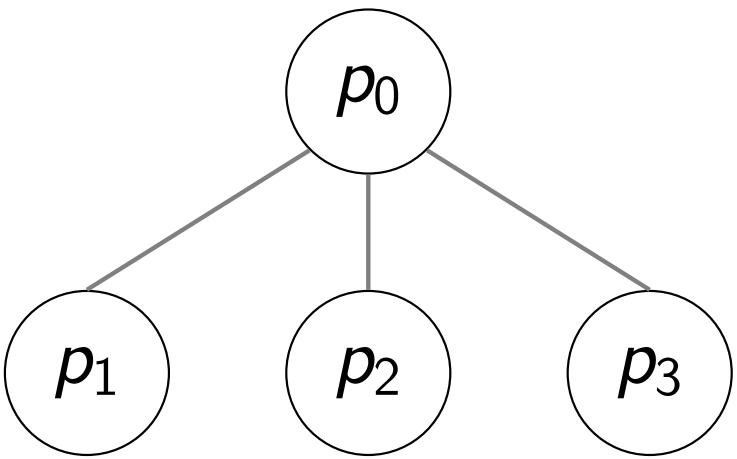
Parts:

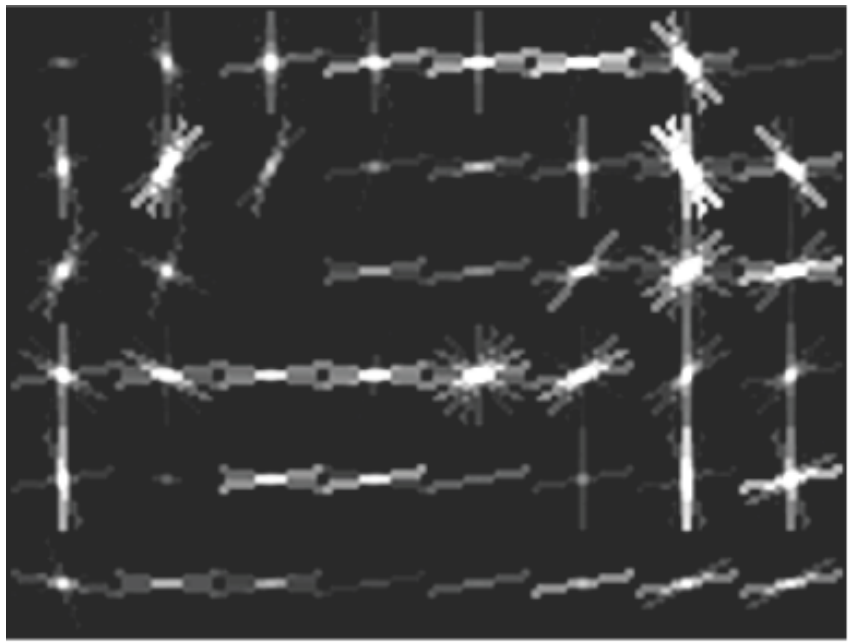
visible 6

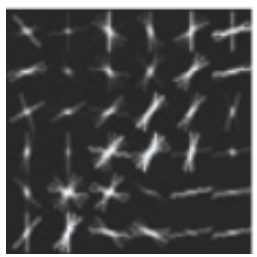
occluded $16 - 15$

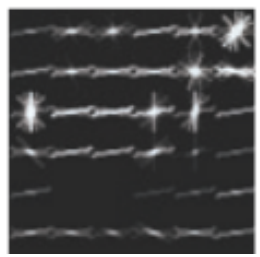
OC-DPM

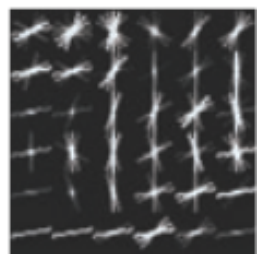
$$C = \{1, ..., C_{visible}\} \cup C_{invisble}$$







