ICRA'2016 Tutorial on Vision for Robotics

IEEE Robotics & Automation Society

Visual Servoing

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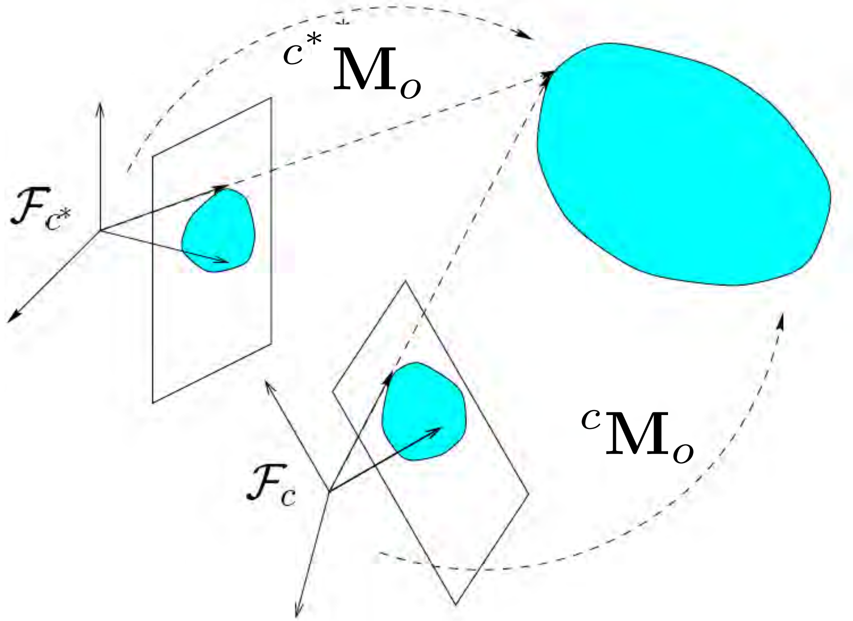
How to control robot motion from vision?

1st basic idea: determine only once the displacement to be done (open loop/saccade)

$$^{c^*}\mathbf{M}_c = {}^{c^*}\mathbf{M}_o \, {}^{c}\mathbf{M}_o^{-1}$$



Advantages:

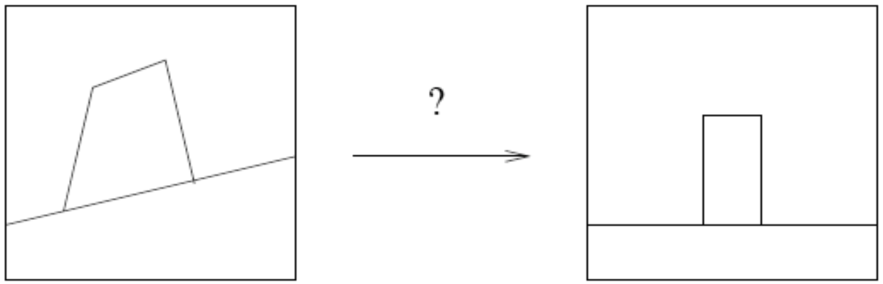
- Only one image to be processed and one very fast displacement to be achieved if the full system is perfectly calibrated

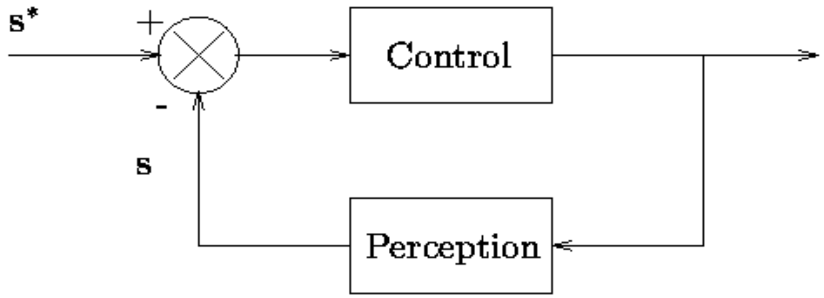
Drawbacks:

- Not robust to modeling and calibration errors
- Iterating may help, or not… Object detection for each new image

What is visual servoing?

Vision-based closed loop control of a dynamic system
by iterative minimization of a visual error (Lyapunov function)





Advantages:

- Positioning accuracy
- Robustness with respect to modeling and calibration errors
- Reactive to changes (target tracking)

Drawbacks:

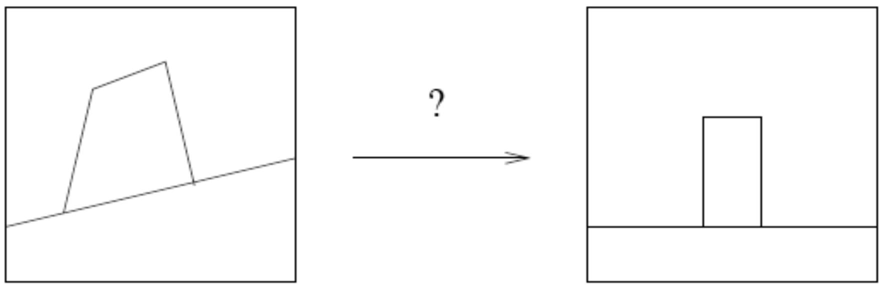
- Need many images to be processed

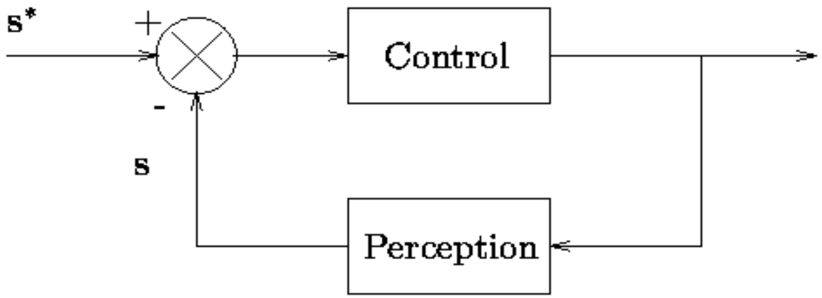
What is visual servoing?

Usual steps:

- extract and track visual measurements near video rate
- design visual features and control schemes from the available measurements
- taking into account the system and environment constraints

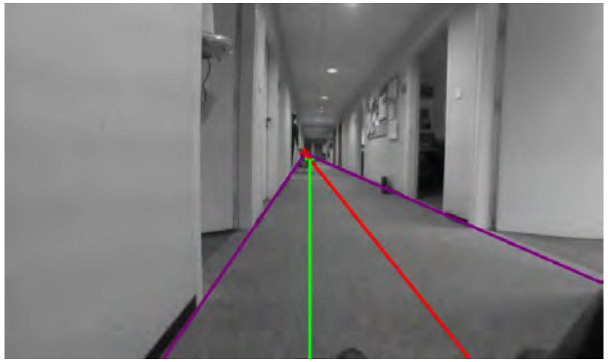
for an adequate system behavior (stability, robustness, …)

