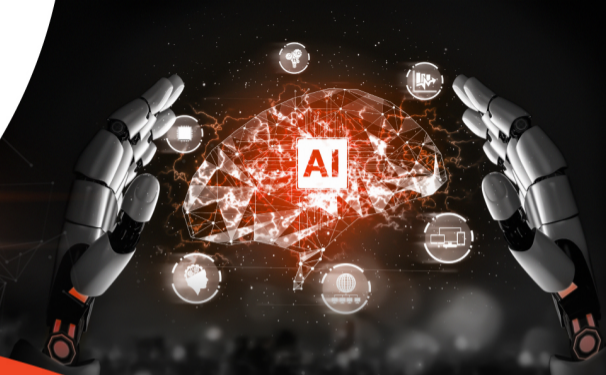


Agimus Winter School
11/12/2023 - 15/12/2023
Banyuls (France)



Model-based object pose tracking

Médéric Fourmy
Czech Technical University, Prague



Object pose tracking



Initial pose



Converged

Object pose tracking



Initial pose



Converged

- ▶ Assumptions: object detected, matched with model, initial pose

Object pose tracking



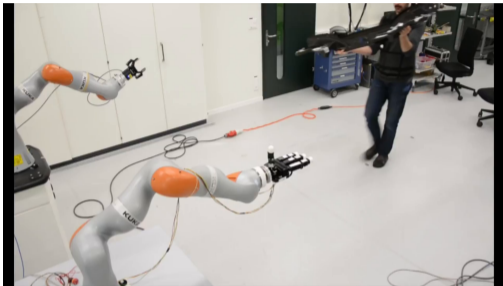
Initial pose



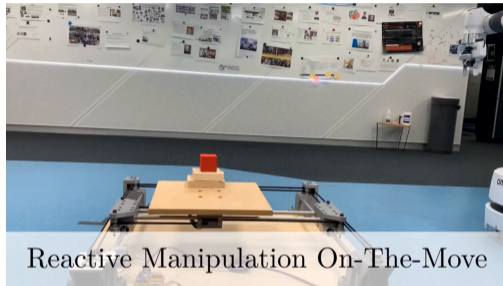
Converged

- ▶ Assumptions: object detected, matched with model, initial pose
- ▶ Local refinement of ${}^cT_b \in SE(3)$ pose using a single RGB(-D) camera

Motivation: dynamic manipulation



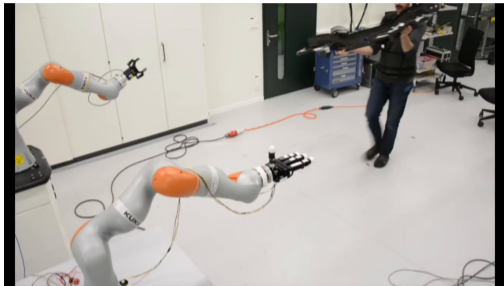
Human to robot handover [MFB18]



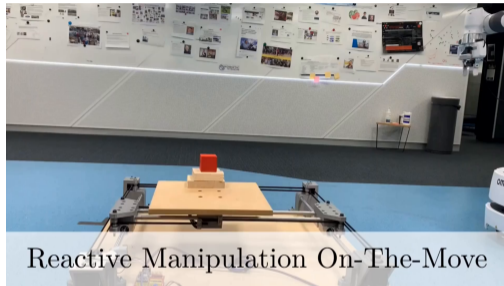
Reactive Manipulation On-The-Move

Object grasping on the move [Bur+23]

Motivation: dynamic manipulation



Human to robot handover [MFB18]



Reactive Manipulation On-The-Move

Object grasping on the move [Bur+23]

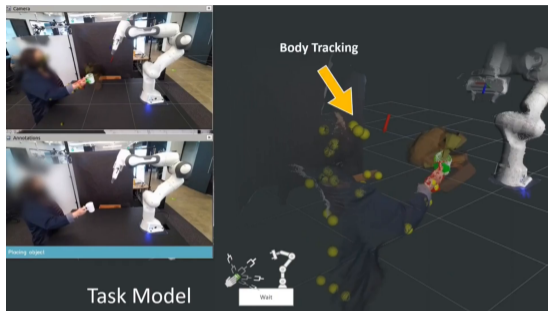
- ▶ Low latency estimation to close the loop
- ▶ Grasping level precision (\sim cm)