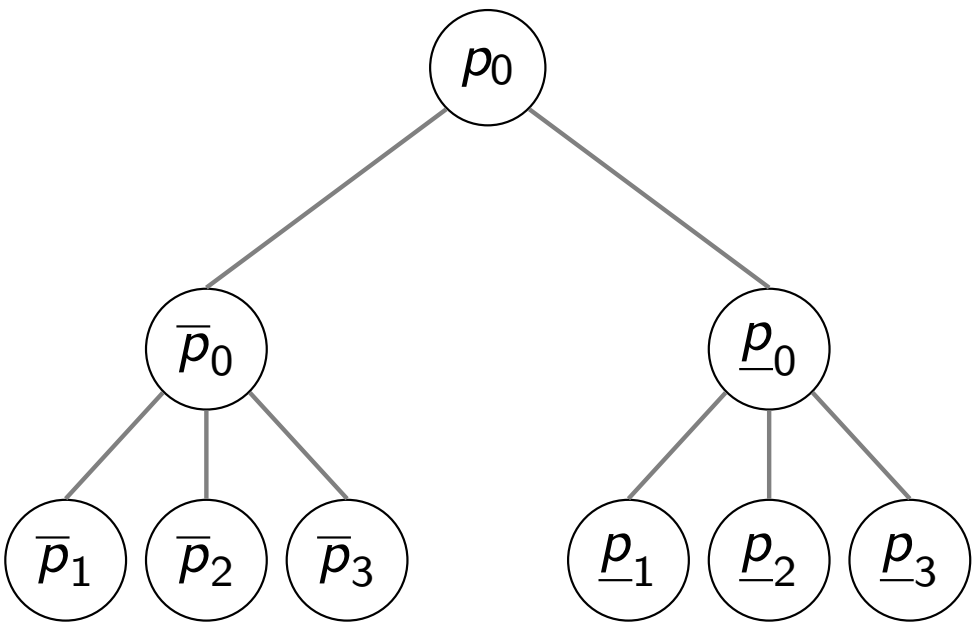


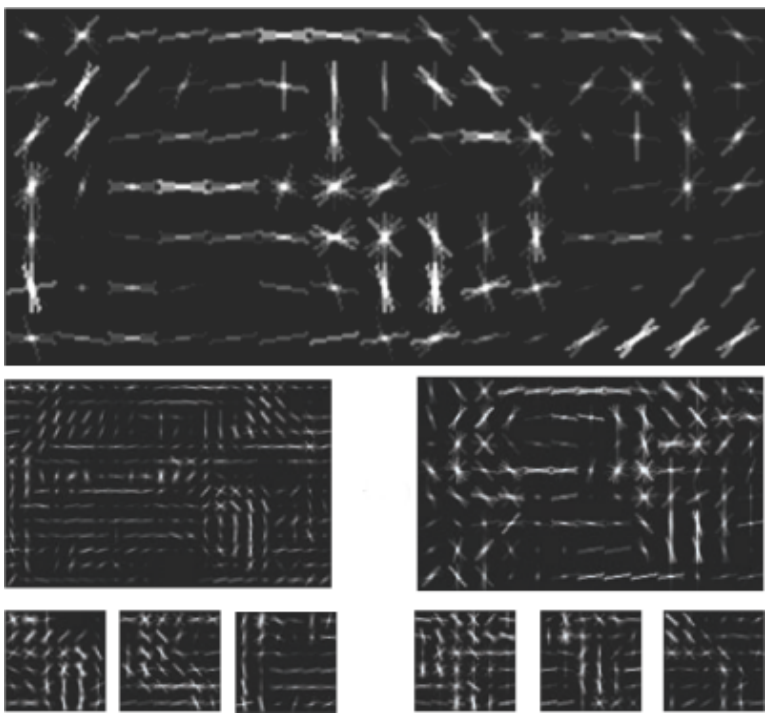


- like standart dpm
- trained with occlusion

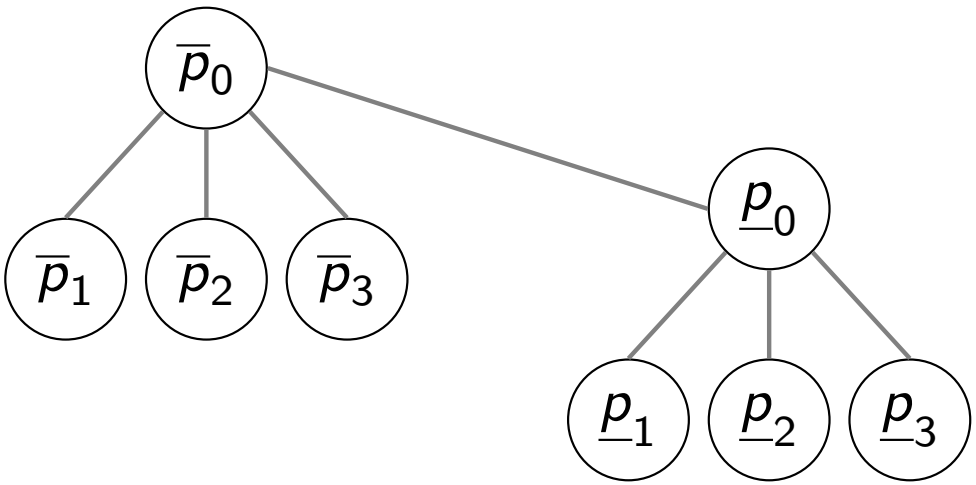
SYM-DPM

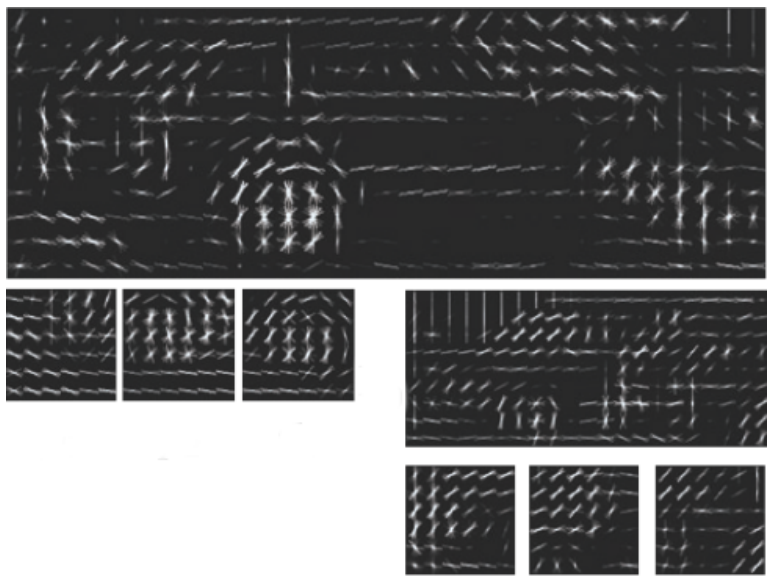
$$E'_c(p; I) = \langle v^c_{joint}, \Phi(p_0; I)\rangle + \langle \overline{w}, \Phi(\overline{p}_0, p_{joint})\rangle + \langle \underline{w}, \Phi(\underline{p}_0, p_{joint})\rangle$$
$$+ E_c(\overline{p}_0; I) + E_c(\underline{p}_0; I)$$