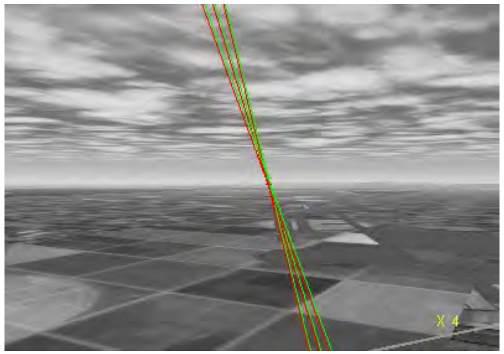


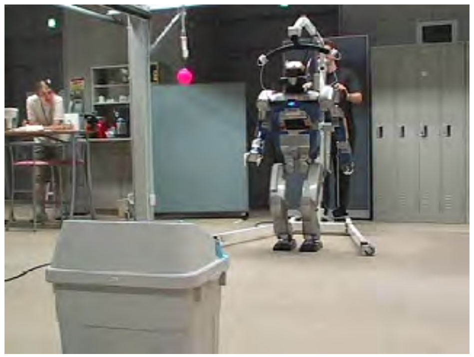


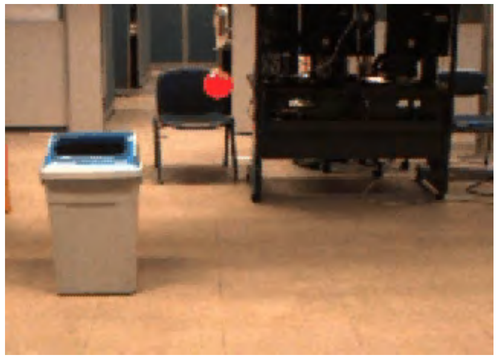
A wide spectrum of applications

Just need a camera and a robot



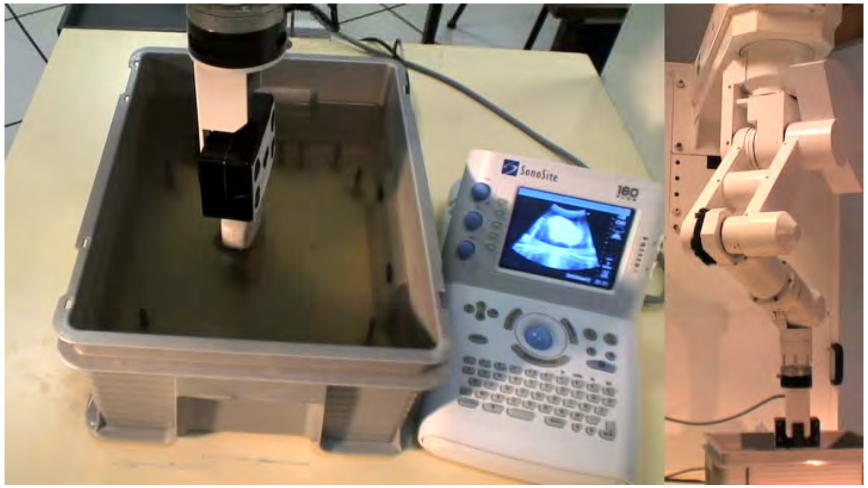




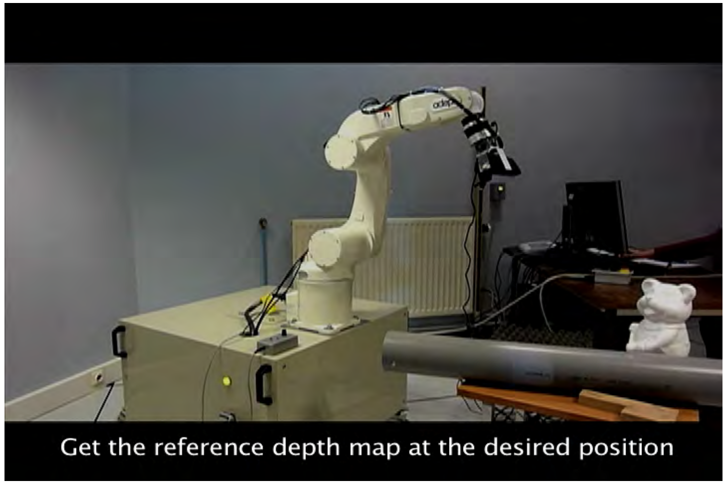


Whatever sort of vision sensor

Omnidirectional camera

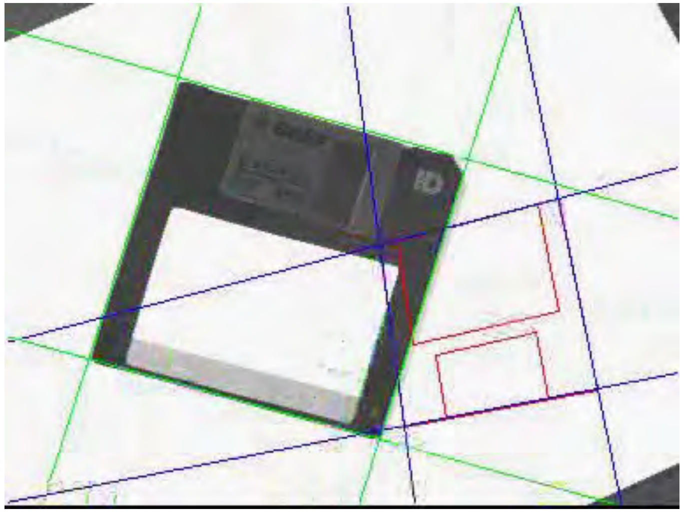


2D US probe



RGB-D sensor

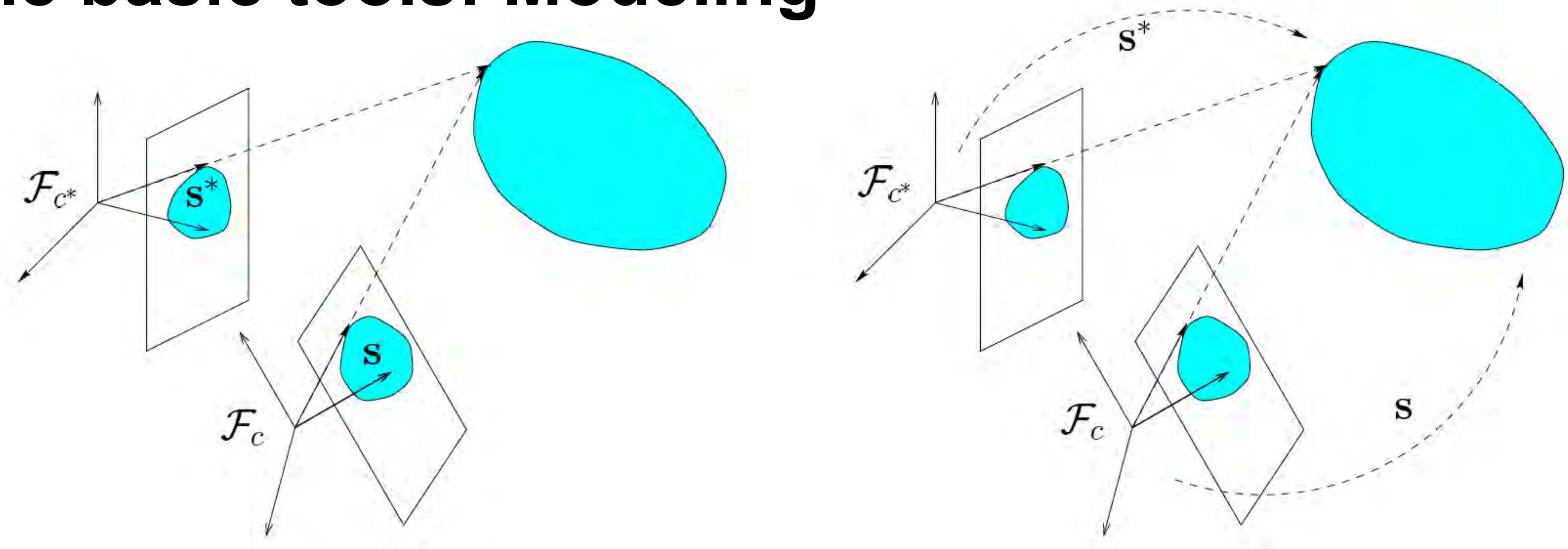
Just need a camera



Pose estimation / 3D tracking can be formulated as Virtual Visual Servoing

Just need a computer

The basic tools: Modeling



2D visual features (IBVS) / 3D visual features (PBVS)

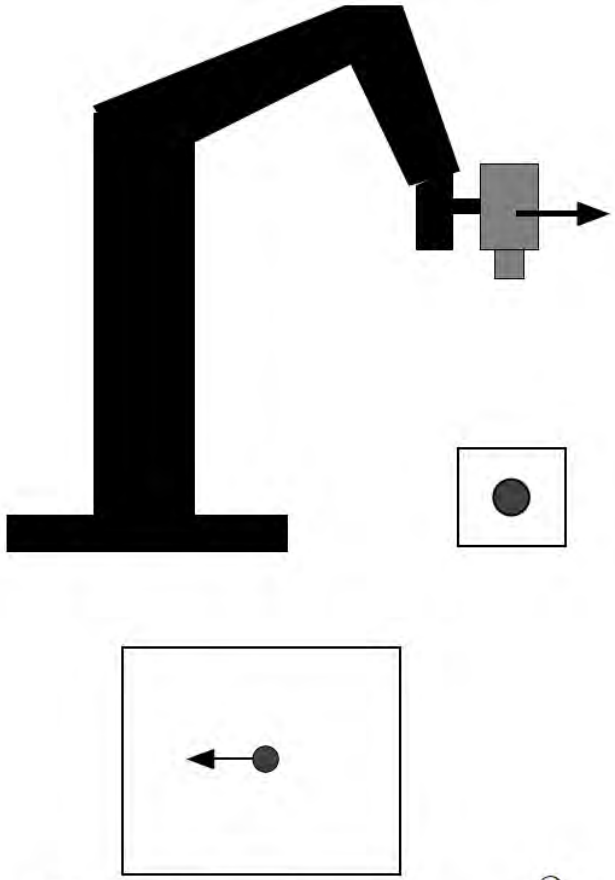
Same principle in both cases (but not same properties)

Visual features: $\mathbf{s} = \mathbf{s}(\mathbf{p}(t)) \quad \Rightarrow \quad \dot{\mathbf{s}} = \mathbf{L_s}\mathbf{v} = \mathbf{J_s}\dot{\mathbf{q}}$