Handover from point cloud grasp prediction



Model predictive control for fluid human-to-robot handovers [Yan+22]

Handover from point cloud grasp prediction



Model predictive control for fluid human-to-robot handovers [Yan+22]

- ▶ Generates grasp proposals from point cloud (GraspNet)

Handover from point cloud grasp prediction



Model predictive control for fluid human-to-robot handovers [Yan+22]

- ▶ Generates grasp proposals from point cloud (GraspNet)
- ▶ Runs on 6 GPUs in parallel

Handover from point cloud grasp prediction



Model predictive control for fluid human-to-robot handovers [Yan+22]

- ▶ Generates grasp proposals from point cloud (GraspNet)
- ▶ Runs on 6 GPUs in parallel
- ▶ What if we have a decent object model?

Overview

1. Model based object tracking, a short tour
2. Region based object tracking
3. Object localization and tracking for control





Model based object tracking

A short tour

Edges tracking

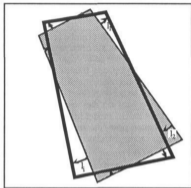


Figure 2: Diagram to show a sample of perpendicular distances, i_i

- ▶ **Model:** 3D geometric primitives
- ▶ **Method:** Local search for image edges from contour points, least squares

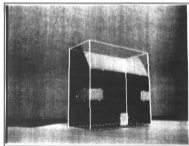


Figure 4: RAPID tracking box in a static situation

RAPID [HS90]

Edges tracking

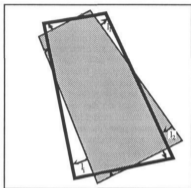


Figure 2: Diagram to show a sample of perpendicular distances, i_i

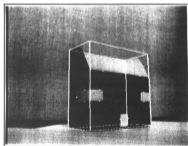


Figure 4: RAPID tracking box in a static situation

RAPID [HS90]

- ▶ **Model:** 3D geometric primitives
- ▶ **Method:** Local search for image edges from contour points, least squares
- ▶ First real time methods
- ▶ Sensitive to incorrect matches (background clutter, self occlusion), additional modelling step

Keypoint matching



Hybrid tracking, ViSP [Com+06]

- ▶ **Model:** 3D point with descriptors
- ▶ **Method:** 3D-2D matching, minimize reprojection error (PnP problem)

Keypoint matching



Hybrid tracking, ViSP [Com+06]

- ▶ **Model:** 3D point with descriptors
- ▶ **Method:** 3D-2D matching, minimize reprojection error (PnP problem)
- ▶ Efficient and robust if rich texture
- ▶ Fails for object with low texture

Deep learning

Right: Predicted 6D pose of the novel object
Left: Contours of the prediction overlaid on input image



- ▶ **Model:** textured mesh
- ▶ **Method:** render and compare, regress delta pose

Megapose, tracking mode (2022) [Lab+22]
Also: PoseRBPF [Den+21],
se(3)-TrackNet [Wen+20]...

Deep learning

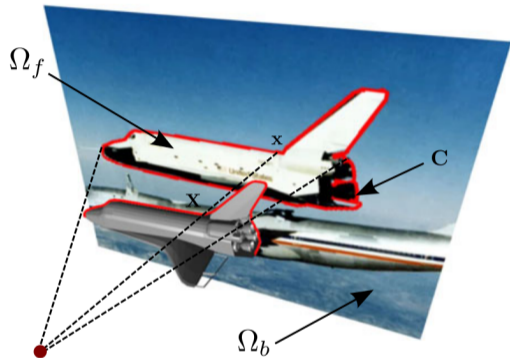
Right: Predicted 6D pose of the novel object
Left: Contours of the prediction overlaid on input image



Megapose, tracking mode (2022) [Lab+22]
Also: PoseRBPF [Den+21],
se(3)-TrackNet [Wen+20]...

