Robotics 2

Visual servoing

Prof. Alessandro De Luca

DIPARTIMENTO DI INGEGNERIA INFORMATICA
AUTOMATICA E GESTIONALE ANTONIO RUBERTI

SAPIENZA
UNIVERSITÀ DI ROMA

Visual servoing

- objective

  use information acquired by vision sensors (cameras) for feedback control of the pose/motion of a robot (or of parts of it)

$\boxed{+}$ data acquisition ~ human eye, with very large information content in the acquired images

$\boxed{-}$ difficult to extract essential data, nonlinear perspective transformations, high sensitivity to ambient conditions (lightening), noise

Some applications

automatic navigation of robotic systems (agricolture, automotive)

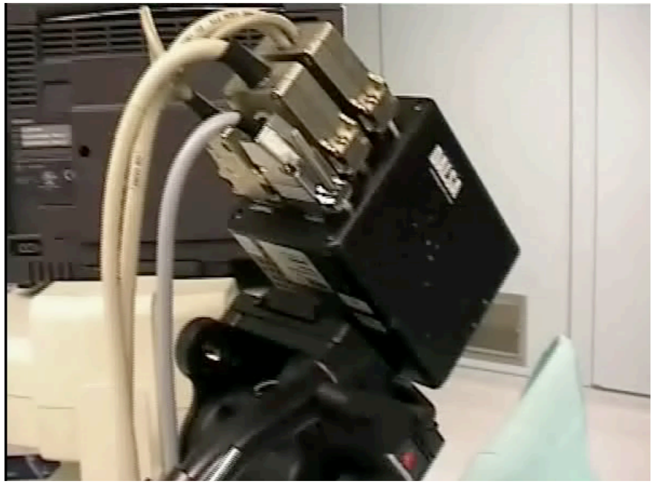
video

video

surveillance

bio-motion synchronization (surgical robotics)

video



video

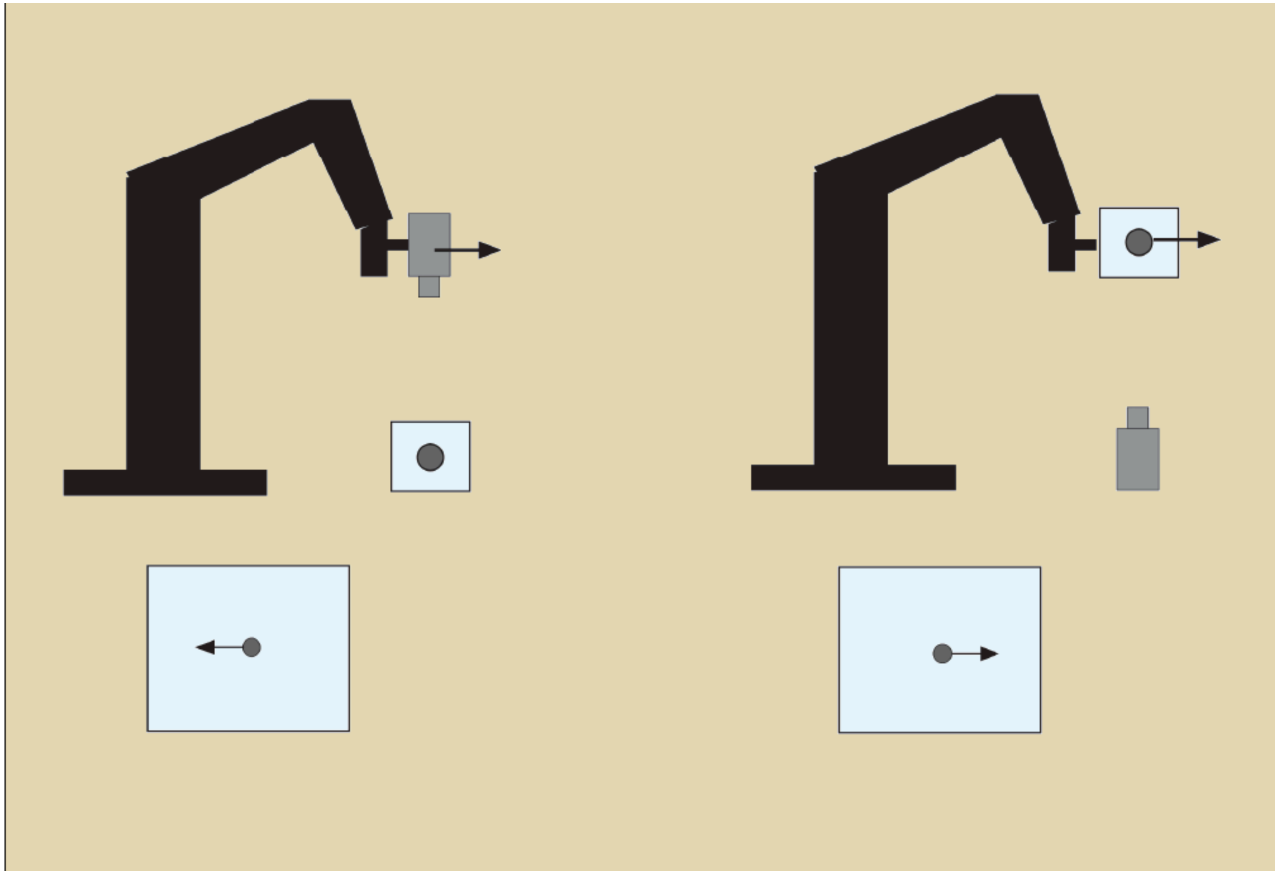
Image processing

- real-time extraction of characteristic parameters useful for robot motion control
  - features: points, area, geometric center, higher-order moments, …
- low-level processing
  - binarization (threshold on grey levels), equalization (histograms), edge detection, …
- segmentation
  - based on regions (possibly in binary images)
  - based on contours
- interpretation
  - association of characteristic parameters (e.g., texture)
  - problem of correspondence of points/characteristics of objects in different images (stereo or on image flows)

Configuration of a vision system

- one, two, or more cameras
  - grey-level or color
- 3D/stereo vision
  - obtained even with a single (moving) camera, with the object taken from different (known) points of view
- camera positioning
  - fixed (eye-to-hand)
  - mounted on the manipulator (eye-in-hand)
- robotized vision heads
  - motorized (e.g., stereo camera on humanoid head or pan-tilt camera on Magellan mobile robot)

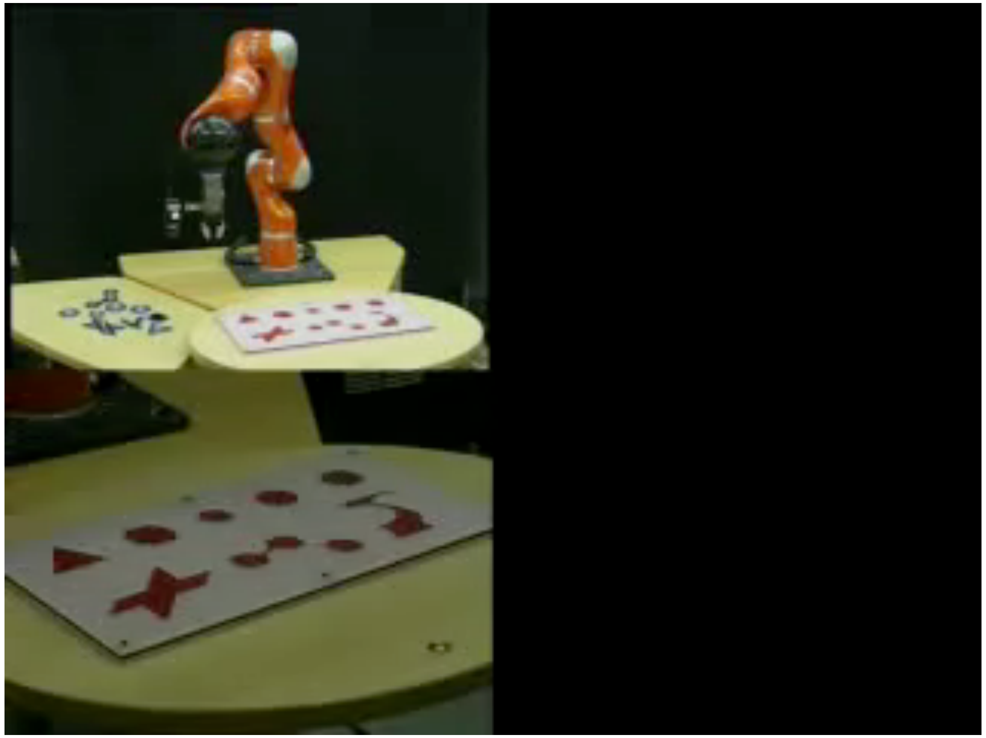
Camera positioning



eye-in-hand　　　　eye-to-hand

Vision for assembly

video

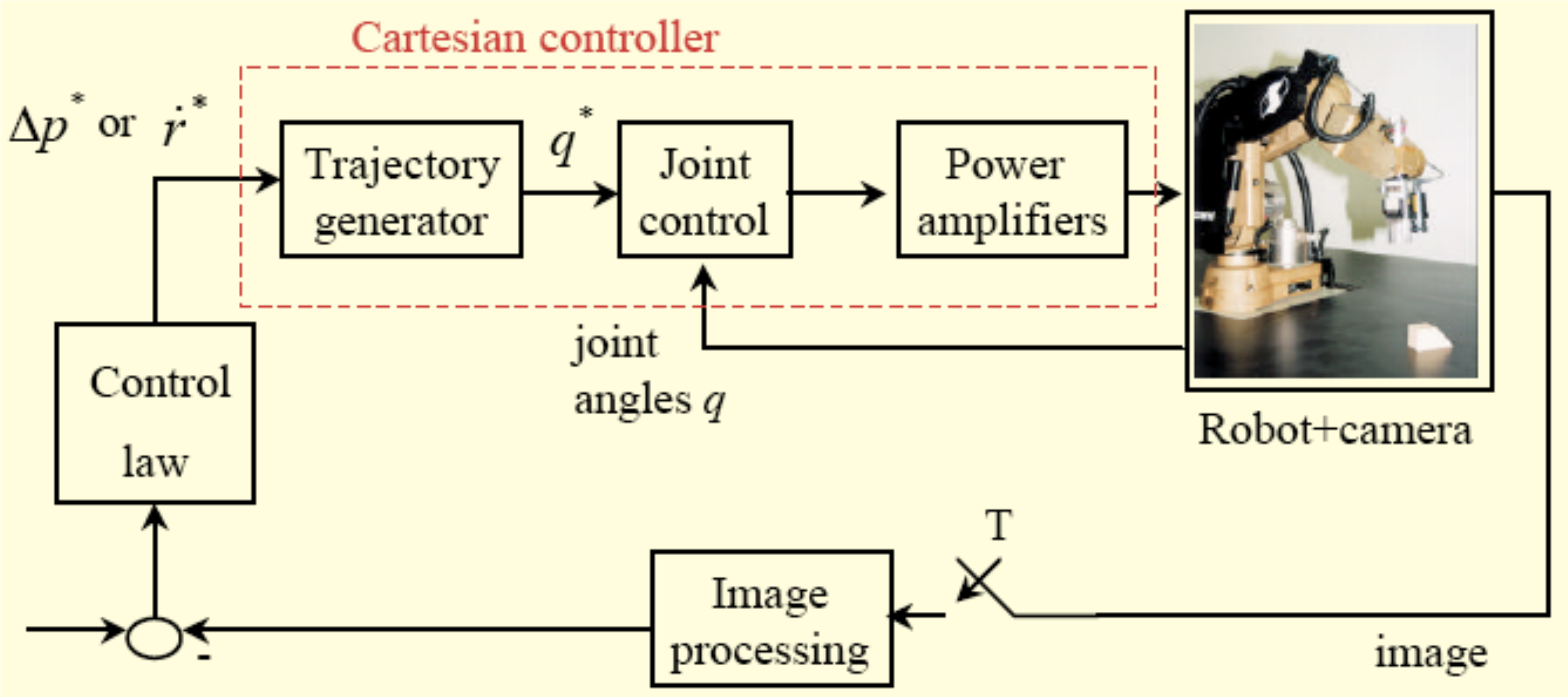


video

PAPAS-DLR system
(eye-in-hand, hybrid force-vision)

robust w.r.t. motion of
target objects

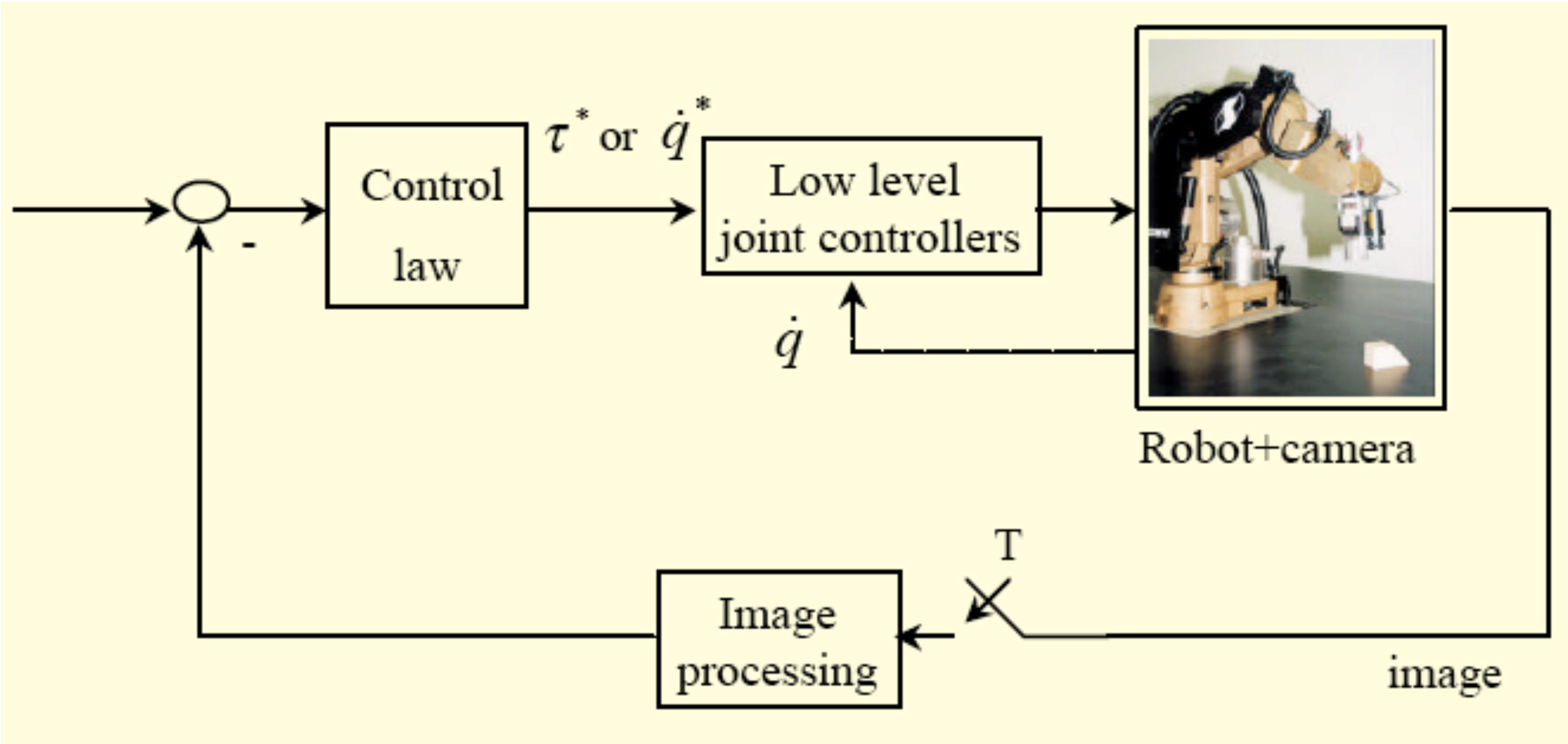
Indirect/external visual servoing



vision system provides set-point references to a Cartesian motion controller

- "easy" control law (same as without vision)
- appropriate for relatively slow situations (control sampling $f = 1/T < 50$Hz)

