3rd SUMMER EUROPEAN UNIVERSITY

Surgical robotics – Montpellier, September 2007

VISUAL SERVOING
with applications in medical robotics

Florent Nageotte, Michel de Mathelin

Louis Pasteur University – Strasbourg

LSIIT – Control, Vision & Robotics Research Group

UMR CNRS 7005

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction
- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

LSiiT

Overview

- **Part I : Fundamentals of visual servoing**
  - **Background and definitions**
  - **Servoing architectures and classification**
  - **Position-based visual servoing**
  - **Image-based visual servoing**
  - **Visual servoing without feature extraction**
- **Part II : Medical robotics applications**
  - **Laparoscopic surgery**
  - **Internal organ motion tracking**

Visual servoing principle

- Control the end-effector of a robot using a vision sensor (2D sensor).

E.g : position the effector of a robot w.r.t. an object

- Similar to registration but the velocity of the robot is generally continuously updated

- Minimize a task function dependent of the error between the current pose of the robot and the reference pose

- Creates a virtual link between robot and object

- ⇒ Image processing, computer vision and control issues

LSiiT

A. Coordinates and pose

- **Coordinates of point P with respect to coordinate frame i :**

$$ {}^{i}P $$

- **Position and orientation of frame i with respect to frame j :**

$$ \textbf{Pose} = {}^{j}p_i = \begin{bmatrix} T_x \\ T_y \\ T_z \\ \alpha \\ \beta \\ \gamma \end{bmatrix} $$

T_x, T_y, T_z: translation vector = ${}^{j}T_i$ — *origin of frame* i *w.r. to frame* j

α, β, γ: rotation angles $\Rightarrow$ ${}^{j}R_i$ — *rotation matrix*

B. Coordinate transformations

- Coordinates of point ${}^{i}P$ with respect to coordinate frame j :

$$ {}^{j}P = {}^{j}T_{i} + {}^{j}R_{i}\,{}^{i}P $$

- Coordinates of vector ${}^{i}V$ with respect to frame j :

$$ {}^{j}V = {}^{j}R_{i}\,{}^{i}V $$

- Homogeneous transformation from frame i to frame j :

$$ {}^{j}H_{i} = \begin{bmatrix} {}^{j}R_{i} & {}^{j}T_{i} \\ 0 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} {}^{j}P \\ 1 \end{bmatrix} = {}^{j}H_{i} \begin{bmatrix} {}^{i}P \\ 1 \end{bmatrix} \qquad \begin{bmatrix} {}^{j}V \\ 0 \end{bmatrix} = {}^{j}H_{i} \begin{bmatrix} {}^{i}V \\ 0 \end{bmatrix} $$

$$ {}^{j}H_{i} = {}^{j}H_{k}\,{}^{k}H_{i} $$

C. Velocity of a rigid object

- **Velocity screw of frame *i* with respect to frame *j* in frame *j* coordinates:**

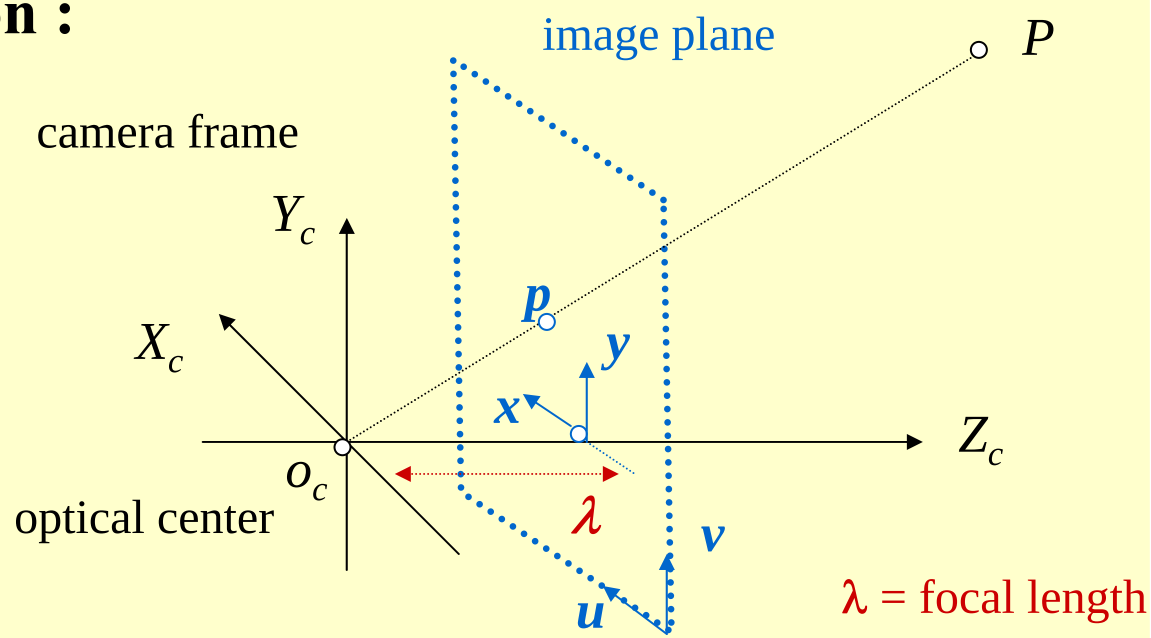
$$ {}^{j}\left({}^{j}\dot{r}_{i}\right) = \begin{bmatrix} v_x \\ v_y \\ v_z \\ \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \begin{matrix} \left.\begin{matrix} \\ \\ \\ \end{matrix}\right\} \text{translational velocity} = {}^{j}\left({}^{j}V_{i}\right) \\ \left.\begin{matrix} \\ \\ \\ \end{matrix}\right\} \text{rotational velocity} = {}^{j}\left({}^{j}\Omega_{i}\right) \end{matrix} $$

- **Velocity of point *P* rigidly attached to frame *i* with respect to frame *j* expressed in frame *j* coordinates :**

$$ {}^{j}\dot{P} = {}^{j}\left({}^{j}\Omega_{i}\right) \times {}^{j}P + {}^{j}\left({}^{j}V_{i}\right) = {}^{j}\left({}^{j}\Omega_{i}\right) \times \left({}^{j}R_{i}\,{}^{i}P + {}^{j}T_{i}\right) + {}^{j}\left({}^{j}V_{i}\right) $$

D. Camera projection model

Perspective projection :



^{c}P = **coordinates of point** P **with respect to the camera frame** c

$$ {}^{c}P = \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ y \end{bmatrix} = \lambda \begin{bmatrix} \dfrac{x_c}{z_c} \\ \dfrac{y_c}{z_c} \end{bmatrix} \Rightarrow \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} u_0 + \lambda\, k_u \dfrac{x_c}{z_c} \\ v_0 + \lambda\, k_v \dfrac{y_c}{z_c} \end{bmatrix} $$

pixels

D. Camera projection model

$$z_c \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \lambda k_u & 0 & u_0 \\ 0 & \lambda k_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = K \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix}$$

- Intrinsic camera parameters obtained by calibration

- Mathematical model of a perfect optical system / physical phenomenon (distorsions, etc.)

- Numerical sensor : aliasing, dynamical behaviour (limited bandwidth)

- Other models apply for other types of « visual » sensors, e.g., C-arm, CT-scan, ultrasound probe, …

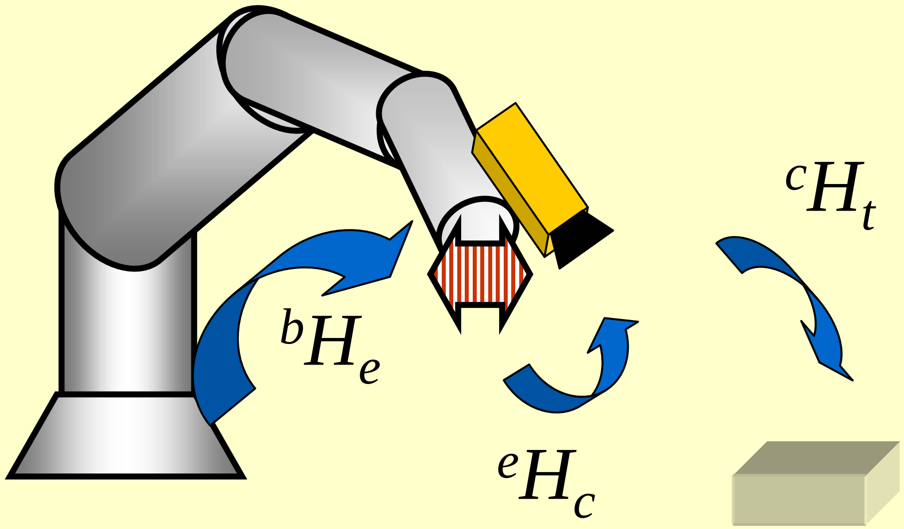
LSiiT

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction
- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