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

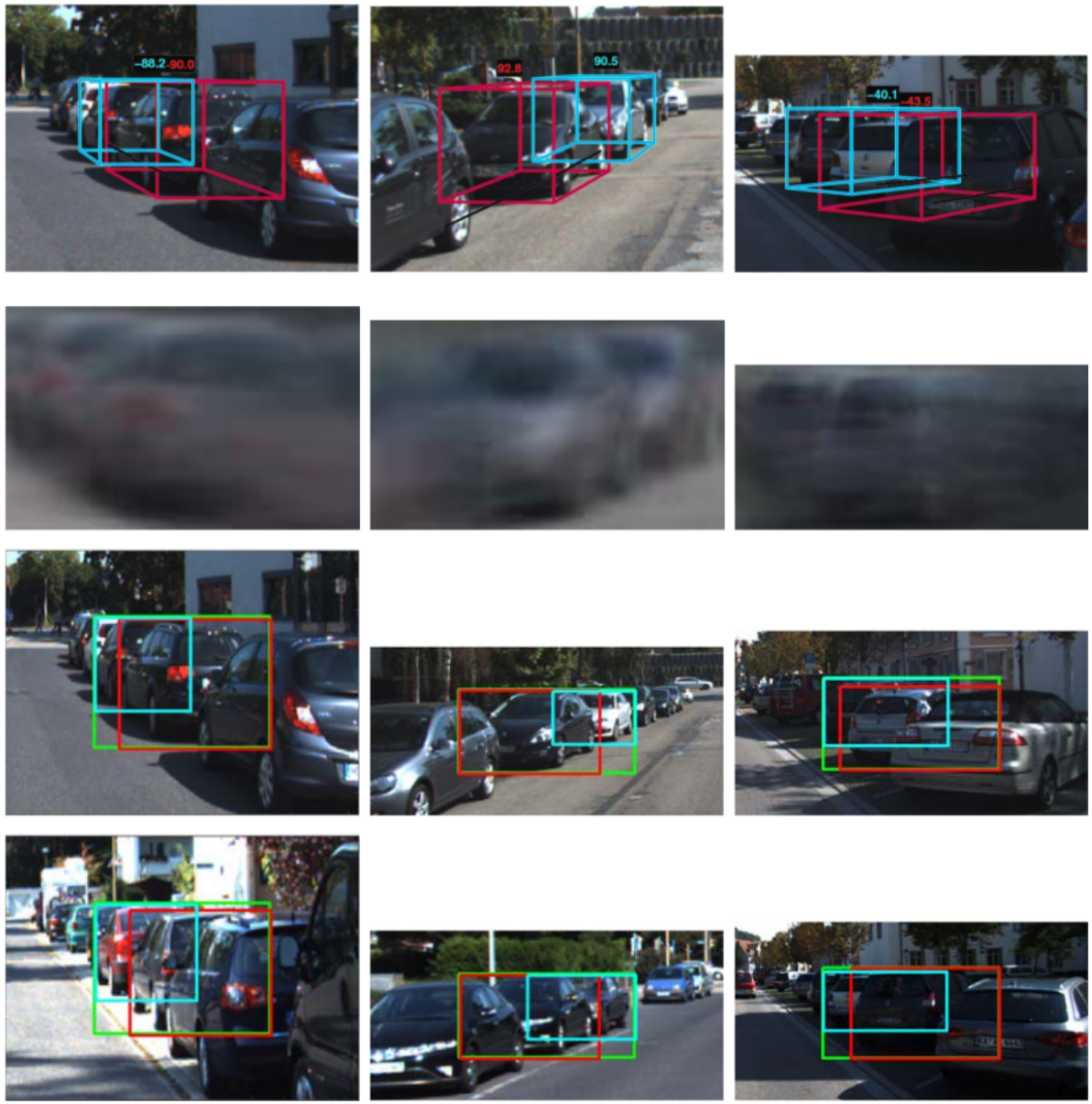
iii occluder is/is not occluded

iv degree of occlusion of occludee

Rule-based clustering

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

Mining Trainingsdata



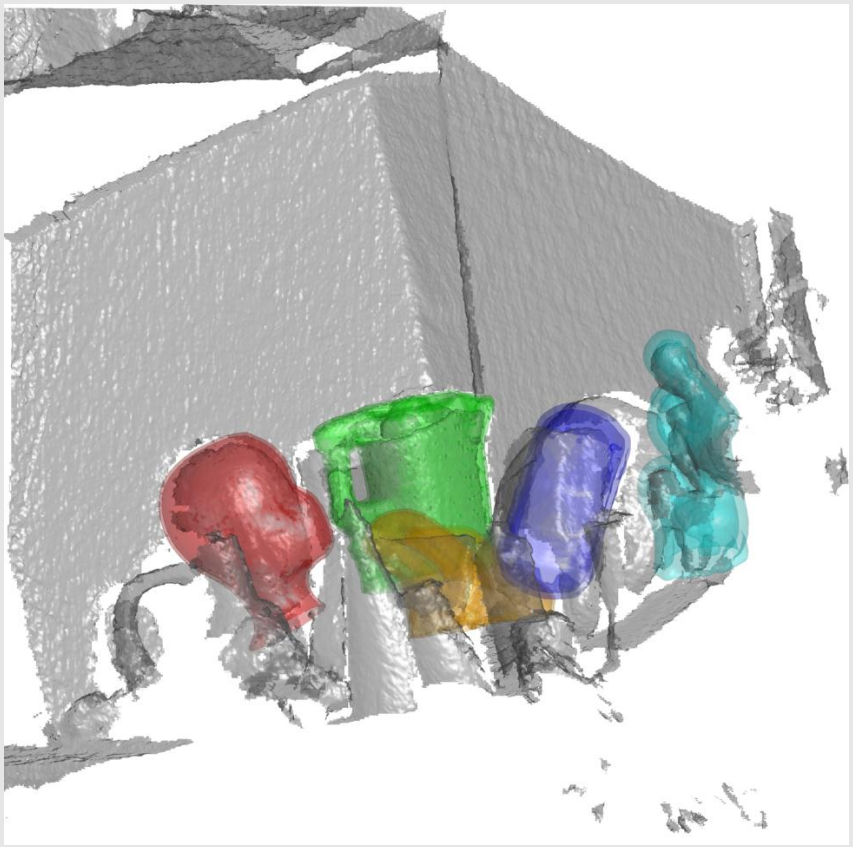
Results

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

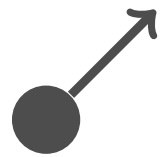
Output : 6D-Object-Pose

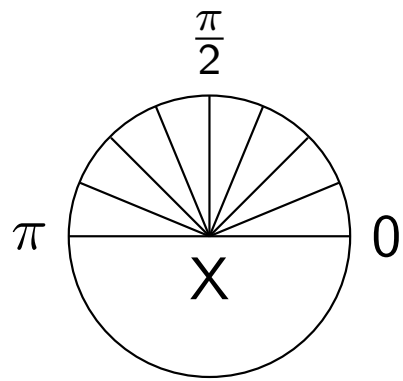