- $\mathbf{L_s}$: interaction matrix, $\mathbf{J_s}$: feature Jacobian
- $\mathbf{v} = (\boldsymbol{v}, \boldsymbol{\omega}) \in se_3$: instantaneous camera velocity in camera frame

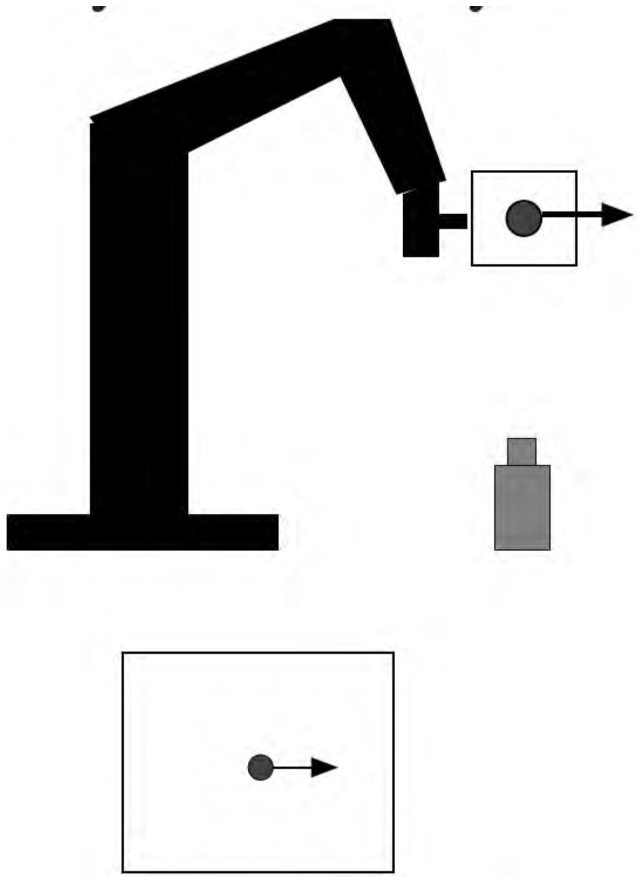
The basic tools: the feature Jacobian

Eye-in-hand system



$$
\begin{aligned}
\dot{\mathbf{s}} &= \mathbf{L}_{\mathbf{s}}\,{}^{c}\mathbf{V}_{n}\,{}^{n}\mathbf{J}_{n}(\mathbf{q})\,\dot{\mathbf{q}} + \frac{\partial \mathbf{s}}{\partial t} \\
&= \mathbf{J}_{\mathbf{s}}\,\dot{\mathbf{q}} + \frac{\partial \mathbf{s}}{\partial t}
\end{aligned}
$$

Eye-to-hand system



$$
\begin{aligned}
\dot{\mathbf{s}} &= -\mathbf{L}_{\mathbf{s}}\,{}^{c}\mathbf{V}_{n}\,{}^{n}\mathbf{J}_{n}(\mathbf{q})\,\dot{\mathbf{q}} + \frac{\partial \mathbf{s}}{\partial t} \\
&= -\mathbf{L}_{\mathbf{s}}\,{}^{c}\mathbf{V}_{\emptyset}\,{}^{\emptyset}\mathbf{V}_{n}\,{}^{n}\mathbf{J}_{n}(\mathbf{q})\,\dot{\mathbf{q}} + \frac{\partial \mathbf{s}}{\partial t}
\end{aligned}
$$

The basic tools

Modeling: $\dot{\mathbf{s}} = \mathbf{L_s v}$

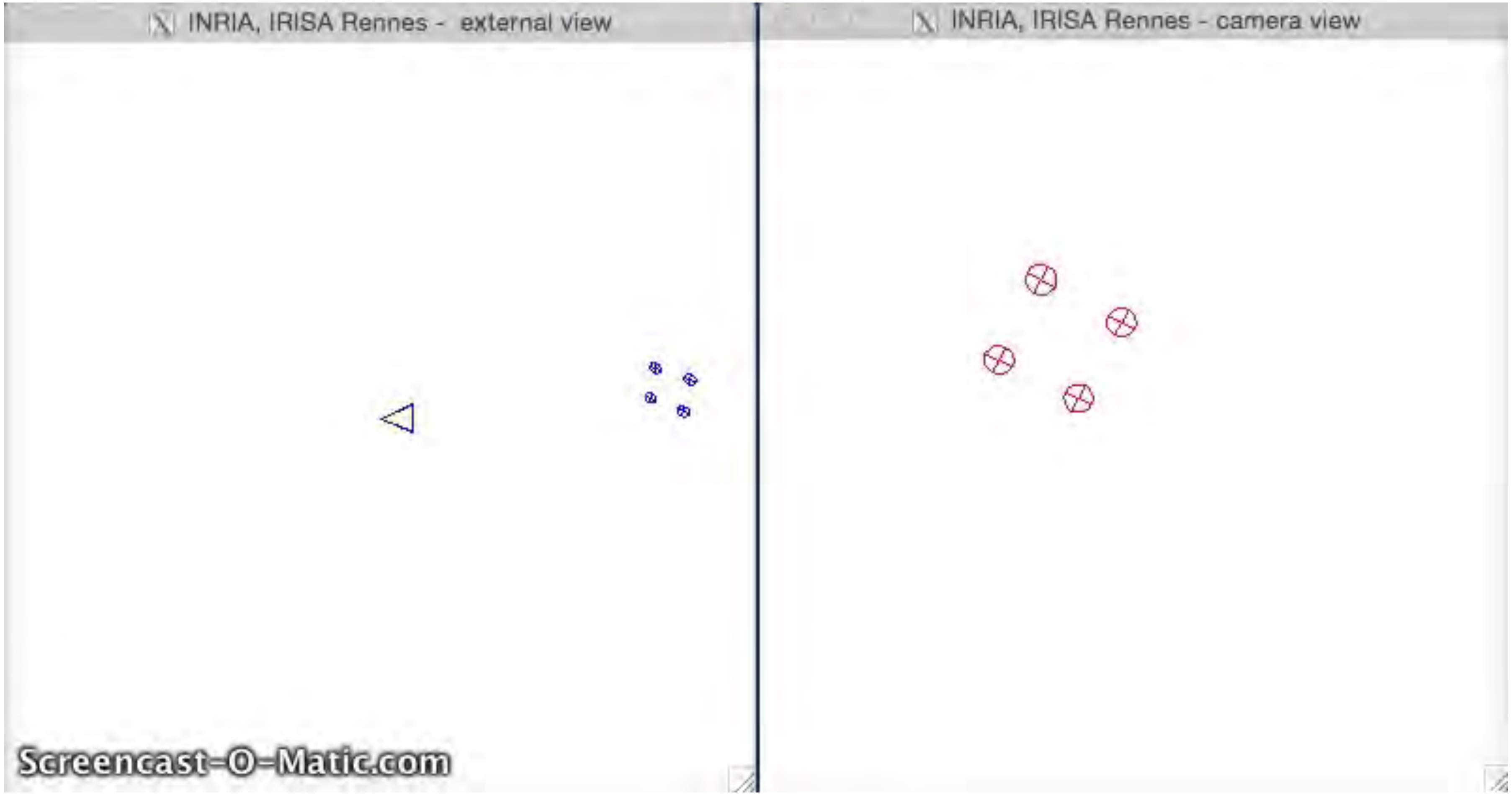
Control: $\mathbf{v} = -\lambda \, \widehat{\mathbf{L_s}}^+ (\mathbf{s} - \mathbf{s}^*)$ to try to ensure $\dot{\mathbf{s}} = -\lambda(\mathbf{s} - \mathbf{s}^*)$

(exponential decoupled decrease)

Stability analysis: $\mathcal{L} = \frac{1}{2}\|\mathbf{s} - \mathbf{s}^*\|$

$\dot{\mathcal{L}} = -\lambda \, (\mathbf{s} - \mathbf{s}^*)^T \, \mathbf{L_s}\widehat{\mathbf{L_s}}^+ (\mathbf{s} - \mathbf{s}^*)$ Usually, LAS only