LSiiT

A. Eye-in-hand configuration

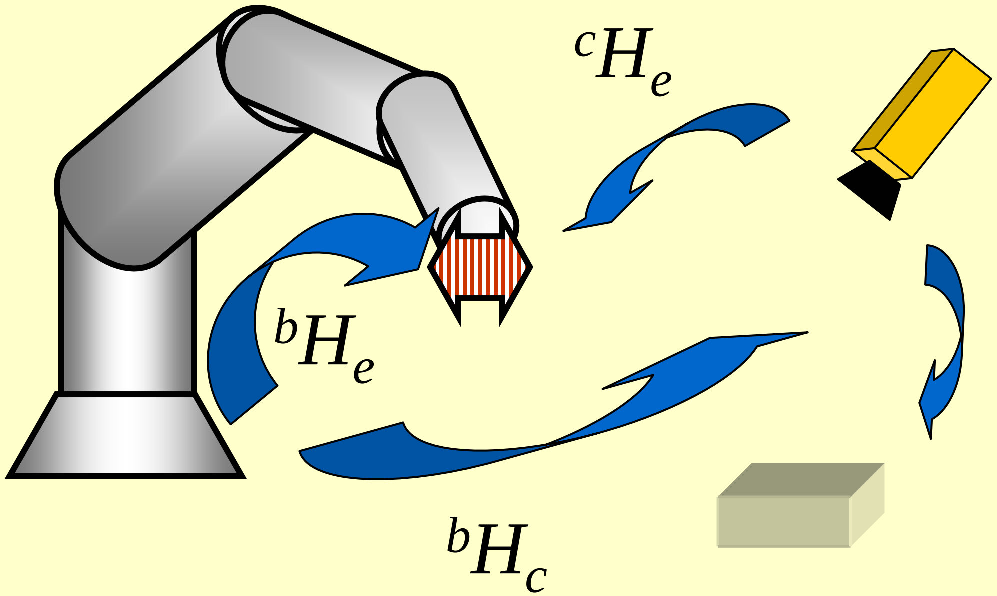


$^{e}H_{c}$ must be known (calibration) or the reference position must be learned (showing)