- ▶ **Model:** textured mesh
- ▶ **Method:** render and compare, regress delta pose
- ▶ Robust to occlusions, clutter, etc. Sota on standard benchmarks
- ▶ High-end GPUs at run-time, costly training, generalization (\sim)

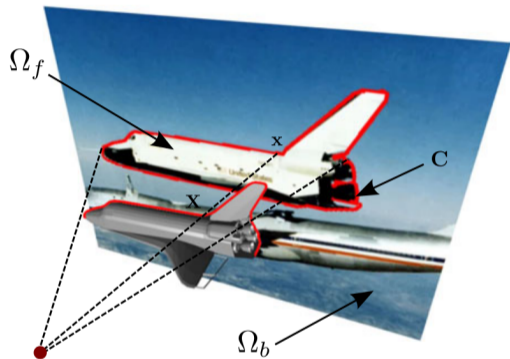
Region based tracking



PWP3D [PR12]

- ▶ **Model:** mesh (no texture)
- ▶ **Method:** probabilistic silhouette alignment, Newton's method

Region based tracking



PWP3D [PR12]

- ▶ **Model:** mesh (no texture)
- ▶ **Method:** probabilistic silhouette alignment, Newton's method
- ▶ Robust to occlusions, clutter, very efficient (1 object \rightarrow \sim 1000 FPS on CPU)
- ▶ Assumes foreground and background colors sufficiently different



Region based tracking

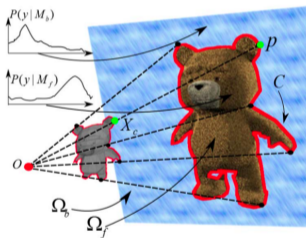


SRT3D, sparse region based tracking [Sto+22]

Dense region based tracking for pose tracking

Objective: find cT_b that maximizes likelihood of segmentation

$$P({}^cT_b | \text{img}) = \prod_{x \in \Omega} (h_b(\phi) \cdot P_b + h_f(\phi) \cdot P_f)$$



Foreground/background probability distributions [Zha+14]

Signed Distance Function (SDF)

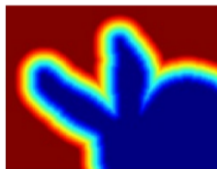
Objective: find cT_b that maximizes likelihood of segmentation

$$P({}^cT_b | \text{Img}) = \prod_{x \in \Omega} (h_b(\phi) \cdot P_b + h_f(\phi) \cdot P_f)$$

▶ $\phi = f({}^cT_b)$: SDF, from rendered contour



Contour from cT_b



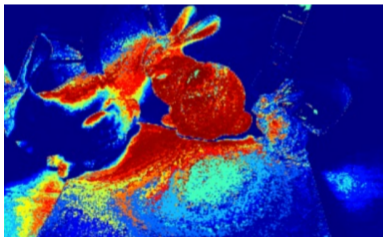
SDF

Color statistics and activation

Objective: find cT_b that maximizes likelihood of segmentation

$$P({}^cT_b | \text{Img}) = \prod_{x \in \Omega} (h_b(\phi) \cdot P_b + h_f(\phi) \cdot P_f)$$

- ▶ P_b, P_f : background/foreground color distributions
- ▶ h_b, h_f : background/foreground activation functions



Example of P_f visualization [Keh+17]

ExecuteTrackingStep

$${}^cT_b = {}^cT_b^0$$

$$P_b, P_f = P_b^0, P_f^0$$

for $i = 1$ to N_update_stats **do**

for $j = 1$ to N_newton **do**

$$\text{cost}({}^cT_b) = -\log P({}^cT_b | \text{Img})$$

$$g, H = \text{ComputeCostGradientHessian}({}^cT_b, P_b, P_f)$$

$$\nu_b = -(H + \lambda_{\text{tikho}} I_6)^{-1} \cdot g$$

$${}^cT_b = \text{UpdatePose}({}^cT_b, \nu_b)$$

end for

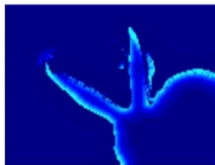
$$P_b, P_f = \text{UpdateColorStatistics}({}^cT_b)$$

end for

Are dense computations necessary?



