3D object modelling, recognition and tracking with an application to action learning VVV18

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Is this Vision?

"Now! *That* should clear up a few things around here!"

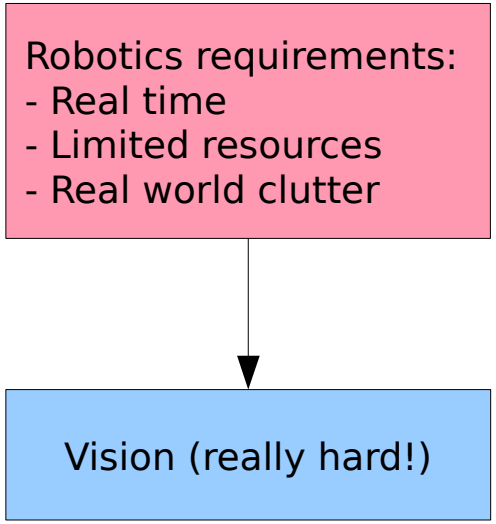
Is this Vision?

"Now! *That* should clear up a few things around here!"

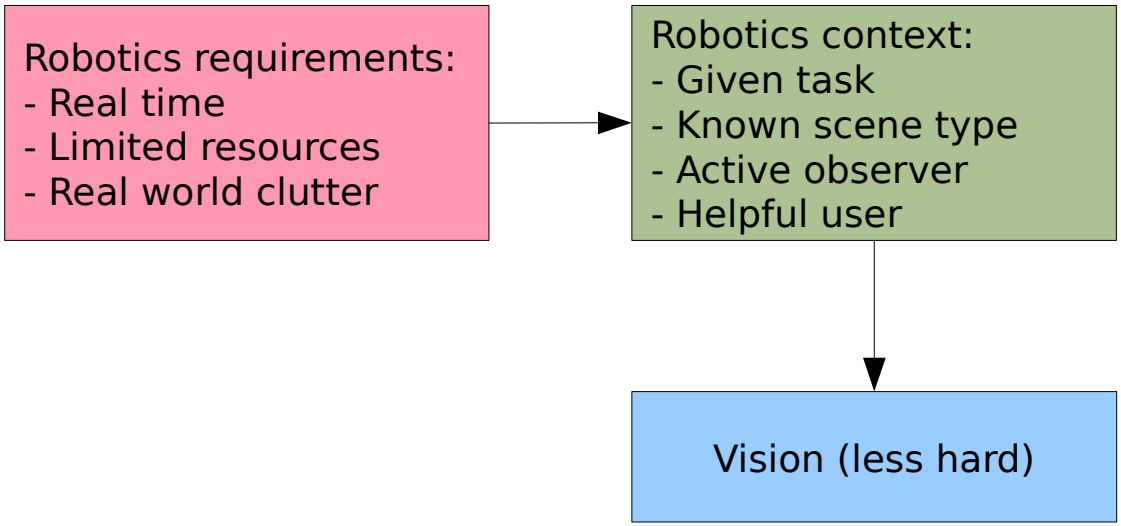
What is vision for *robotics?*

Vision (hard!)

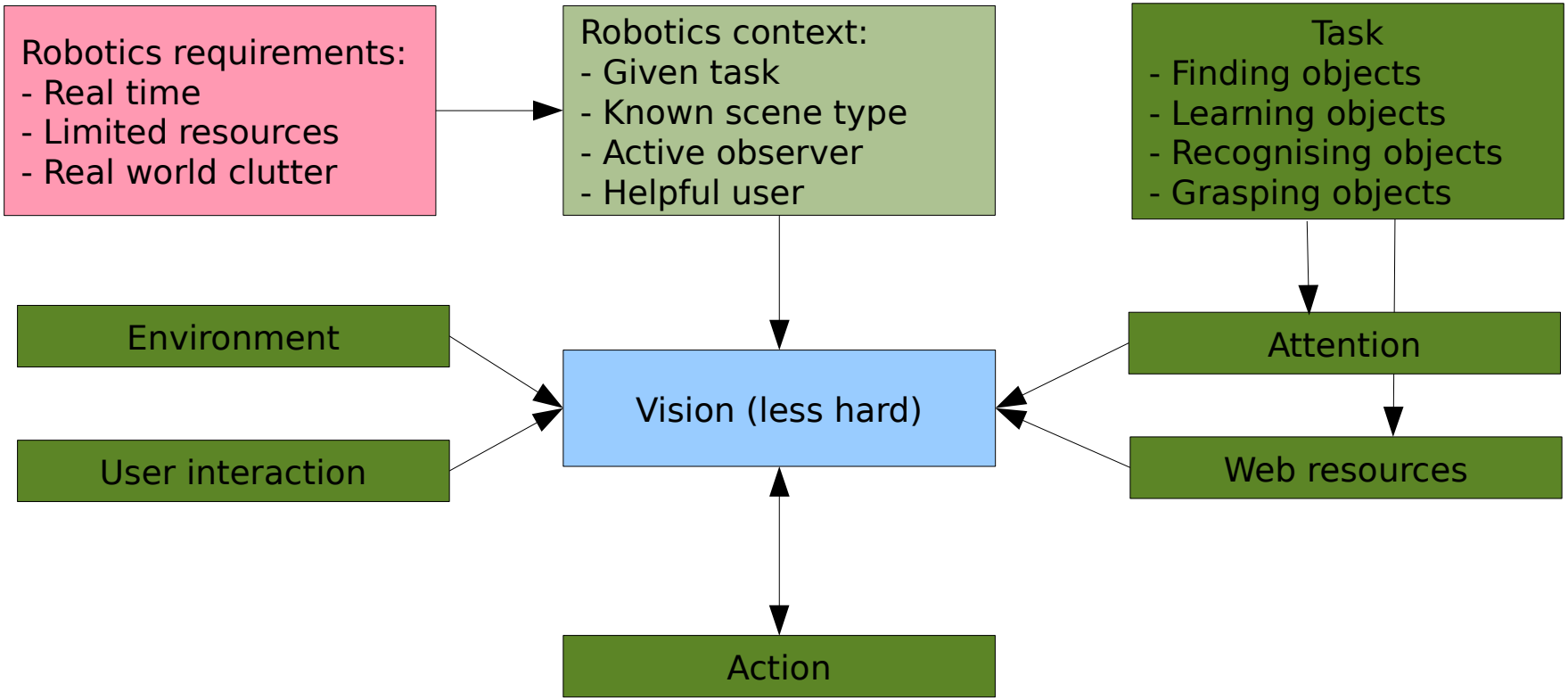
What is vision for *robotics?*



What is vision for *robotics?*



What is vision for *robotics?*



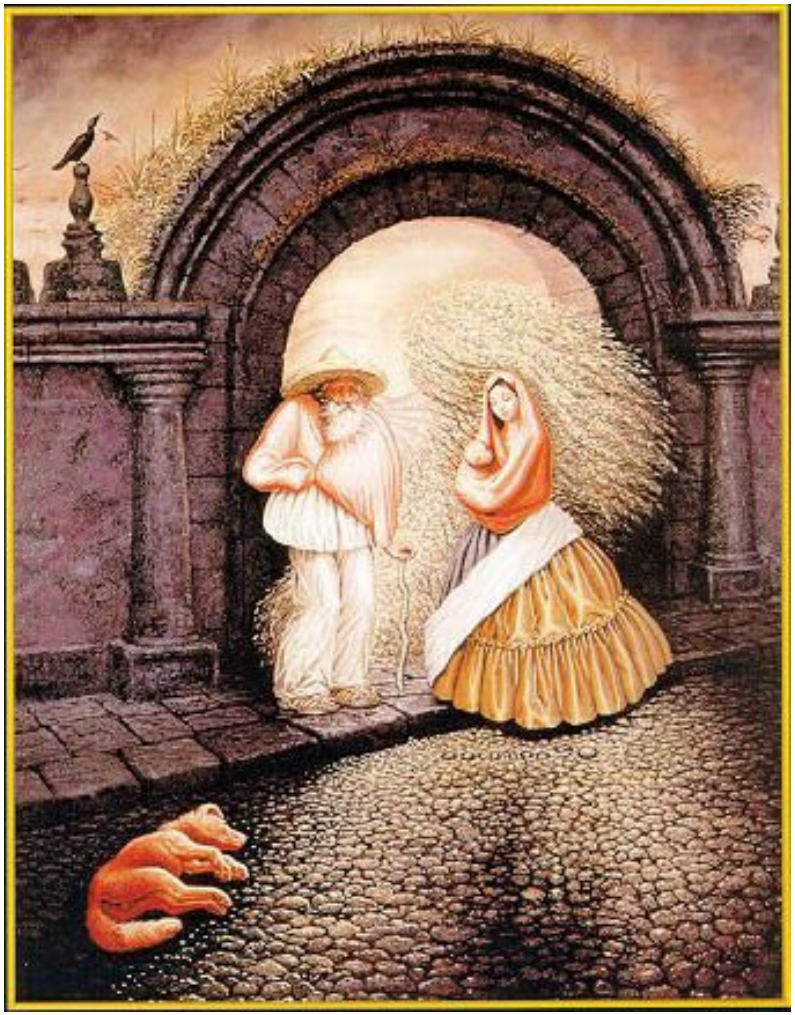
Object X

- Object **detection**, figure-ground **segmentation**, perceptual grouping = find relevant entities (to task)
- Object instance **recognition** = recognising one known object
- Object **categorisation/classification** = recognising objects belonging to a category (bottle, animal)
- Object **tracking** = recognise in image sequence while propagating state

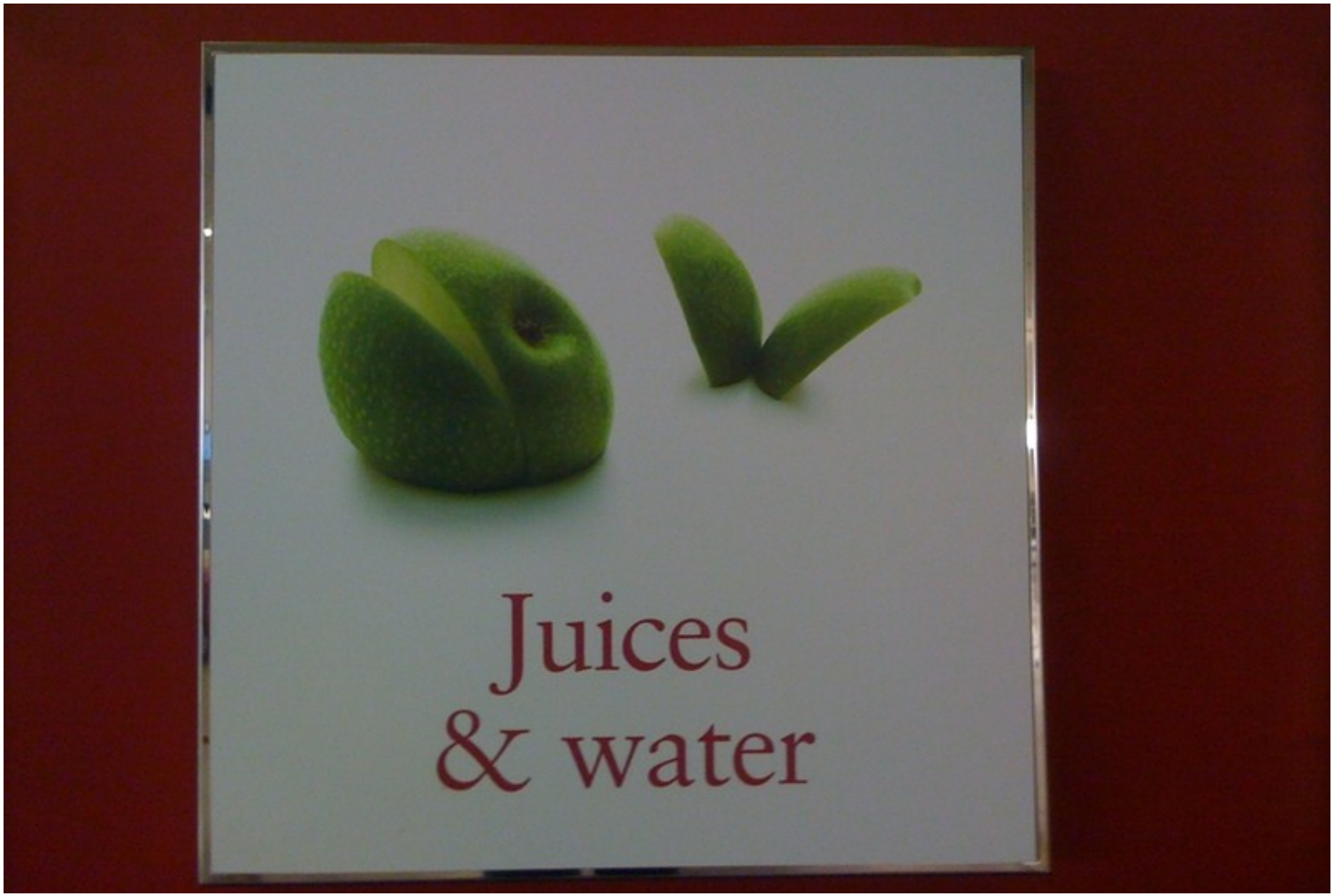
Overview

- **Detection / segmentation**
- Modelling
- Recognition
- Classification
- Tracking
- Attention
- Application to action learning

What is the object?