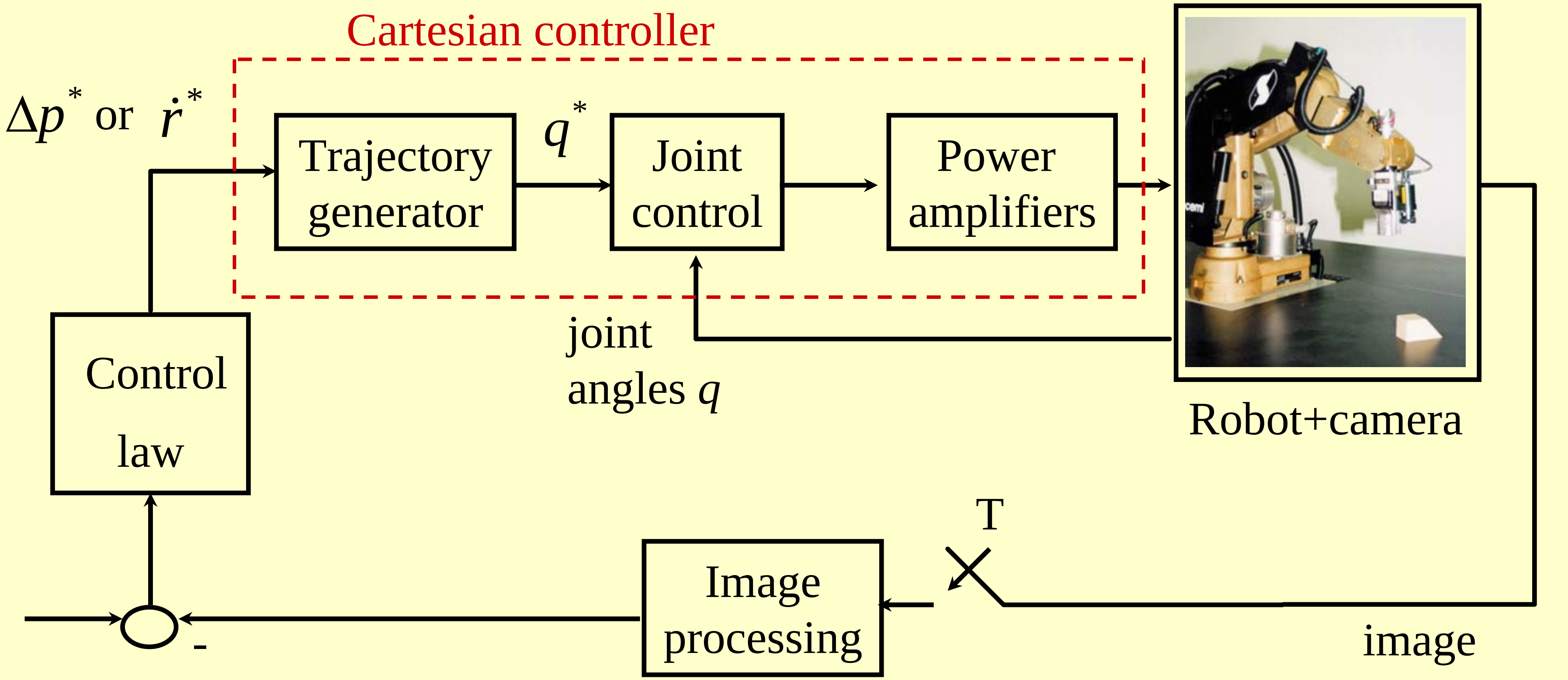
B. External camera configuration

${}^cH_e$ must be measured or

${}^bH_c$ must be known

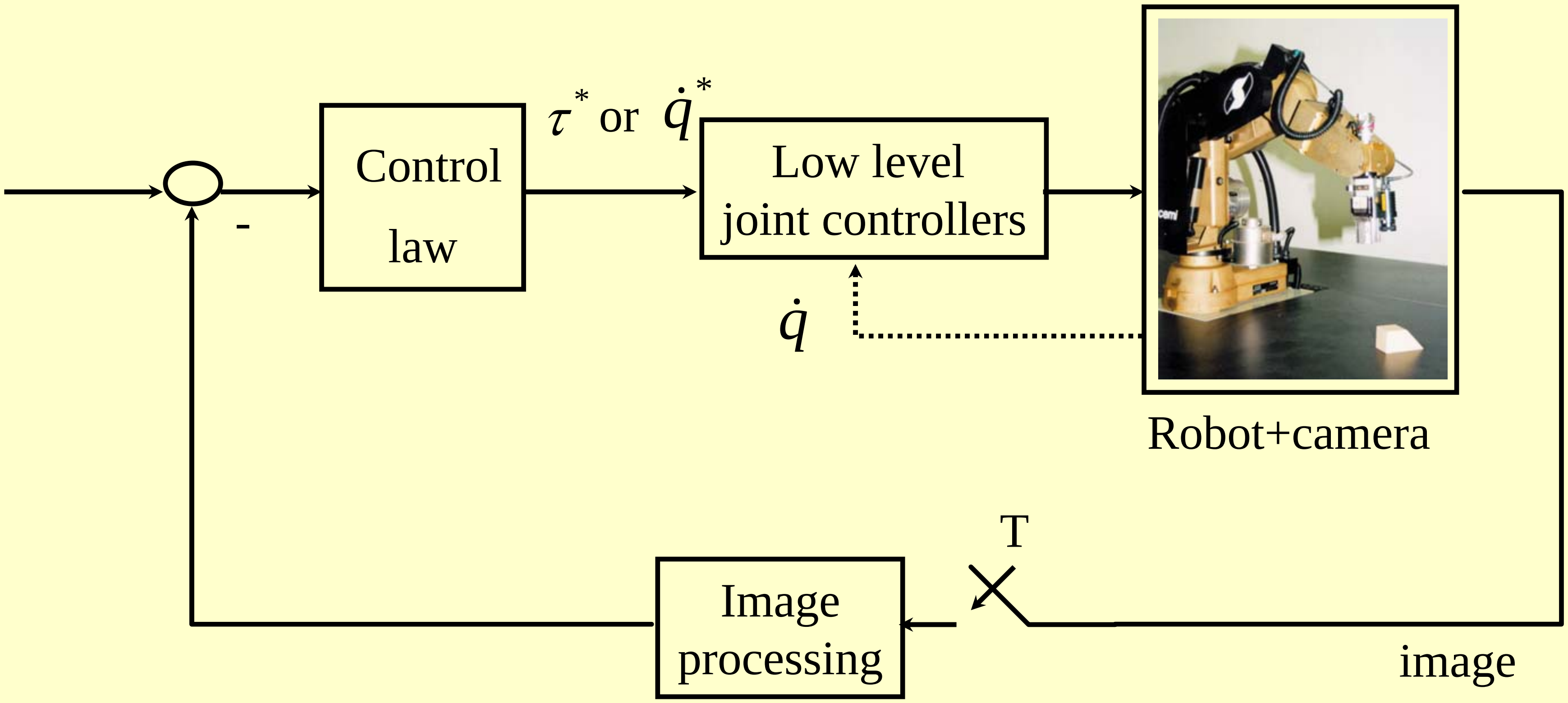


A. Indirect visual servoing



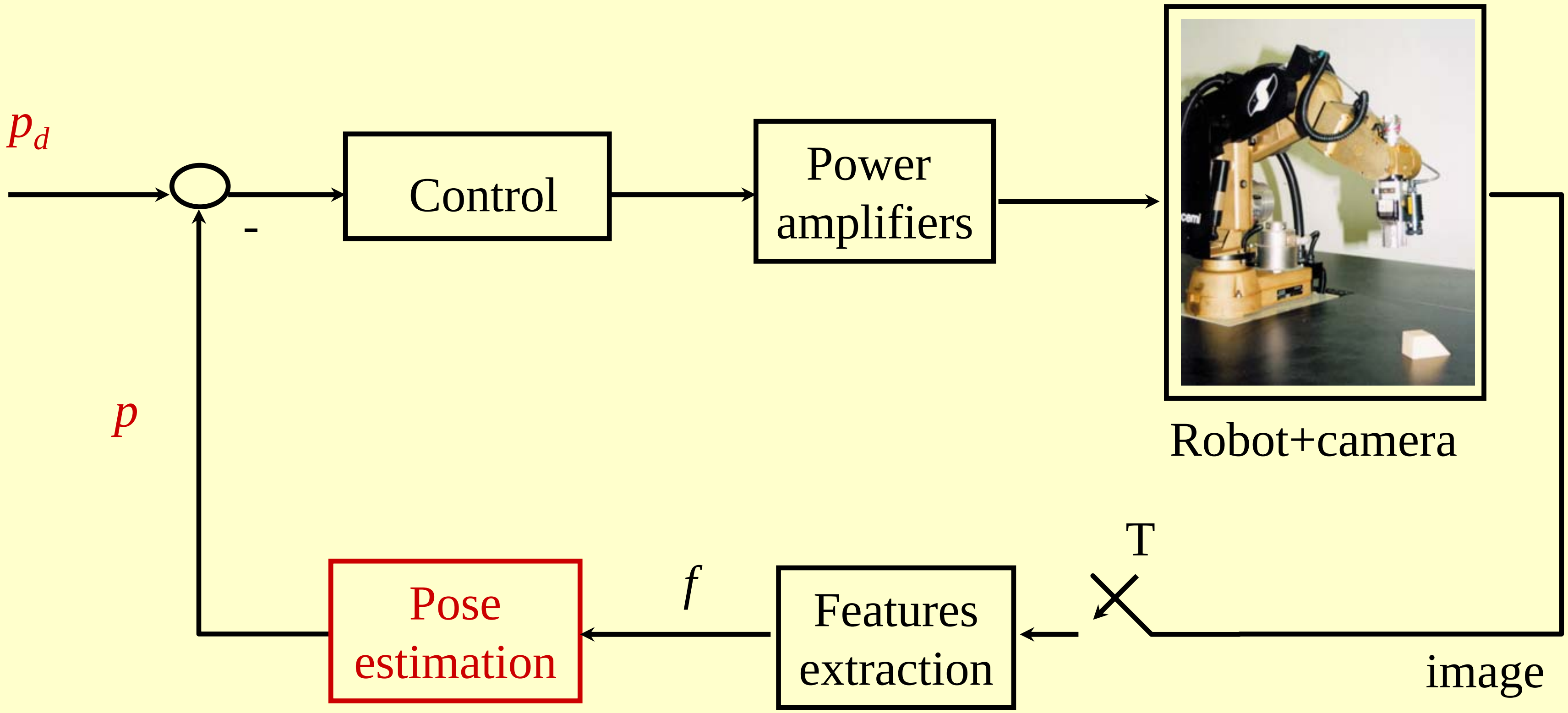
- Suitable for slow visual servoing ($T^{-1} < 50$ Hz)
- Control law is easier to design

B. Direct visual servoing



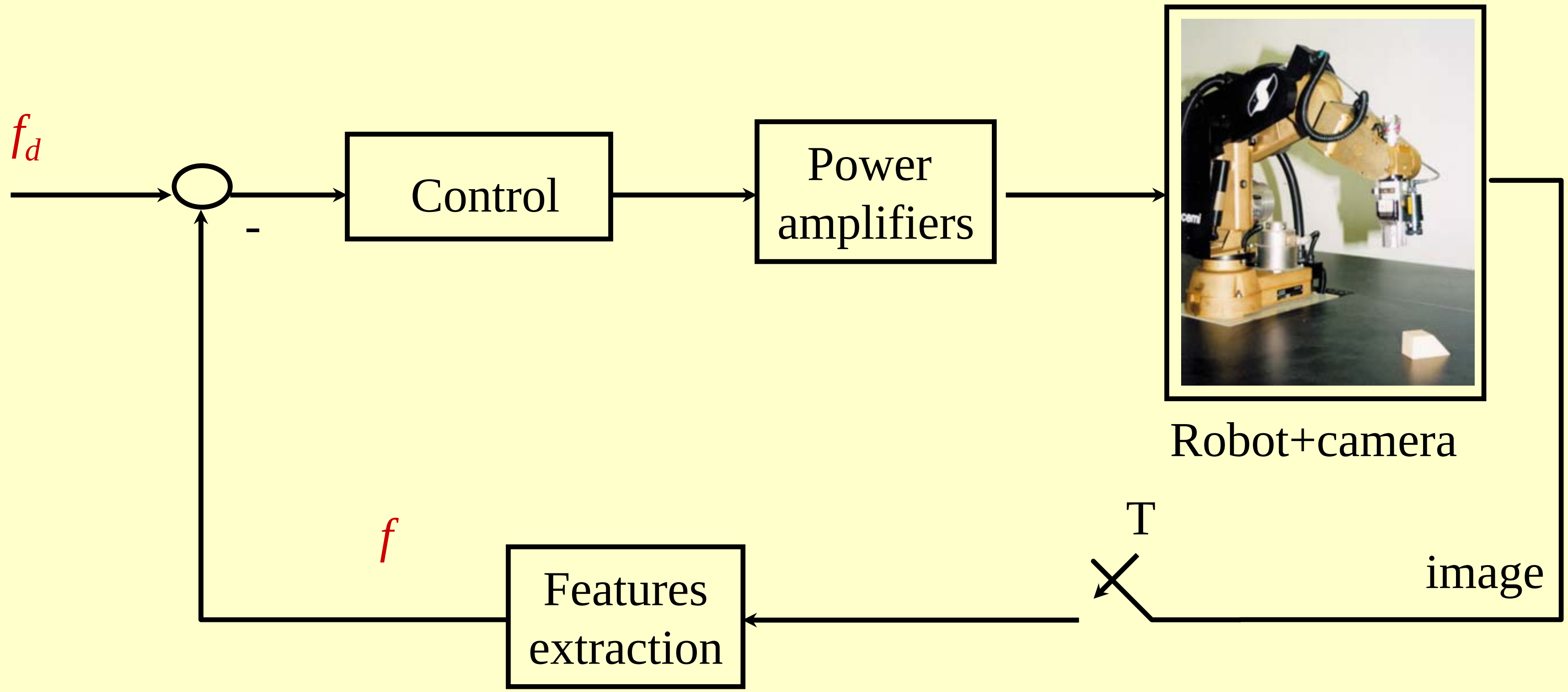
•Suitable for fast visual servoing (T^{-1} >= 50 Hz)
•Control law design is more complex (robot dynamics must be taken into account)

A. Position-based visual servoing (3D visual servoing)



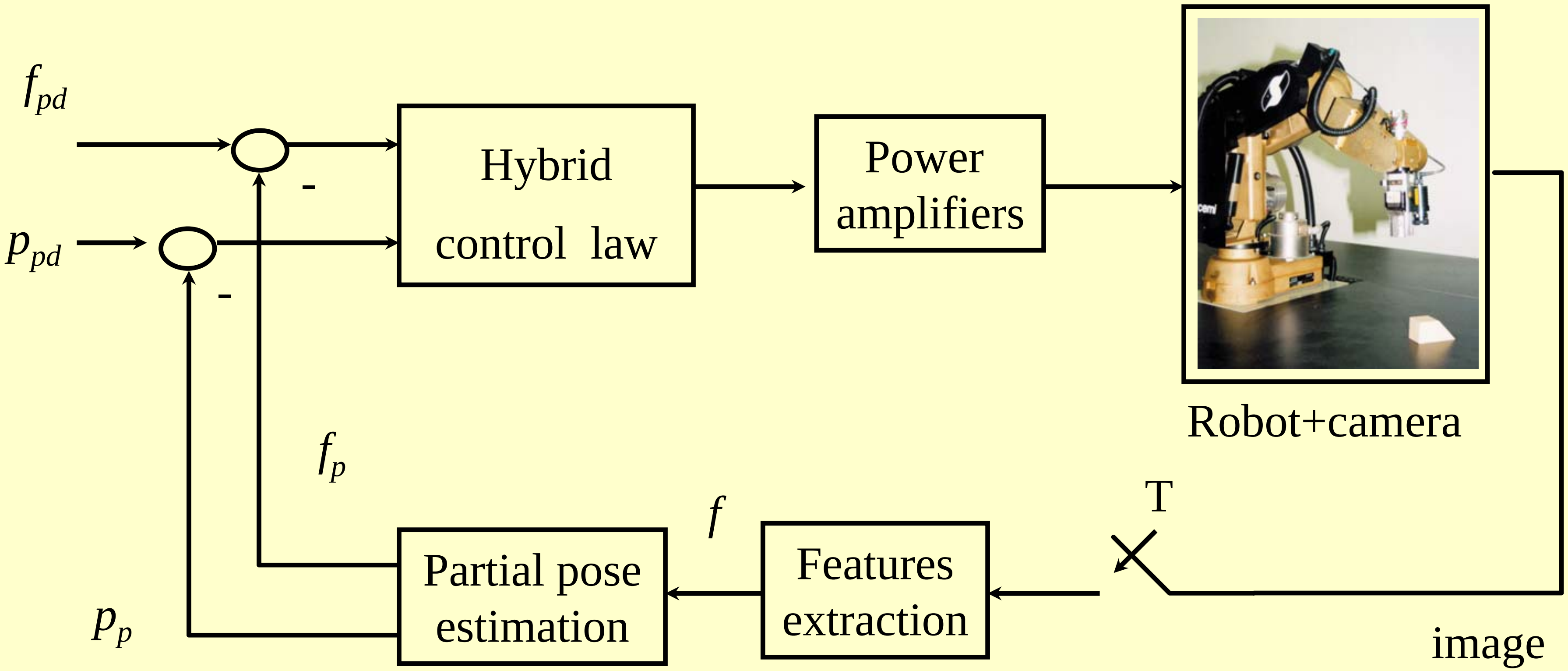
- A model of the object must be known or multiple images should be used
- Calibration errors may induce large pose estimation errors
- Control law design is easier
- Possible loss of target for large errors