Contour prediction

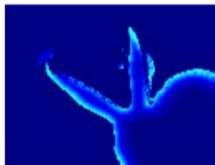


Residuals – $\log P({}^cT_b | \text{Img})$

Are dense computations necessary?



Contour prediction



Residuals – $\log P({}^cT_b | \text{Img})$

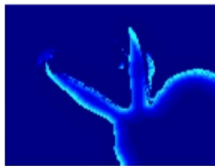
Observations:

- ▶ Important residuals only close to predicted contour
- ▶ Neighbor contour points produce similar gradients
- ▶ Dense SDF computation is expensive (Repeated rendering and Direct transform)

Are dense computations necessary?



Contour prediction



Residuals $-\log P({}^cT_b|I_{img})$

Observations:

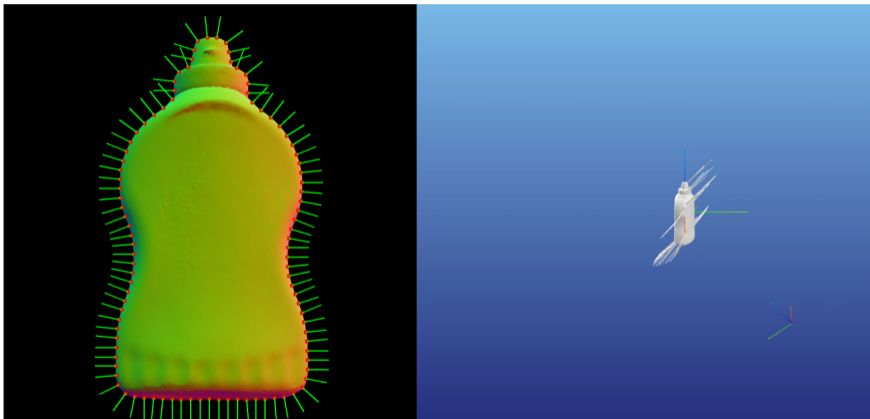
- ▶ Important residuals only close to predicted contour
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Sparse Region based method [Keh+17]

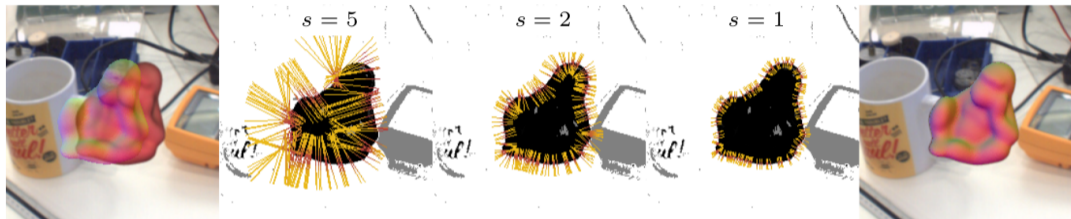
- ▶ Idea1: Sample contour control points
- ▶ Idea2: Precomputation of template views

Sparse view precomputations

Typically by using a geodesic polyhedron (e.g. 2562 views)