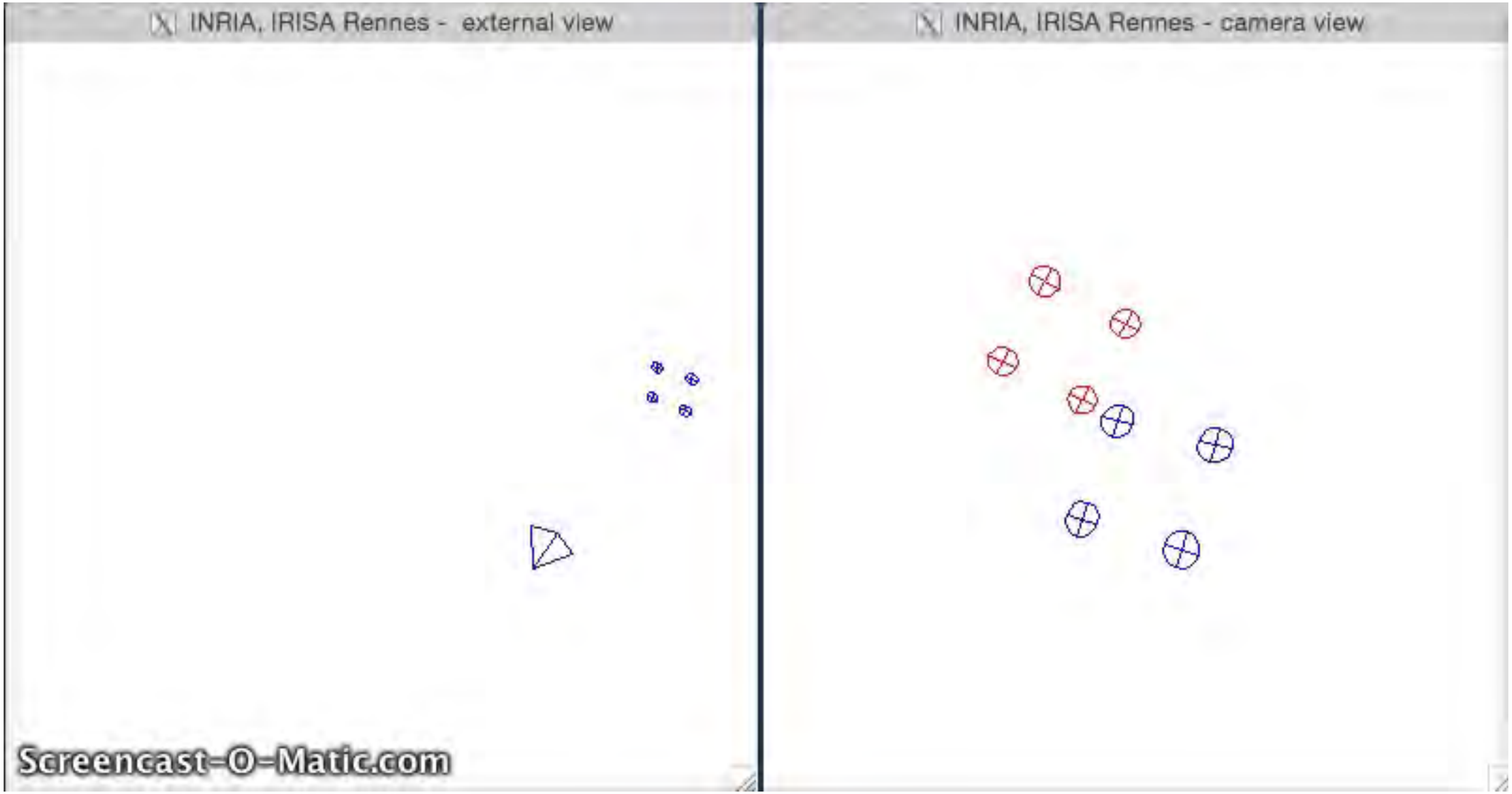
Usually LAS only: potential local minimum (for 6 dof)



$$\mathbf{s} = (x_1, y_1, ..., x_4, y_4) \qquad \mathbf{v} = -\lambda \mathbf{L}_{\mathbf{s}}^{+}(\mathbf{s} - \mathbf{s}^*)$$

This local minimum can be avoided with another choice of $\mathbf{s}$ or $\widehat{\mathbf{L}_{\mathbf{s}}}^{+}$

Usually LAS only: potential local minimum (for 6 dof)



$$\mathbf{s} = (x_1, y_1, ..., x_4, y_4) \qquad \mathbf{v} = -\lambda \mathbf{L}_{\mathbf{s}^*}^{+} (\mathbf{s} - \mathbf{s}^*)$$

Local minimum avoided by using $\widehat{\mathbf{L}_\mathbf{s}}^{+} = \mathbf{L}_{\mathbf{s}^*}^{+}$ (very coarse approximation)

The basic tools

Modeling: $\dot{\mathbf{s}} = \mathbf{L_s} \mathbf{v}$

Control: $\mathbf{v} = -\lambda \, \widehat{\mathbf{L_s}}^{+} (\mathbf{s} - \mathbf{s}^*)$

For an image point:

$$\mathbf{L_x} = \begin{bmatrix} -1/Z & 0 & x/Z & xy & -(1+x^2) & y \\ 0 & -1/Z & y/Z & 1+y^2 & -xy & -x \end{bmatrix}$$

The depth Z_i of each point appears for the 3 translational dof (true $\forall \mathbf{s} \in 2\mathrm{D}$)

- Can be approximated: $Z_i(t) = Z_i^*$
- Can be estimated: $Z_i(t) = \widehat{Z_i}(t)$
  - by triangulation with stereovision
  - from pose if 3D object model available
  - up to a scale factor from epipolar geometry/homography with current & desired images
  - from structure from known motion

The basic tools

Modeling: $\dot{\mathbf{s}} = \mathbf{L_s v}$

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For an image point:

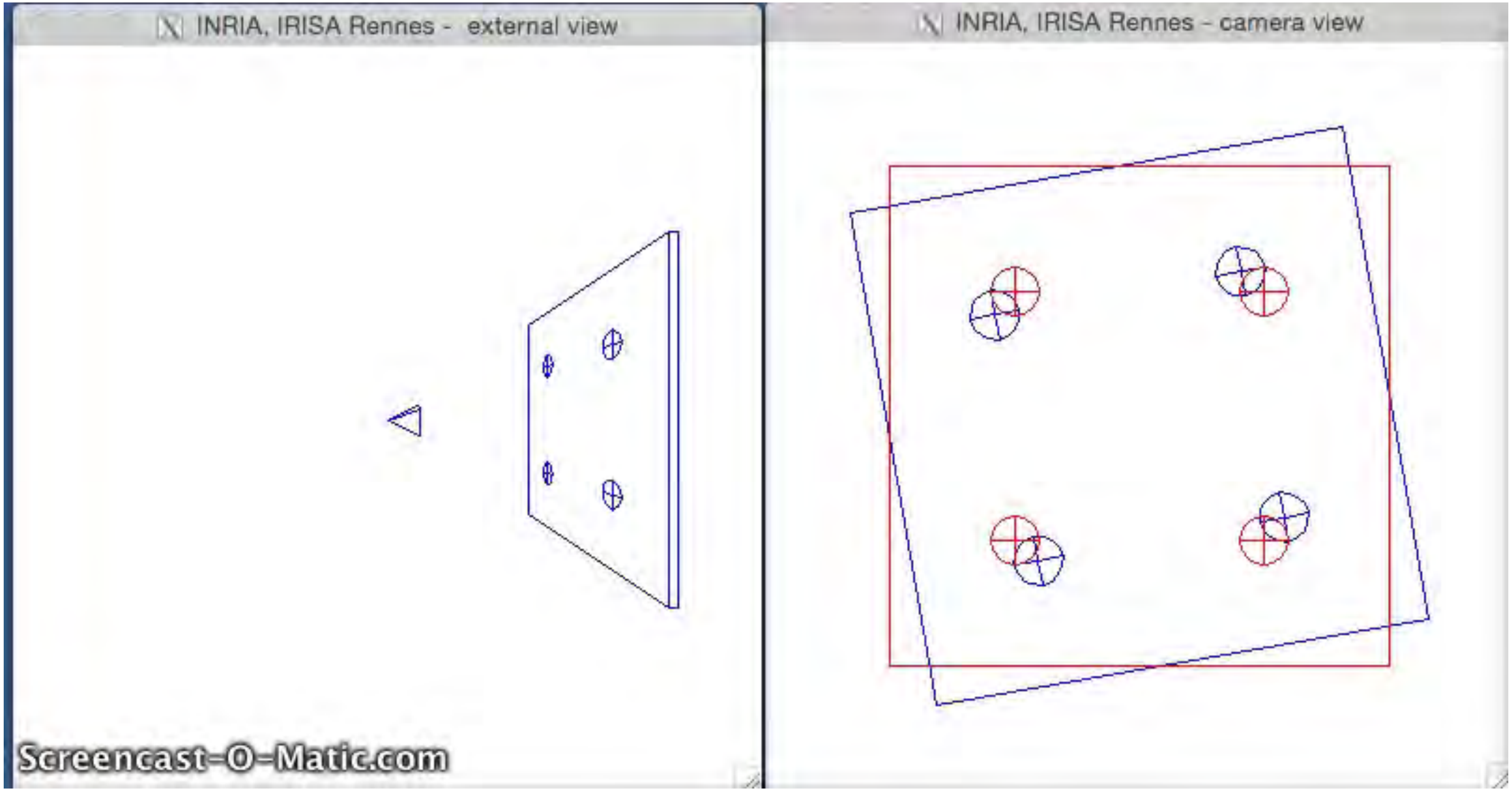
$$\mathbf{L_x} = \begin{bmatrix} -1/Z & 0 & x/Z & xy & -(1+x^2) & y \\ 0 & -1/Z & y/Z & 1+y^2 & -xy & -x \end{bmatrix}$$

$$\mathbf{L}_{(\rho,\theta)} = \begin{bmatrix} \frac{-\cos\theta}{Z} & \frac{-\sin\theta}{Z} & \frac{\rho}{Z} & (1+\rho^2)\sin\theta & -(1+\rho^2)\cos\theta & 0 \\ \frac{\sin\theta}{\rho Z} & \frac{-\cos\theta}{\rho Z} & 0 & \frac{\cos\theta}{\rho} & \frac{\sin\theta}{\rho} & -1 \end{bmatrix}$$