B. Image-based visual servoing (2D visual servoing)



- Smaller computational burden
- Eliminates errors due to calibration
- More complex control law
- Workspace limits can be hit for large errors

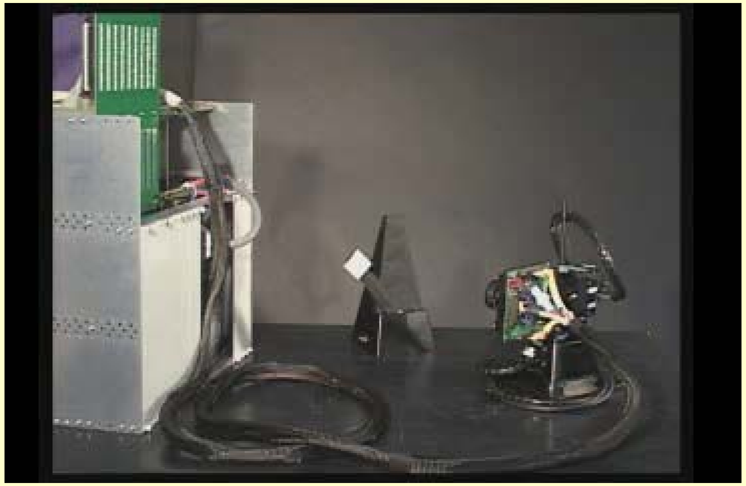
C. Hybrid visual servoing (e.g. 2D1/2 visual servoing)



- Smaller errors due to calibration
- Simplified model of the target
- Better properties of motion (in the image and in 3D)

I.24 Bandwidth of the visual servo-loop

- **A. Slow visual servoing**
  - Sampling frequency < 50Hz
  - Indirect visual servoing
  - Robot transfer function model without dynamics
  - Proportional control law (P)



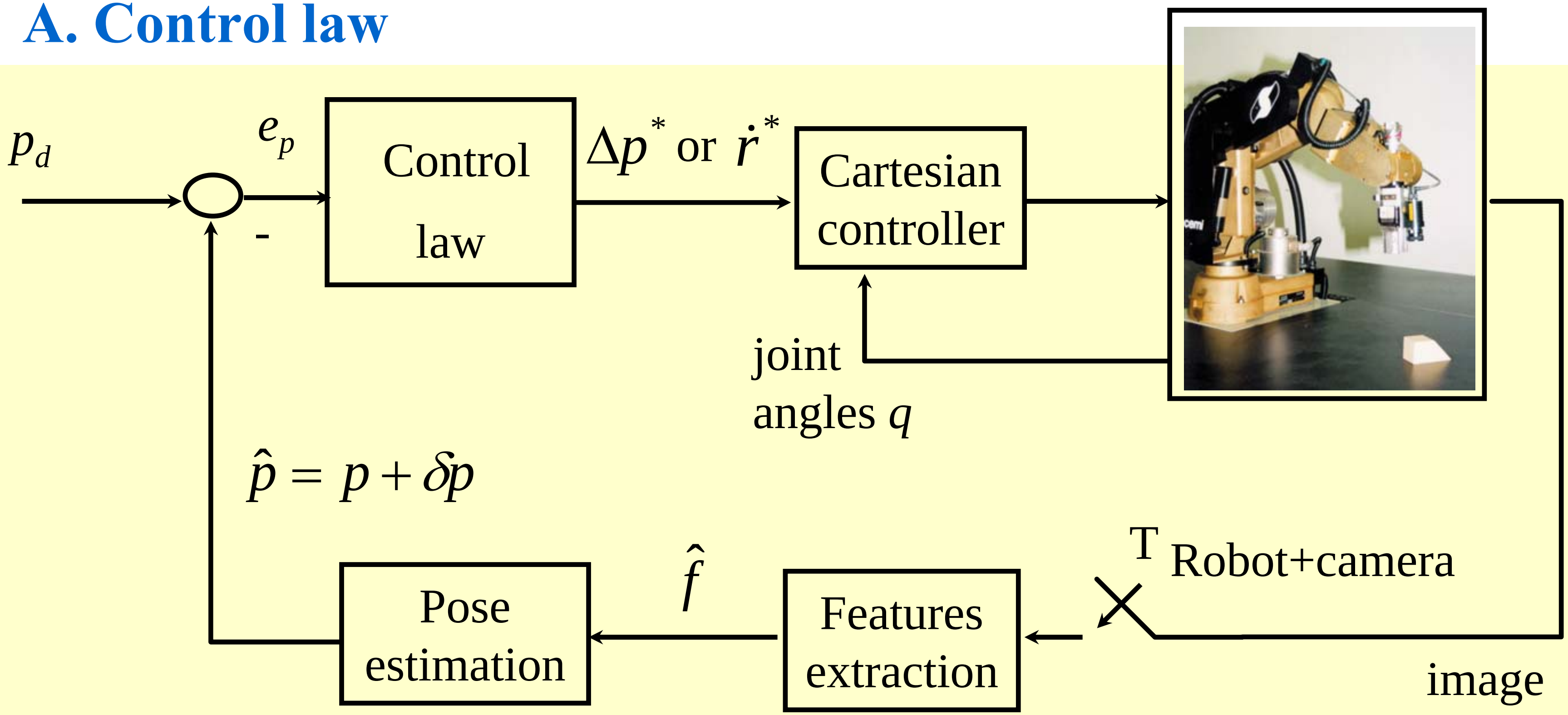
- **B. Fast visual servoing**
  - Sampling frequency >= 50 Hz
  - Direct visual servoing
  - Dynamical model of the robot must be taken into account
  - More advanced control laws : PID, predictive, robust, non-linear, …

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction
- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

I.3 Position-based visual servoing
I.31 Indirect visual servoing

A. Control law



- e_p generally expressed as translation vector and θu
- Look-then-move strategy (T very large, asynchronous) : $\Delta p^* = e_p$
- Pseudo-continuous strategy : $\dot{p} = J_p^T \, \dot{r}$ ⇨ Control law : $\dot{r}^* = k \, J_p^{T^{-1}} \, e_p$

B. Obtaining reference p_d

• Reference position of the end-effector is given w.r.t an object

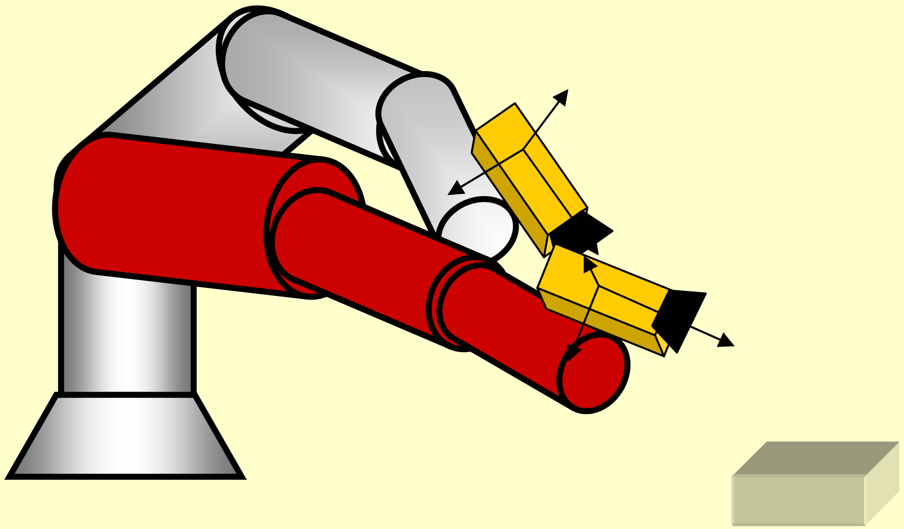
⇒ Computation of the corresponding position of the camera w.r.t the object (eye-in-hand)

⇒ requires the knowledge of ${}^{e}H_{c}$

• Learning of the image in the final position and pose estimation of the camera

C. Interaction matrix Jp

- Case of a eye-in-hand system



$$e_p = \begin{bmatrix} {}^{c*}T_c \\ {}^{c*}\theta u \end{bmatrix}$$

$$\dot{e}_p = \begin{bmatrix} {}^{c*}\dot{C} \\ {}^{c*}({}^{c*}\Omega_c) \end{bmatrix} = \begin{bmatrix} {}^{c*}R_c\,{}^{c}R_e(V_e + \Omega_e \times EC) \\ {}^{c*}R_c\,{}^{c}R_e\Omega_e \end{bmatrix} = \begin{bmatrix} {}^{c*}R_c\,{}^{c}R_e & -{}^{c*}R_c\,{}^{c}R_e EC \\ 0 & {}^{c*}R_c\,{}^{c}R_e \end{bmatrix} \begin{bmatrix} V_e \\ \Omega_e \end{bmatrix}$$

D. Pose estimation

- Camera calibration : *Tsaï (IEEE Trans. Rob. Aut., 1987), Zhang (ICCV 99)*
- Pose estimation :
  - Analytical : 3 or 4 points : *Tsaï (co-planar target)*
  - Numerical Iterative *:*
    - *DeMenthon (IEEE Trans. PAMI 1992, Int. J. Comp. Vision 1995),*
    - VVS *(Marchand, Eurographics 2002),*
    - Minimization of reprojection error (gradient, Levenberg-Marquardt, etc.)