Direct/internal visual servoing



replace Cartesian controller with one based on vision that directly computes joint reference commands

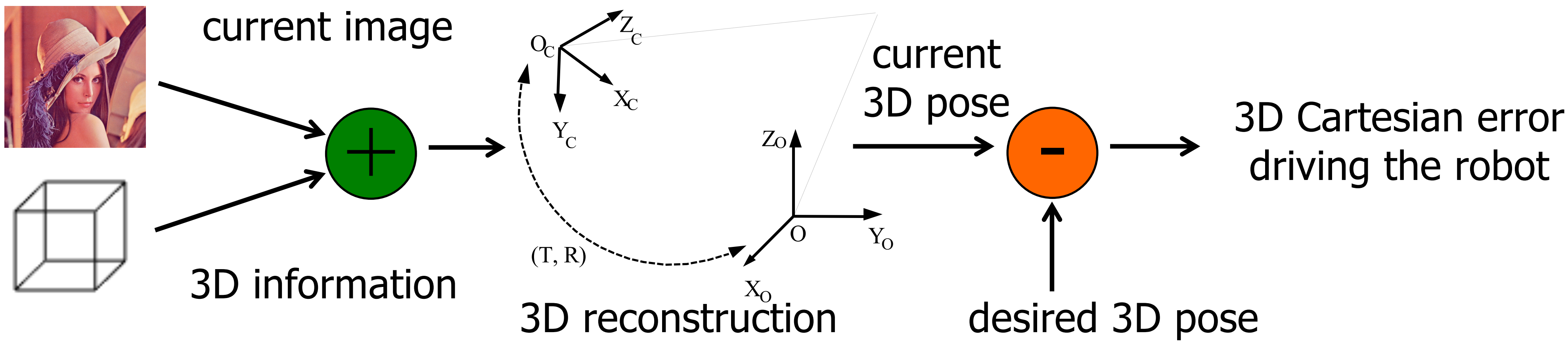
- control law is more complex (involves robot kinematics/dynamics)
- preferred for fast situations (control sampling $f = 1/T > 50$Hz)

Classification of visual servoing schemes

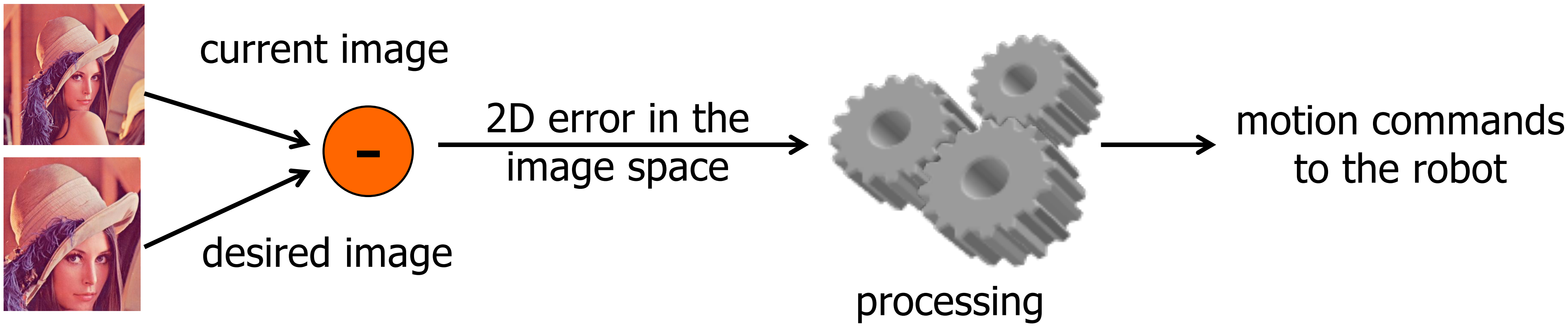
- position-based visual servoing (**PBVS**)
  - information extracted from images (features) is used to reconstruct the current 3D pose (pose/orientation) of an object
  - combined with the knowledge of a desired 3D pose, we generate a Cartesian pose error signal that drives the robot to the goal
- image-based visual servoing (**IBVS**)
  - error is computed directly on the values of the features extracted on the 2D image plane, without going through a 3D reconstruction
  - the robot should move so as to bring the current image features (what it "sees" with the camera) to their desired values
- some mixed schemes are possible (e.g., 2½D methods)

Comparison between the two schemes

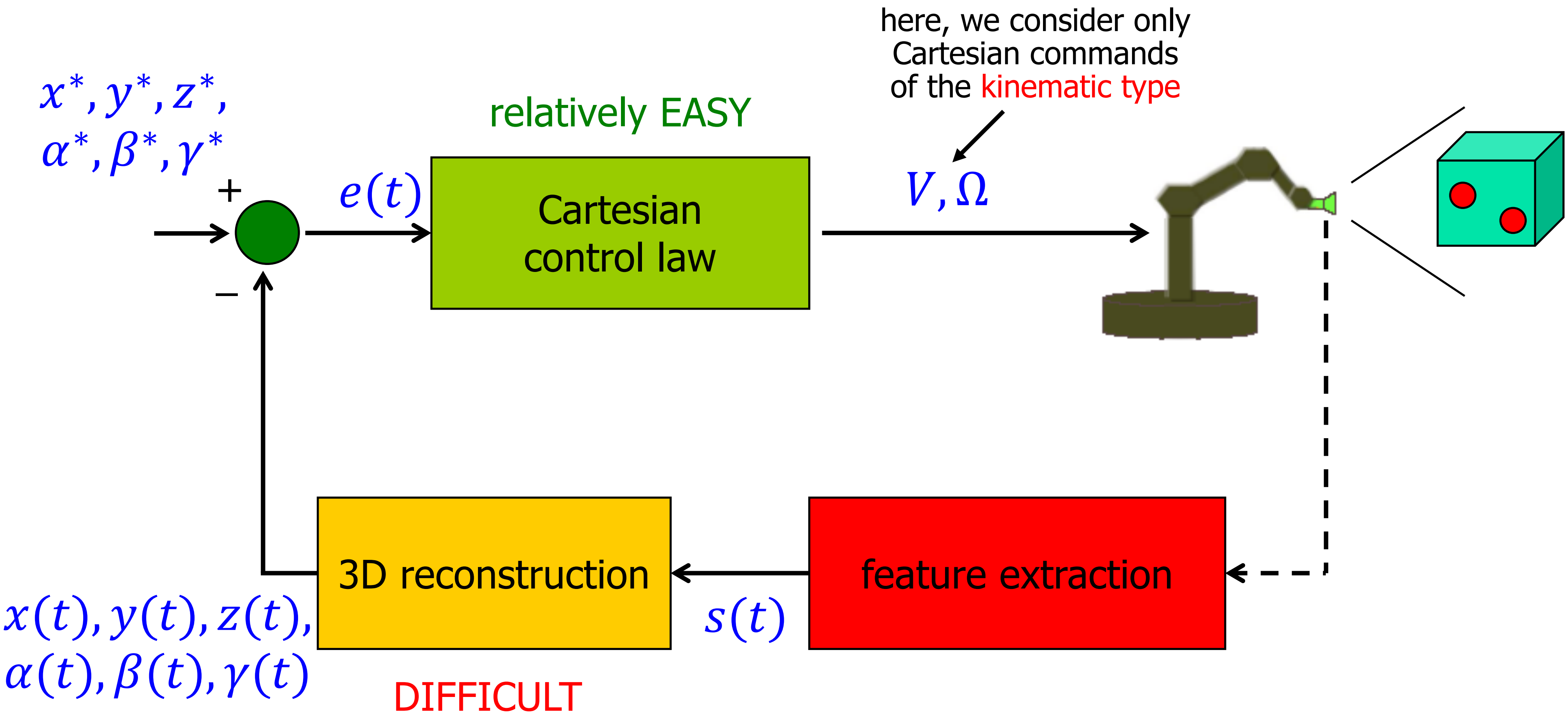
- position-based visual servoing (**PBVS**)



- image-based visual servoing (**IBVS**)



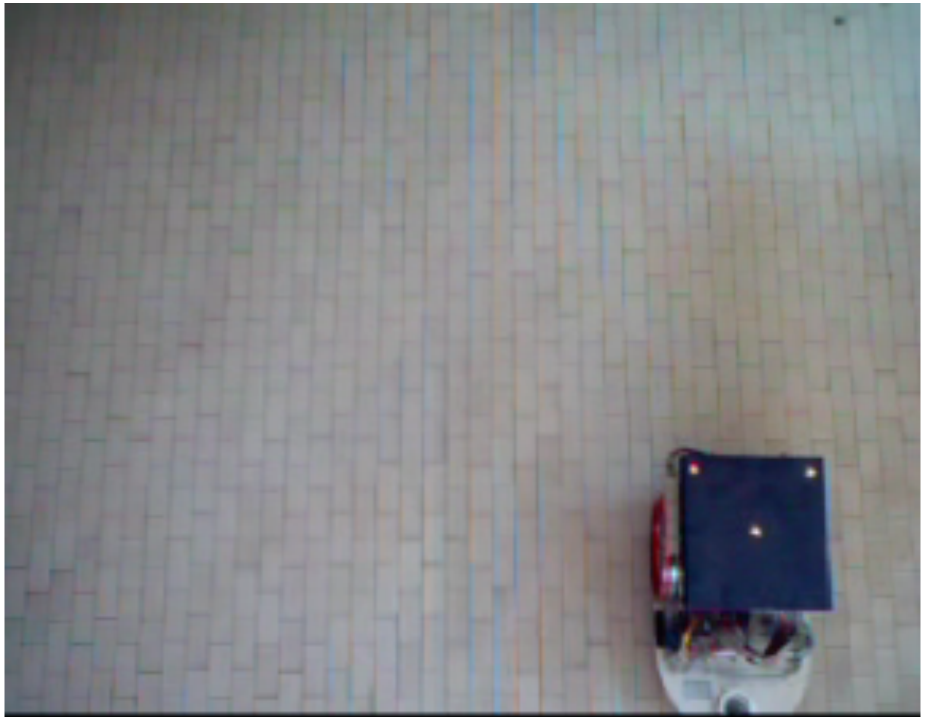
PBVS architecture



highly sensitive to camera calibration parameters

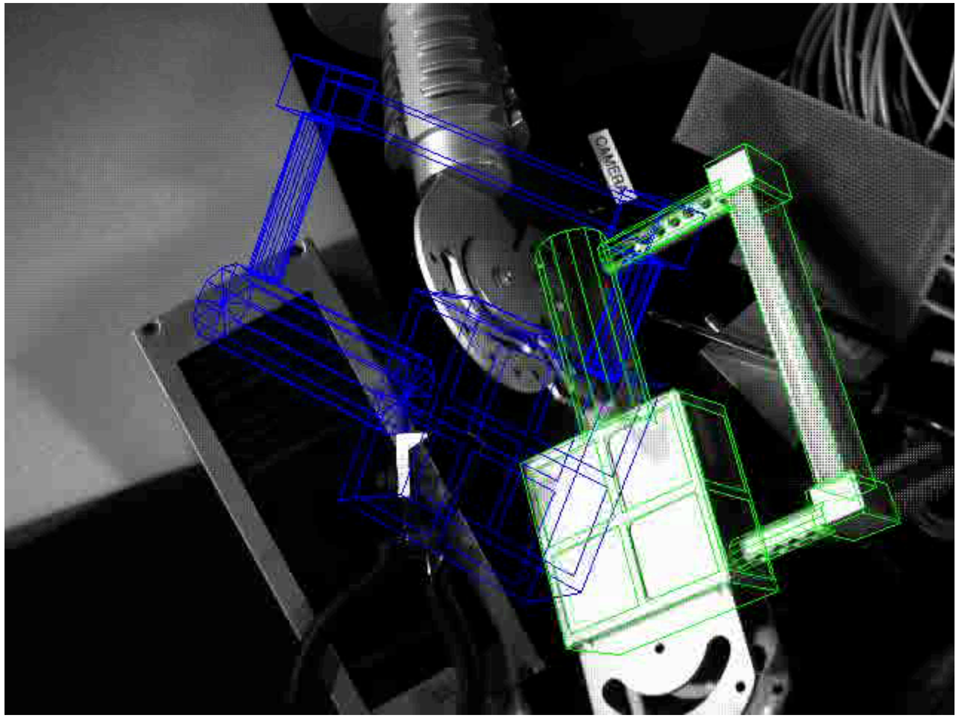
Examples of PBVS

video



eye-to-"robot" (SuperMario)

video



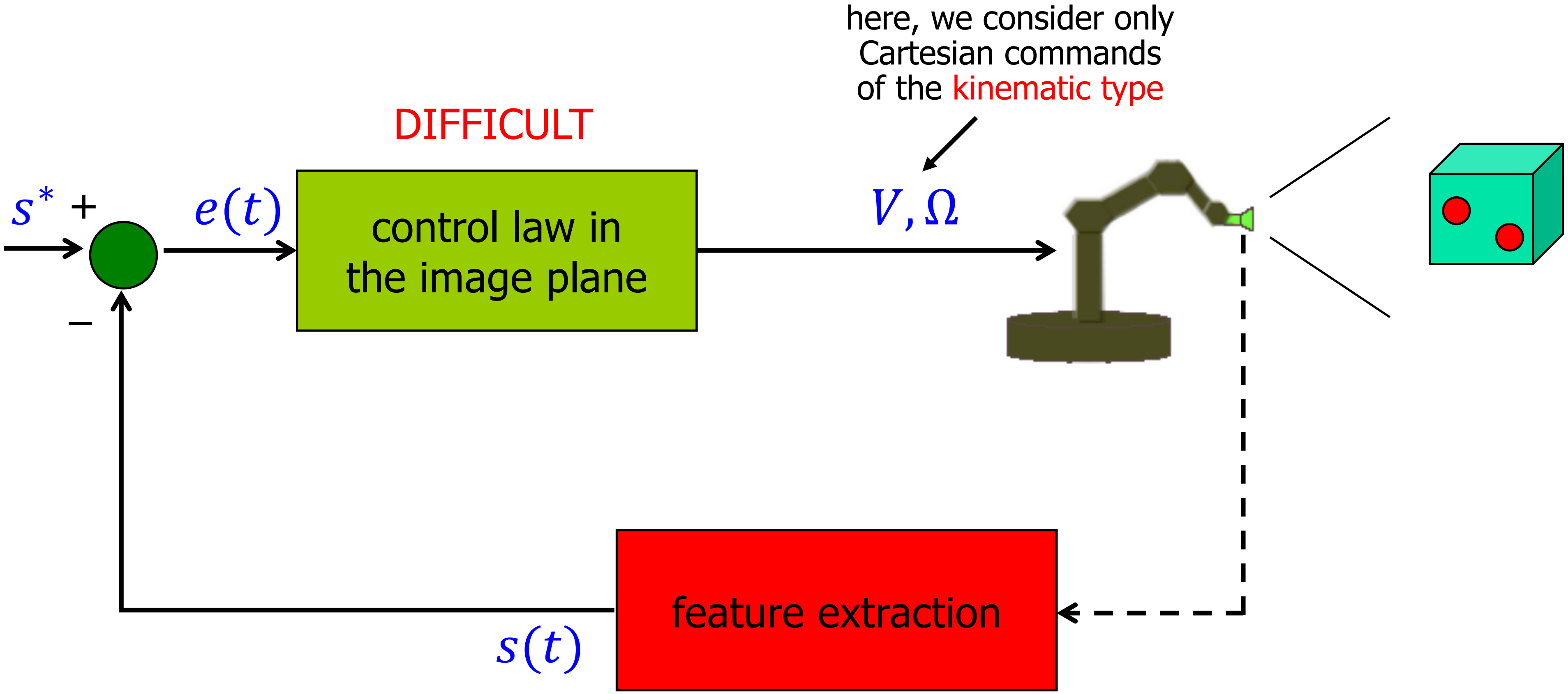
eye-in-hand (Puma robot)

position/orientation of the camera and scene geometry

known a priori!