Intoduction

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

Edgelet

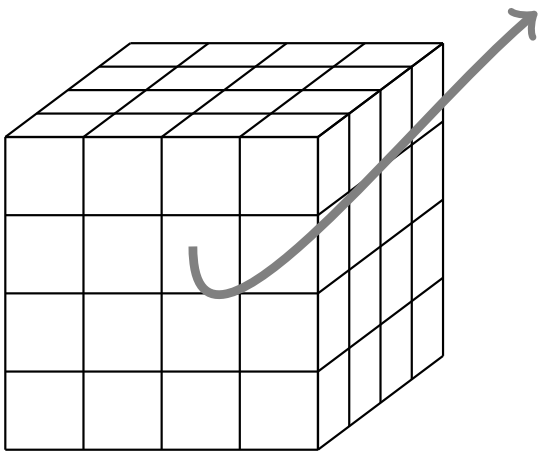
- N points per Pointcloud j
- FOR ALL $i \in \{1, ..., N\}$
  - calc λ_1 and λ_2
  - $r = \frac{\lambda_1}{\lambda_2}$
  - $r \rightarrow$ curvatureMap
- hysteresisThesholding(curvatureMap);
- nonmaximalSuppression(curvatureMap);
- hysteresisThesholding(depthMap);
- projectToPointcloud(curvatureMap,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