E. Stability and robustness

Stability is not an issue : Look-then-move strategy is always stable and low speed vision loop: $\dot{r} \approx \dot{r}^*$ ⇒ $\dot{p} = k\, J_p^T\, J_p^{T^{-1}} e_p$ ⇒ Exponential convergence

J_p depends on camera position w.r. to end-effector (eye-in-hand configuration)

Stability if

$$J_P\, \hat{J}_P^{-1} > 0$$

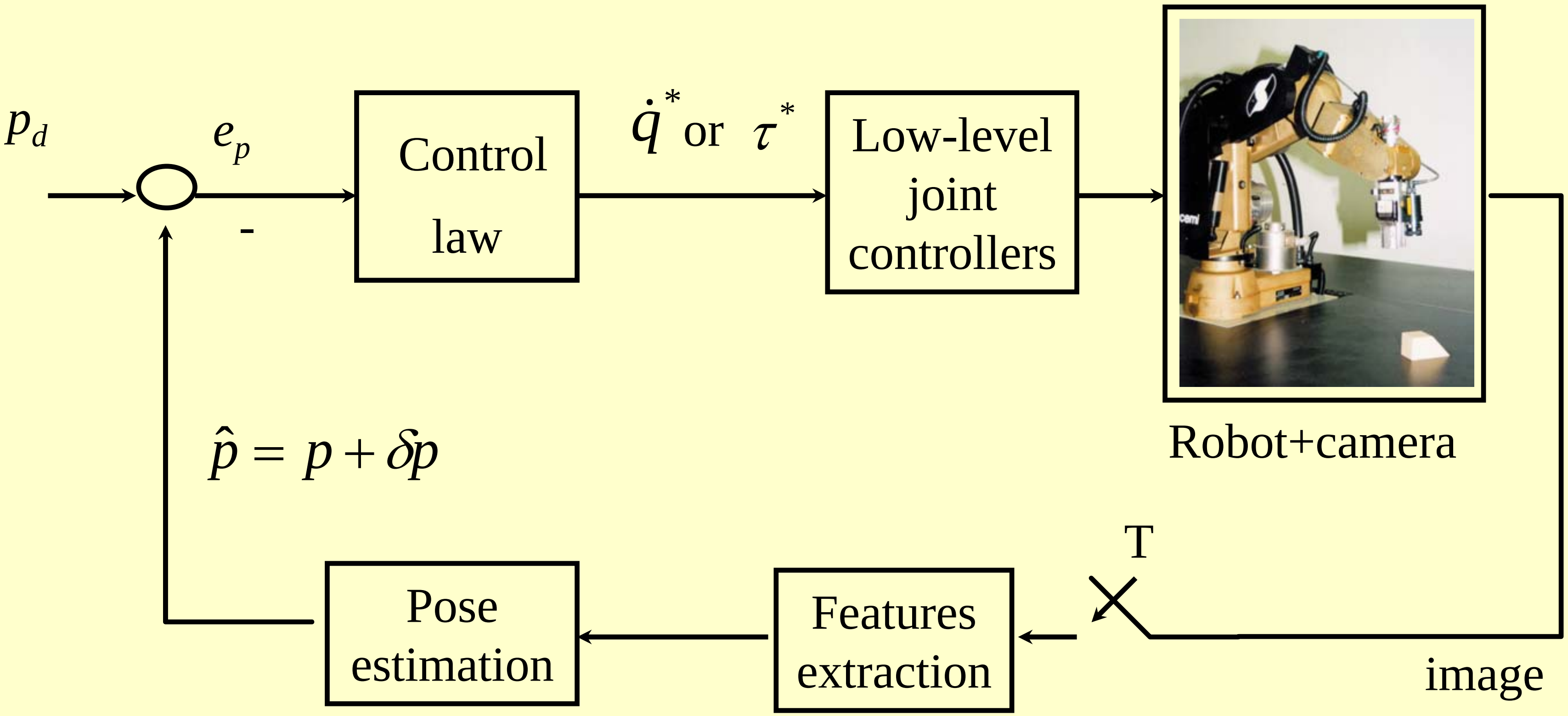
Measurement error is an issue: δp can be very large !

- Main sources of uncertainty :
  - Camera intrinsic parameters
  - Camera position w.r. to end-effector if eye-in-hand configuration
  - Camera position w.r. to the robot base and robot kinematic chain if external camera, except if end-effector pose is estimated by vision
  - Feature detection error : $\delta f = \hat{f} - f$

⇒Improvement: use learning of p_c by showing when possible

I.3 Position-based visual servoing
I.32 Direct visual servoing

A. Control law



$\dot{p} = J_p^T \dot{r} = J_p^T \; J_R(q)\,\dot{q}$ ⇒ Control law : $\dot{q}^* = k \; J_R^{-1}(q) \; J_p^{T^{-1}} e_p$

B. Stability and robustness (1)

Stability may be an issue:

- Low speed vision loop : ⇒ $\dot{q} \approx \dot{q}^*$

⇒ $\dot{p} = kJ_p^T \; J_R(q) \; J_R^{-1}(q) J_p^{T^{-1}} e_p$ ⇒ Exponential convergence

- High speed vision loop :
  - Linearized approach : $\dot{q}(s) \approx F(s,q)\, \dot{q}^*(s)$

⇒ $p \approx \dfrac{1}{s} J_p^T J_R(q)\, F(s,q)\dot{q}^*$

Joint-level velocity feedback loops have a linearizing and decoupling effect

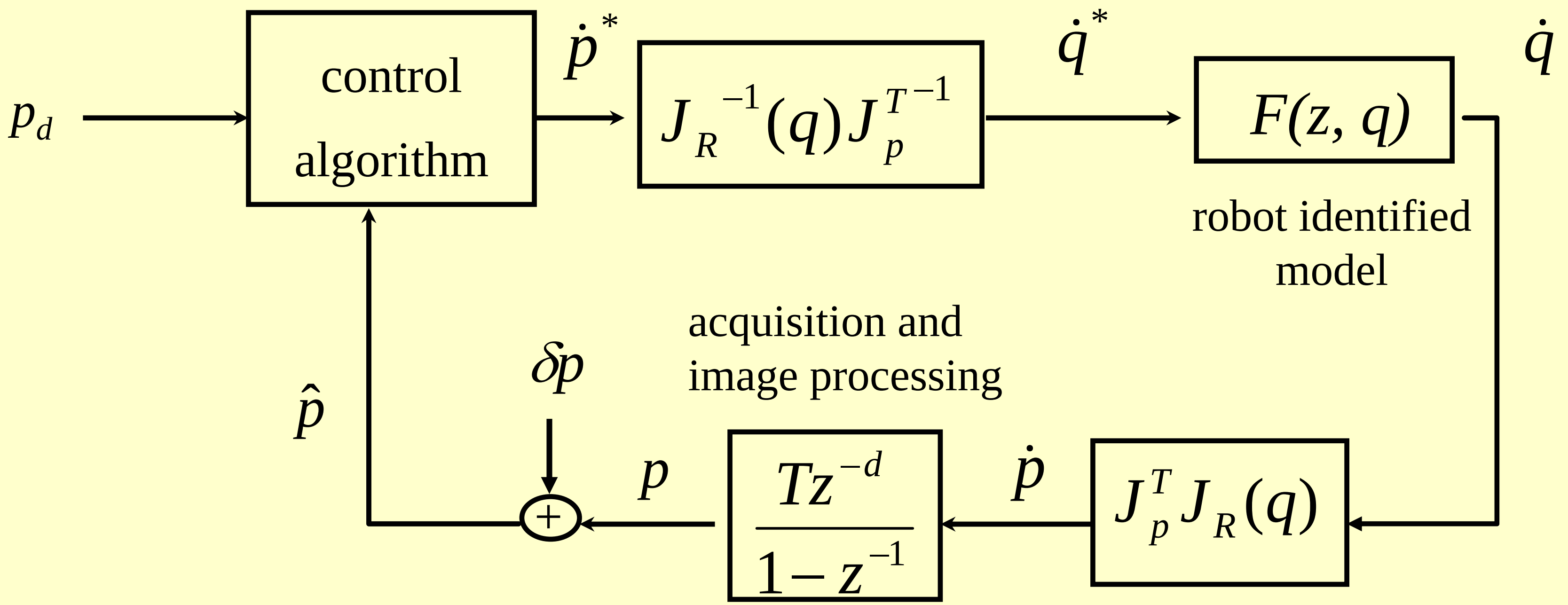
⇒ Control law: $\dot{q}^* = J_R^{-1}(q)\; J_p^{T^{-1}} \dot{p}^*$ with $\dot{p}^*$ computed using a LPV discrete-time model of the vision loop

This approach works in practice with 6DOF vision loop !

LSiiT

B. Stability and robustness (2)

LPV discrete-time model



⇨ GPC of a 6DOF robot vision loop :
J. Gangloff & M. de Mathelin (Advanced Robotics, vol 17, no 10, déc. 2003)

LSiiT

B. Stability and robustness (3)

- Non linear approach : rigid link robot manipulator model

$$\tau = M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) + f_r(q,\dot{q})$$

Inertia — Coriolis, centripetal — gravity — friction

- PD control scheme *(Arimoto)*: $\tau^* = g(q) - K_v\dot{q} - K_p e_q$ with $e_q = q - q_d$

- Passivity-based scheme *(Slotine & Li):* $\zeta = \dot{q}_d - \Lambda e_q$

$$\tau^* = M(q)\dot{\zeta} + C(q,\dot{q})\zeta + g(q) - K_v\dot{e}_q - K_p e_q$$

High complexity for 6DOF !