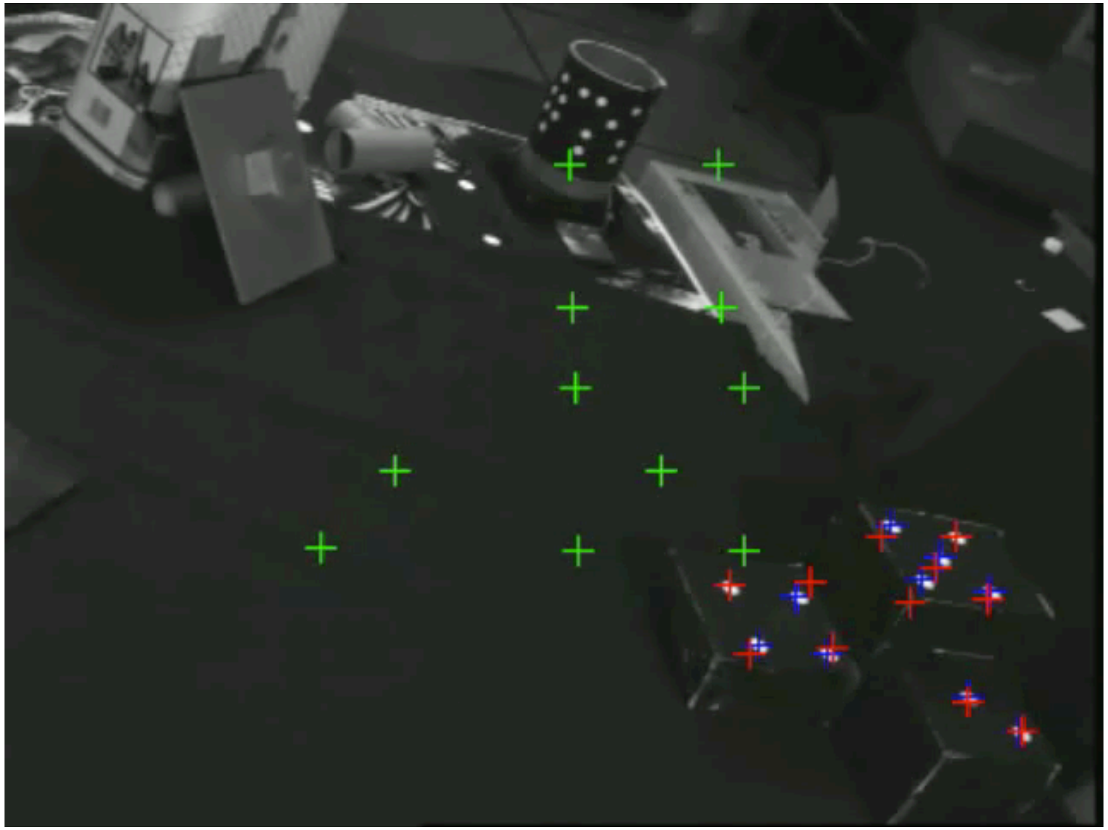
position and orientation of the robot (with mobile or fixed base)

IBVS architecture



almost insensitive to intrinsic/extrinsic camera calibration parameters

An example of IBVS



video

here, the features are points (selected from the given set, or in suitable combinations)

desired feature positions
current feature positions

→ the error in the image plane (task space!) drives/controls the motion of the robot

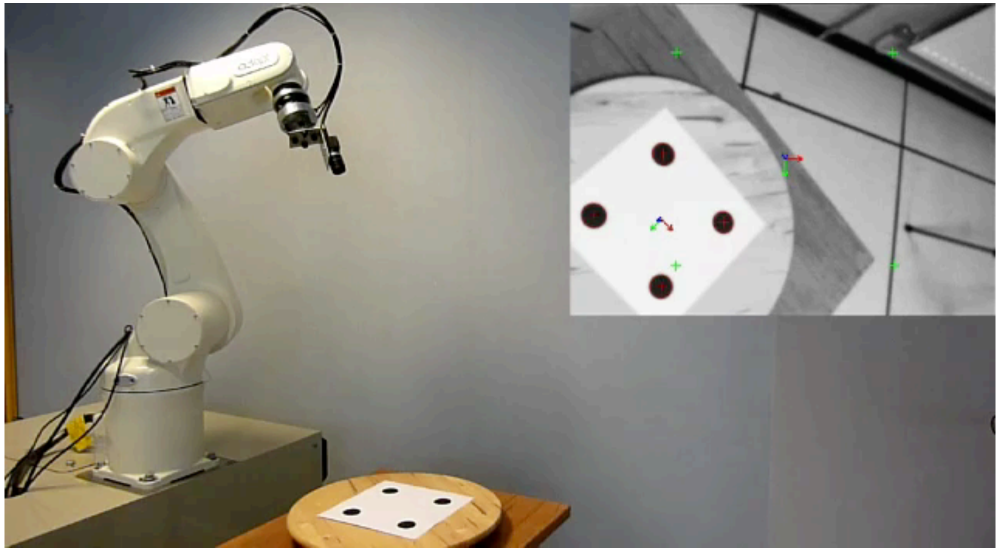
PBVS vs IBVS

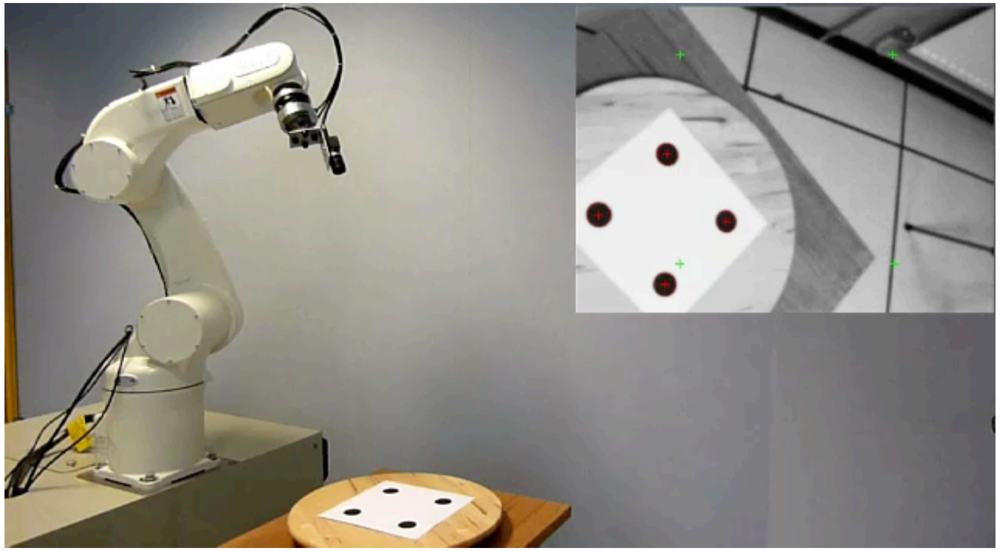
PBVS = position-based visual servoing

IBVS = image-based visual servoing

video

video





F. Chaumette, INRIA Rennes

reconstructing the instantaneous (relative) 3D pose of the object

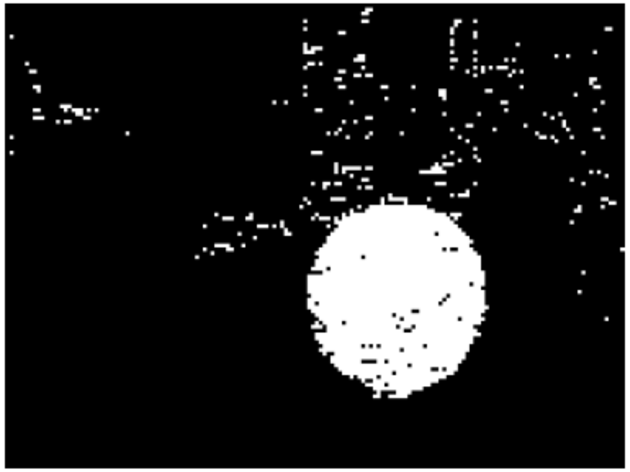
using (four) point features extracted from the 2D image

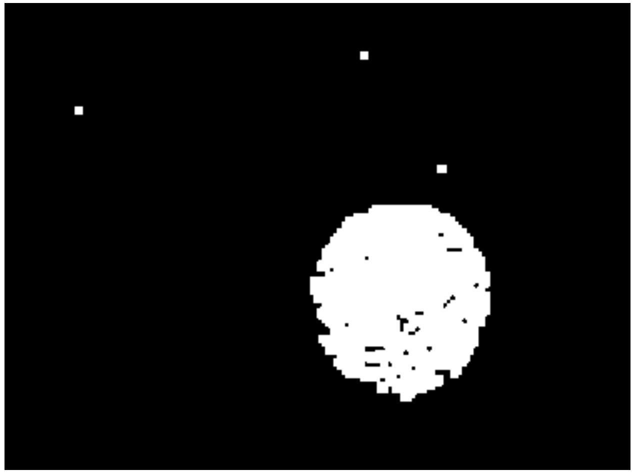
...and intermediate 2½-D visual servoing...

Steps in an IBVS scheme

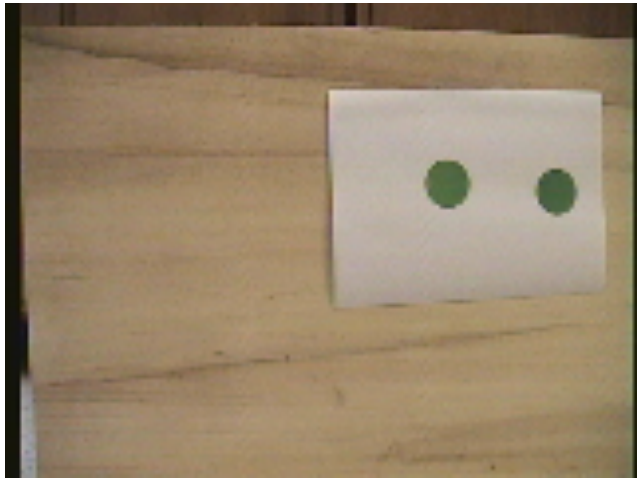
- image acquisition
  - frame rate, delay, noise, ...
- feature extraction
  - with image processing techniques (it could be a difficult and time consuming step!)
- comparison with "desired" feature values
  - definition of an error signal in the image plane
- generation of motion of the camera/robot
  - perspective transformations
  - differential kinematics of the manipulator
  - control laws of kinematic (most often) or dynamic type (e.g., PD + gravity cancelation --- see reference textbook)

Image processing techniques





binarization in RGB space → erosion and dilation

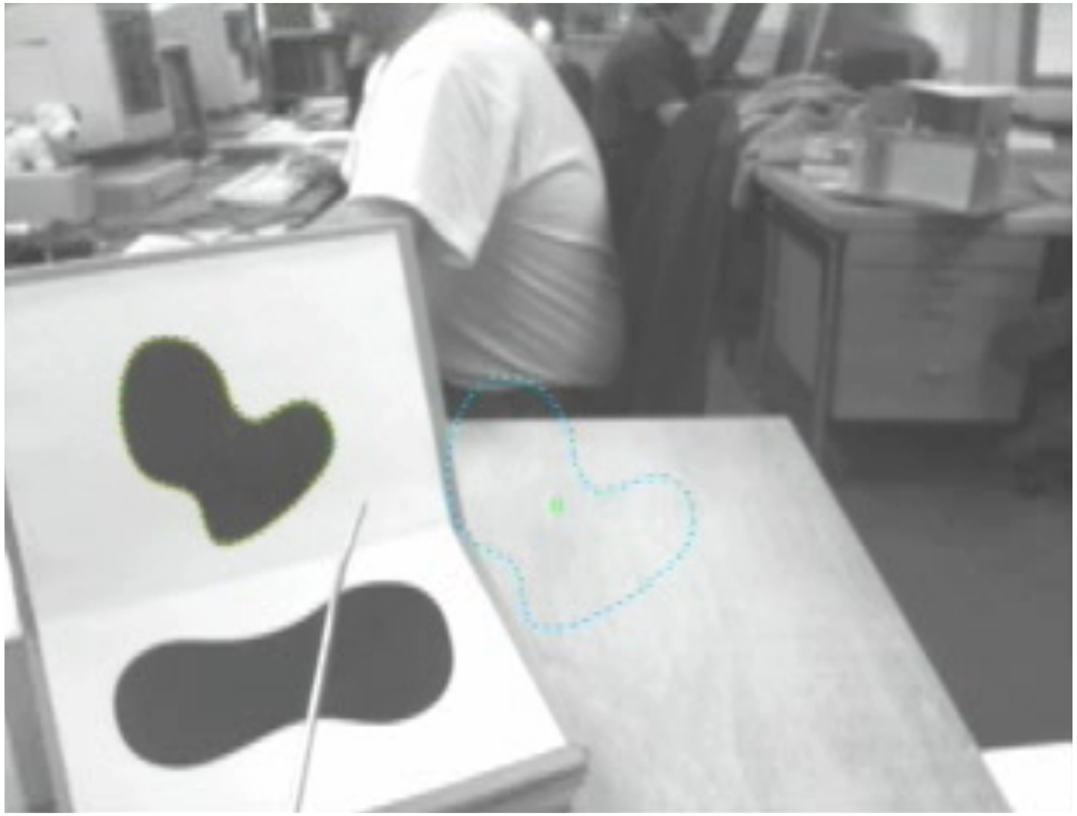


binarization in HSV space → dilation

What is a feature?