Different choices of $\mathbf{s}$ will induce different image & robot behaviors

One open problem for 6 dof (solved for 4 dofs)

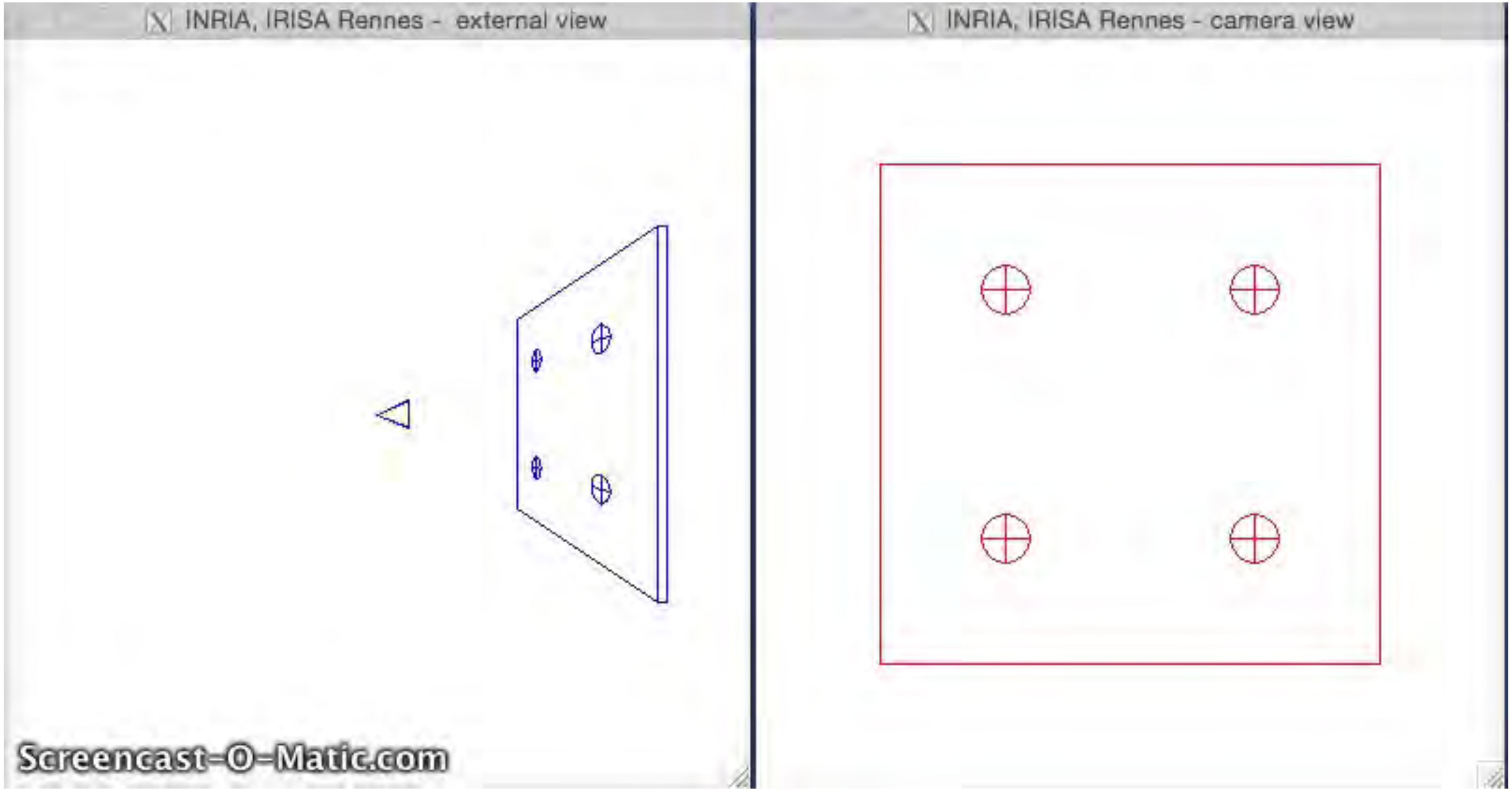
What are the visual features for an optimal behavior?



$$\mathbf{s} = (x_1, y_1, ..., x_4, y_4)$$

What are the good visual features?

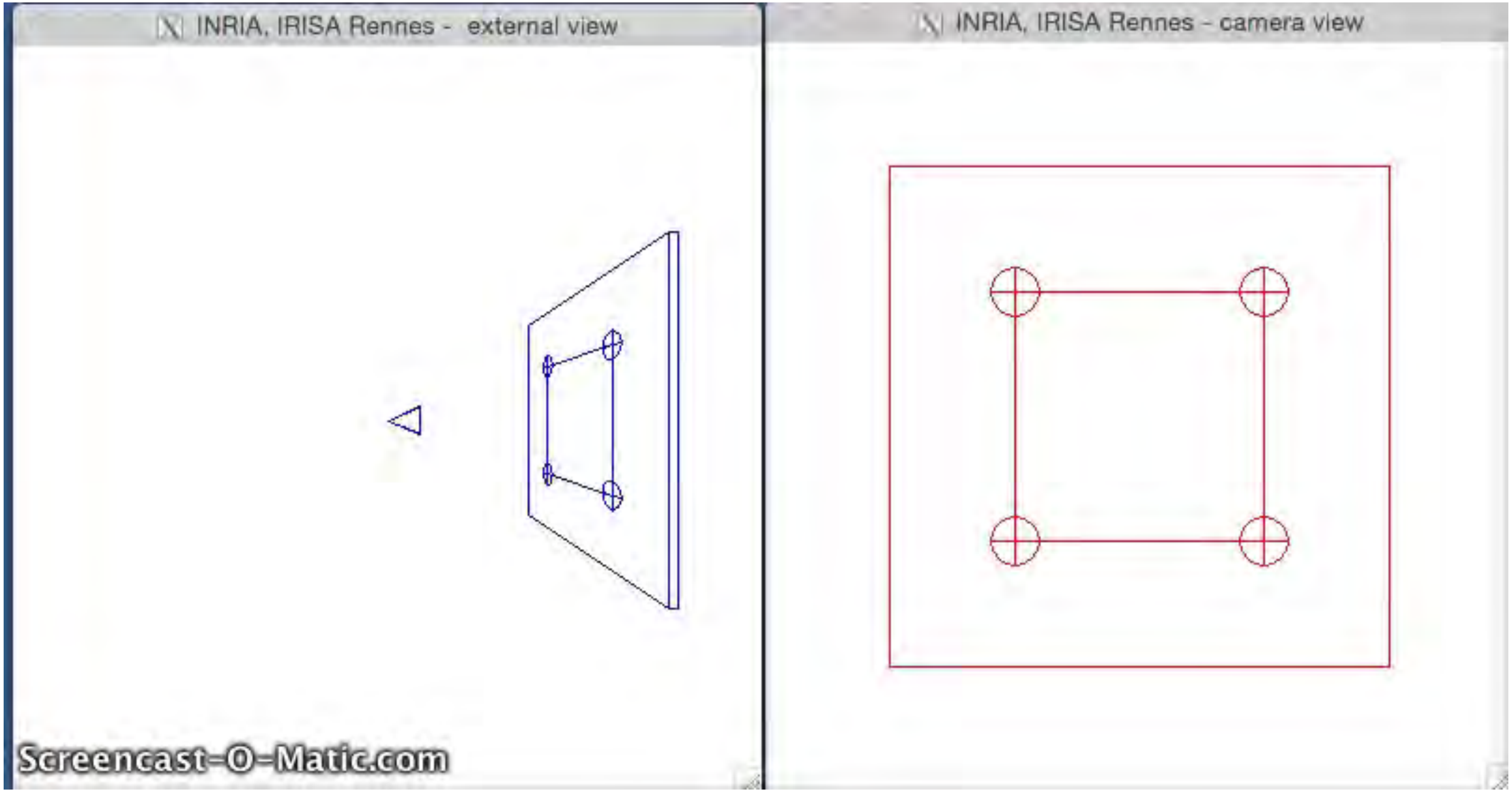
A very bad choice



$$\mathbf{s} = (x_1, y_1, ..., x_4, y_4)$$

What are the good visual features?