⇨ Problems: - asymptotic stability is proven with no friction
- q_d and $\dot{q}_d$ are generally unknown
- joint flexibilities and backlash

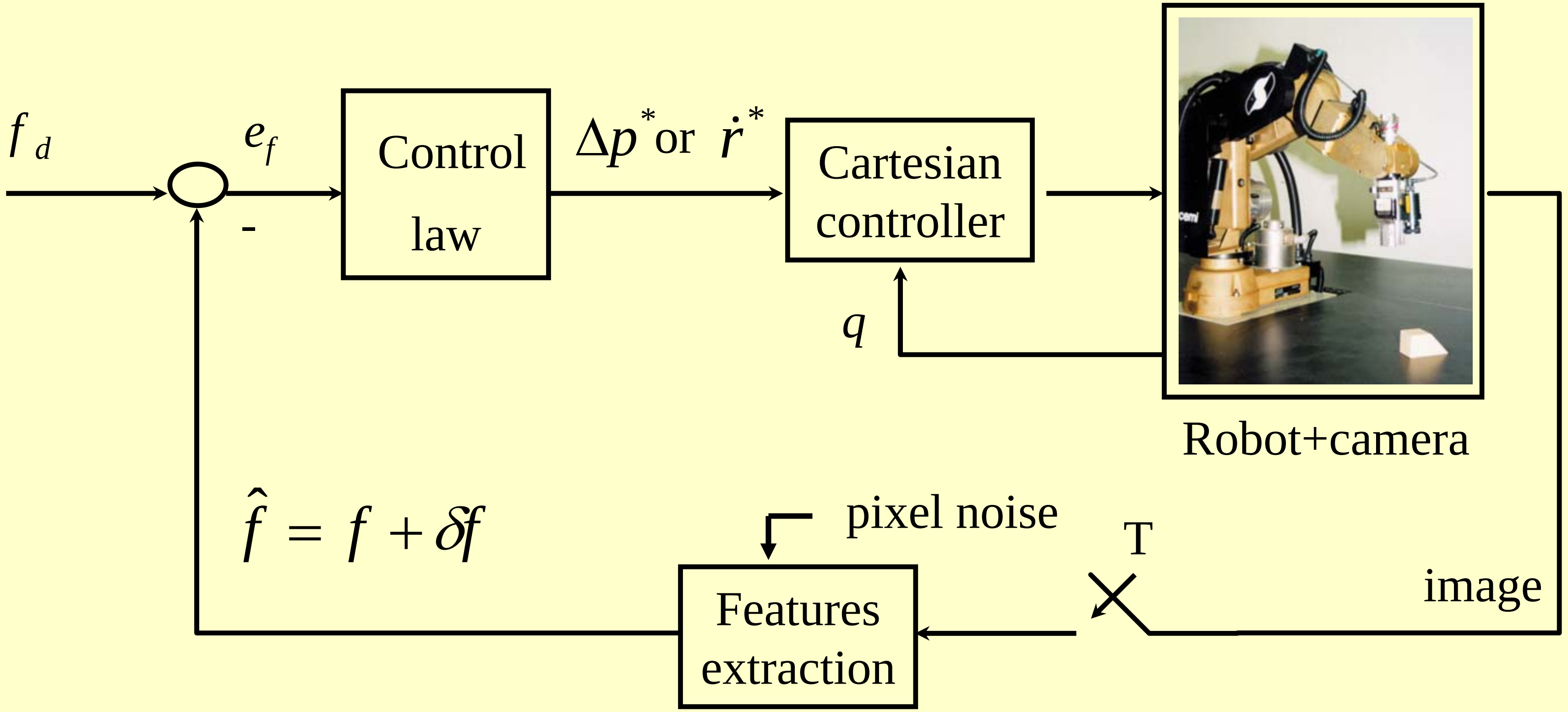
LSiiT

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction
- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

I.4 Image-based visual servoing
I.41 Indirect visual servoing

A. Control law



- Look-then-move strategy : select Δp^* or Δq^* to decrease a cost function of e_f
- Pseudo-continuous strategy : $\dot{f} = J_I \; \dot{r}$ ⇒ Control law : $\dot{r}^* = k \; J_I^{+} \; e_f$

B. Obtaining reference f_d

• Computation of the perspective projection of the object in the reference position ⇒ requires a model of the object

⇒ requires the knowledge of ${}^{e}H_{c}$

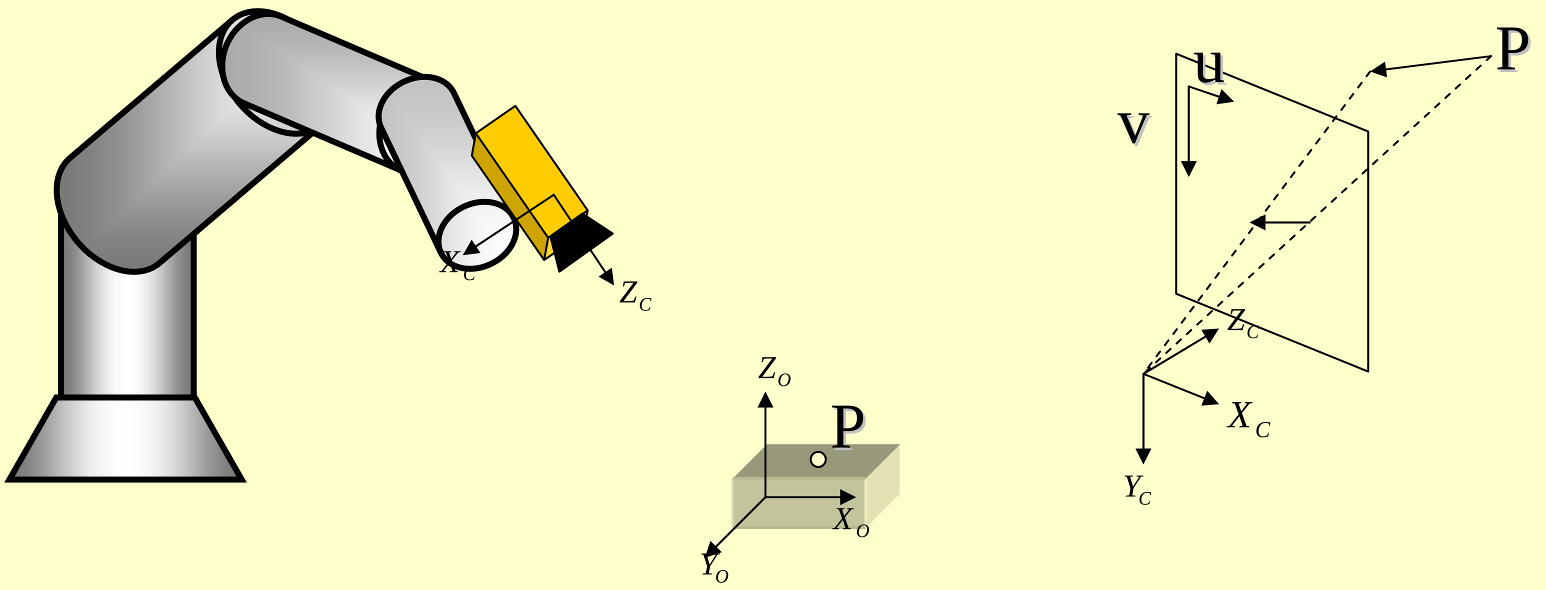
⇒ requires an accurate model of camera

• Learning of the image in the final position

C. Image jacobian or interaction matrix

Image Jacobian J_I : p x n matrix (p feature vector dimension, n # dof of effector). Depends on kind of features used.

Exemple : case of a point P seen by a camera attached to the effector of a robot



$$ {}^cP = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \quad {}^c\left({}^o\dot{r}_c\right) = \begin{bmatrix} v_x \\ v_y \\ v_z \\ \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \Rightarrow \quad {}^c\dot{P} = {}^c\left({}^o\Omega_c\right) \times {}^cP + {}^c\left({}^oV_c\right) $$

$$ {}^c\dot{P} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} z\omega_y - \frac{(v-v_0)z}{\lambda k_v}\omega_z + v_x \\ \frac{(u-u_0)z}{\lambda k_u}\omega_z - z\omega_x + v_y \\ \frac{z}{\lambda}\left(\frac{(v-v_0)}{k_v}\omega_x - \frac{(u-u_0)}{k_u}\omega_y\right) + v_z \end{bmatrix} $$

image coordinates in pixel: (u,v)

$$ \Rightarrow \begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} \frac{\lambda k_u}{z} & 0 & -\frac{(u-u_0)}{z} & -\frac{(u-u_0)(v-v_0)}{\lambda k_v} & \frac{(\lambda k_u)^2 + (u-u_0)^2}{\lambda k_u} & -\frac{k_u(v-v_0)}{k_v} \\ 0 & \frac{\lambda k_v}{z} & -\frac{(v-v_0)}{z} & -\frac{(\lambda k_v)^2 + (v-v_0)^2}{\lambda k_v} & \frac{(u-u_0)(v-v_0)}{\lambda k_u} & \frac{k_v(u-u_0)}{k_u} \end{bmatrix} {}^c({}^o\dot{r}_c) $$

$$ {}^c({}^o\dot{r}_c) = \begin{bmatrix} {}^cR_e & -{}^cR_eEC \\ 0 & {}^cR_e \end{bmatrix} \begin{bmatrix} V_e \\ \Omega_e \end{bmatrix} \Rightarrow \dot{f} = \begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = J_I \begin{bmatrix} V_e \\ \Omega_e \end{bmatrix} $$

I.4 Image-based visual servoing
I.41 Indirect visual servoing

J_I depends on intrinsic parameters and on pose !
Also depends on pose of camera w.r.t effector

- J_I must be estimated ⇨ $\hat{J}_I$
- J_I must be full rank for controlling all degrees of freedom (at least 3 points required)
- End-effector with n dofs ⇨ only n features components can be controlled in the image.