- image feature: any interesting characteristic or geometric structure extracted from the image/scene
  - points
  - lines
  - ellipses (or any other 2D contour)
- feature parameter(s): any numerical quantity associated to the selected feature in the image plane
  - coordinates of a point
  - angular coefficient and offset of a line
  - center and radius of a circle
  - area and center of a 2D contour
  - generalized moments of an object in the image
    - can also be defined so as to be scale- and rotation-invariant

Example of IBVS using moments



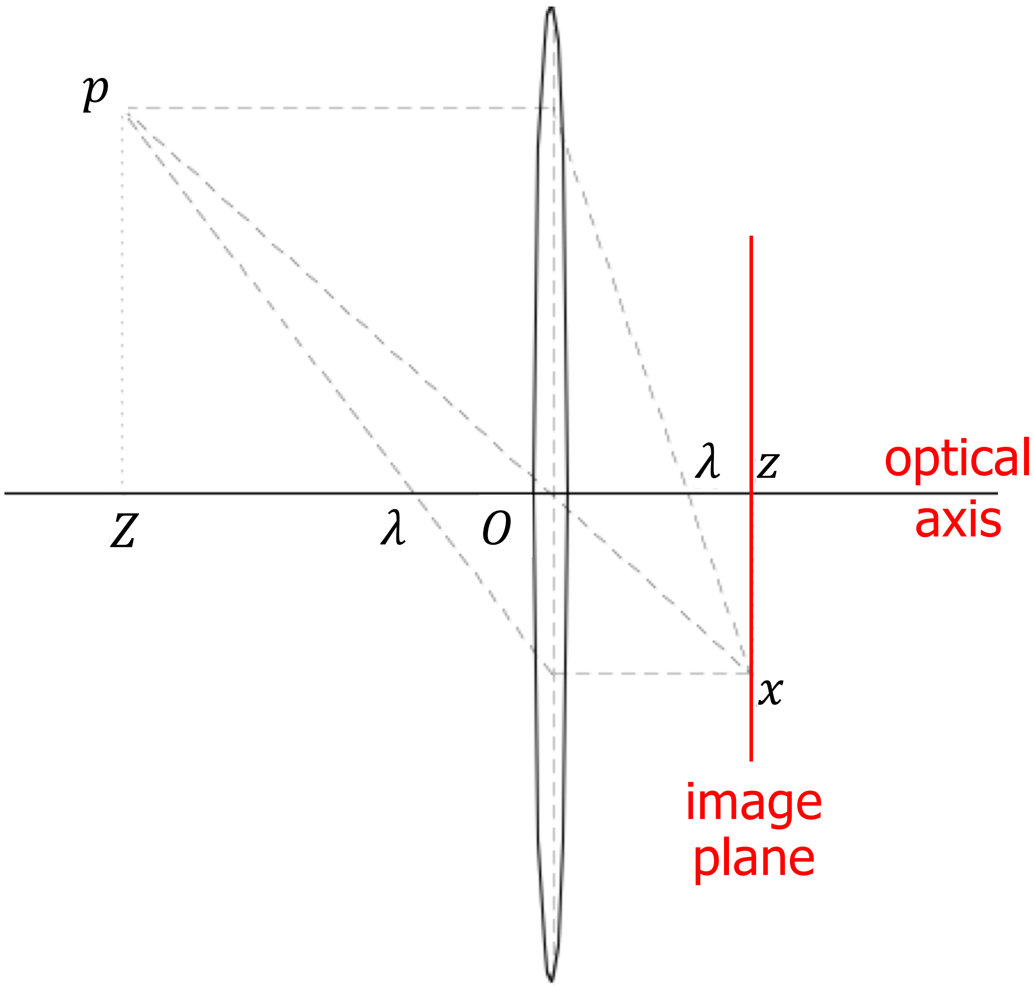
video

- avoids the problem of "finding correspondences" between points
- however, it is not easy to control the motion of all 6 dofs of the camera when using only moments as features

Camera model

- set of lenses to focus the incoming light
  - (converging) thin lenses
  - pinhole approximation
  - catadioptric lens or systems (combined with mirrors)
- matrix of light sensitive elements (pixels in image plane), possibly selective to RGB colors ~ human eye
- frame grabber "takes shots": an electronic device that captures individual, digital still frames as output from an analog video signal or a digital video stream
  - board + software on PC
  - frame rate = output frequency of new digital frames
  - it is useful to randomly access a subset (area) of pixels

Thin lens camera model



- geometric/projection optics
- rays parallel to the optical axis are deflected through a point at distance λ (focal length)
- rays passing through the optical center O are not deflected

fundamental equation of a thin lens

$$\underbrace{\frac{1}{Z} + \frac{1}{z} = \frac{1}{\lambda}}_{\text{dioptric (optical) power}}$$

proof? left as exercise ...

Pinhole camera model

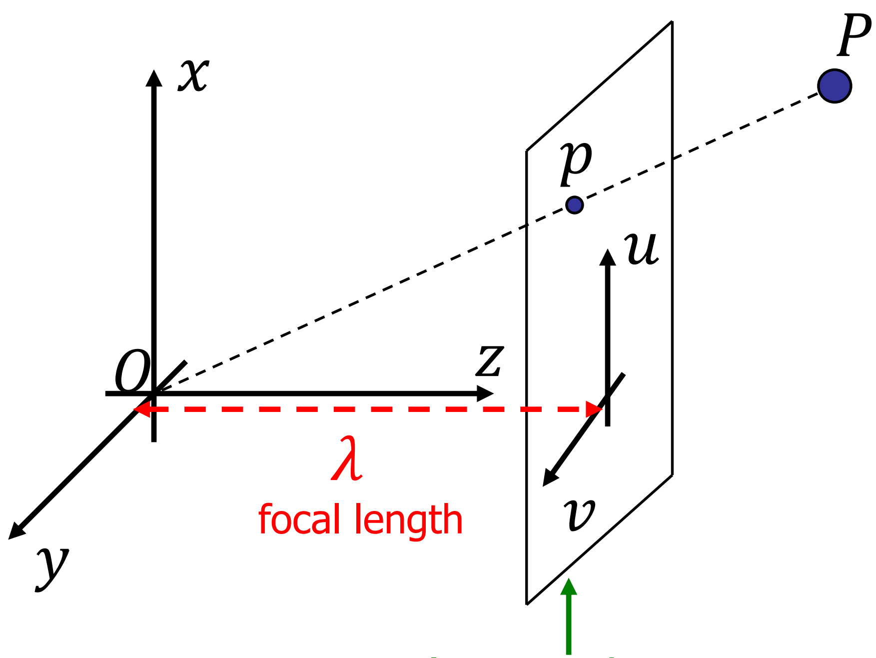


image plane with an array of light sensitive elements (actually located symmetrically to the optical center O, but this model avoids a change of signs...)

- when thin lens wideness is neglected
- all rays pass through optical center
- from the relations on similar triangles one gets the perspective equations

$$u = \lambda \, \frac{X}{Z} \qquad v = \lambda \, \frac{Y}{Z}$$

to obtain these from discrete pixel values, an offset and a scaling factor should be included in each direction

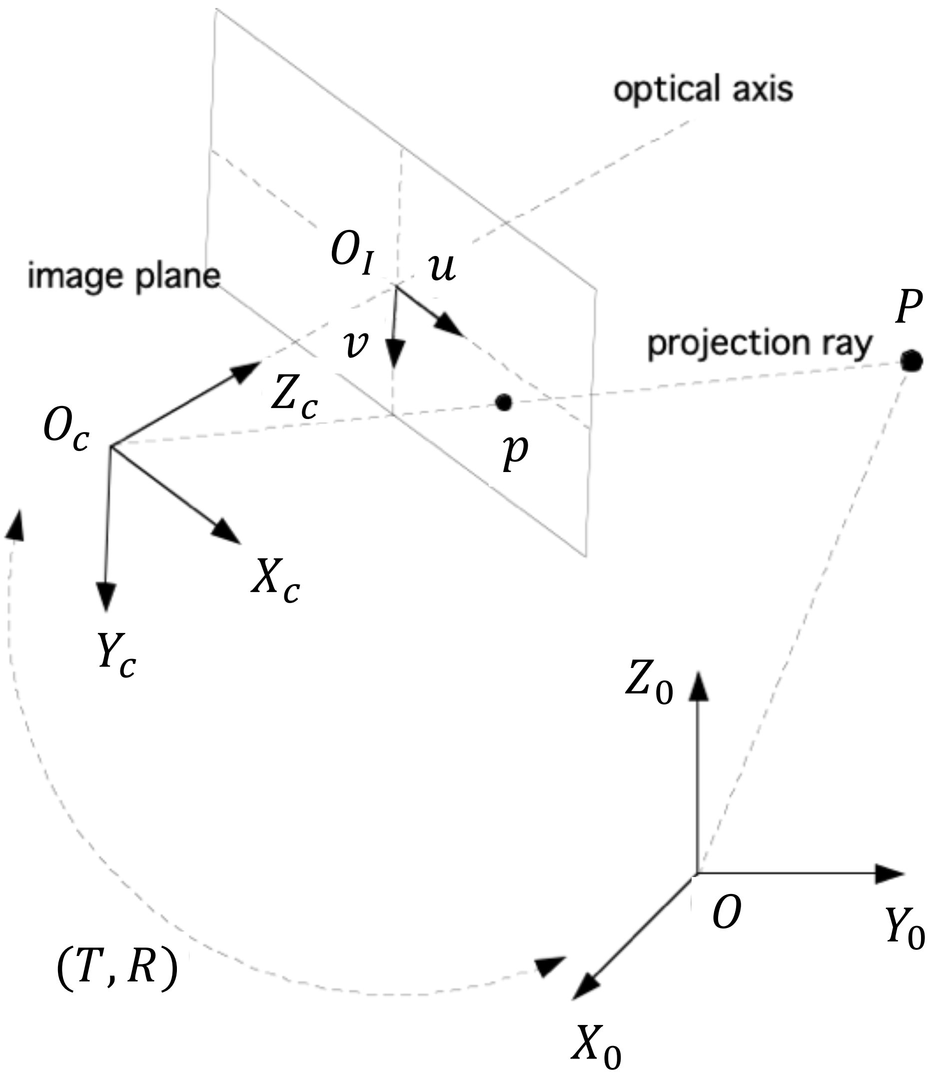
sometimes normalized values (u', v') are used (dividing by the focal length)

with

$$P = (X, Y, Z)$$ Cartesian point (in camera frame)

$$p = (u, v, \lambda)$$ representative point on the image plane

Reference frames of interest



- absolute reference frame

$$\mathcal{F}_0 : \{O, \vec{X}_0, \vec{Y}_0, \vec{Z}_0\}$$

- camera reference frame

$$\mathcal{F}_c : \{O_c, \vec{X}_c, \vec{Y}_c, \vec{Z}_c\}$$

- image plane reference frame

$$\mathcal{F}_I : \{O_I, \vec{u}, \vec{v}\}$$

- position/orientation of $\mathcal{F}_c$ w.r.t. $\mathcal{F}_0$

$$(T, R)$$

(translation, rotation)

Interaction matrix

- given a set of feature(s) parameters $f = [f_1 \quad \cdots \quad f_k]^T \in \mathbb{R}^k$
- we look for the (kinematic) differential relation between motion imposed to the camera and motion of features on the image plane

$$\dot{f} = J(\cdot) \begin{bmatrix} V \\ \Omega \end{bmatrix}$$

- $(V, \Omega) \in \mathbb{R}^6$ is the camera linear/angular velocity, a vector expressed in $\mathcal{F}_c$
- $J(\cdot)$ is a $k \times 6$ matrix, known as interaction matrix
- in the following, we consider mainly point features
  - other instances (areas, lines, …) can be treated as extensions of the presented analysis

Computing the interaction matrix
point feature, pinhole model

- from the perspective equations $u = \lambda \frac{X}{Z}$, $v = \lambda \frac{X}{Z}$, we have

$$\begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} \frac{\lambda}{Z} & 0 & -\frac{u}{Z} \\ 0 & \frac{\lambda}{Z} & -\frac{v}{Z} \end{bmatrix} \begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{Z} \end{bmatrix} = J_1(u, v, \lambda) \begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{Z} \end{bmatrix}$$

- the velocity $(\dot{X}, \dot{Y}, \dot{Z})$ of a point P in frame $\mathcal{F}_c$ is actually due to the roto-translation (V, Ω) of the camera (P is assumed fixed in $\mathcal{F}_0$)
- kinematic relation between $(\dot{X}, \dot{Y}, \dot{Z})$ and (V, Ω)

$$\begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{Z} \end{bmatrix} = -V - \Omega \times \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

Note: ALL quantities are expressed in the camera frame $\mathcal{F}_c$ without explicit indication of subscripts

Computing the interaction matrix (cont)
point feature, pinhole model

- the last equation can be expressed in matrix form

$$\begin{bmatrix}\dot X\\ \dot Y\\ \dot Z\end{bmatrix} = \begin{bmatrix}-1 & 0 & 0 & 0 & -Z & Y\\ 0 & -1 & 0 & Z & 0 & -X\\ 0 & 0 & -1 & -Y & X & 0\end{bmatrix}\begin{bmatrix}V\\ \Omega\end{bmatrix} = J_2(X,Y,Z)\begin{bmatrix}V\\ \Omega\end{bmatrix}$$

- combining things, the interaction matrix for a point feature is

$$\begin{bmatrix}\dot u\\ \dot v\end{bmatrix} = J_1 J_2 \begin{bmatrix}V\\ \Omega\end{bmatrix} = \begin{bmatrix}-\frac{\lambda}{Z} & 0 & \frac{u}{Z} & \frac{uv}{\lambda} & -\left(\lambda + \frac{u^2}{\lambda}\right) & v\\ 0 & -\frac{\lambda}{Z} & \frac{v}{Z} & \lambda + \frac{v^2}{\lambda} & -\frac{uv}{\lambda} & -u\end{bmatrix}\begin{bmatrix}V\\ \Omega\end{bmatrix}$$

$$= J_p(u,v,Z)\begin{bmatrix}V\\ \Omega\end{bmatrix}$$

p = point (feature)

here, λ is assumed to be known

Comments

- the interaction matrix in the map

$$\begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = \boxed{J_p(u, v, Z)} \begin{bmatrix} V \\ \Omega \end{bmatrix}$$

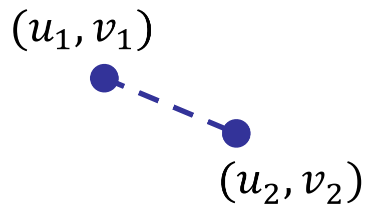
  - depends on the actual value of the feature and on its depth Z
  - since $\dim \ker J_p = 4$, there exist ∞^4 motions of the camera that are unobservable (for this feature) on the image
    - for instance, a translation along the projection ray
  - when more point features are considered, the associated interaction matrices are stacked one on top of the other
    - p point features: the interaction matrix is $k \times 6$, with $k = 2p$

Other examples of interaction matrices

- distance between two point features

$$d = \sqrt{(u_1 - u_2)^2 + (v_1 - v_2)^2}$$

$$\dot{d} = \frac{1}{d}\begin{bmatrix} u_1 - u_2 & v_1 - v_2 & u_2 - u_1 & v_2 - v_1 \end{bmatrix} \begin{bmatrix} \dot{u}_1 \\ \dot{v}_1 \\ \dot{u}_2 \\ \dot{v}_2 \end{bmatrix}$$



$$= J_p(u_1, u_2, v_1, v_2) \begin{bmatrix} J_{p1}(u_1, v_1, Z_1) \\ J_{p2}(u_2, v_2, Z_2) \end{bmatrix} \begin{bmatrix} V \\ \Omega \end{bmatrix}$$