A perfect choice for this particular configuration



$$\mathbf{s} = (\rho_1, \theta_1, ..., \rho_4, \theta_4)$$

The basic tools

Modeling: $\dot{\mathbf{s}} = \mathbf{L_s} \mathbf{v}$

Control: $\mathbf{v} = -\lambda \widehat{\mathbf{L_s}}^{+} (\mathbf{s} - \mathbf{s}^*)$

$\mathbf{L_s}$ known for many visual features:

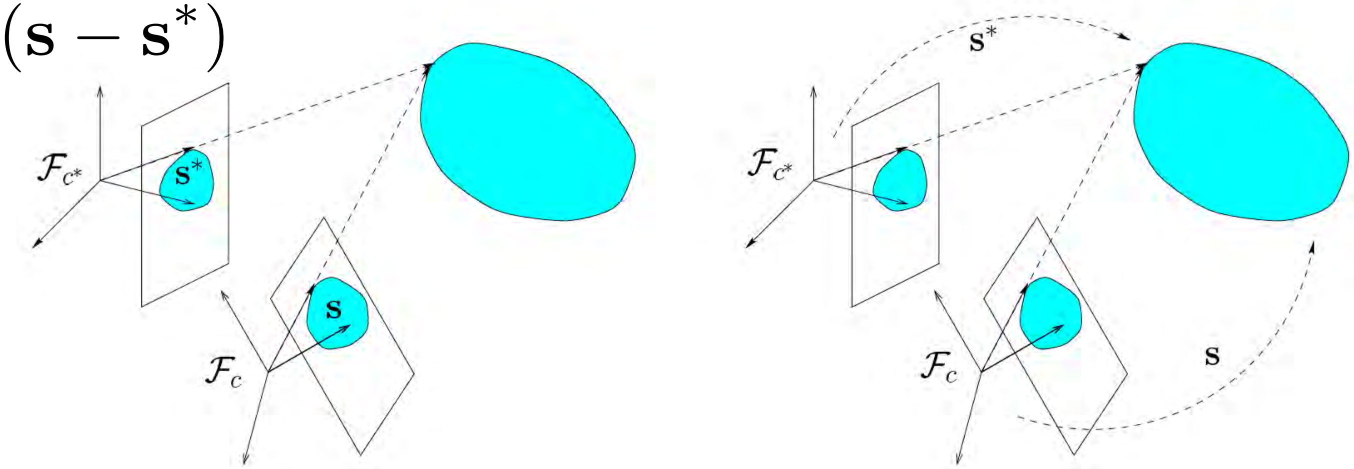
- In 3D, directly from kinematics: ${}^{c}\mathbf{t}_o,\ {}^{c^*}\mathbf{t}_c,\ \theta\mathbf{u}$: GAS if 3D is perfect
- In 2D:
  - Point, segment, straight line, circle, cylinder, sphere, …
  - Moments for planar or almost planar shapes

If $\mathbf{L_s}$ unknown, it can be estimated (off-line, on-line, by learning) but be careful to non-linearity and stability

From your application (robot dof, object, task), search for the best choice

My 2 cents on the endless debate: IBVS vs PBVS

$$\mathbf{v} = -\lambda \, \widehat{\mathbf{L}_{\mathbf{s}}}^{+} (\mathbf{s} - \mathbf{s}^*)$$



2D visual features (IBVS) / 3D visual features (PBVS)

For IBVS, 3D appears in $\widehat{\mathbf{L}_{\mathbf{s}}}$ but not in $\mathbf{s}$

So 3D noise will affect the transient, but not the accuracy at the goal

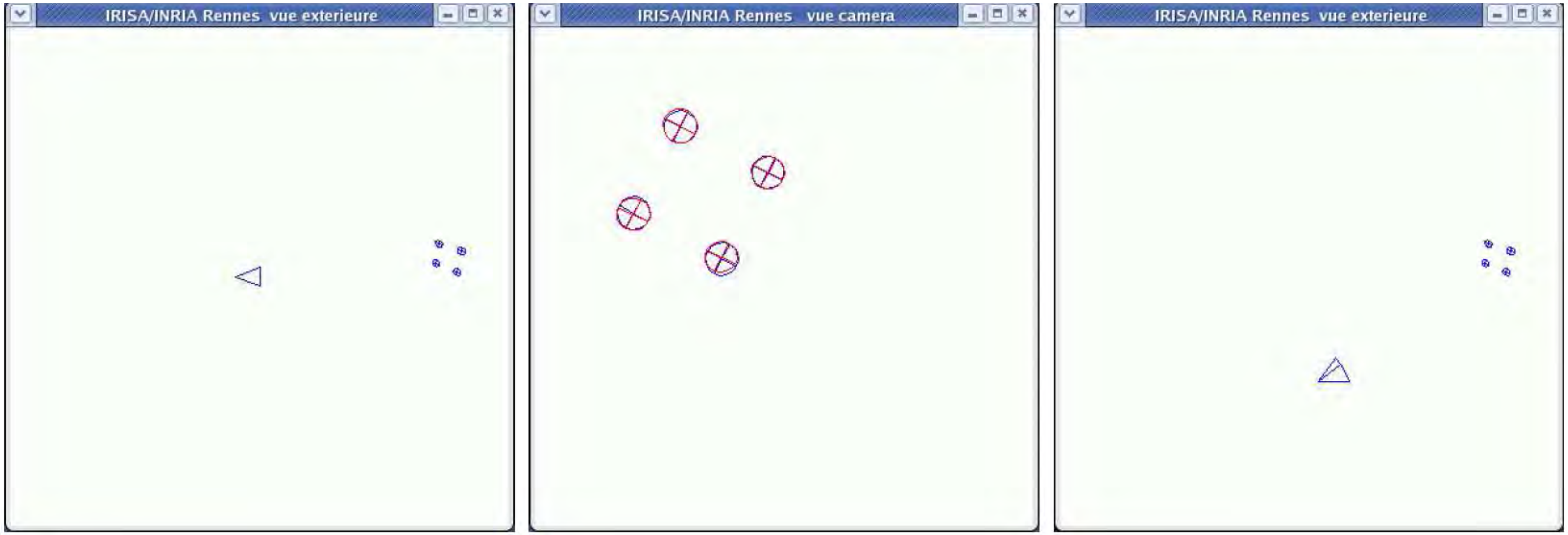
This is not the case for PBVS

Pose estimation may be unstable

$$\text{Estimated pose } \hat{\mathbf{p}}(t) = \hat{\mathbf{p}}(\mathbf{x}(t), \mathbf{X}, x_c, y_c, f_x, f_y)$$

$$\Rightarrow \quad \dot{\hat{\mathbf{p}}}(t) = \frac{\partial \hat{\mathbf{p}}}{\partial \mathbf{x}} \dot{\mathbf{x}} = \frac{\partial \hat{\mathbf{p}}}{\partial \mathbf{x}} \mathbf{L_x} \mathbf{v} \quad \Rightarrow \quad \mathbf{L}_{\hat{\mathbf{p}}} = \frac{\partial \hat{\mathbf{p}}}{\partial \mathbf{x}} \mathbf{L_x}$$

where $\mathbf{L_x}$ is known but $\frac{\partial \hat{\mathbf{p}}}{\partial \mathbf{x}}$ is unknown (and sometimes unstable)



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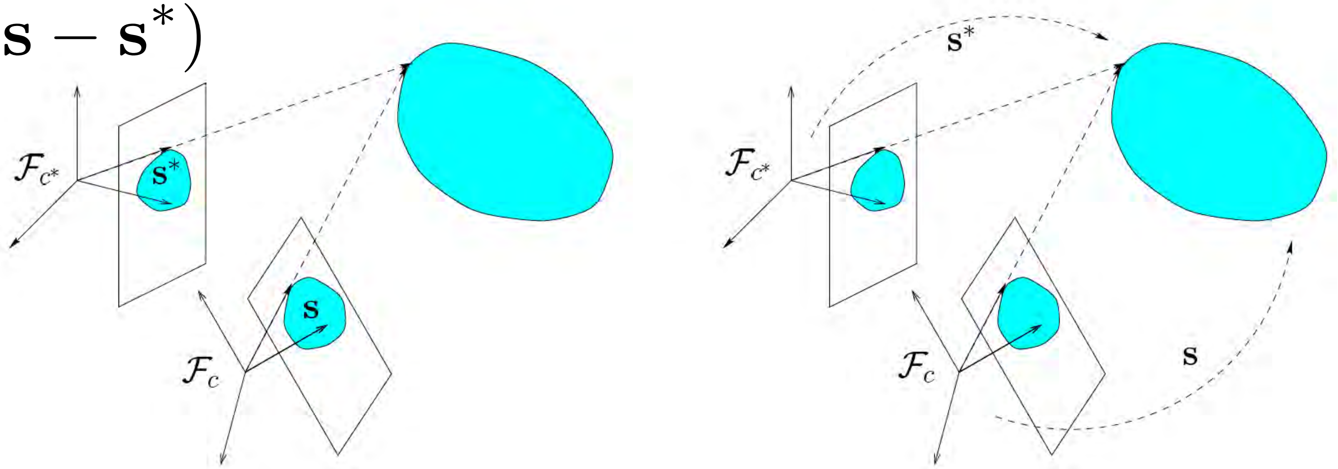