- Expressions of image jacobian for classical geometrical objects : straight lines, spheres, cylinders etc.
  in *F. Chaumette, thesis 90* and *Espiau, TRA 92*

… and for any planar objects using moments in
Tahri O and Chaumette, F, IEEE TR 2005, 21(6)

D. Stability and robustness (1)

Low speed : $\dot{r} \approx \dot{r}^*$

⇨ $\dot{f} = k\, J_I\, J_I^{+} e_f$ ⇨ Exponential convergence

- Behaves as a gradient descent optimization : may be stuck in local minima ! ⇨ 2nd order optimization *Malis, E., Improving vision-based control using efficient second-order minimization techniques, 2004*

- The norm of e_f decreases, but some components may increase during motion (possible loss of features)
- If more features than dofs, least square of error minimization

- no control in the cartesian space ⇨ better behaviour for small errors

LSiiT

D. Stability and robustness (2)

- Main source of uncertainty : *Ji* ⇒ $\dot{f} = k\, J_I\, \hat{J}_I^{+} e_f$

⇒ Exponential convergence if $J_I\, \hat{J}_I^{+} > 0$

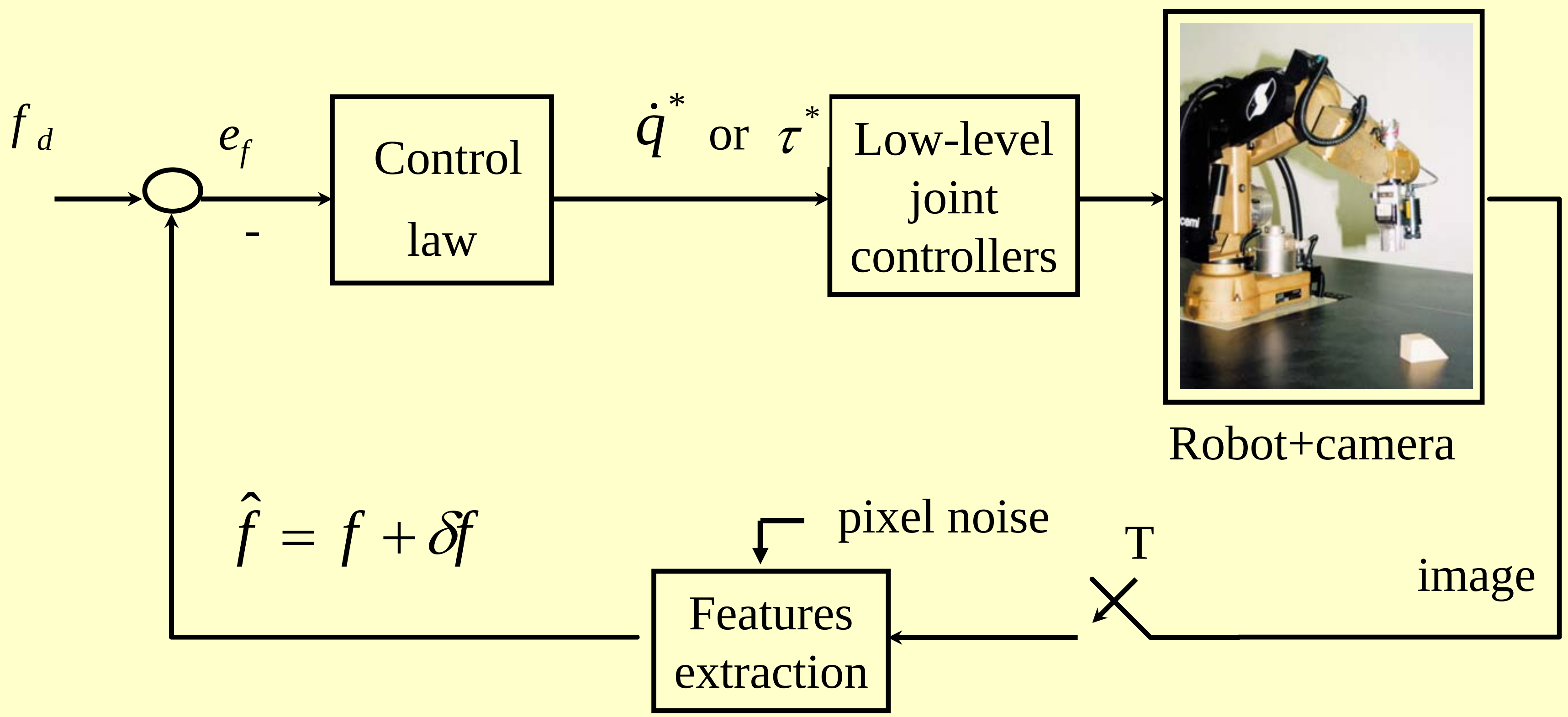
Easily guaranteed : coarse calibration and coarse pose estimation are generally sufficient.

- No proof of global stability in function of k
- Error in the final position
  - independent of errors on camera / effector position
  - independent of erros on intrinsic parameters of the camera if reference image has been learned
  - function of pixel noise

- Pixel noise attenuation : pick more features ⇒ smaller δf
- Problem of reaching the workspace limits ⇒ Hybrid visual servoing

Malis, E., 21/2D visual servoing TRA 99

A. Control law



$$\dot{f} = J_I \dot{r} \quad = J_I J_R(q)\, \dot{q}$$ ⇨ Control law : $$\dot{q}^* = k\, J_R^{-1}(q)\, \hat{J}_I^+ e_f$$

B. Stability and robustness (1)

Stability may be an issue:

- Low speed vision loop : ⇨ $\dot{q} \approx \dot{q}^*$

⇨ $\dot{f} = k\, J_I J_R(q)\, J_R^{-1}(q) \hat{J}_I^{+} e_f$ ⇨ Exponential convergence if $J_I\, \hat{J}_I^{+} > 0$

- High speed vision loop :
  - Linearized approach : $\dot{q}(s) \approx F(s,q)\, \dot{q}^*(s)$

⇨ $f \approx \frac{1}{s} J_I J_R(q)\, F(s,q) \dot{q}^*$

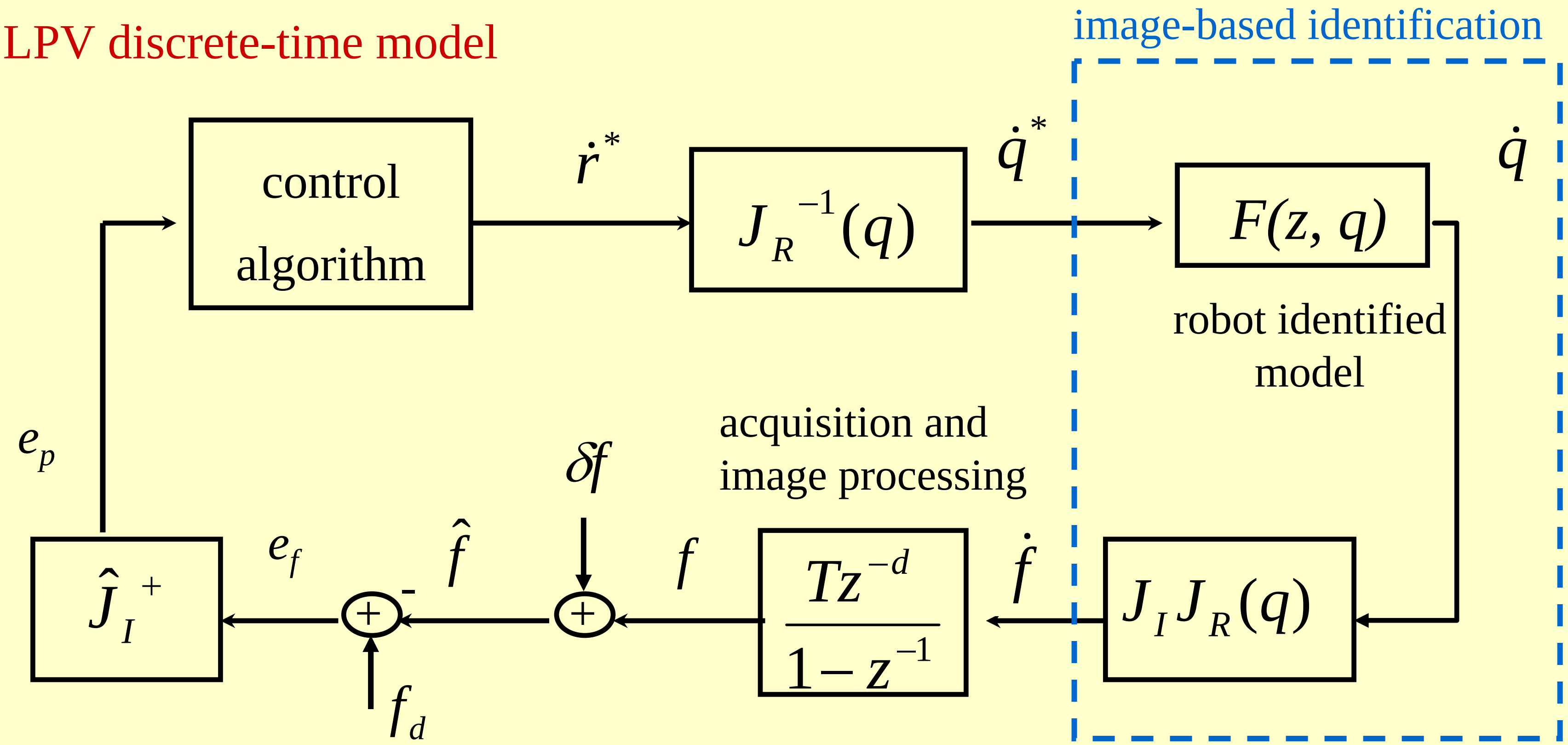
⇨ Control law: $\dot{q}^* = J_R^{-1}(q)\, \dot{r}^*$ with $\dot{r}^*$ computed using a LPV discrete-time model of the vision loop

This approach works in practice with 6DOF vision loops !