- image moments

$$m_{ij} = \iint_{\mathcal{R}(t)} x^i y^i dx\, dy$$

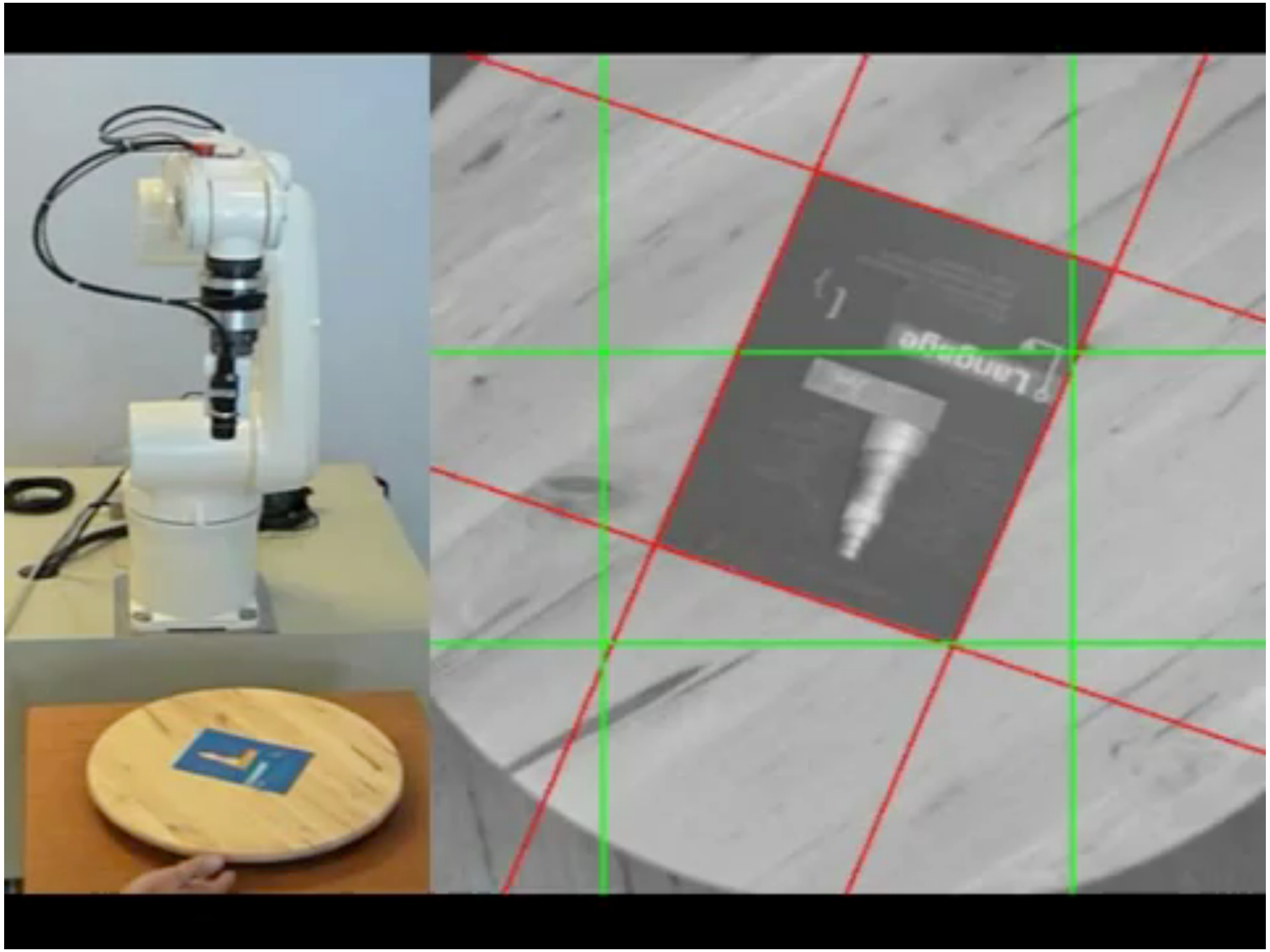
$\mathcal{R}(t)$ region of the image plane occupied by the object

  - useful for representing also qualitative geometric information (area, center, orientation of an approximating ellipse, …)
  - by using Green formulas and the interaction matrix of a generic point feature

$$\Rightarrow \quad \dot{m}_{ij} = L_{ij} \begin{bmatrix} V \\ \Omega \end{bmatrix}$$

(see F. Chaumette: "Image moments: A general and useful set of features for visual servoing", IEEE Trans. on Robotics, August 2004)

IBVS with straight lines as features



video

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Robot differential kinematics

- eye-in-hand case: camera is mounted on the end-effector of a manipulator arm (with fixed base or on a wheeled mobile base)
- the motion (V, Ω) to be imposed to the camera coincides with the desired end-effector linear/angular velocity and is realized by choosing the manipulator joint velocity (or, more in general, the feasible velocity commands of a mobile manipulator)

$$\begin{bmatrix} V \\ \Omega \end{bmatrix} = J_m(q)\dot{q} = J_m(q)u$$

velocity control input

for consistency with the previous interaction matrix, these Jacobians must be expressed in the camera frame $\mathcal{F}_c$

Geometric Jacobian of a manipulator

... or the NMM Jacobian of a mobile manipulator

with $q \in \mathbb{R}^n$ being the robot configuration variables

- in general, an hand-eye calibration is needed for this Jacobian

Image Jacobian

- combining the step involved in the passage from the velocity of point features on the image plane to the joint velocity/feasible velocity commands of the robot, we finally obtain

$$\dot{f} = J_p(f, Z) J_m(q) u = J(f, Z, q) u$$

- matrix $J(f, Z, q)$ is called the Image Jacobian and plays the same role of a classical robot Jacobian
- we can thus apply one of the many standard kinematic (or even dynamics-based) control techniques for robot motion
- the (controlled) output is given by the vector of features in the image plane (the task space!)
- the error driving the control law is defined in this task space

Kinematic control for IBVS

- defining the error vector as $e = f_d - f$, the general choice

$$u = J^{\#}\left(\dot{f}_d + ke\right) + \left(I - J^{\#}J\right)u_0$$

minimum norm solution

term in $\ker J$ does not "move" the features

will exponentially stabilize the task error to zero (up to singularities, limit joint range/field of view, features exiting the image plane, ...)

- in the redundant case, vector u_0 (projected in the image Jacobian null space) can be used for optimizing behavior/criteria
- the error feedback signal depends only on feature values
- there is still a dependence of J on the depths Z of the features
  - use the constant and "known" values at the final desired pose

$$J(f, Z^*, q)$$

  - or, estimate on line their current values using a dynamic observer

Example with NMM

- mobile base (unicycle) + 3R manipulator
- eye-in-hand configuration

- 5 commands
  - linear and angular velocity of mobile base
  - velocities of the three manipulator joints
- task specified by 2 point features $\longrightarrow$ 4 output variables

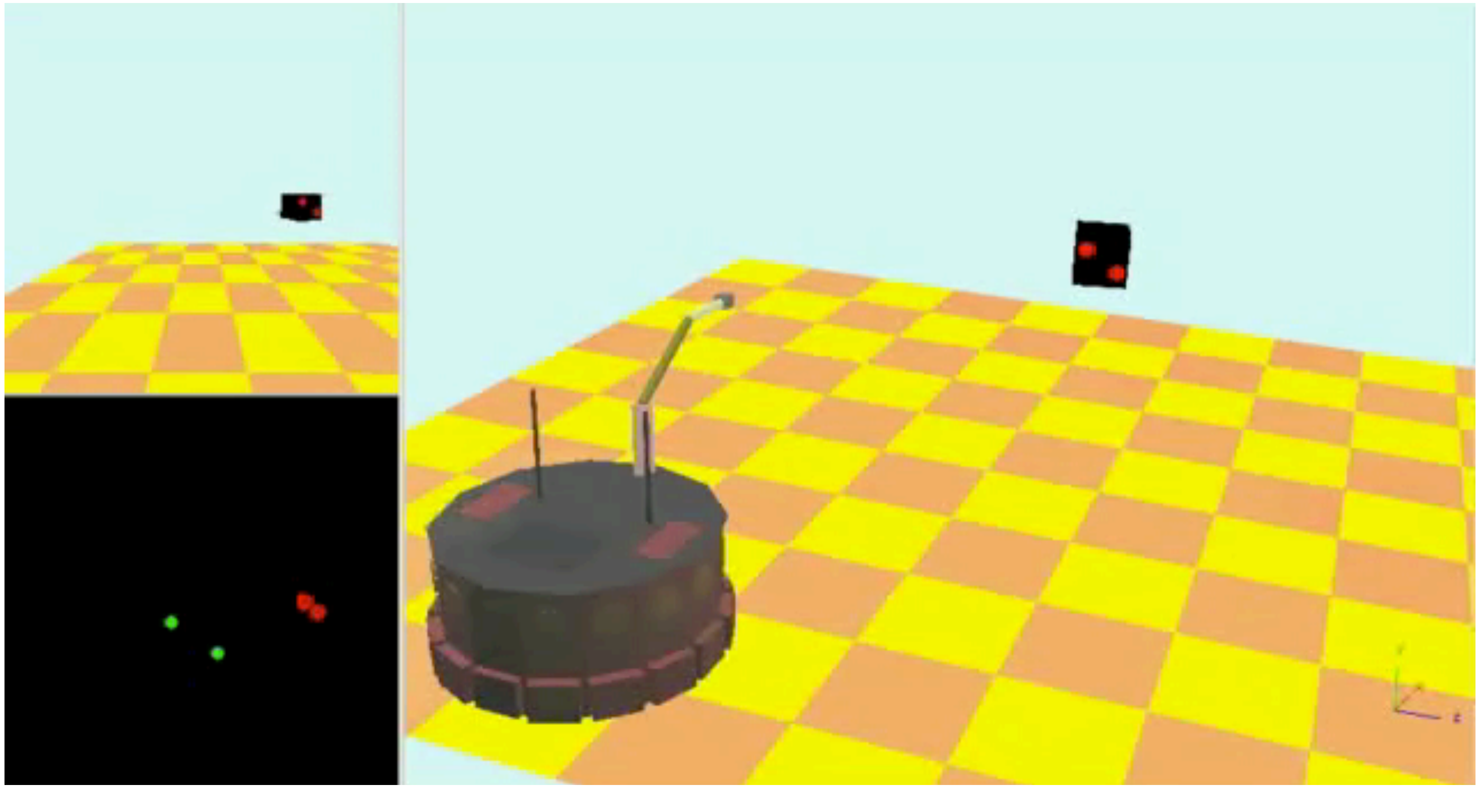
$$f = [f_{u1} \quad f_{v1} \quad f_{u2} \quad f_{v2}]^T$$

- 5 – 4 = 1 degree of redundancy (w.r.t. the task)

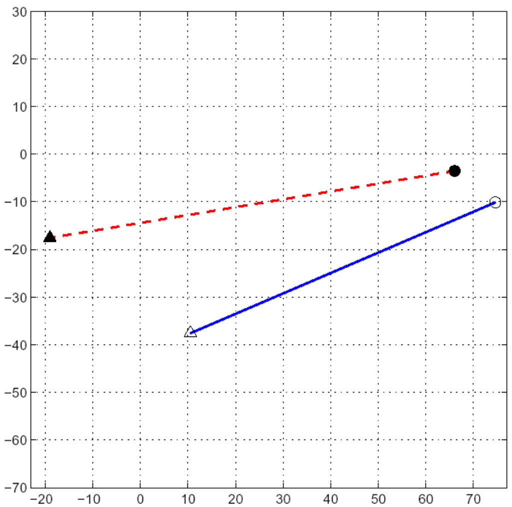
Simulation

view from camera

processed image



video



behavior of the 2 features

- simulation in Webots
- current value of Z is supposed to be known
- diagonal task gain matrix k (decoupling!)
- "linear paths" of features motion on the image plane

IBVS control with Task Sequencing

- approach: regulate only one (some) feature at the time, while keeping "fixed" the others by unobservable motions in the image plane
- Image Jacobians of single point features (e.g., $p = 2$)

$$\dot{f}_1 = J_1 u, \qquad \dot{f}_2 = J_2 u$$

- the first feature f_1 is regulated during a first phase by using

$$u = J_1^{\#} k_1 e_1 + (I - J_1^{\#} J_1) u_0$$

- feature f_2 is then regulated by a command in the null-space of the first task

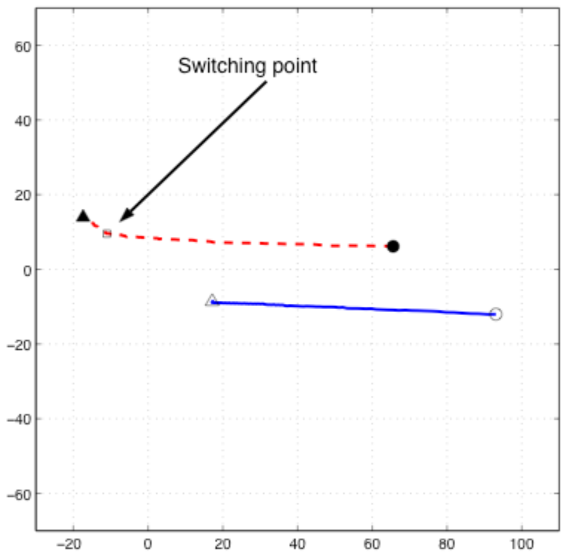
$$u = (I - J_1^{\#} J_1) J_2^T k_2 e_2$$

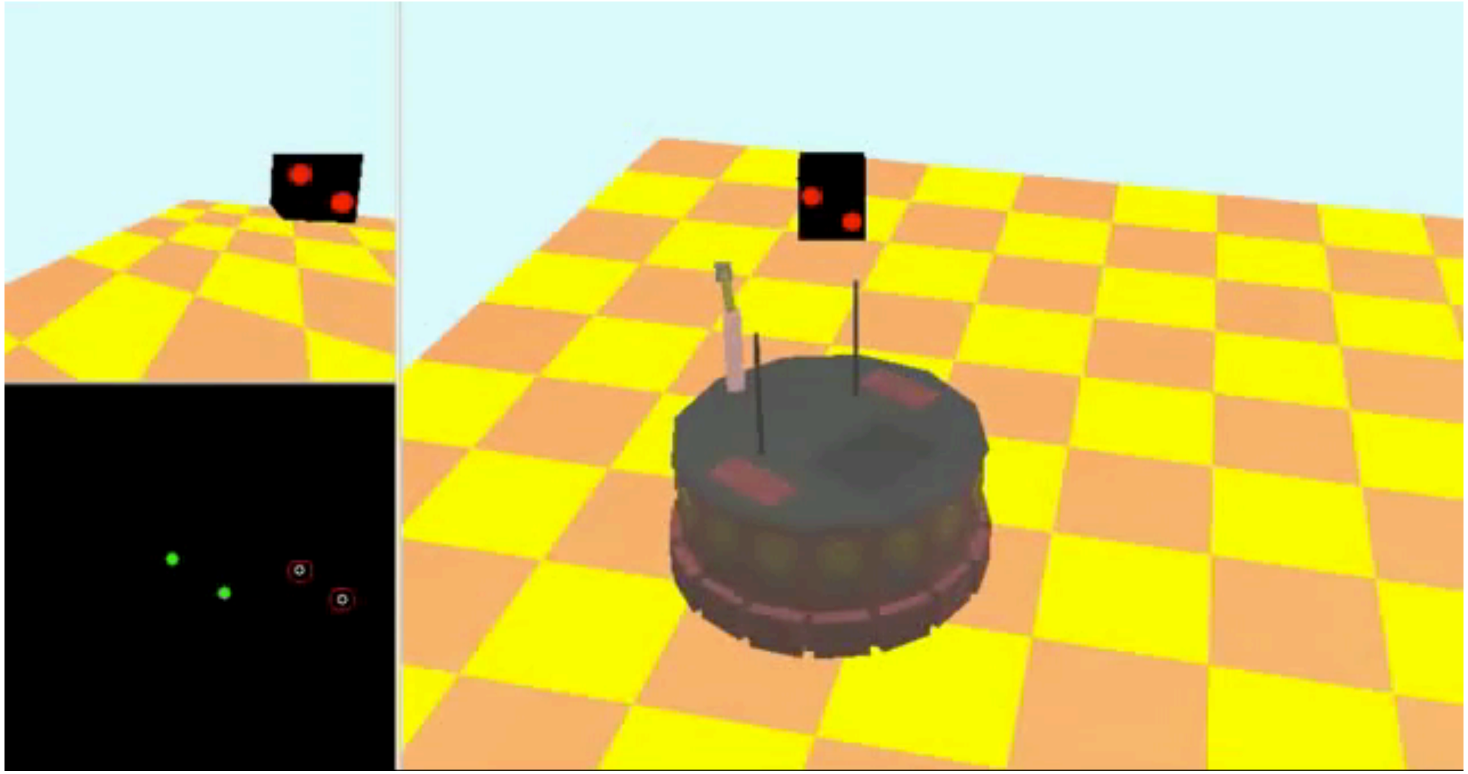
- in the first phase there are two (more) degrees of redundancy w.r.t. the "complete" case, which can be used, e.g., for improving robot alignment to the target
- if the complete case is not redundant: singularities are typically met without Task Sequencing, but possibly prevented with TS ...