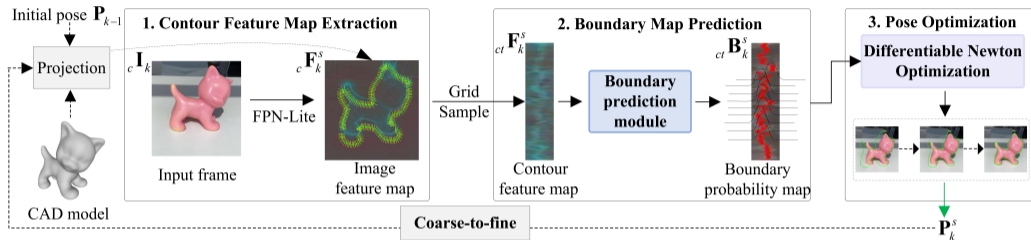


Correspondance lines reformulation



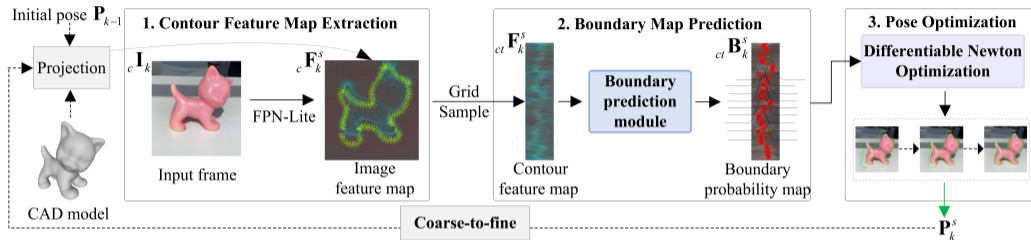
Correspondance lines, coarse to fine iterations [Sto+20]

Hybrid learning + optimization region based tracking



Deep Active Contour for Real-time 6-DoF Object Tracking [Wan+23]

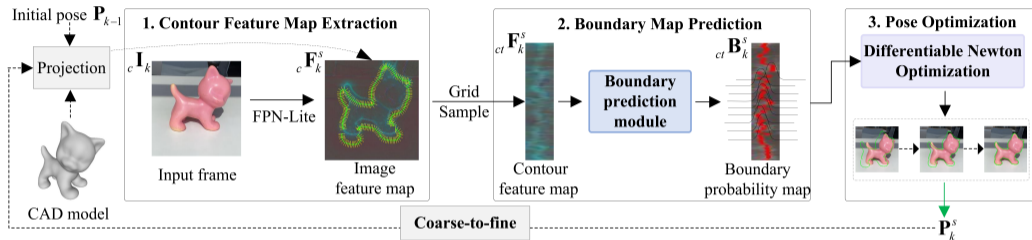
Hybrid learning + optimization region based tracking



Deep Active Contour for Real-time 6-DoF Object Tracking [Wan+23]

- Replace histograms by learning contour probability prediction

Hybrid learning + optimization region based tracking



Deep Active Contour for Real-time 6-DoF Object Tracking [Wan+23]

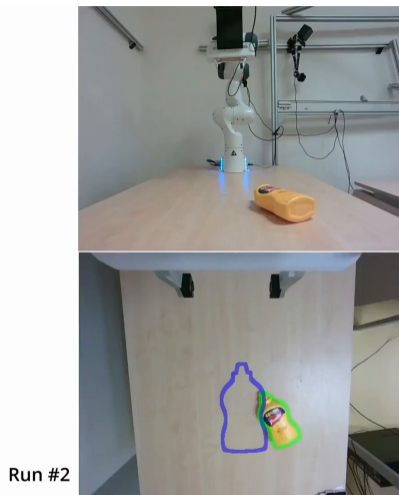
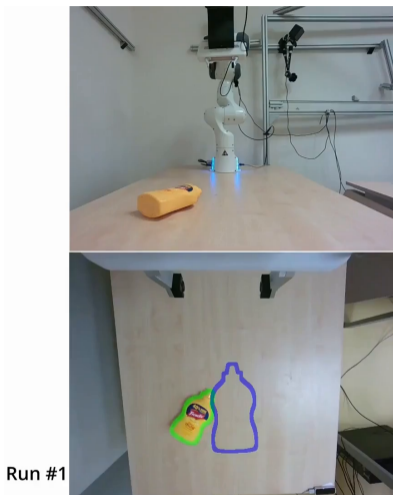
- ▶ Replace histograms by learning contour probability prediction
- ▶ Trained end to end with differentiable optimization