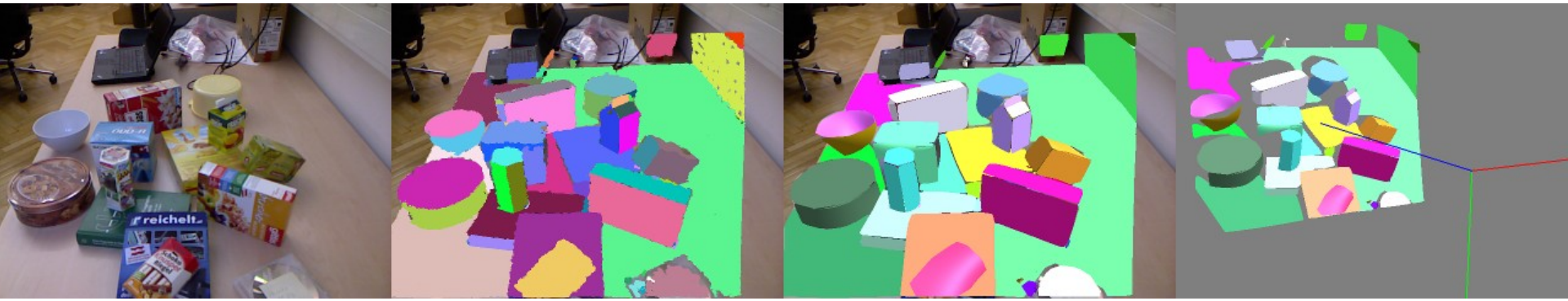


What is the object?



Object Segmentation

- Identify, in a **general** way, which bits of the scene could be **task relevant** objects
- Amidst **distractors, occlusions**
- [Ückermann ea IROS 2012]
- [Mishra ea ICRA 2012]
- [Katz ea RSS 2013]
- [Hager ea IJRR 2011]

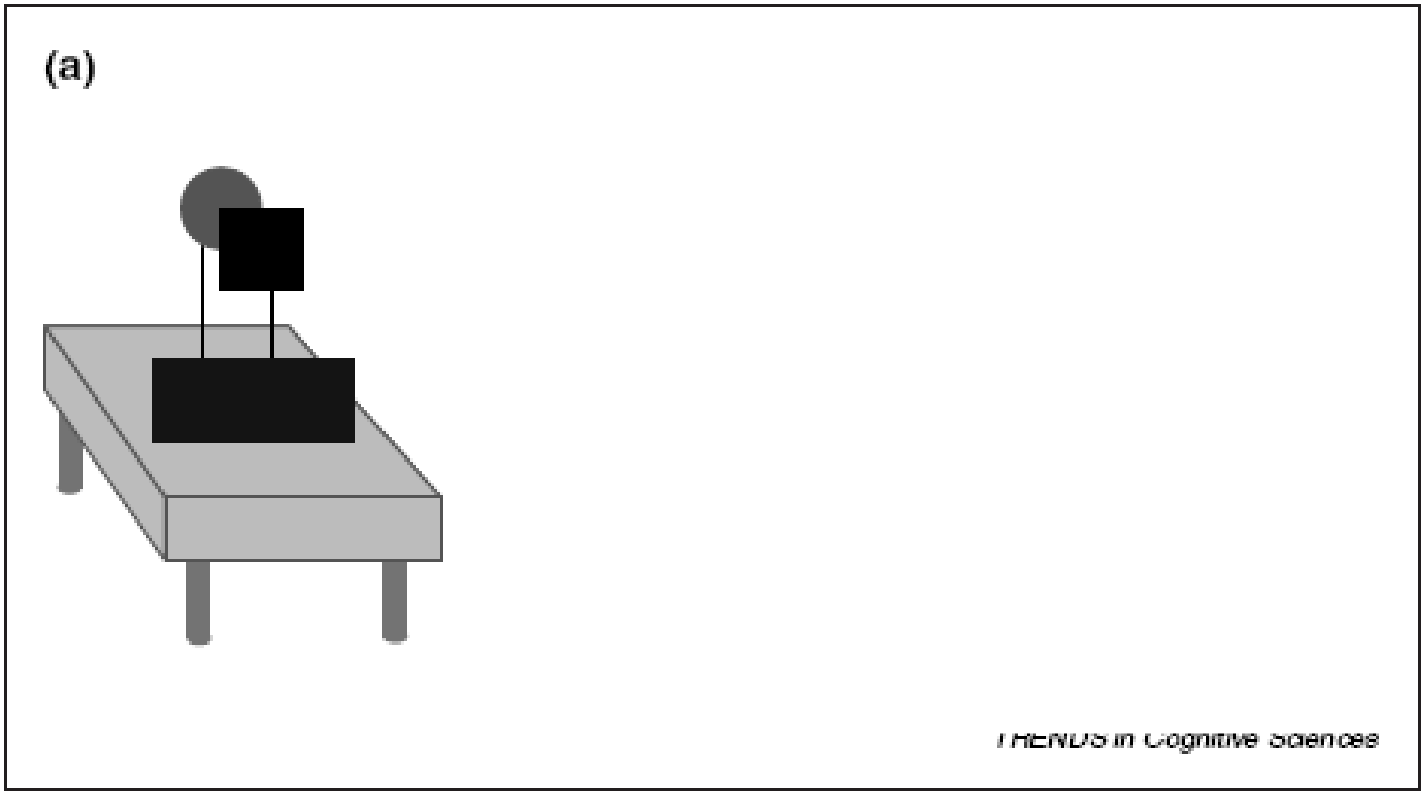


From coloured point clouds ... ... to separated object hypotheses

[Richtsfeld ea JVCI'14]

Generic view principle

"Qualitative (e.g. topological) image structure is stable with respect to small changes of viewpoint."



[M. K. Albert: Surface perception and the Generic View Principle, 2001.]

Object Segmentation

Gestalt principles

- Proximity
- Similarity
- Continuity
- Closure
- Symmetry
- Common region
- Element connectedness
- Common fate
- Good Gestalt

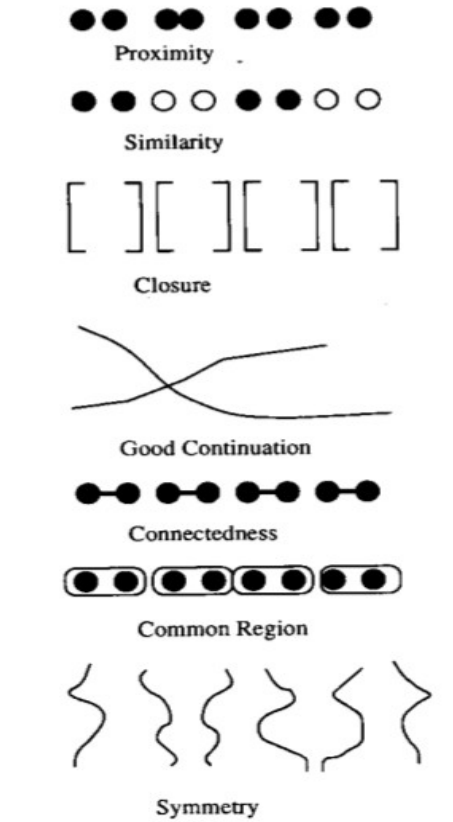
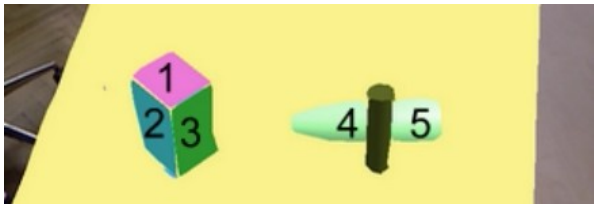


Fig. 3. Gestalt laws of grouping.

Object Segmentation: Grouping



Relations btw. neighboring surfaces

- r_co ... similarity of patch colour
- r_rs ... relative patch size similarity
- r_tr ... similarity of patch texture quantity
- r_ga ... gabor filter match
- r_fo ... fourier filter match
- r_co3 ... color similarity on 3D patch borders
- r_cu3 ... mean curvature on 3D patch borders
- r_cv3 ... curvature variance on 3D patch borders
- r_di2 ... mean depth on 2D patch borders
- r_vd2 ... depth variance on 2D patch borders

Relations btw. non-neighboring surfaces

- r_co ... similarity of patch colour
- r_rs ... relative patch size similarity
- r_tr ... similarity of patch texture quantity
- r_ga ... gabor filter match
- r_fo ... fourier filter match
- r_md ... minimum distance between patches
- r_nm ... angle between mean surface normals
- r_nv ... difference of variance of surface normals
- r_ac ... mean angle of normals of nearest contour p.
- r_dn ... mean distance in normal direction of nearest contour p.

Object Segmentation: Grouping

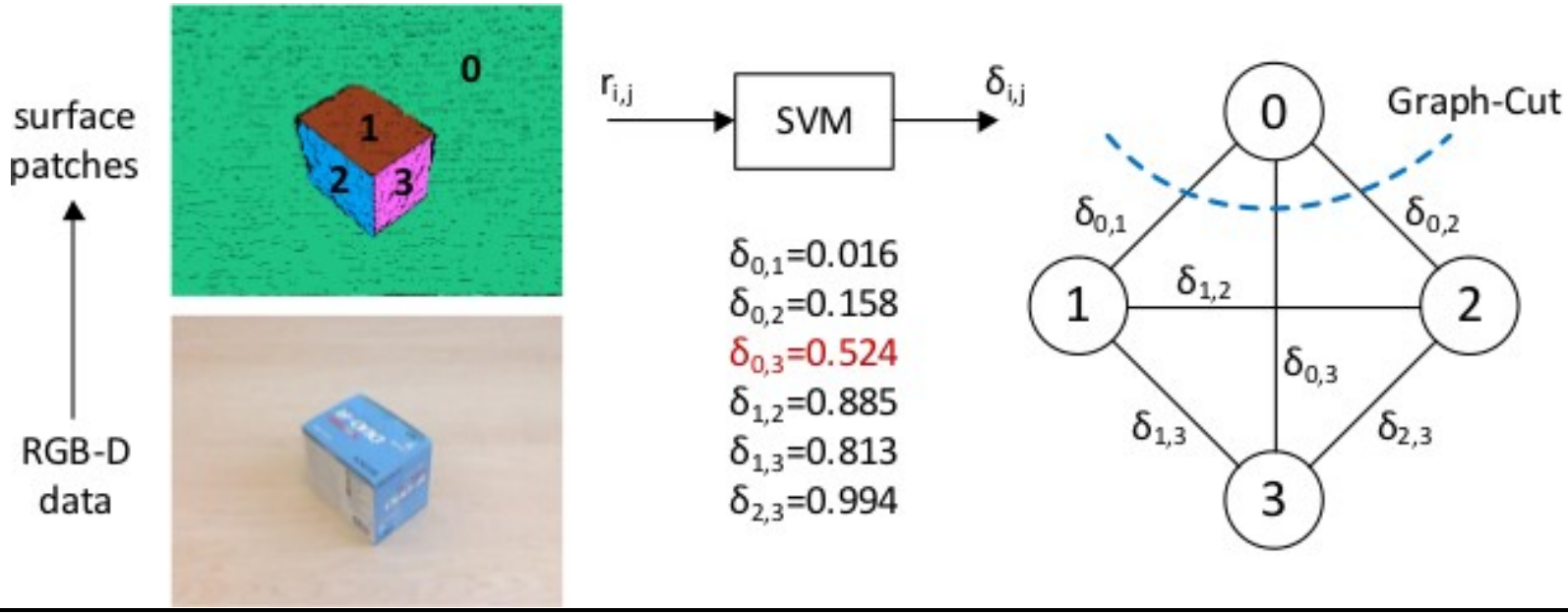
Global decision using graph cut

- Train Support Vector Machines (SVMs) on feature vectors, using annotated training data