Simulation with TS scheme

mobile base (unicycle) + polar 2R arm: Image Jacobian is square (4×4)

point feature 1
(regulated in
first phase)
point feature 2
(in second phase)





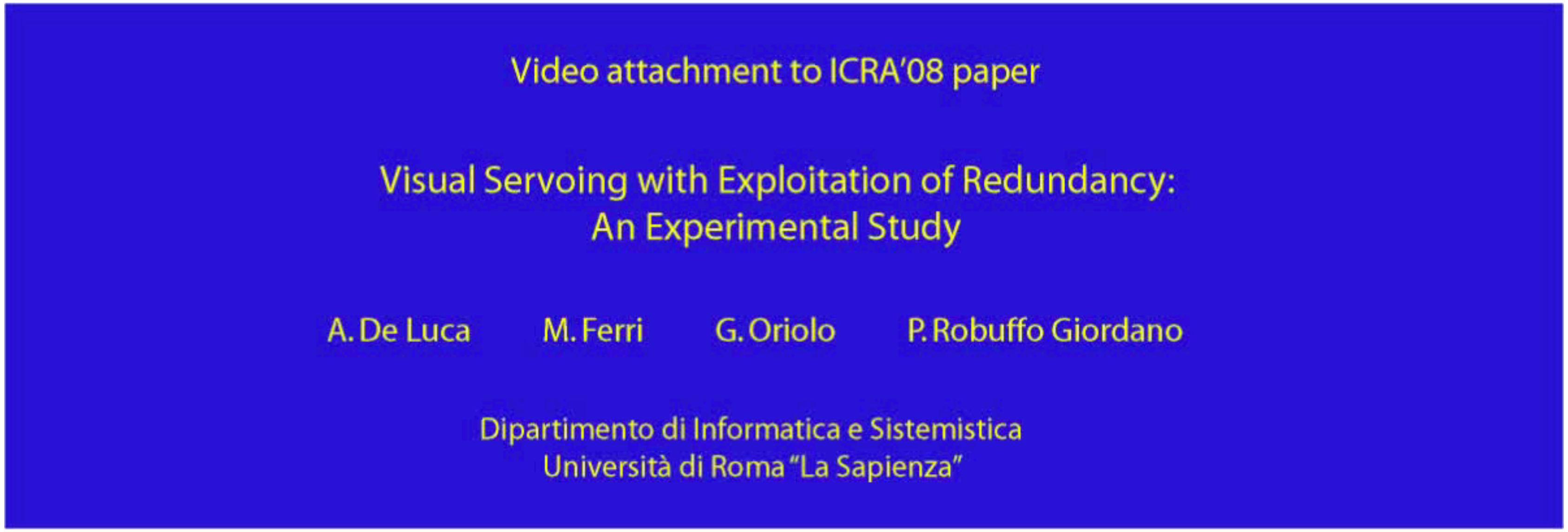
video

behavior of
the 2 features

- simulation in Webots
- current value of Z is supposed to be known

Experiments

Magellan (unicycle) + pan-tilt camera (same mobility of a polar 2R robot)



video

- comparison between Task Priority (TP) and Task Sequencing (TS) schemes
- both can handle singularities (of Image Jacobian) that are possibly encountered
- camera frame rate = 7 Hz

In many practical cases…

- the uncertainty in a number of relevant data may be large
  - focal length λ (intrinsic camera parameters)
  - hand-eye calibration (extrinsic camera parameters)
  - depth Z of point features
  - ….
- one can only compute an approximation of the Image Jacobian (both in its interaction matrix part, as well as in the robot Jacobian part)
- in the closed loop, error dynamics on features becomes

$$\dot{e} = -J\,\hat{J}^{\#}Ke$$

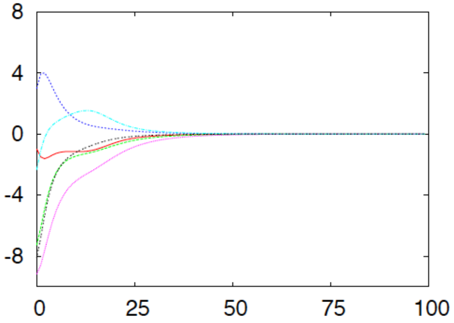
  - ideal case: $J\,J^{\#} = I$ real case: $J\,\hat{J}^{\#} \neq I$
- it is possible to show that a sufficient condition for local convergence of the error to zero is

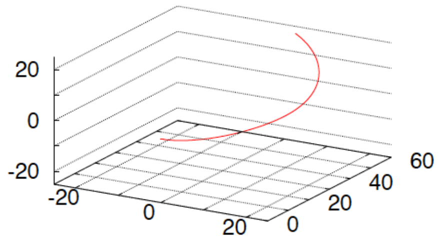
$$\boxed{J\,\hat{J}^{\#} > 0}$$

Approximate Image Jacobian

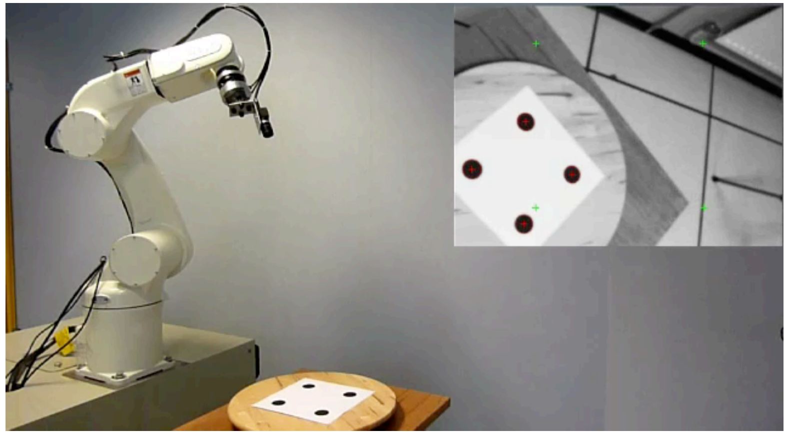
- use a constant Image Jacobian $\hat{J}(Z^*)$ that is computed at the desired target s^* (with a known, fixed depth Z^*)

$$\dot{q} = J^{\#}(Z)Ke$$



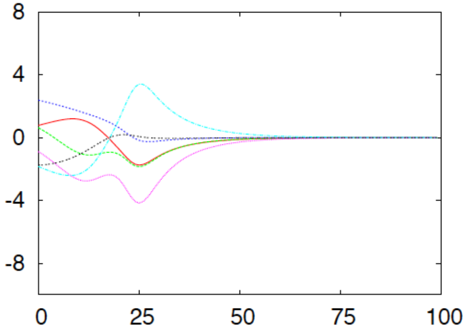


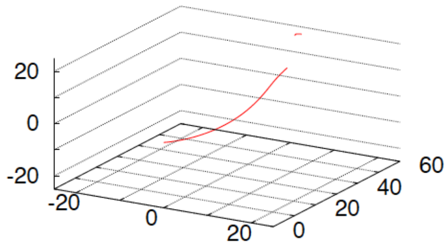
video



F. Chaumette, INRIA Rennes

$$\boxed{\dot{q} = \hat{J}^{\#}(Z^*)Ke}$$





video

An observer of the depth Z

- it is possible to estimate on line the current value (possibly time-varying) of the depth Z, for each considered point feature, using a dynamic observer
- define $x = [u \quad v \quad 1/Z]^T$, $\hat{x} = [\hat{u} \quad \hat{v} \quad 1/\hat{Z}]^T$ as current state and estimated state, and $y = [u \quad v]^T$ as measured output
- a (nonlinear) observer of x with input $u_c = [V \quad \Omega]^T$

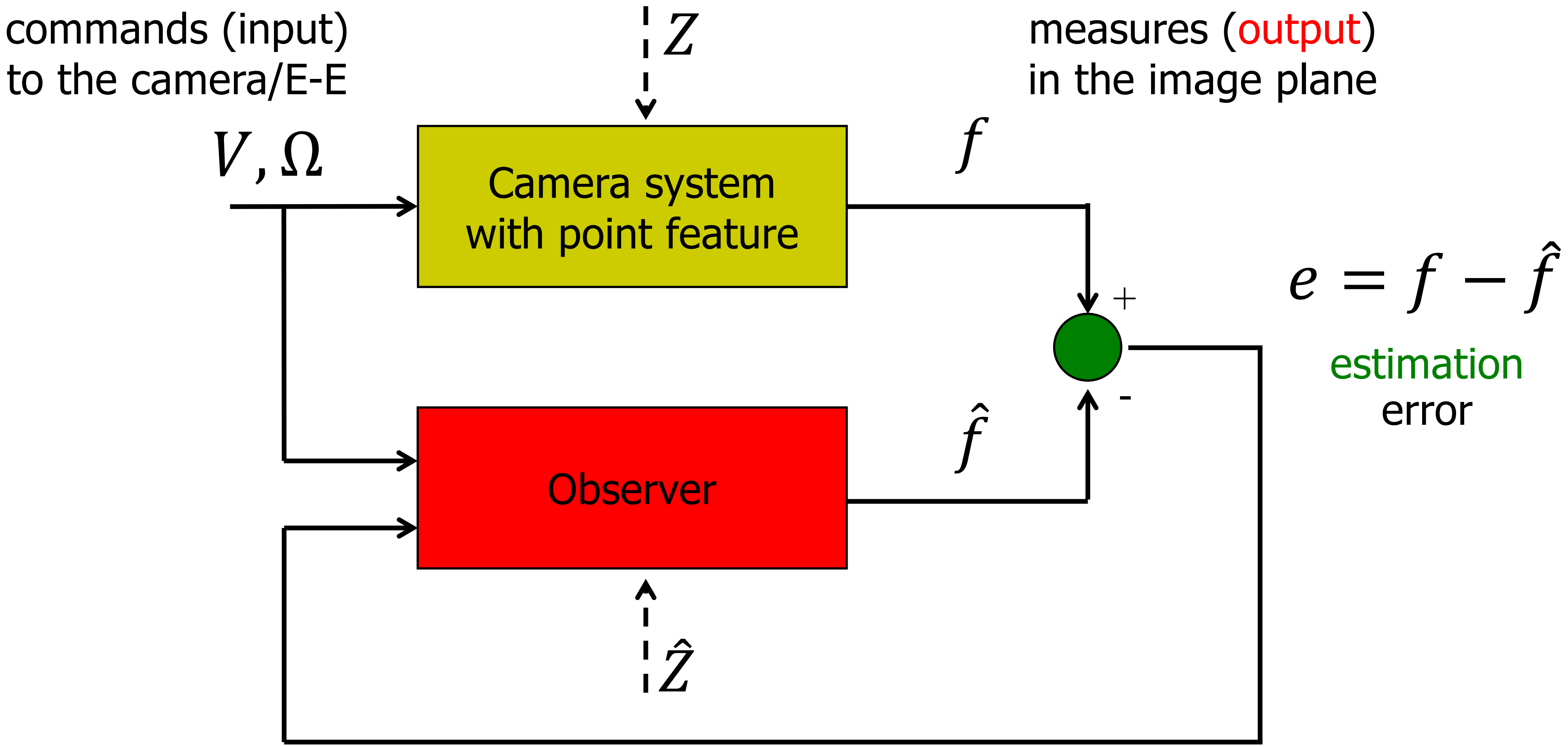
$$\dot{\hat{x}} = \alpha(\hat{x}, y)u_c + \beta(\hat{x}, y, u_c)$$

guarantees $\lim_{t\to\infty} \|x(t) - \hat{x}(t)\| = 0$ provided that

  - linear velocity of the camera is not zero
  - the linear velocity vector is not aligned with the projection ray of the considered point feature

$\Rightarrow$ these are persistent excitation conditions (~ observability conditions)