Feature Vector

$w \times h \times d$



Voxel v

1	2	...	8

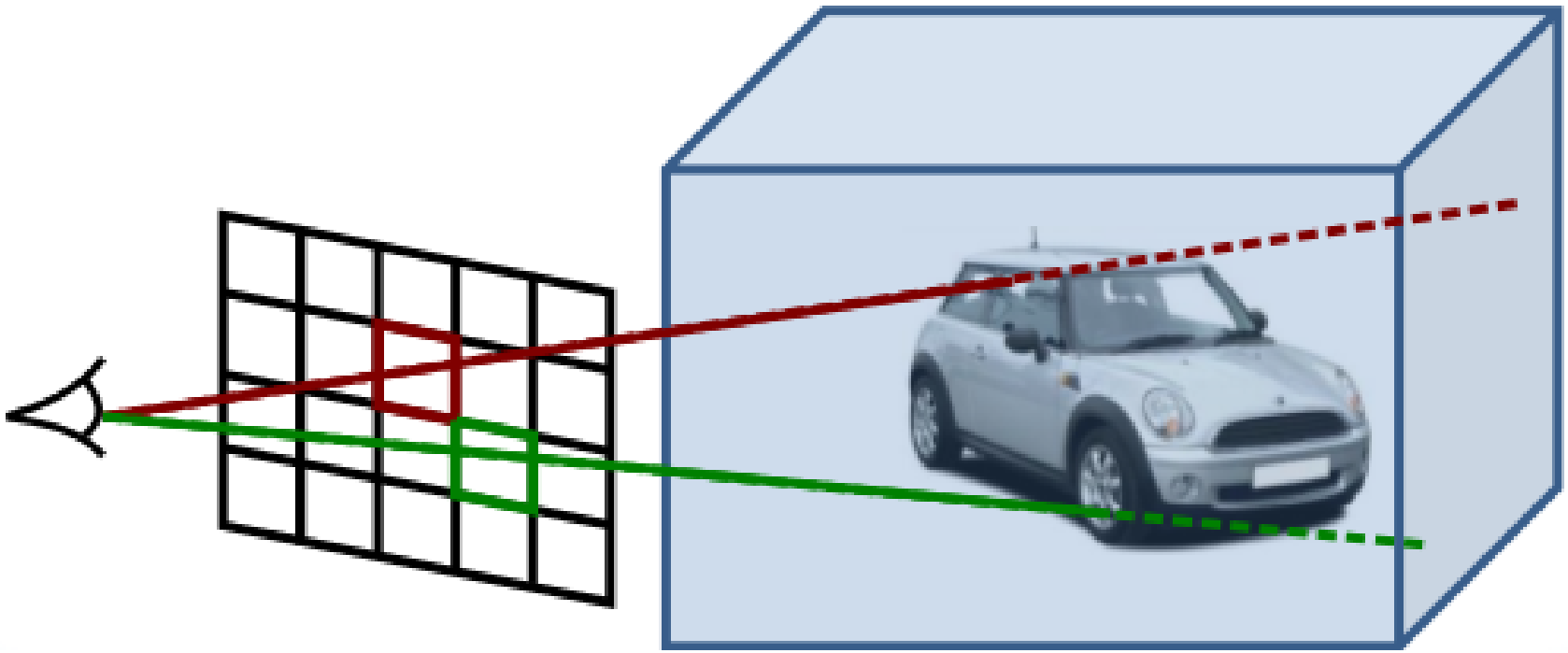
$$x_i^v = \begin{cases} 1 & \text{if } i \text{ is dominant} \\ 0 & \text{else } i\text{is not dominant} \end{cases}$$

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

The resulting feature vector is the concatenation of all voxels:

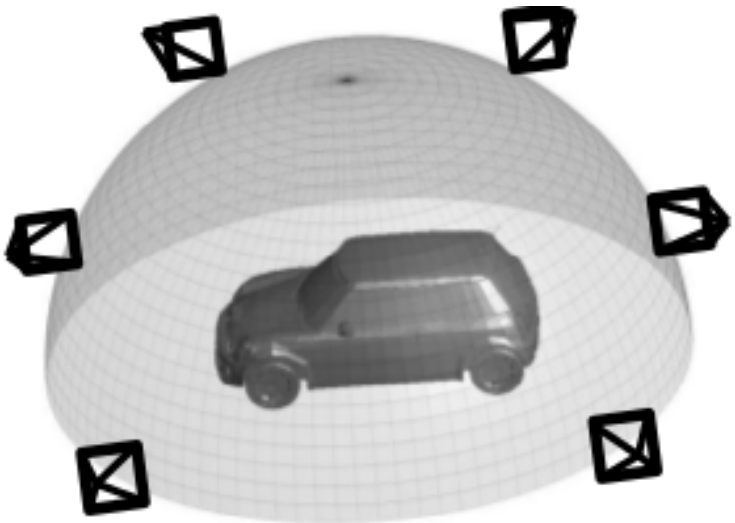
$$w \times h \times d \times 8$$

Box Model For Occluder



- Occluders only 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

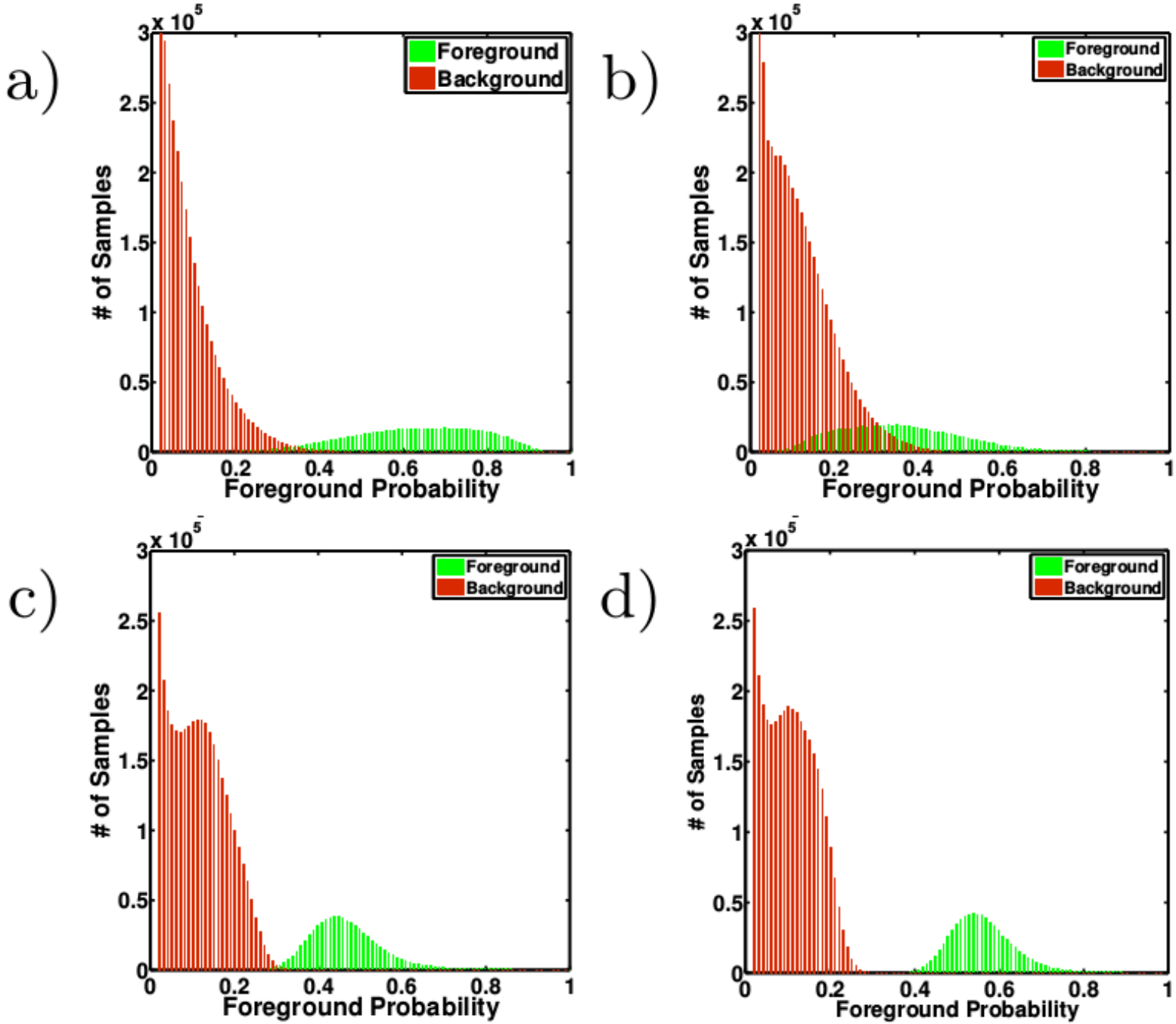
(> 0) - dominant or not visible voxel

- 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 and Conclusion

	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

- redundanze
- training with occlusion
- semantic (scene understanding)

Discussion

?


Ujwal Bonde, Vijay Badrinarayanan, and Roberto Cipolla. "Computer Vision – ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part II". In: ed. by David Fleet et al. Cham: Springer International Publishing, 2014. Chap. Robust Instance Recognition in Presence of Occlusion and Clutter, pp. 520–535. ISBN: 978-3-319-10605-2. DOI: 10.1007/978-3-319-10605-2_34. URL: http://dx.doi.org/10.1007/978-3-319-10605-2_34.


Andreas Geiger. "Are We Ready for Autonomous Driving? The KITTI Vision Benchmark Suite". In: *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. CVPR '12. Washington, DC, USA: IEEE Computer Society, 2012, pp. 3354–3361. ISBN: 978-1-4673-1226-4. URL: http://dl.acm.org/citation.cfm?id=2354409.2354978.


Andreas Geiger et al. “Vision meets Robotics: The KITTI Dataset”. In: *International Journal of Robotics Research (IJRR)* (2013).


Stefan Hinterstoisser et al. “Multimodal templates for real-time detection of texture-less objects in heavily cluttered scenes.” In: *ICCV*. Ed. by Dimitris N. Metaxas et al. IEEE Computer Society, 2011, pp. 858–865. ISBN: 978-1-4577-1101-5. URL: http://dblp.uni-trier.de/db/conf/iccv/iccv2011.html#HinterstoisserHCIKNL11.