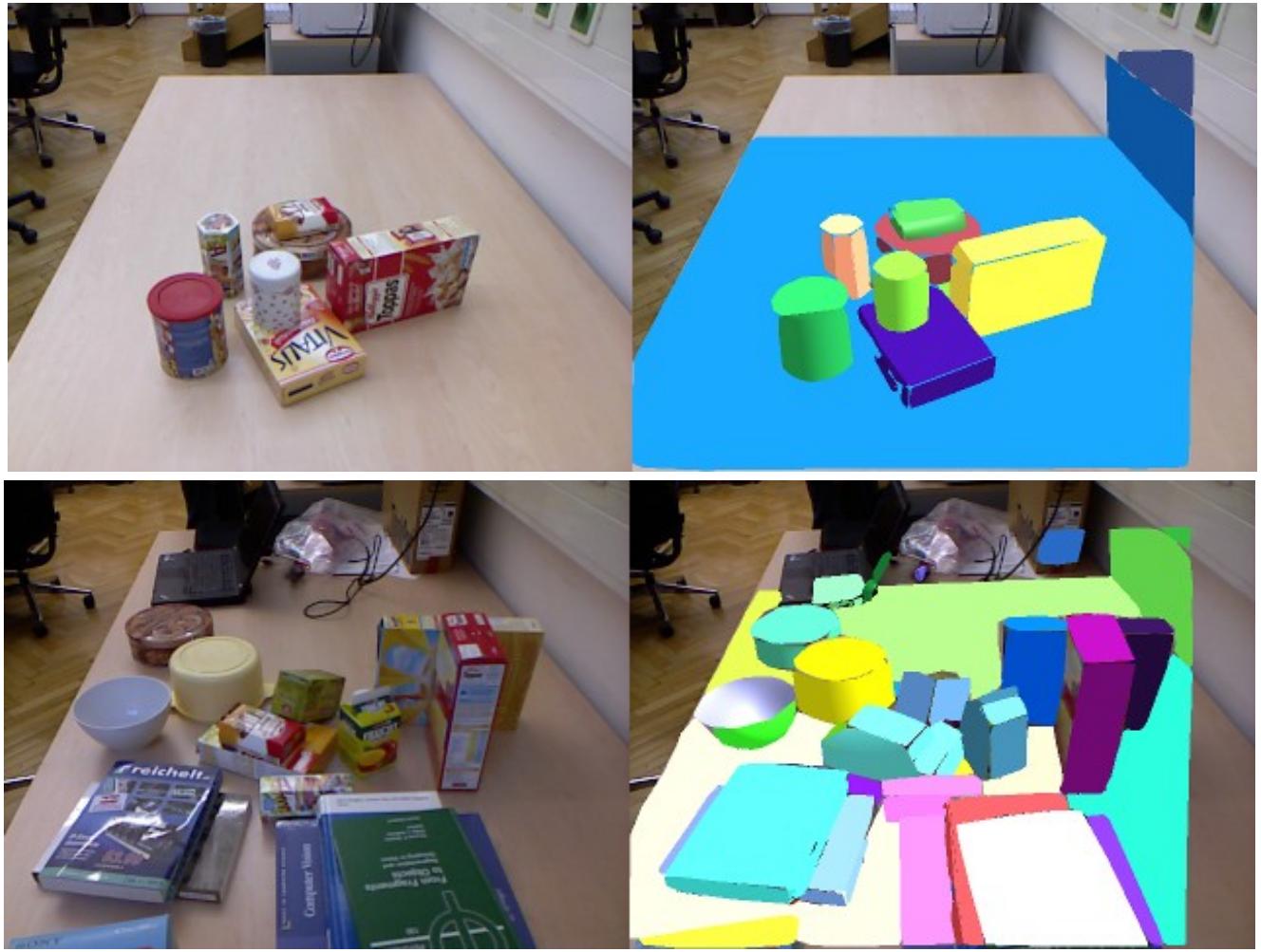
  r_st = (r_co, r_rs, r_tr, r_ga, r_fo, r_co3, r_cu3, r_cv3, r_di2, r_vd2)

  r_as = (r_co, r_rs, r_tr, r_ga, r_fo, r_md, r_nm, r_nv, r_ac, r_dn)

- Use predicted probability of “same object” as pairwise terms for graph cut



Object Segmentation



Object Segmentation Database (OSD) [Richtsfeld ea IROS'12]

Overview

- Detection / segmentation
- **Modelling**
- Recognition
- Classification
- Tracking
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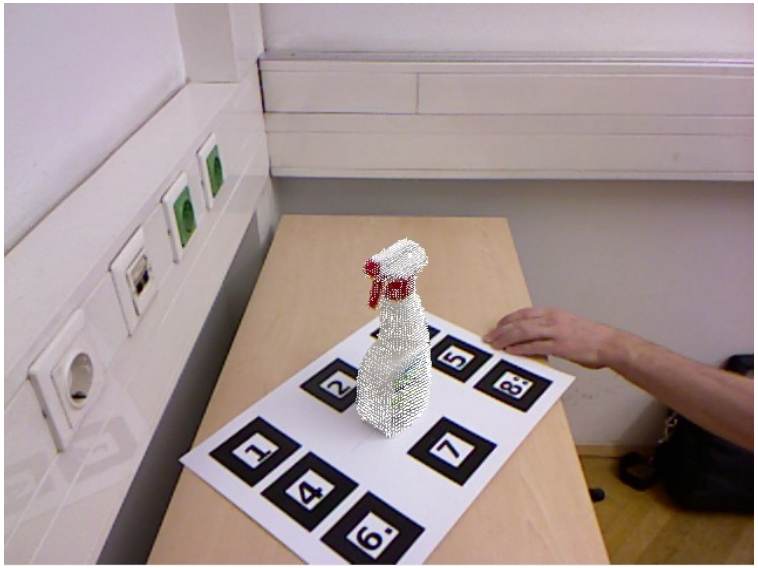
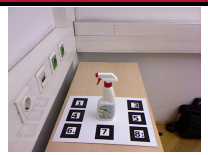
- Application to action learning

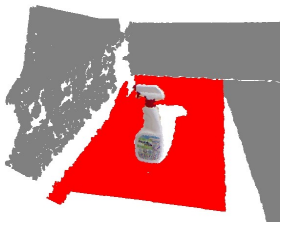
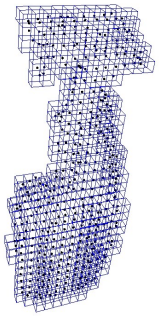
Object modelling

- Learn **individual** object models
- One shot to a **few views**
- Build database of known objects



Object modelling



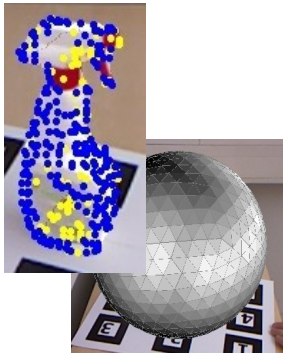
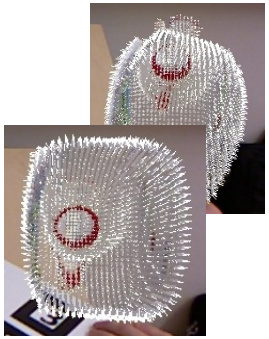



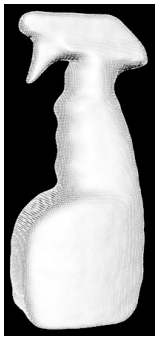

Input
- image
- point cloud

Segmentation
- Ground plane detection
- Euclidean clustering

Pose estimation
- Guess (SIFT)
- Scan alignment (ICP)

Voxel grid update
- Point weights
- Surface normals



Create recognition model
- Key-frame selection
- SIFT (yellow) [Lowe 2004]
- SHOT (blue) [Tombari 2010]

Loop closing
- Document indexing [Sivic 2003]
- Error distribution [Sprickerhof 2009]

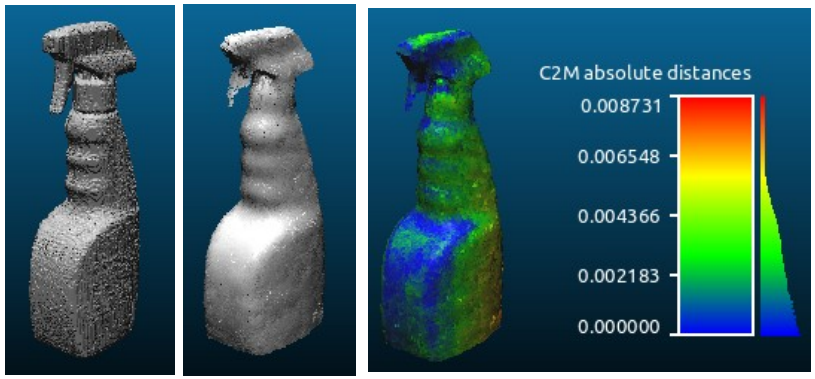
Point cloud
- Adaptive threshold

Surface modelling
- Poisson triangulation

Object Modelling

- RTM Toolbox (Recognition, Tracking, Modelling)

Object modelling

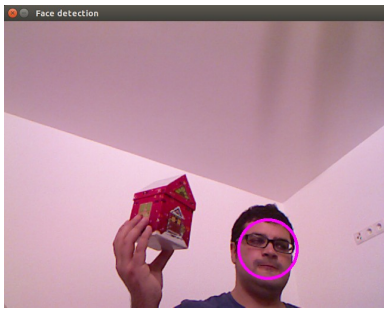


Reconstructed (left) vs. laser scanned (right): 2.16 ± 1.53mm [KIT object database]

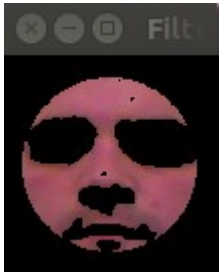
[Prankl ea IROS 2015]

In-hand Modelling

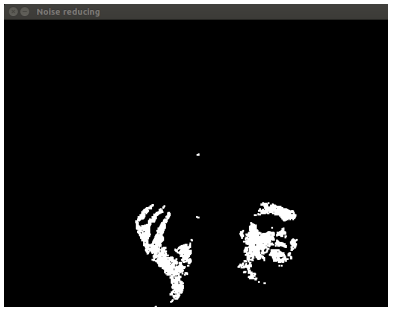
- User-assisted modelling while holding in hand [Streicher 2018]