Block diagram of the observer



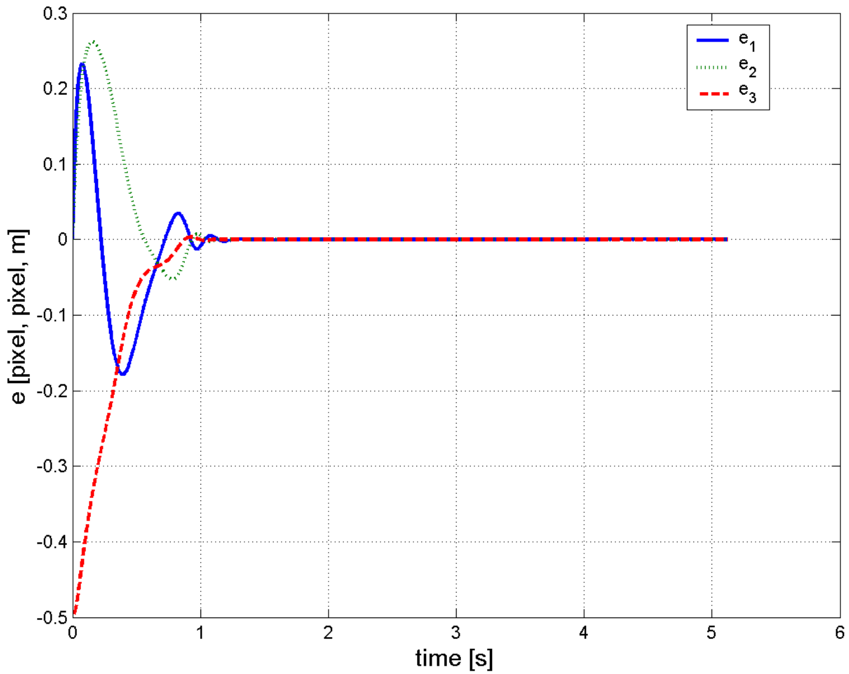
Results on the estimation of Z

real and estimated initial state

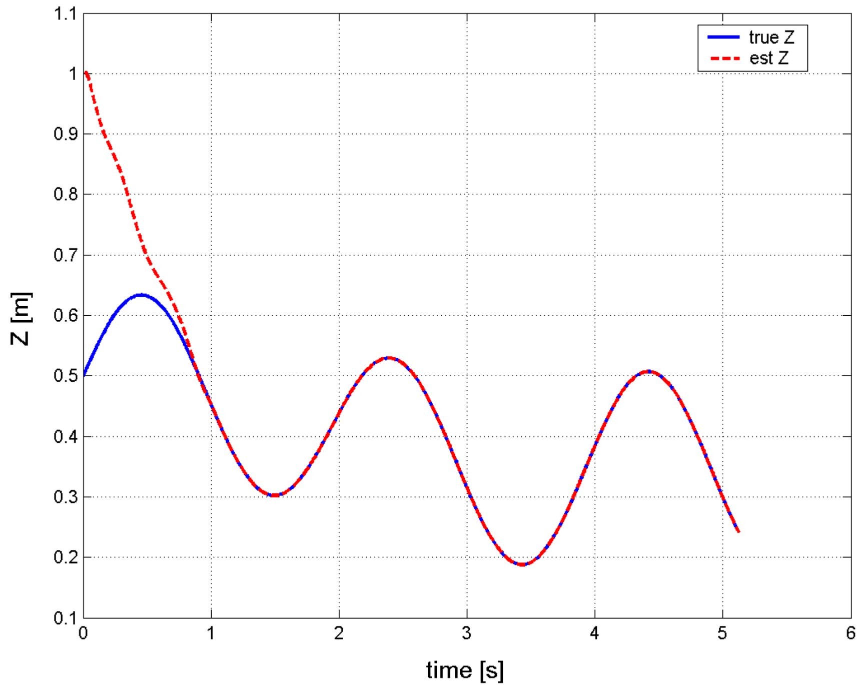
$$x(t_0) = [10 \quad -10 \quad 2]^T$$
$$\hat{x}(t_0) = [10 \quad -10 \quad 1]^T$$

$$v_x(t) = 0.1 \ \cos 2\pi t$$
$$v_z(t) = 0.5 \ \cos \pi t$$
$$\omega_x(t) = 0.6 \ \cos(\pi/2)t$$
$$\omega_z(t) = 1$$

open-loop commands

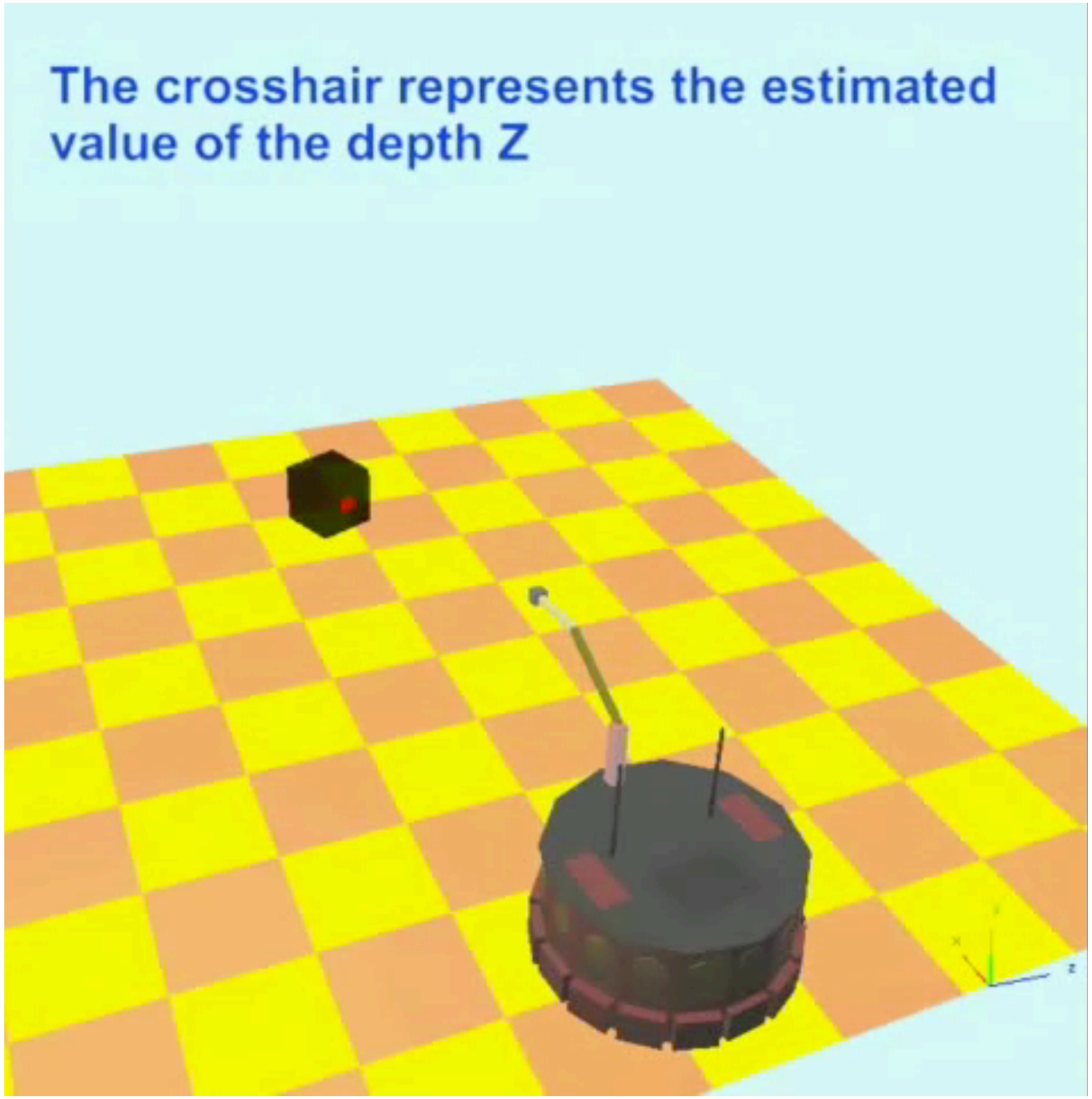


estimation errors $e(t)$



$Z(t)$ and $\hat{Z}(t)$

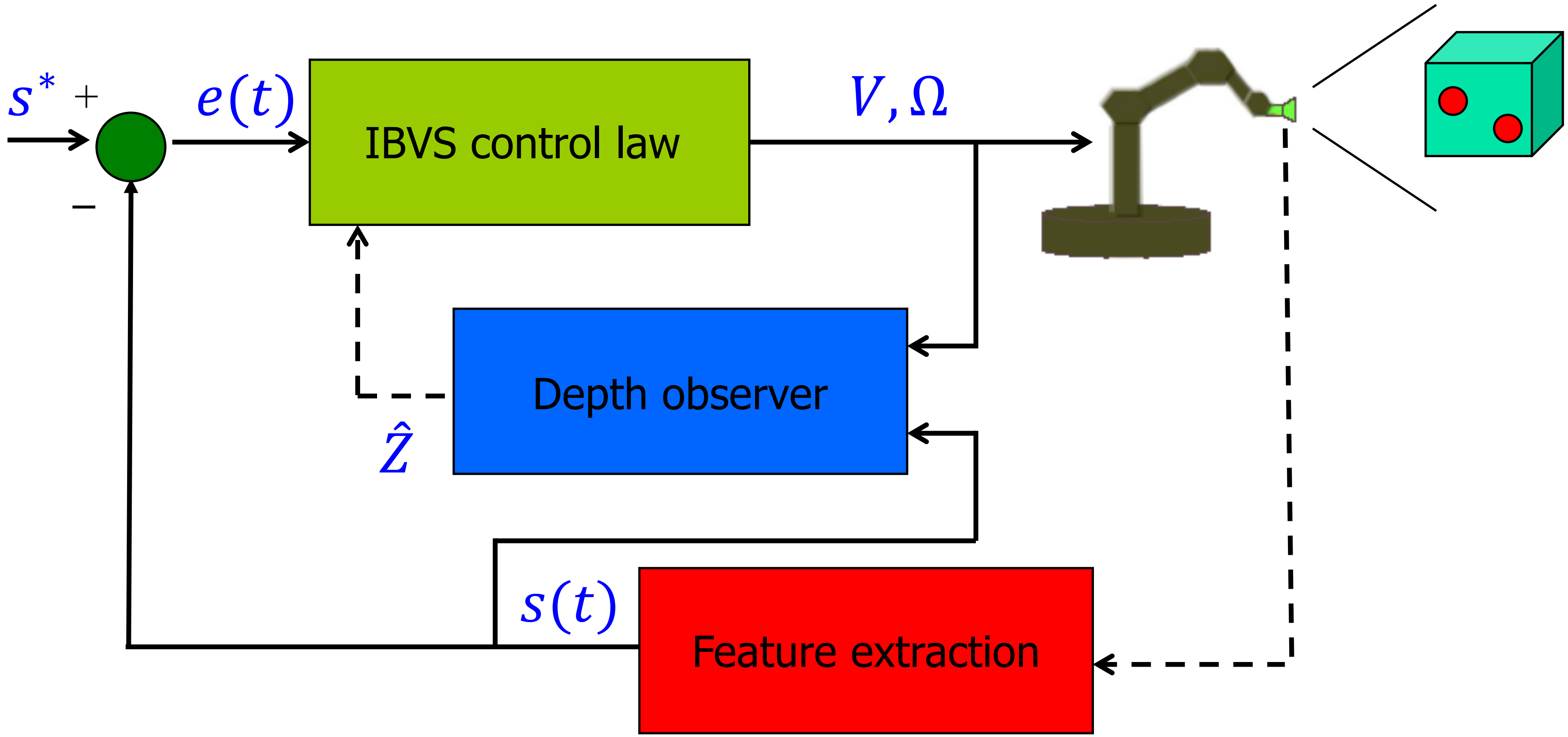
Simulation of the observer
with stepwise displacements of the target



video

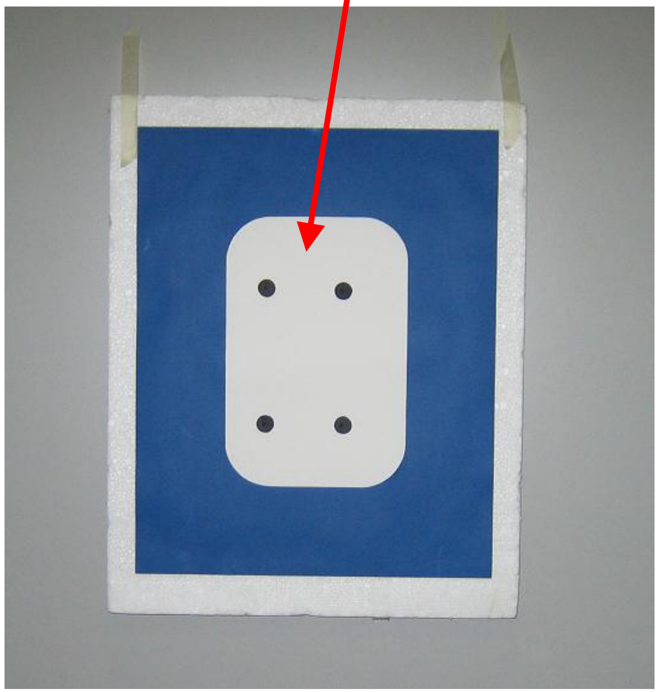
IBVS control with observer

- the depth observer can be easily integrated on line with any IBVS control scheme



Experimental set-up

- visual servoing with fixed camera on a skid-steering mobile robot
- very rough eye-robot calibration
- unknown depths of target points (estimated on line)



a "virtual" 5th feature is also used
as the average of the four point features

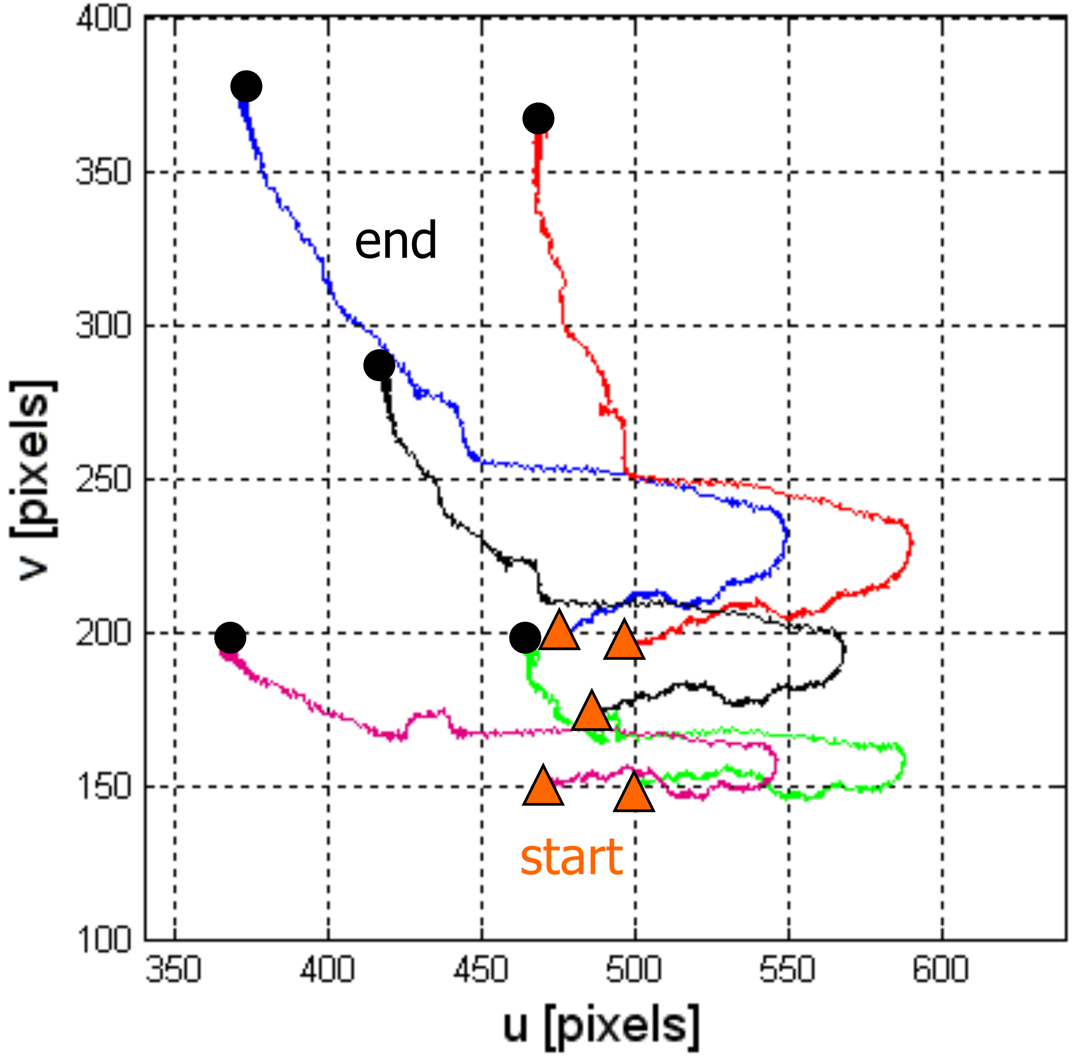
Experiments

- motion of features on the image plane is not perfect...
- the visual regulation task is however correctly realized

external view | camera view

video (c/o Università di Siena)