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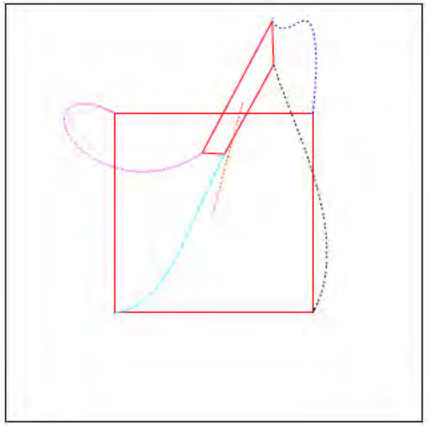
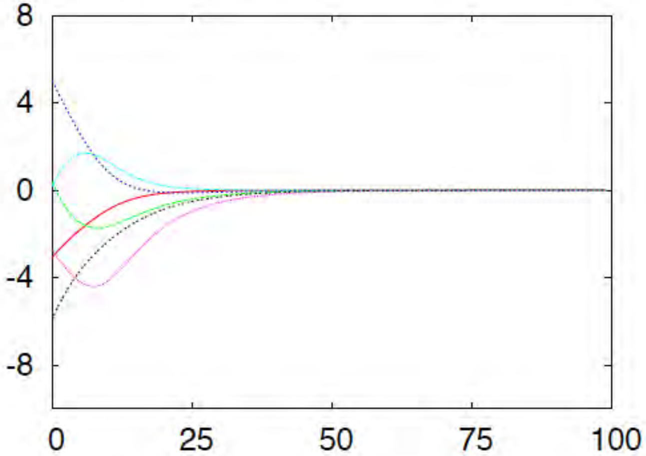
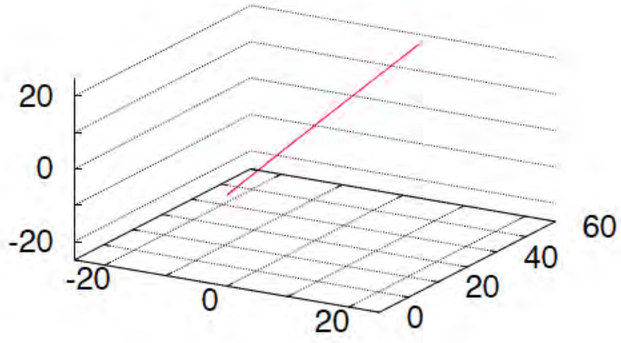
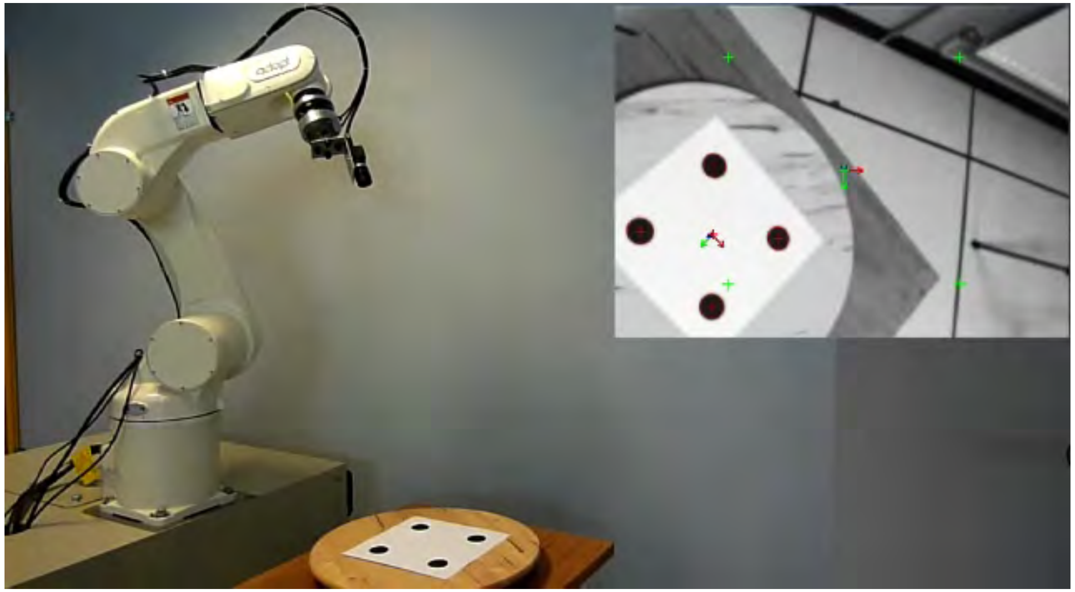
And the winner was to combine 2D and 3D visual features (2 ½ D VS)…

Results using $\mathbf{s} = ({}^{c^*}\mathbf{t}_c, \mathbf{x}_g, \theta u_z)$









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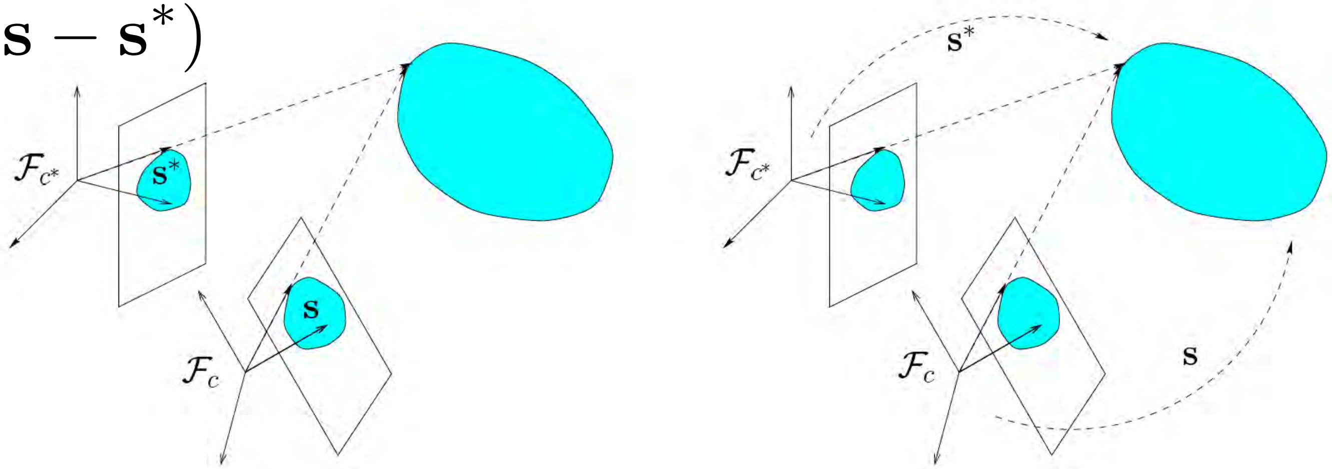

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Now, try to design IBVS with PBVS behavior (search for $\mathbf{s}$ such that $\mathbf{L}_{\mathbf{s}} \approx \mathbf{I}$)

A new family of visual servoing: photometric VS

Remove the image processing part in the usual steps:

- extract and track visual measurements near video rate
- design visual features and control schemes from the available measurements

Advantages:

- Robustness to image processing errors and noise!