Detect face



Get skin color



Mask skin regions

Subtract and find nearest cluster

Grab Cut for precise contours

RTM pipeline: 3D object model

Overview

- Detection / segmentation
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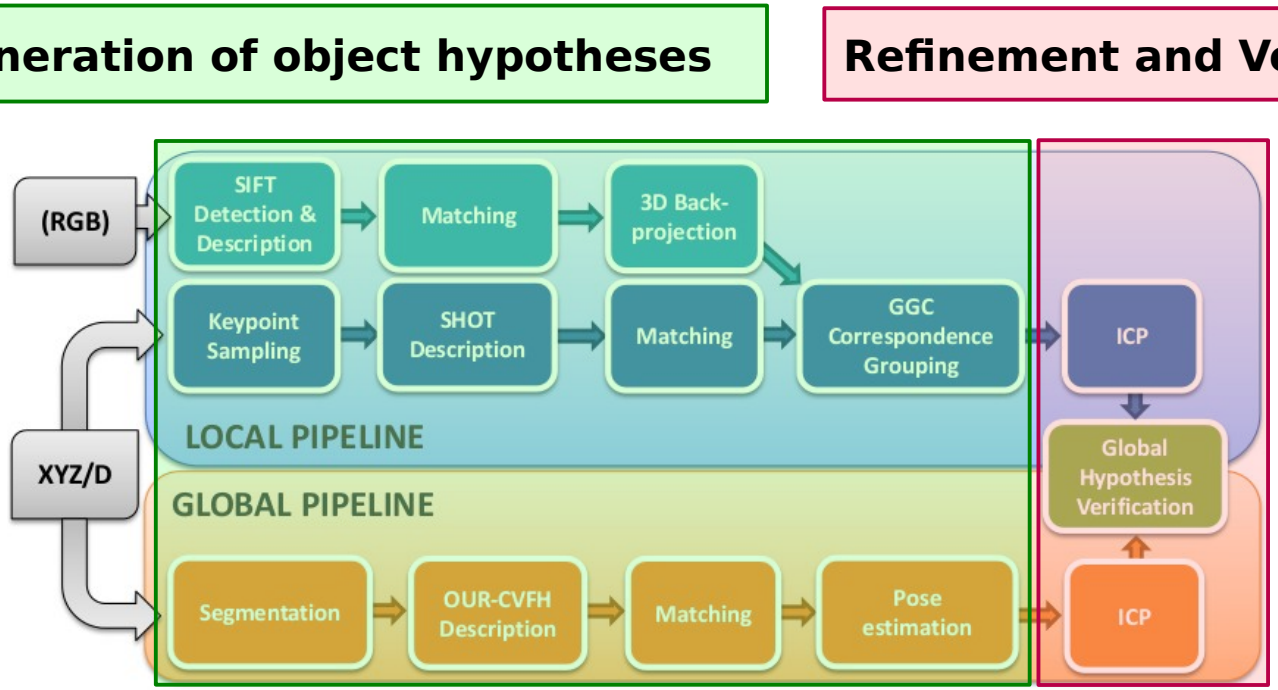
Object Recognition

- Robust recognition of **object instances** in uncontrolled environments: Partial occlusions, clutter, degenerate views, illumination conditions
- **Diverse object properties**: Textured or texture-less, distinctive or uniform shape
- => object **ID** and **6D pose**

Object Recognition

- Framework for multi-cue recognition



[Aldoma ea PAMI'16]

Features - 2D

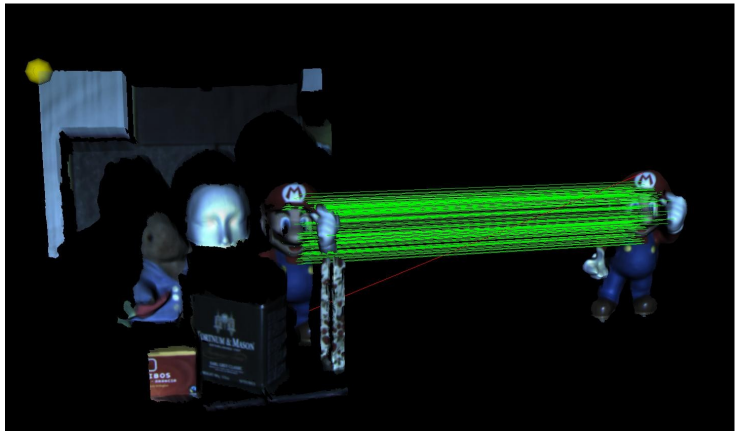
Classic feature based 2D recognition

- Find interest points in both images (e.g. DoG)
- Match corresponding point pairs using descriptors (e.g. SIFT)
- Align, RANSAC for obtaining 6D pose

Features - 3D

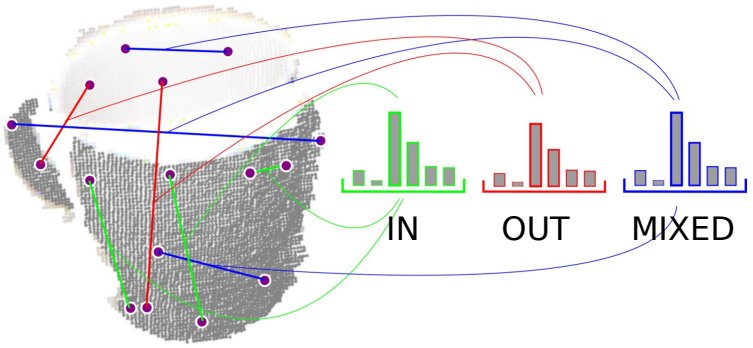
Local descriptors

- SHOT: Unique Signatures of Histograms for Local Surface Description (= 3D SIFT)



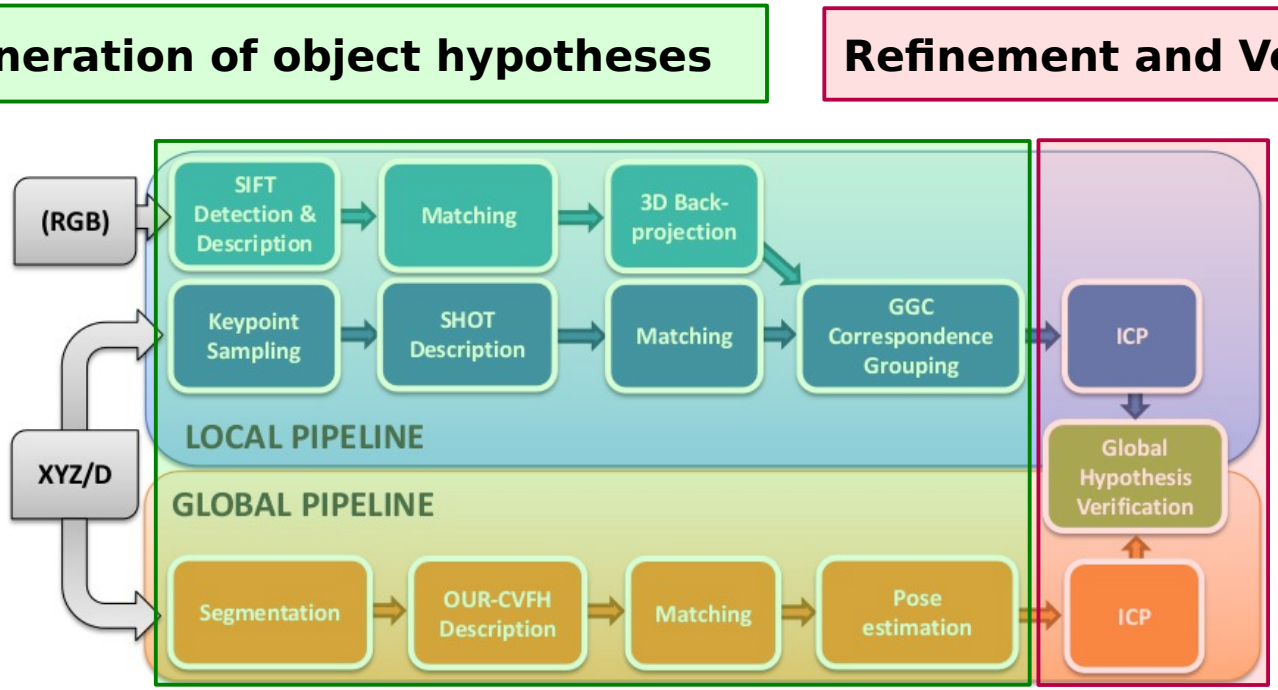
Global descriptors

- Ensemble of Shape Functions (ESF) [Wohlkinger 2011]
  Based on shape distributions [Osada ea 2001], inside/outside/mixed
  Additional histograms for ratio, area and angle



Object Recognition

- Framework for multi-cue recognition



[Aldoma ea PAMI'16]

Multi-hypothesis Recognition

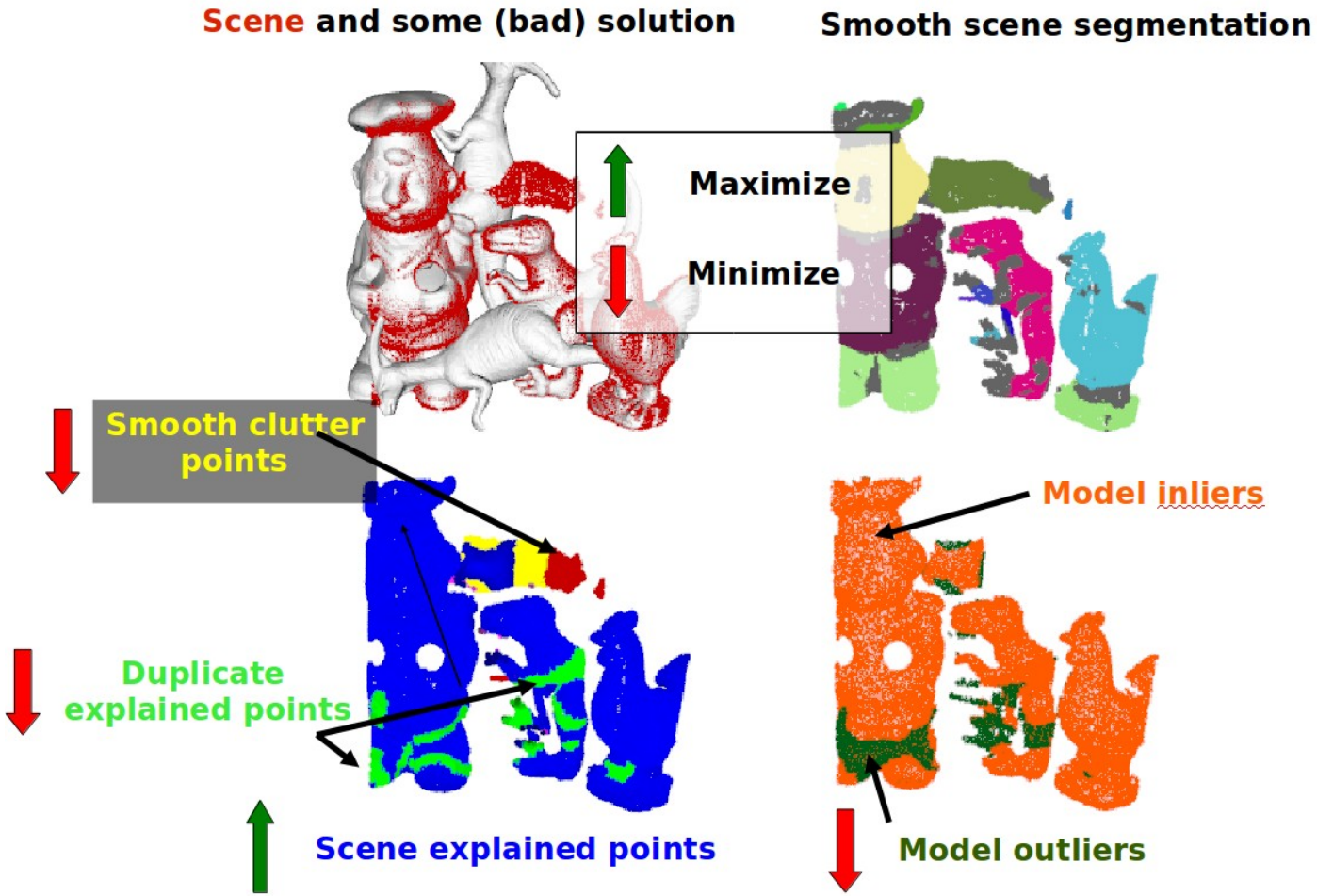
Common hypothesis verification paradigms

- Non-maxima supression to handle duplicate hypotheses, but what if two instance of same object in scene?
- Acceptance thresholds tricky, highly occluded objects vs. false positives
- Disregards interaction among hypotheses

=> Consider **all hypotheses simultaneously in a global model** of the scene in terms of objects