Alexander Krull et al. “6-DOF Model Based Tracking via Object Coordinate Regression.” In: *ACCV (4)*. Ed. by Daniel Cremers et al. Vol. 9006. Lecture Notes in Computer Science. Springer, 2014, pp. 384–399. ISBN: 978-3-319-16816-6. URL: http://dblp.uni-trier.de/db/conf/accv/accv2014-4.html#KrullMBGIR14.


Bojan Pepik et al. “Occlusion Patterns for Object Class Detection.” In: *CVPR*. IEEE, 2013, pp. 3286–3293. URL: http://dblp.uni-trier.de/db/conf/cvpr/cvpr2013.html#PepikSGS13.


Umer Rafi, Juergen Gall, and Bastian Leibe. “A Semantic Occlusion Model for Human Pose Estimation From a Single Depth Image”. In: *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*. June 2015.


Training Deformable Partmodels. *unkown*. [Online; accessed March 18, 2016]. 2016. URL: http://i.stack.imgur.com/Awffz.jpg.


unknown. *Pictorial Structure Model*. [Online; accessed April 17, 2016]. unknown. URL: http://kenschutte.com/thesis/fischler.png.

unkown. *CMU Mocap*. [Online; accessed April 17, 2016]. unkown. URL: http://mocap.cs.cmu.edu/.

unkown. *unkown*. [Online; accessed April 10, 2016]. unkown. URL: http://www.cvlibs.net/datasets/kitti/video/kitti_trailer.jpg.

unkown. *unkown*. [Online; accessed April 10, 2016]. unkown. URL: http://www.webondevices.com/wp-content/uploads/2015/09/pointcloud.jpg.

unkown. *unkown*. [Online; accessed April 4, 2016]. unkown. URL: https://farm6.staticflickr.com/5668/21114849206_759853e42a_z.jpg.