Photometric visual servoing

Visual features: intensity of each pixel $\mathbf{s} = \mathbf{I}(\mathbf{x}(t))$

$\mathbf{I}^*$ $\qquad$ $\mathbf{I}$ $\qquad$ $\mathbf{I} - \mathbf{I}^*$

Modeling: $\mathbf{L_I} = -\nabla \mathbf{I_x}\ \mathbf{L_x}$ (function of the image content)

$\mathcal{L} = \frac{1}{2}\|\mathbf{I} - \mathbf{I}^*\|$ highly non linear

Drawbacks: small convergence domain, strange robot trajectory

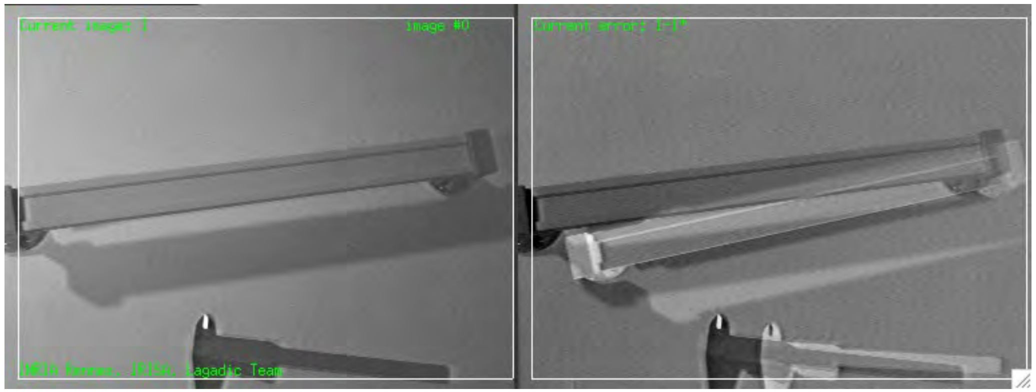
But no feature extraction, tracking nor matching

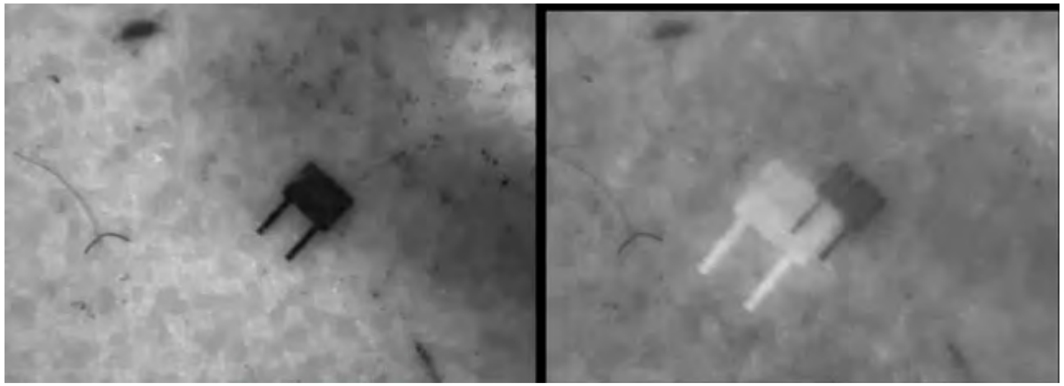
+ excellent positioning accuracy

Photometric visual servoing

Robustness to global illumination changes by using $\mathbf{s} = (\mathbf{I} - \bar{\mathbf{I}})/\sigma_{\mathbf{I}}^2$

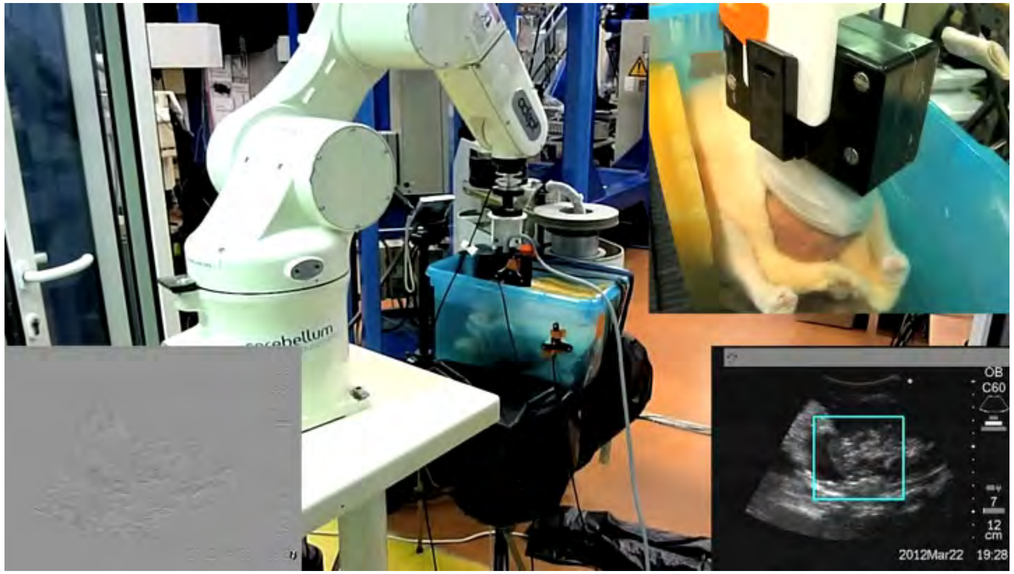
Robustness to outliers (occlusion) by using $\mathbf{s} = \rho_{\mathbf{I}}\ \mathbf{I}$



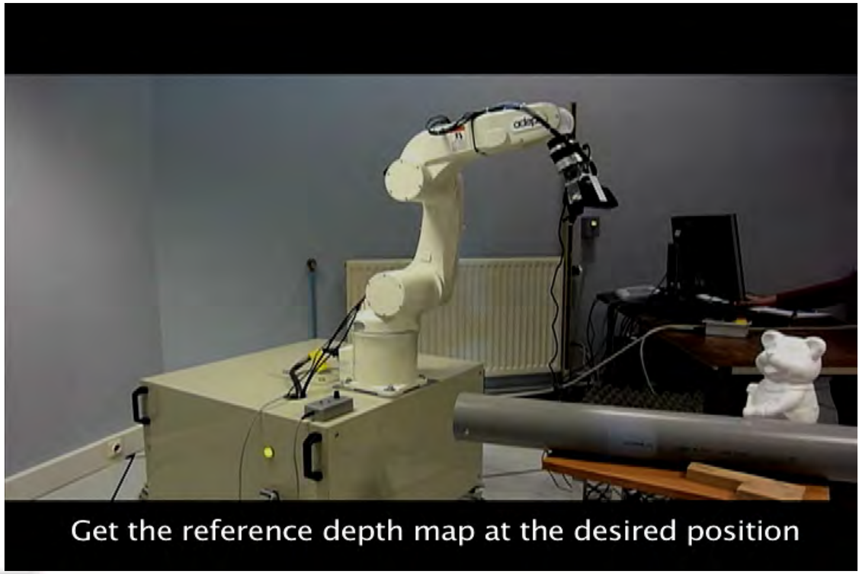


Accuracy < 0.1 µm

Similar on ultrasound images



Similar on depth map from RGB-D sensor: $\mathbf{s} = \rho_{\mathbf{Z}}\, \mathbf{Z}$



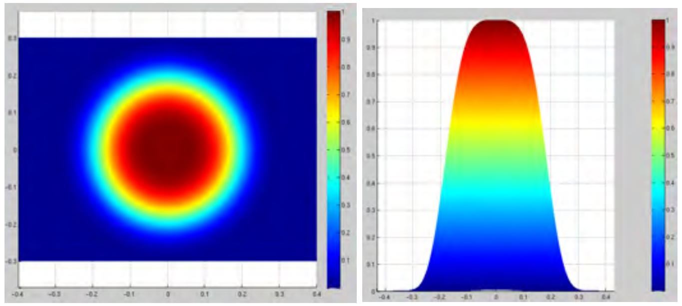
In the same spirit:

- RGB components, spatial gradient image
- Sum of conditional variance: $\mathcal{L} = \|\mathbf{I}(\mathbf{x}) - \widehat{\mathbf{I}}(\mathbf{x})\|$ with $\widehat{\mathbf{I}}(\mathbf{x}) = \epsilon(\mathbf{I}(\mathbf{x}), \mathbf{I}^*(\mathbf{x}))$
- Maximize mutual information between current and desired image
- Histogram-based visual servoing
- Mixture of Gaussian
- Wavelet
- …

Photometric moments

Going back to geometric features for enlarging the convergence domain and improving the robot trajectory

$$m_{pq} = \iint_{\pi} x^p y^q \, w(\mathbf{x}) \, I(\mathbf{x}, t) \, \mathrm{d}x \, \mathrm{d}y$$



Then select adequate moments (area, cog, main orientation, …)

$\mathbf{I}^*$

$\mathbf{I}$

$\mathbf{I} - \mathbf{I}^*$

Other/open issues

- Target tracking
  - PI controller
  - Estimate, predict and compensate the target motion (feed forward)

- Consider constraints:
  - visibility, occlusion, obstacles
  - joint limits, singularities
  - dynamics: non holonomy, under-actuation
    - Path planning in the image, optimal control, MPC
    - Redundancy, task sequencing, stack of tasks

- Multi sensor-based control
  - Modeling, fusion

To go further

- F. Chaumette, S. Hutchinson, P. Corke: Visual servoing, in Chapter 34 of Handbook of Robotics, 2nd edition, expected for IROS'2016.
- Many papers in the field
- Do not hesitate to use ViSP for visual tracking and visual servoing:

visp.inria.fr

Thanks for your attention

Acknowledgments: Lagadic colleagues and the VS worlwide community