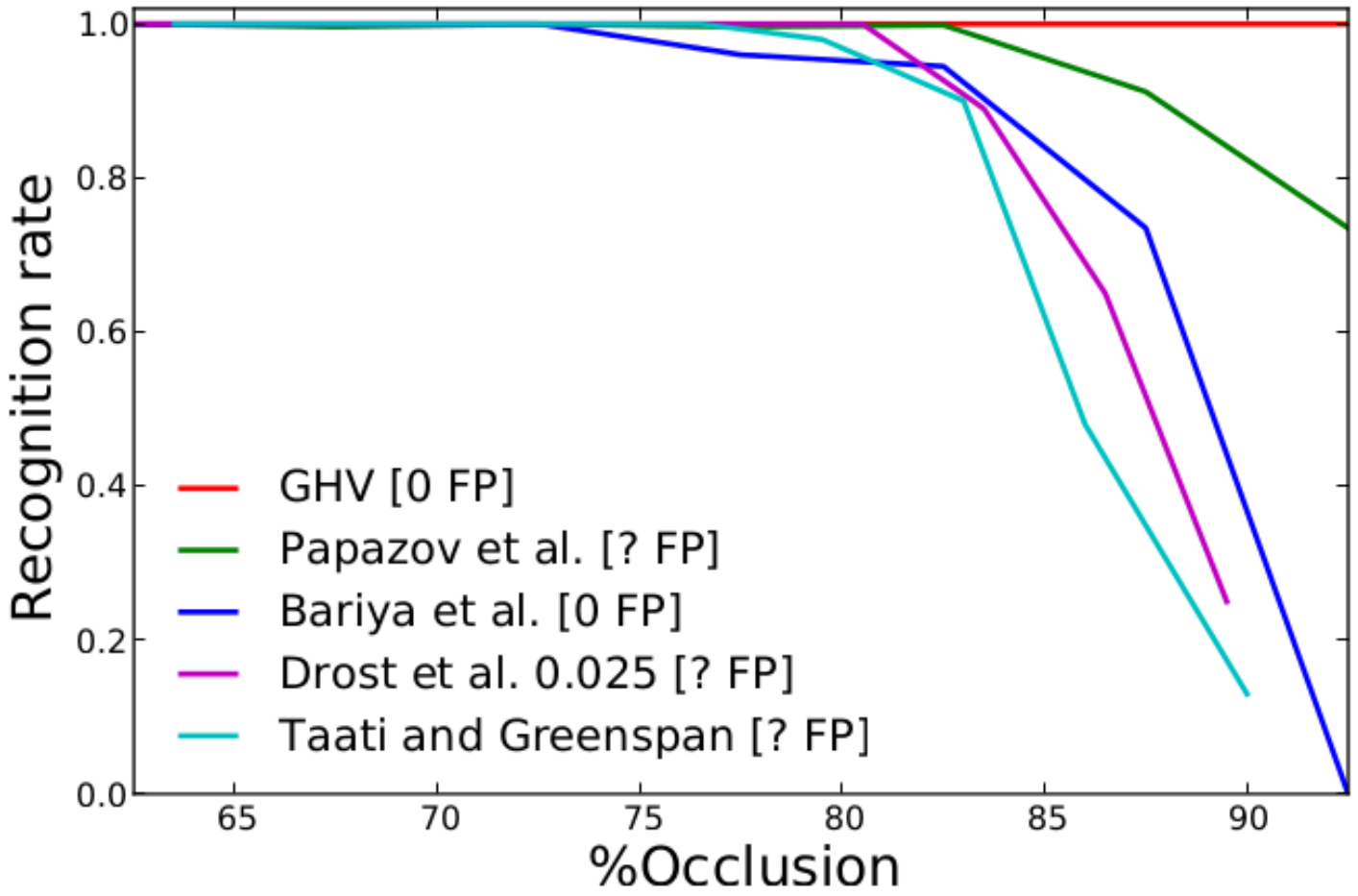
Global Hypothesis Verification

- Binary optimisation with tabu search



Result: high robustness

Laser Scanner dataset



Overview

- Detection / segmentation
- Modelling
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- **Classification**
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- Attention
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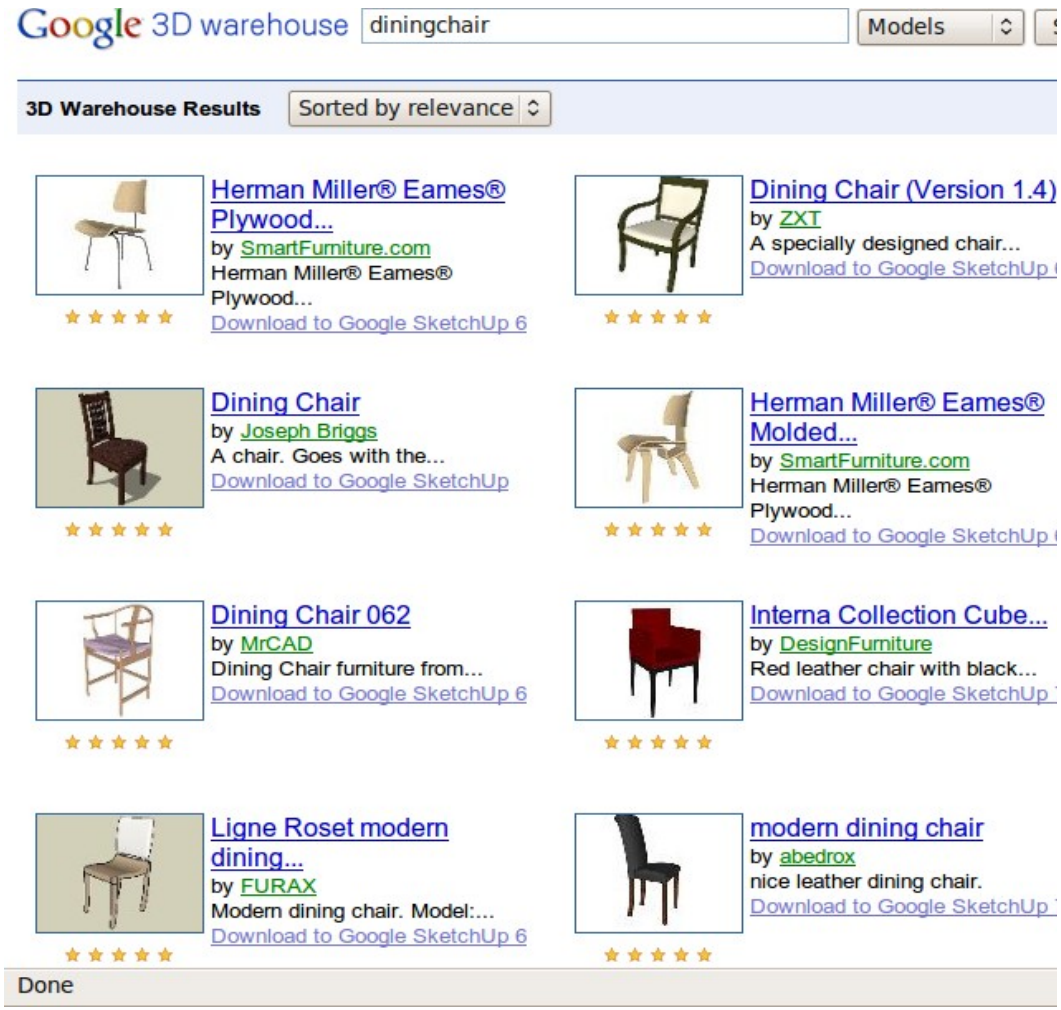
Object Categorisation

- Many objects sharing common characteristics
- Large amounts of **training data, training time**
- **Scalability** with number of classes

Offline Training from Web Models

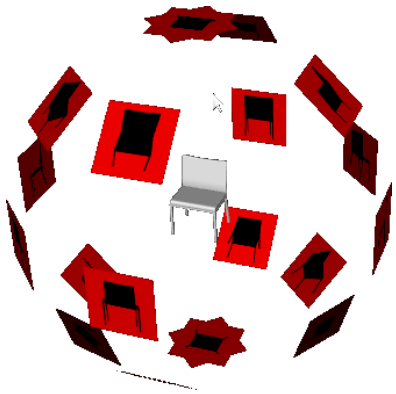
- E.g. “dining chair”
- Get many 3D CAD models, e.g. google 3D warehouse
- Find similar models from synonyms, e.g. Wordnet (mug, cup; chair, stool; etc.)

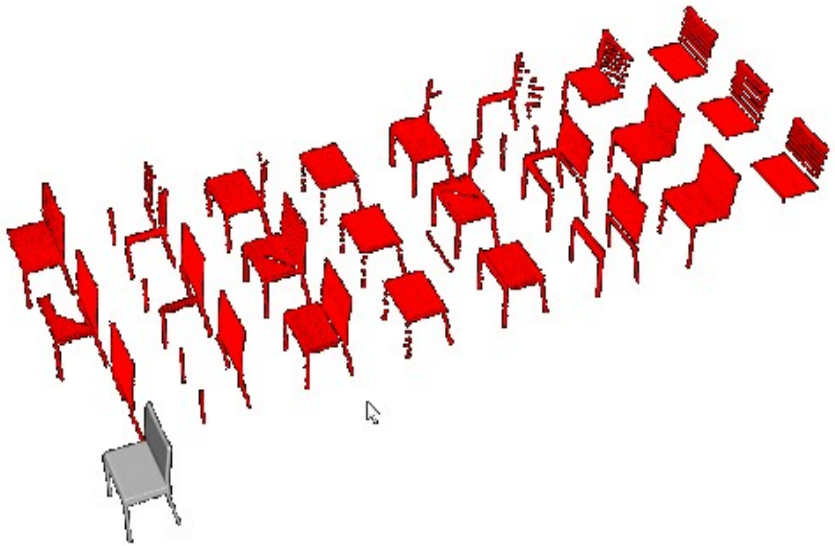


Offline Training from Web Models

Generate training views

- Objects are “perfect” 3D CAD data
- Actual data is 2.5D (RGB-D)
- Create views on object to simulate sensor view, incl. noise
- Dozens of views, for 100s of models