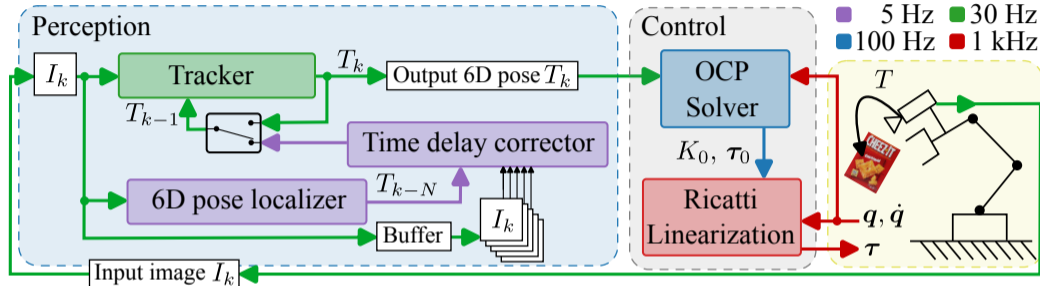
Object localization and tracking

An architecture for vision-based feedback control

Object tracking with manipulator

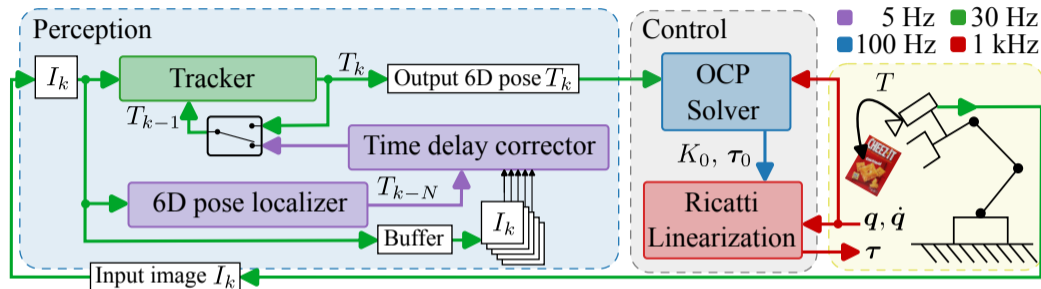


System architecture



Object localization and tracking architecture [Fou+23]

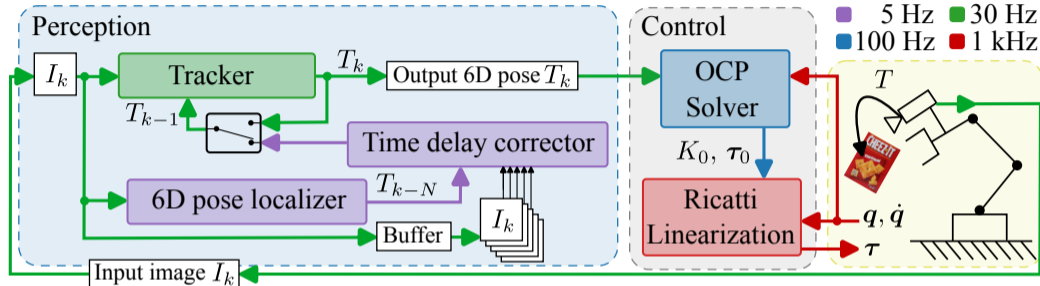
System architecture



Object localization and tracking architecture [Fou+23]

- ▶ Asynchronous object localization and tracking

System architecture



Object localization and tracking architecture [Fou+23]

- ▶ Asynchronous object localization and tracking
- ▶ Torque level MPC (crocodyl) with Riccati based feedback

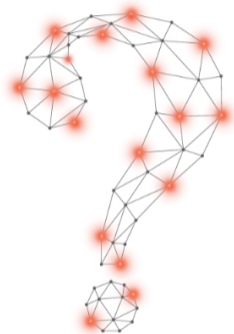
AGIMUS

Practical session

Practical session

- ▶ Pose detection
 - ▶ 2D detection
 - ▶ CosyPose
 - ▶ Megapose
- ▶ Pose tracking
 - ▶ Recorded sequences
 - ▶ Webcam

Questions and Answers



Contact details

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