Evolution of features



- motion of the 5 features (including the average point) in the image plane
- toward end, motion is ≈ linear since the depth observers have already converged to the true values
- computed Image Jacobian is close to the actual one

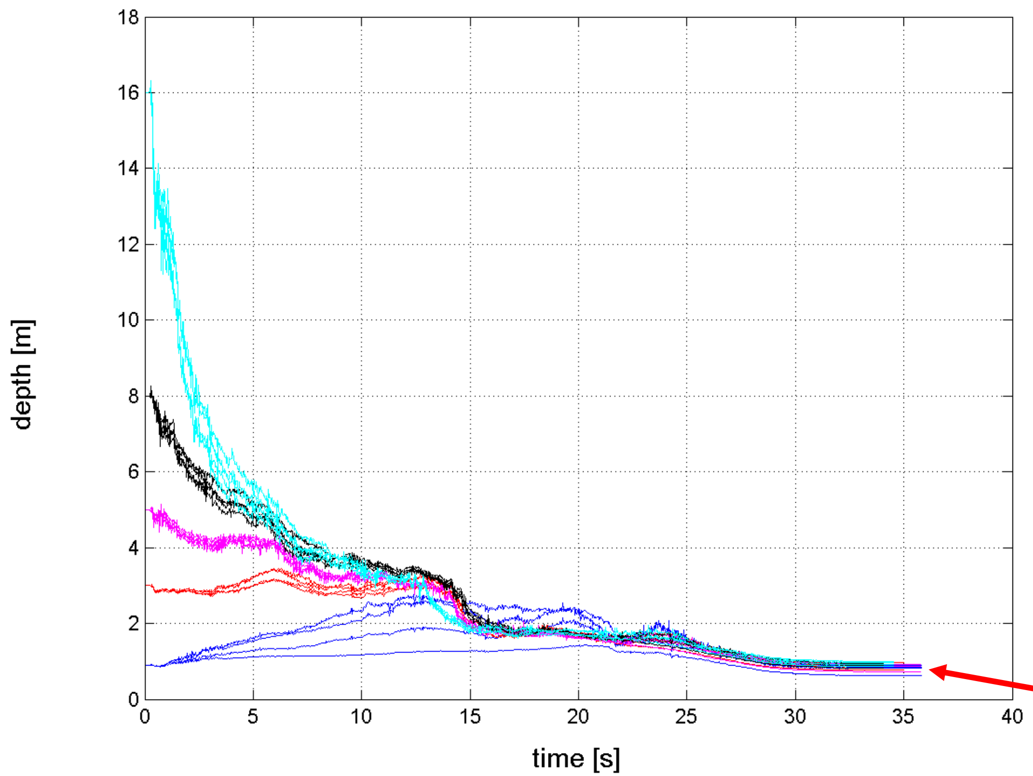
$$\hat{Z} \longrightarrow Z \quad \Longrightarrow \quad \hat{J} \longrightarrow J$$

- "true" initial and final depths

$$Z(t_0) \cong 4 \text{ m} \quad Z_d \cong 0.9 \text{ m}$$

Experiments with the observer

- the same task was executed with five different initializations for the depth observers, ranging between 0.9 m (= true depth in the final desired pose) and 16 m (much larger than in the true initial pose)



the evolutions of the estimated depths for the 4 point features

- initial values of depth estimates in the five tests

$$\begin{cases} \hat{Z}_1(t_0) = 16 \text{ m} \\ \hat{Z}_2(t_0) = 8 \text{ m} \\ \hat{Z}_3(t_0) = 5 \text{ m} \\ \hat{Z}_4(t_0) = 3 \text{ m} \\ \hat{Z}_5(t_0) = 0.9 \text{ m} \end{cases}$$

- true depths in initial pose

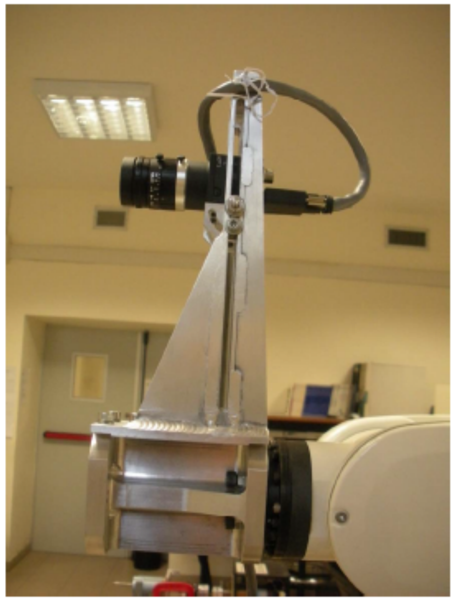
$$Z(t_0) \cong 4 \text{ m}$$

- true depths in final pose

$$Z_d \cong 0.9 \text{ m}$$

Visual servoing with Kuka robot
set-up

- Kuka KR5 sixx R650 manipulator (6 revolute joints, spherical wrist)
- Point Grey Flea©2 CCD camera, eye-in-hand (mounted on a support)
- Kuka KR C2sr low-level controller (RTAI Linux and Sensor Interface)
- image processing and visual servoing on PC (Intel Core2 @2.66GHz)
- high-level control data exchange every 12ms (via UDP protocol)



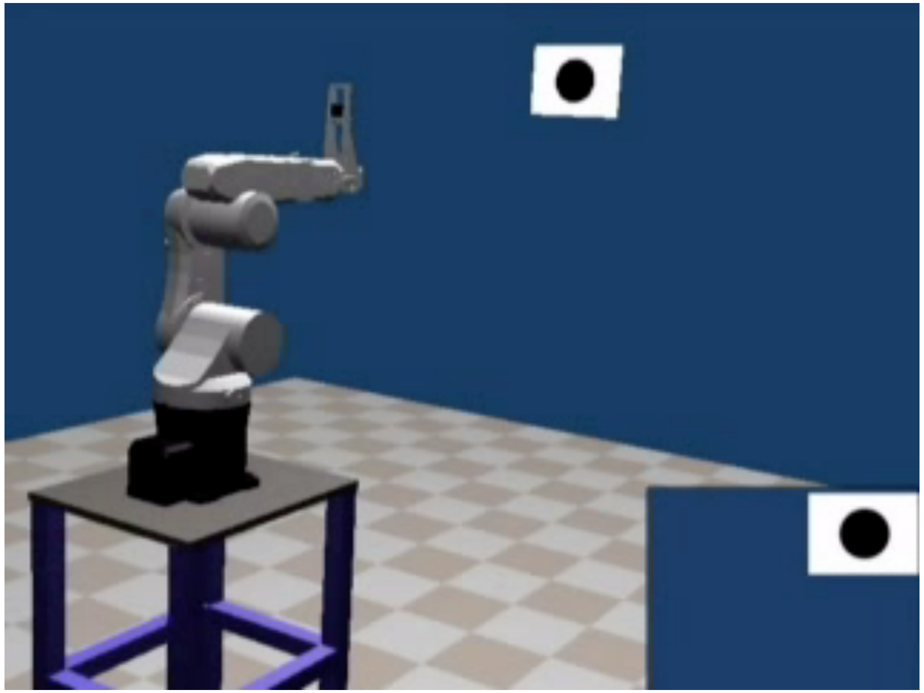
@ DIAG Robotics Laboratory

Visual servoing with Kuka robot

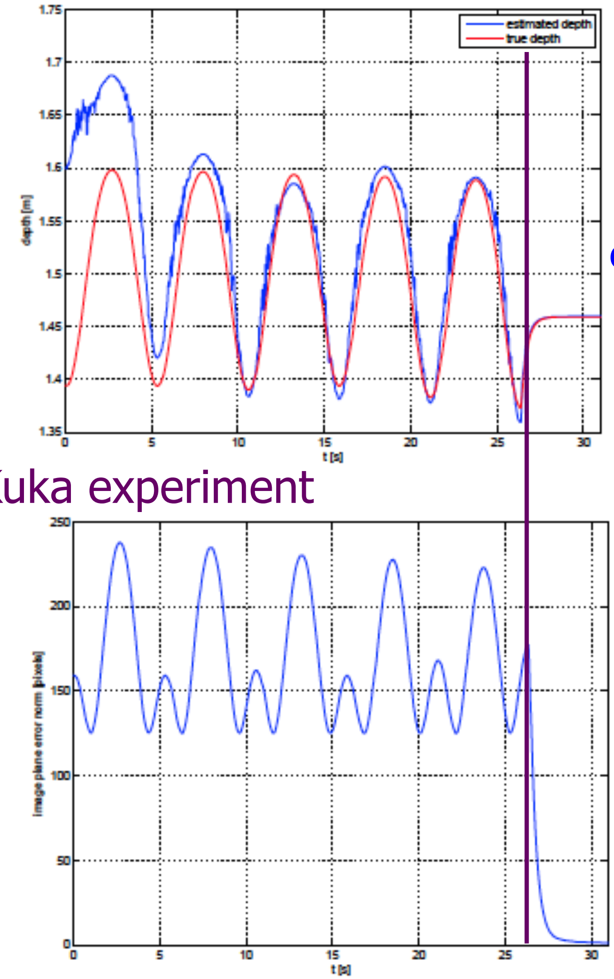
simulation and experiment with the observer

- depth estimation for a fixed target (single point feature)
- simulation using Webots first, then experimental validation
- sinusoidal motion of four robot joints so as to provide sufficient excitation

video



Webots simulation



true and estimated depth

Kuka experiment

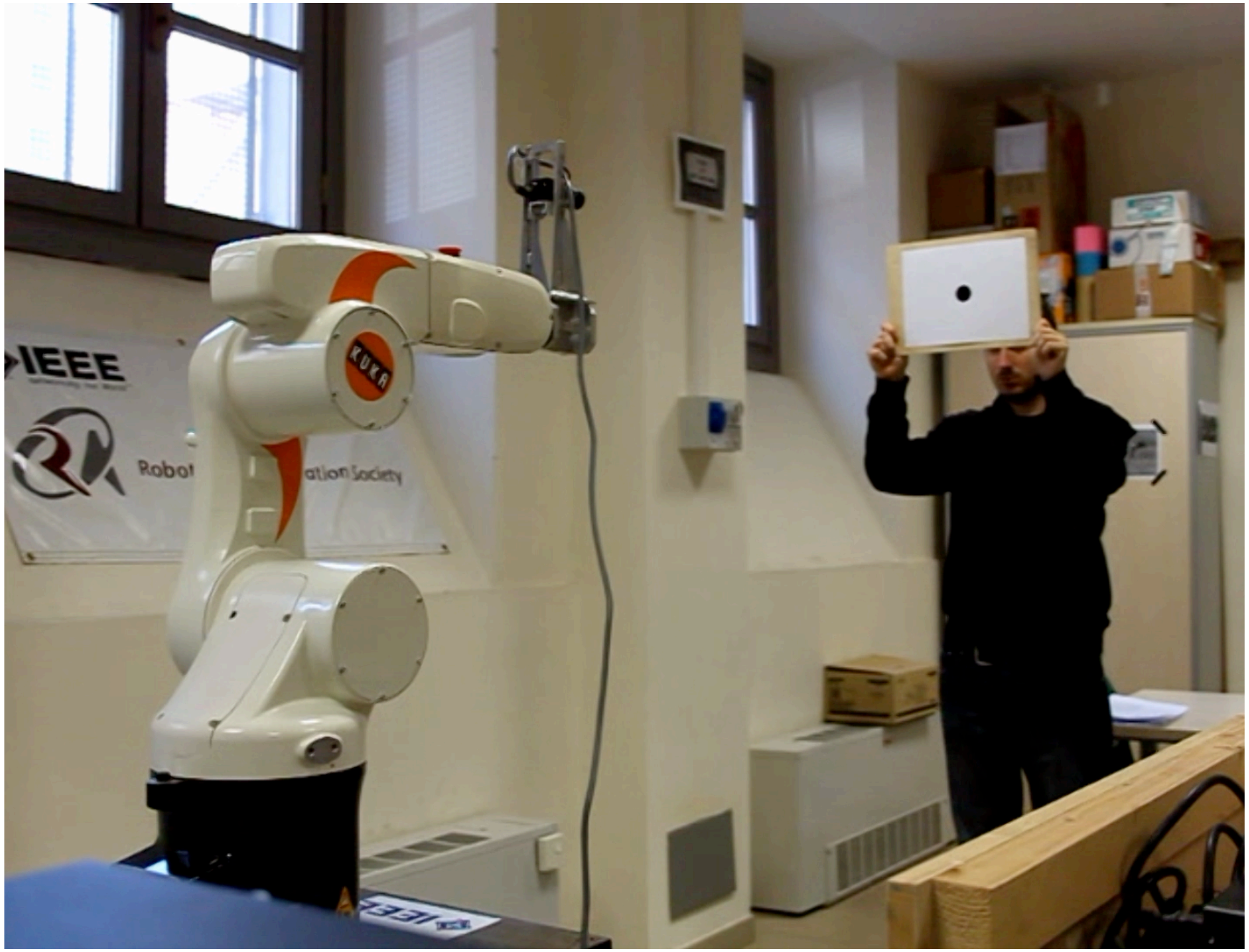
norm of centering error of feature point [in pixels]

goes to zero once control is activated

Visual servoing with Kuka robot

tracking experiment

- tracking a (slowly) time-varying target by visual servoing, including the depth observer (after convergence)



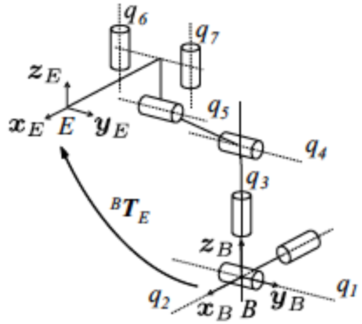
video

Gazing with humanoid head

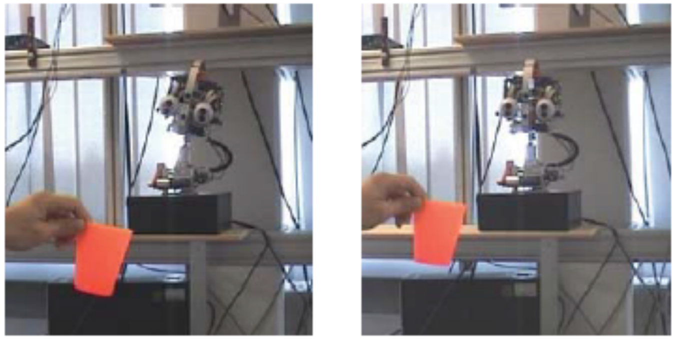
stereo vision experiment

- gazing with a robotized head (7 joints, with $n = 6$ independently controlled) at a moving target (visual task dimension $m = 2$), using redundancy (to keep a better posture and avoid joint limits) and a predictive feedforward

video (c/o Fraunhofer IOSB, Karlsruhe)



$$\dot{q} = J_W^{\dagger}(q)\left(\dot{\theta}_{\text{fb}} + \dot{\theta}_{\text{ff}}\right) - k_0\left(I - J_W^{\dagger}(q)J(q)\right)\nabla_q H_0(q)$$



final head posture
without and with self-motions