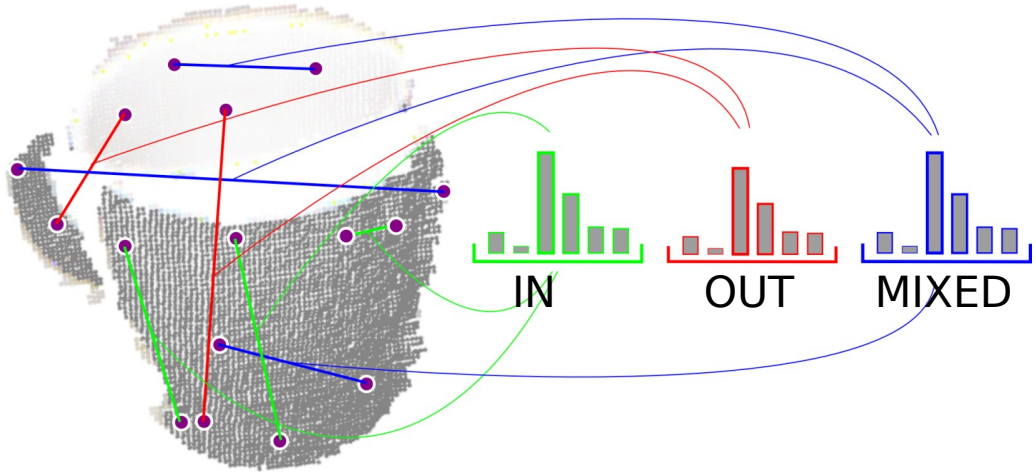


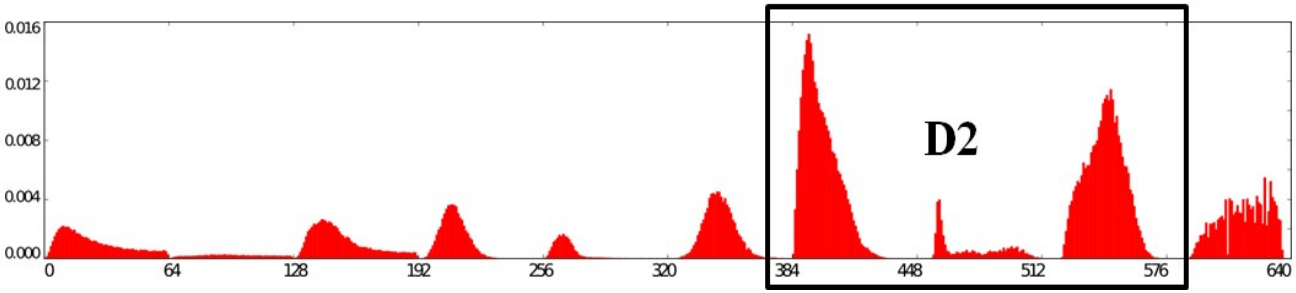


Offline Training

Robust Feature vector

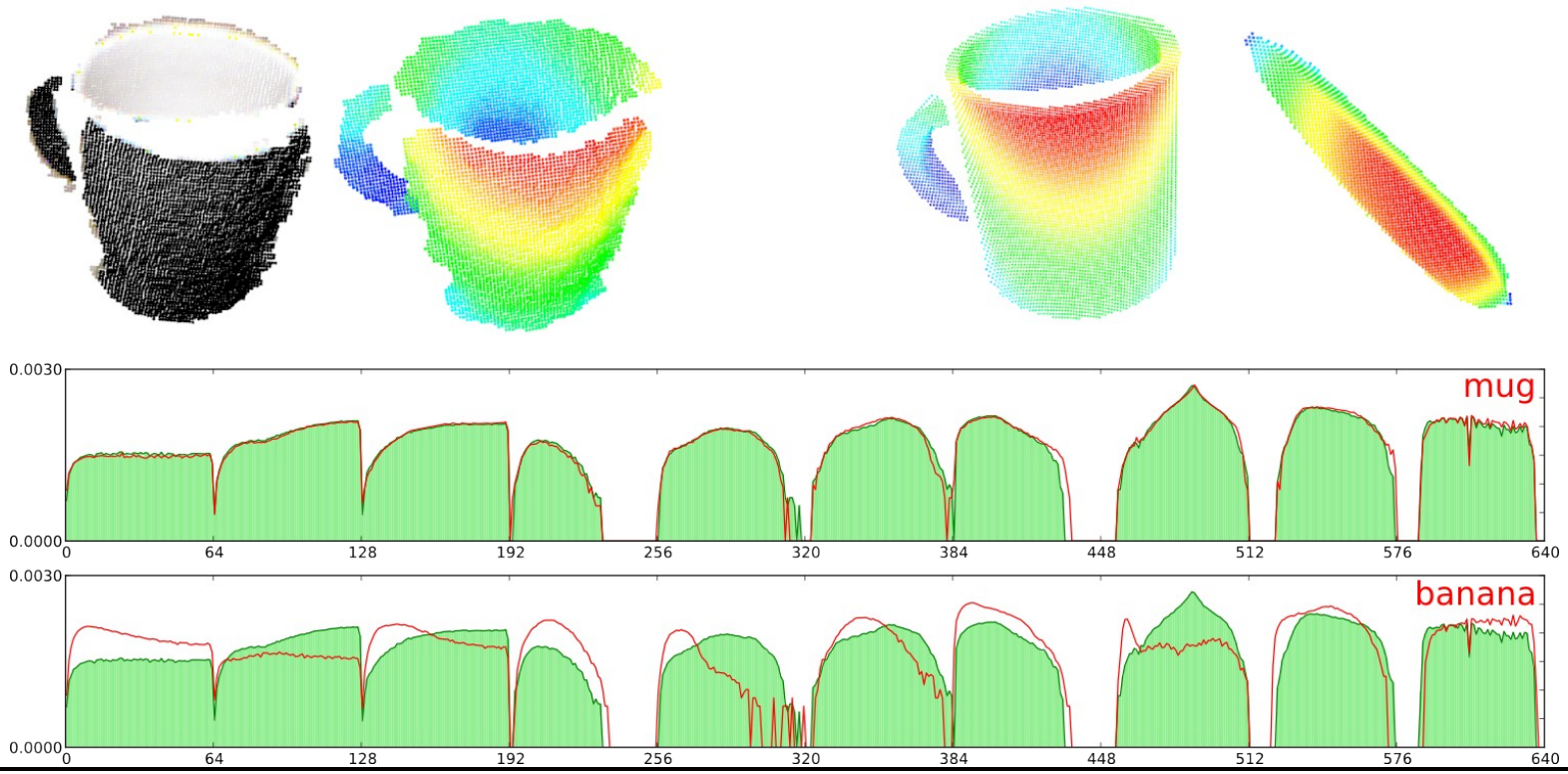
- Ensemble of shape functions (ESF)
- Based on shape distributions [Osada ea 2001]
  inside, outside, mixed
- Additional histograms for pint triplets: ratio, area, angle
- 640 dim. vector





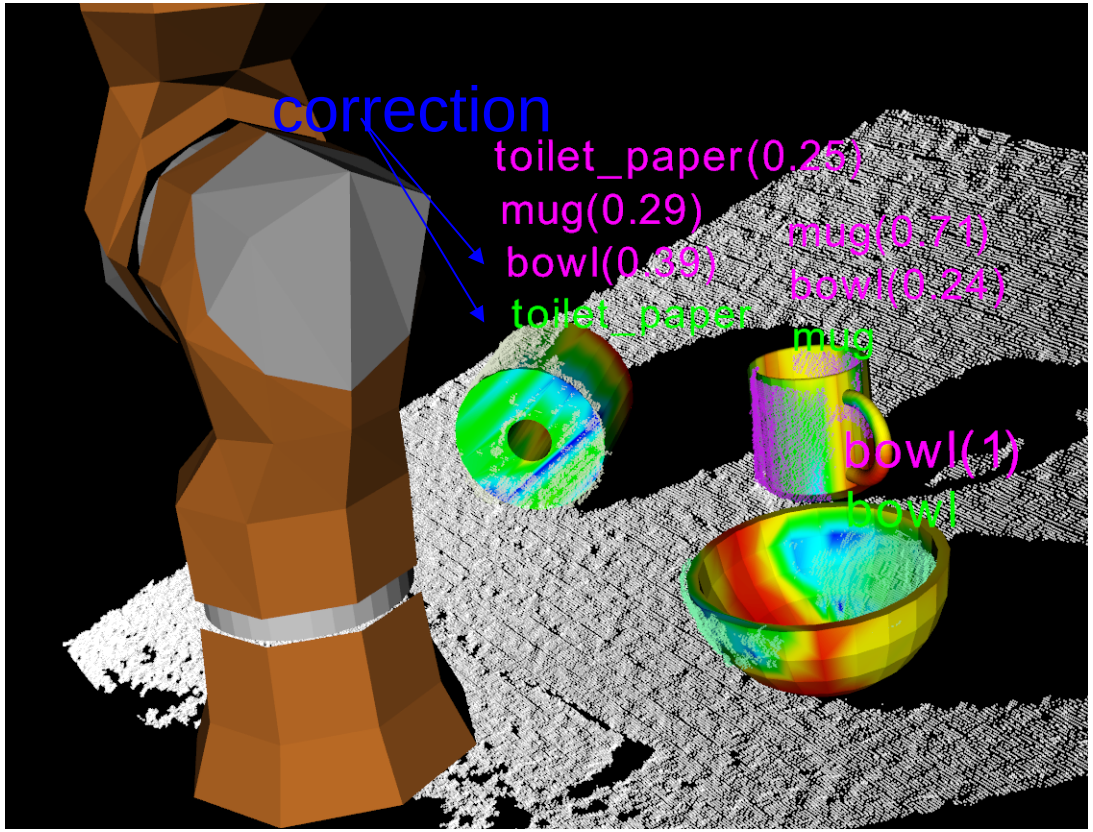
Online Matching: kNN classifier

- Find nearest neighbour in feature space
- Efficient indexing techniques to cope with large database (100,000s views)
- Majority vote from k nearest neighbours



Verification with Pose Fit

- Best view i of model j
- Fit 3D model j to point cloud
- Verify classification, precise pose



Initial classification hypotheses and verified after pose fit

Results: 200 classes

[Wohlkinger ea IROS'11]

Results: 200 classes

NEAREST NEIGHBOR CLASSIFICATION AND MOST CONFUSING CLASS

class name	1-NN	10-NN	confusing class
per scenes OVERALL	58.22 %	78.23 %	
per class OVERALL	49.10 %	71.39 %	
apple	81.40 %	98.45 %	pumpkin
banana	54.79 %	69.86 %	pistol
bottle	48.77 %	79.01 %	suv
bowl	50.00 %	76.47 %	hat
car	11.52 %	43.64 %	suv
donut	20.00 %	62.00 %	cap
hammer	83.41 %	96.10 %	axe
mug	91.96 %	99.46 %	watch
tetra pak	47.09 %	72.09 %	mug
toilet paper	2.11 %	16.84 %	armchair

Results on 3d-net Cat200 database using ESF

[Wohlkinger ea ICRA'12]

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- Detection / segmentation
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- **Tracking**
- Attention
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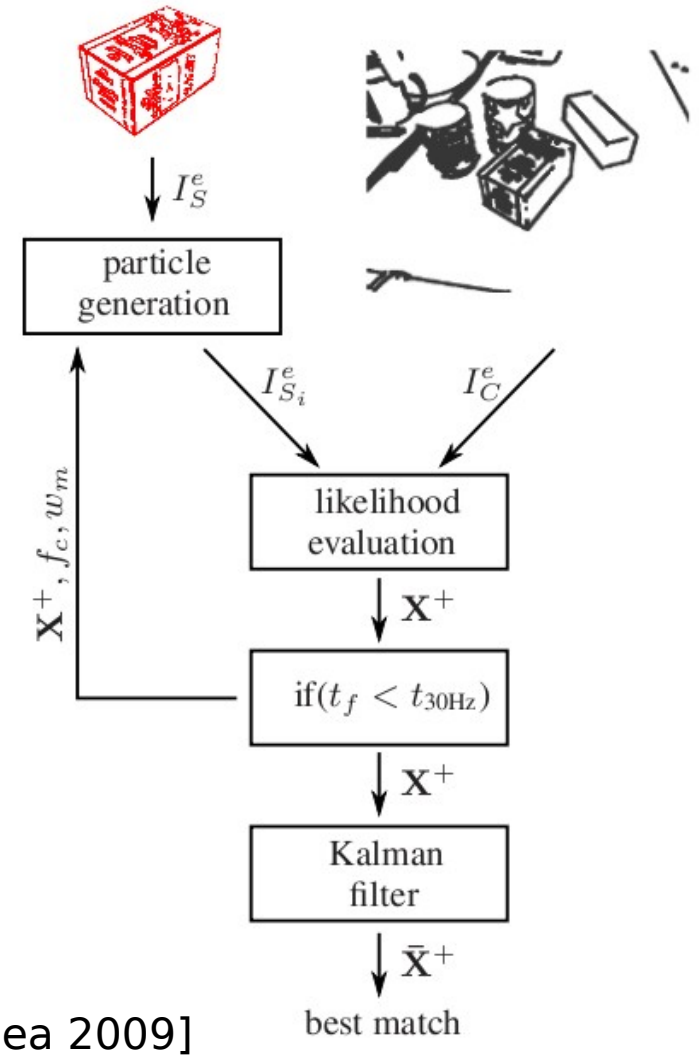
Model Based Object Tracking

- Given: 3D model, estimated 6D pose
- Represent pose estimate (PDF) with a number of hypotheses (particles)
- Propagate pose into next image
- Verify each particle (e.g. matching projected object edges to image edges), GPU implementation
- Weak particles are discarded, good ones are cloned (plus noise)
- Repeat ..



[Mörwald ea 2009]

Object Tracking and Modelling

[Mörwald ea 2011]

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Human attention

- Test showing the necessity and effectiveness of attention for the human visual system
- In the following video, count how many times the players wearing white pass the basketball
- Just observe and count silently, don't distract the other participants
- Ready ...?

Human attention

Play video ..

Human attention

How many passes?

One more test ...

Look at the scene ...


Freiheit
Computer Vision

- How many boxes?
- How many objects had red in them?
- Was the laptop turned on?
- How many books? Gorillas ..?
- Speed of processing in the human visual system [Thorpe ea 1996]: ca. 150 ms to get scene gist

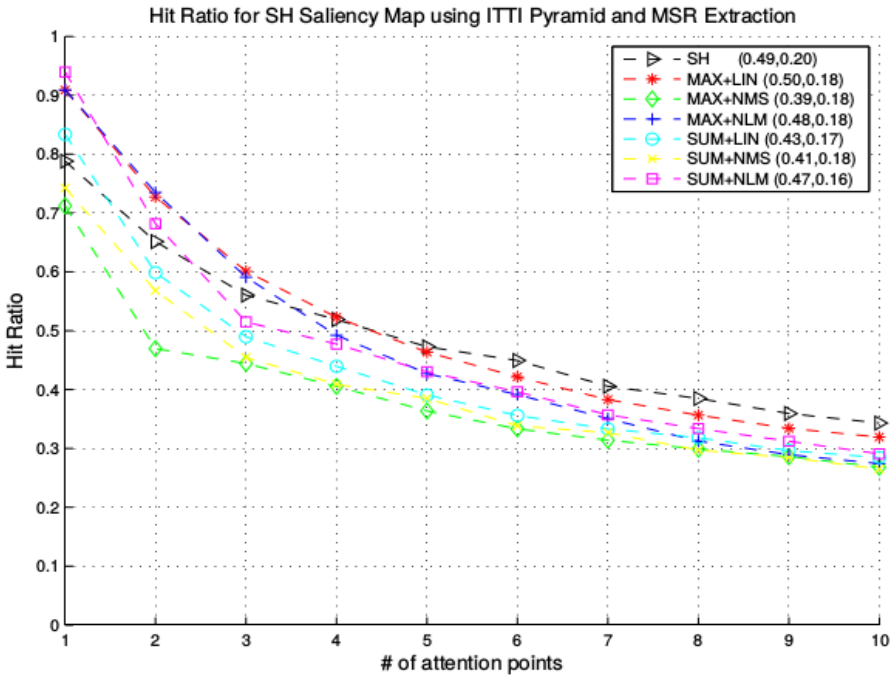
Visual attention

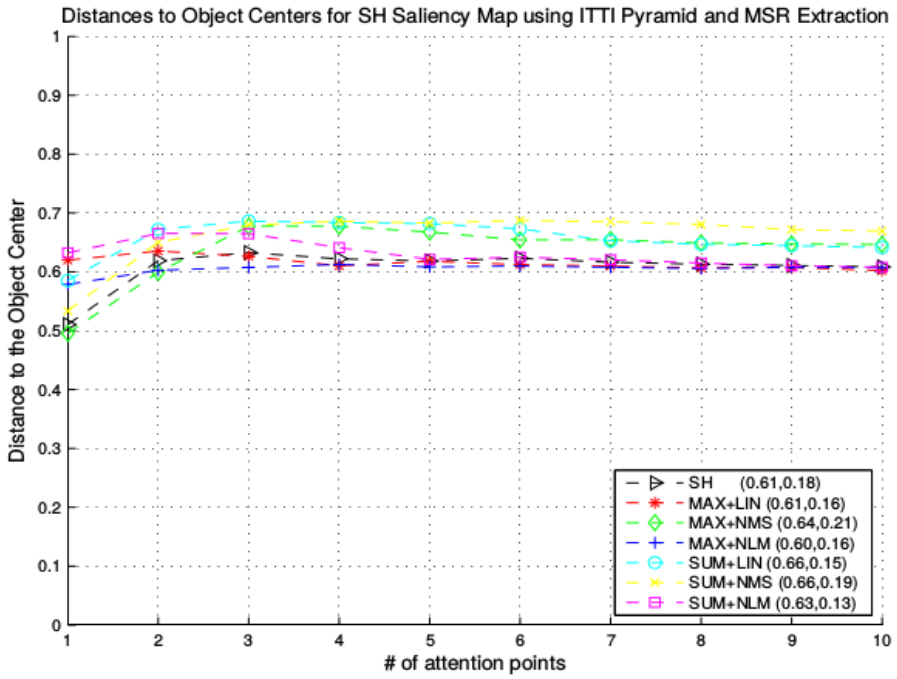
- Humans don't take in the whole scene at once in all details
- So why should we expect robots to?

- Many vision problems become a lot easier (or feasible at all) once the object is large in the image center
- Bottom up saliency (e.g. colour contrast)
- Top down, task-driven attention
- Many saliency computation methods, e.g. surveys [Borji & Itti PAMI'13, Potapova ea IJRR 2017]

Visual attention

Evaluating saliency methods (typical example)

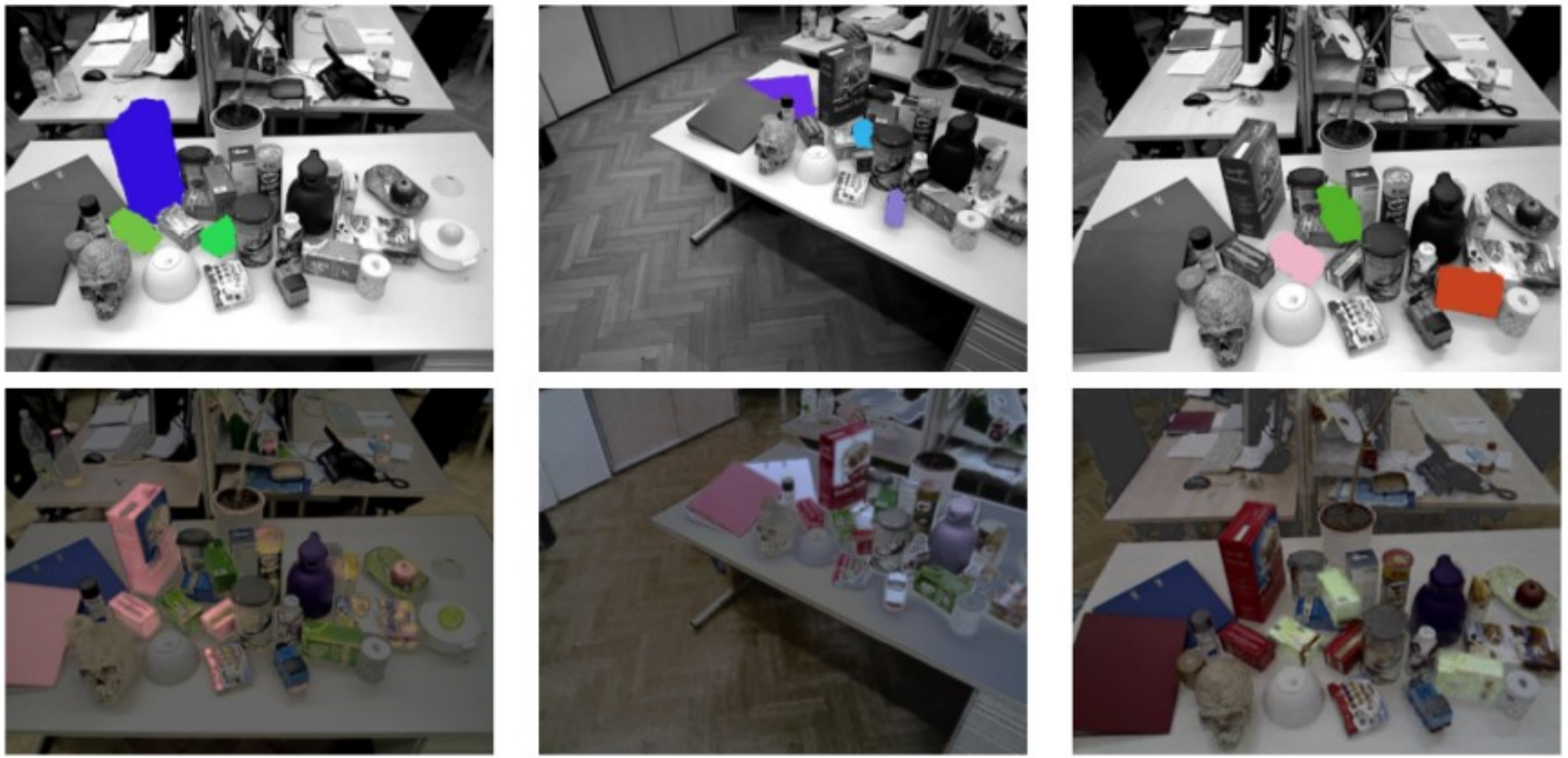




=> Attention per se is meaningless, needs to be understood in task context

=> How to *use* attention

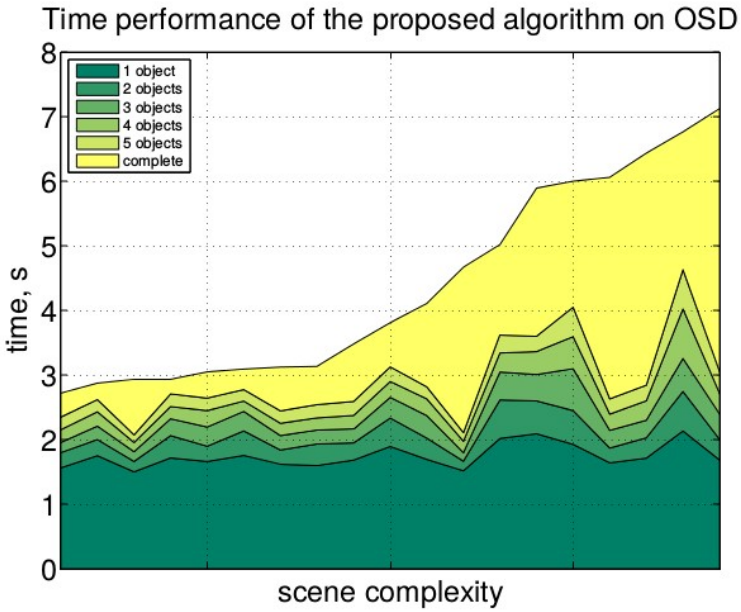
Attention-guided Segmentation

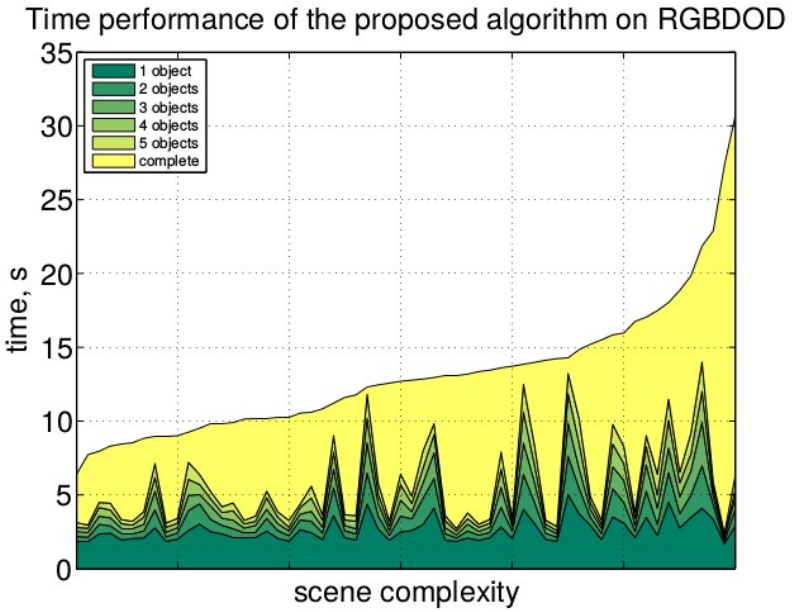


Red Objects *Blue Objects* *Green Objects*

Potapova et al.: Incremental Attention-driven Object Segmentation, Humanoids'14

Attention-guided Segmentation





low *middle* *high*

Object Segmentation Database [19]

low *middle* *high*

RGB-D Object Dataset [13]

Overview

- Detection / segmentation
- Modelling
- Recognition
- Classification
- Tracking
- Attention
- **Application to action learning**

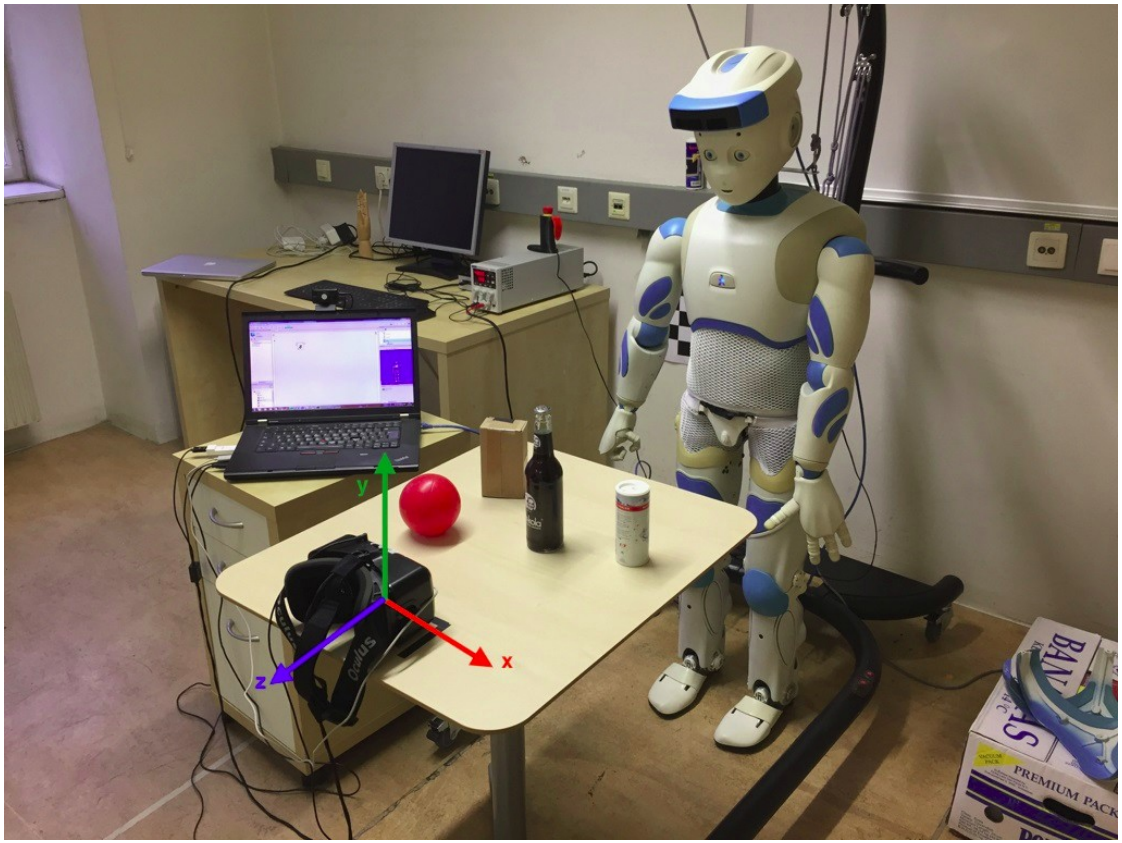
Project RALLI

Robotic Action-Language Learning through Interaction (OFAI, TU Wien, Tufts University)

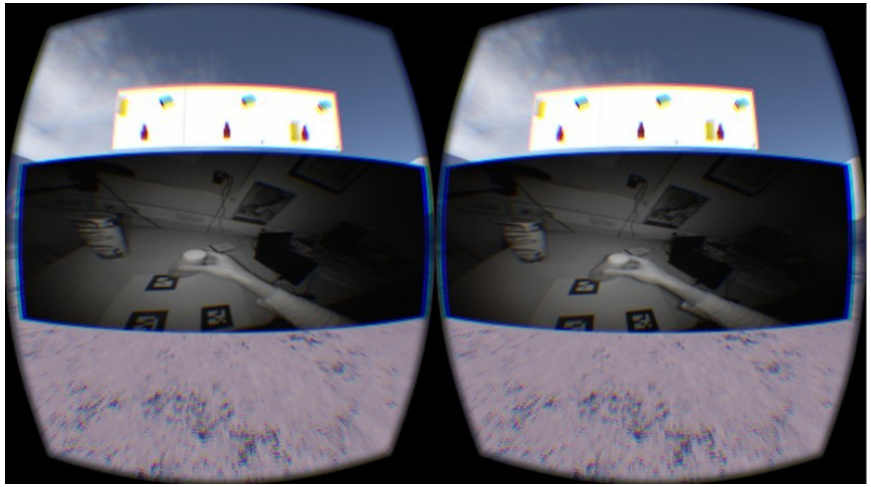
- Motivated by early child development
- Human tutor shows and explains action (“I am pushing the ball”, “I take the bottle” etc.
- Robot learns action verbs and their meaning in terms of object and hand trajectories
- Robot shows that it learned by repeating actions

Project RALLI

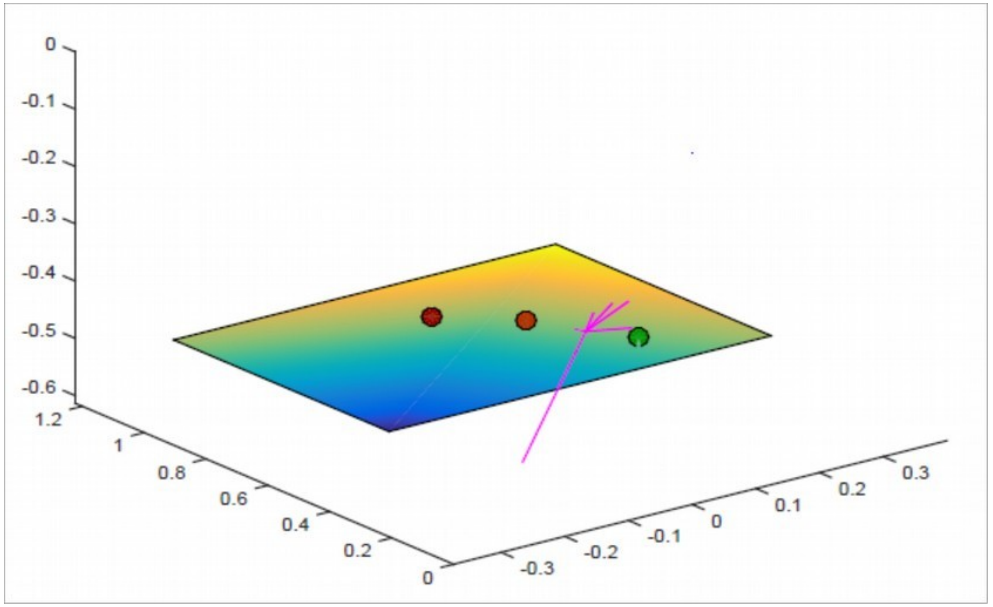
Experimental setup with Romeo (Asus in head), Oculus Rift headset (head tracking) and Leap motion (hand/finger tracking)



Project RALLI



View though the Oculus including the instructions



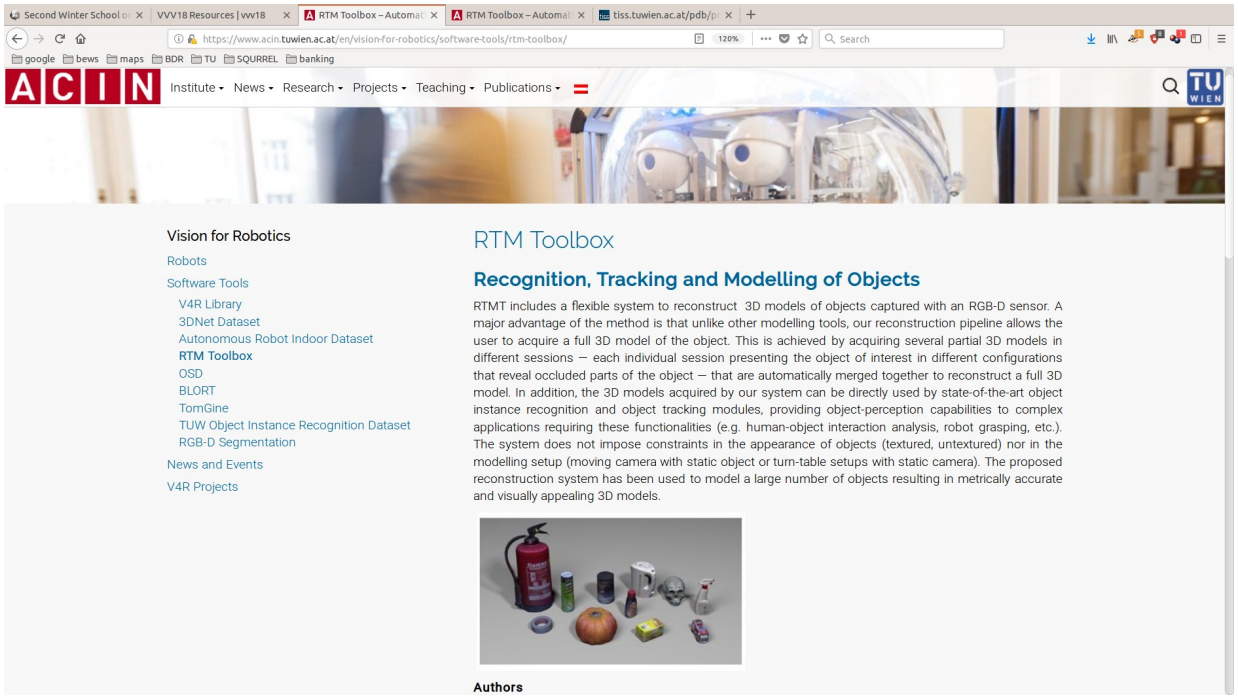
Visualisation of hands and tracked objects

Project RALLI

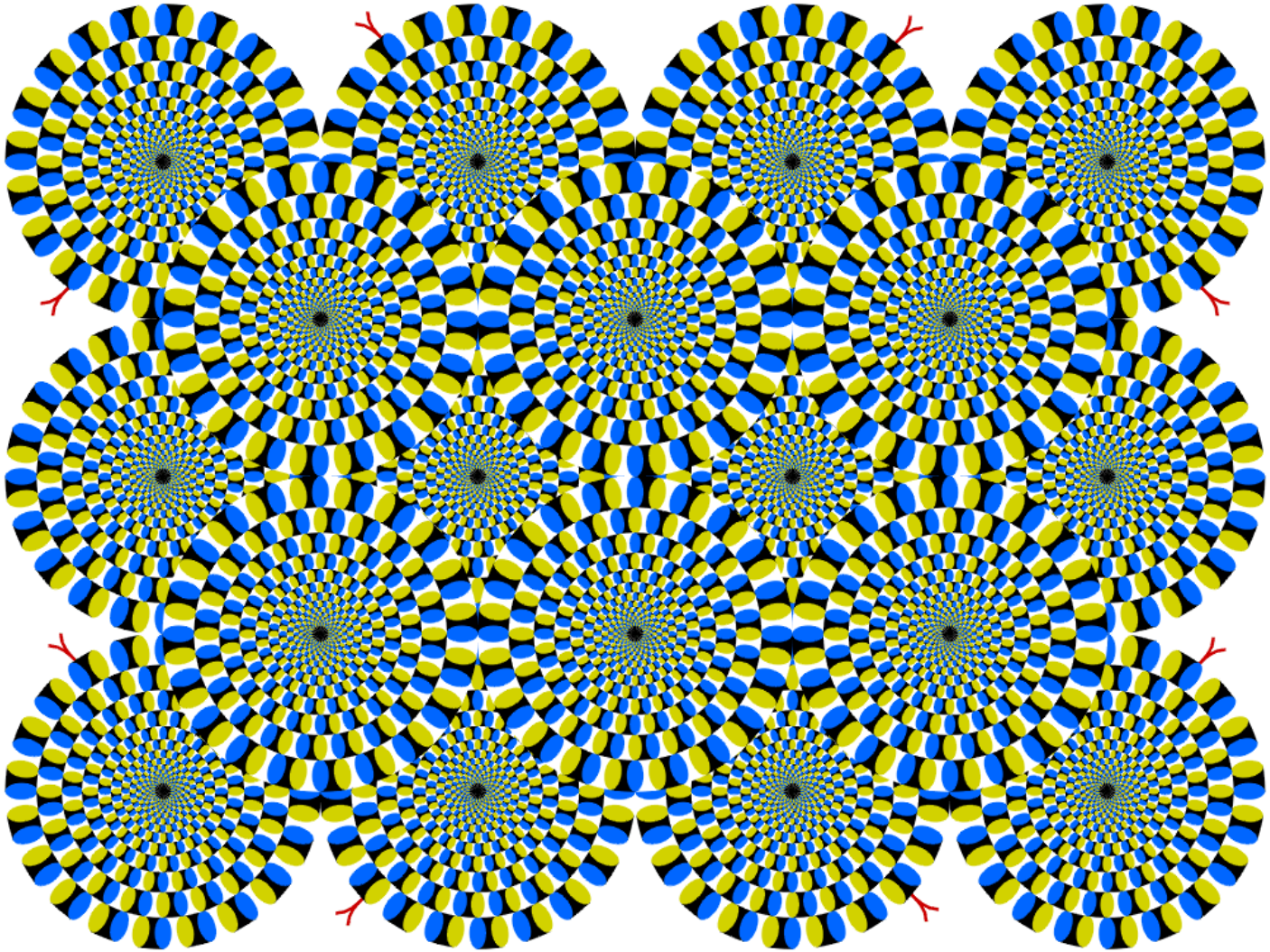
- Example of annotated speech, synchronised with object/hand tracks

Summary

- Present tool box for various robot vision tasks
- https://www.acin.tuwien.ac.at/en/vision-for-robotics/software-tools/v4r-library/
- https://www.acin.tuwien.ac.at/en/vision-for-robotics/software-tools/rtm-toolbox/



Questions?



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