LSiiT

B. Stability and robustness (2)

LPV discrete-time model



⇨ GPC of a 6DOF robot vision loop :
J. Gangloff & M. de Mathelin (Advanced Robotics, vol 17, no 10, déc. 2003)

B. Stability and robustness (3)

- High speed vision loop :
  - Non linear approach : rigid link robot manipulator model

$$\tau = M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) + f_r(q,\dot{q})$$

PD control scheme : *(R. Kelly, IEEE Trans. Rob. Aut., vol 12, 1996)*

$$\tau^* = g(q) - K_v\dot{q} - J_R{}^T(q)K_p\hat{J}_I{}^+e_f$$

Stability is proved only for a 2 DOF robot with no friction

=> Previous restrictions apply

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction
- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

LSiiT

Case of planar objects

- Images linked by a homography

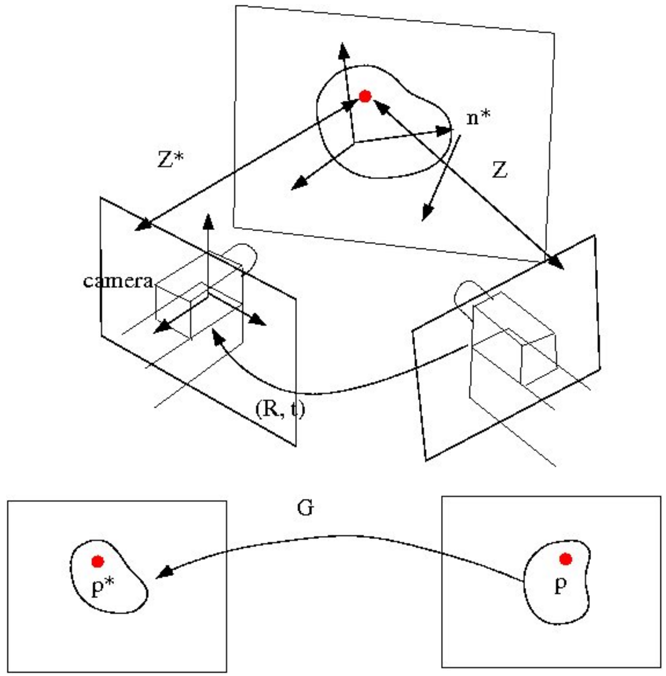
$$p = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = Gp^* = G\begin{bmatrix} u^* \\ v^* \\ 1 \end{bmatrix} \qquad G = \begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{pmatrix}$$

with det(G) = 1

- Computation of G using SSD minimization

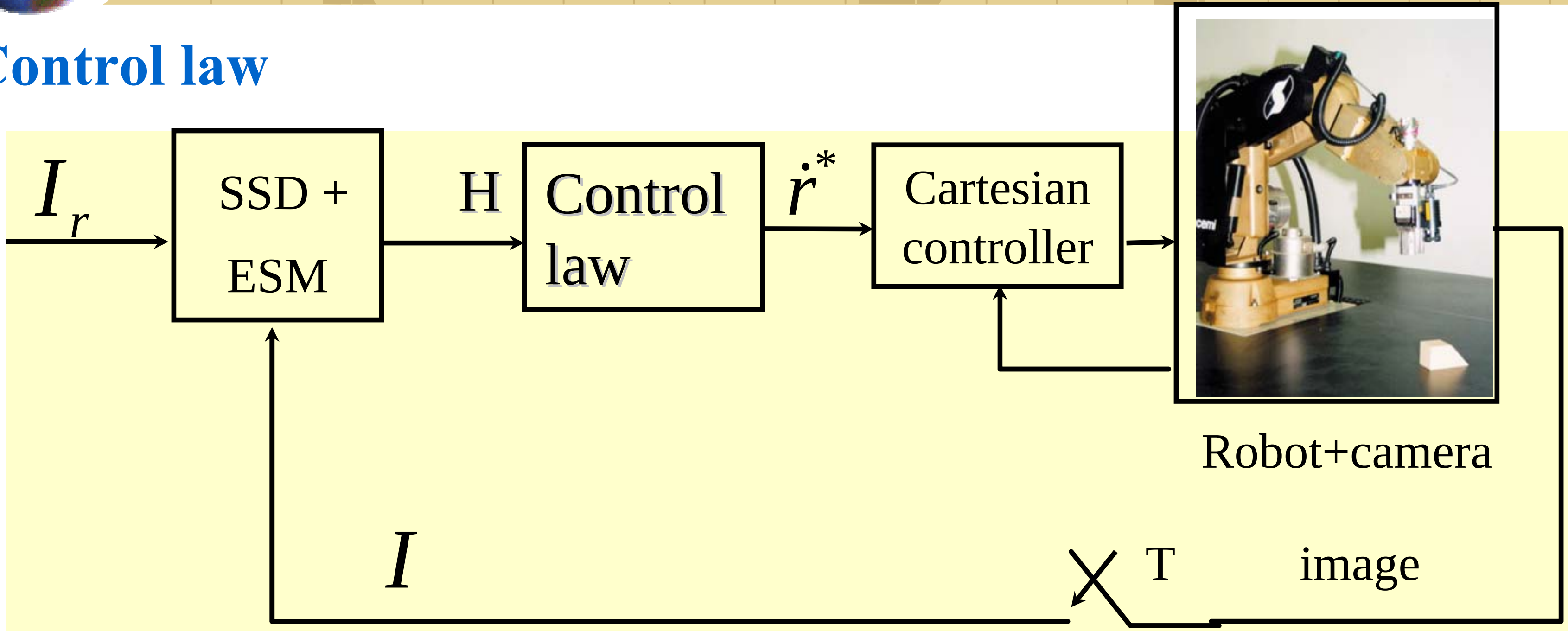
Example : ESM (*S. Benhimane and E. Malis 2004*)

- Computation of euclidean homography $m = K^{-1}GKm^* = Hm^*$



I.5 Visual servoing without feature extraction

Control law



$$\dot{r}^* = -\begin{bmatrix} \lambda_v & 0 \\ 0 & \lambda_\omega \end{bmatrix} \begin{bmatrix} e_v \\ e_\omega \end{bmatrix} \text{ with } e = \begin{bmatrix} e_v \\ e_\omega \end{bmatrix} \quad e_v = (H - I)m^* \text{ and } [e_\omega]_\times = H - H^T$$

$m^* = K^{-1}p^*$ Camera coordinates of a selected point in the reference image

Stability and robustness

S. Benhimane and E. Malis, Homography-based 2D visual servoing, IEEE ICRA 2006

- No need of interaction matrix computation
- Proof of local stability
- Practically : good robustness w.r.t intrinsic parameters
- Large domain of stability
- Recently extended to non-planar objects

LSiiT

Bibliography

- Hager, G. and S. Hutchinson. Special issue on vision-based control of robot manipulators. *IEEE Trans. Rob. Autom.*, vol 12, no 5, 1996.
- Corke, P. *Visual control of robots*. Research studies Press Ltd., Somerset, UK, 1996.
- B. Espiau and F. Chaumette, A new approcah to visual servoing in robotics, *IEEE Transactions on robotics and automation, vol 8, no 3, 1992,*
- S. Benhimane and E. Malis, Homography-based 2D visual servoing, *IEEE ICRA 2006*

LSiiT

Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction

- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

LSiiT

Main applications

- In laparoscopic surgery
- In ophtalmology
- For physiological motion compensation
- In US imaging diagnosis and intervention

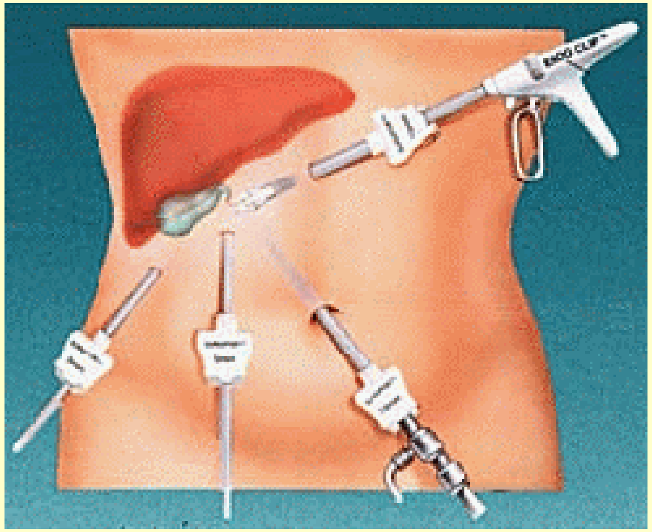
M.A.Vitrani and G.Morel, ICRA 2005 : guidance of surgical instruments

A. Krupa and F. Chaumette, IROS 2005 : control of US probe

Laparoscopic surgery

Small incisions, long-shaft instruments

Endoscopic vision system



- Advantages :
  - Shorter recovery time
  - Lower infection risk
  - Smaller costs
- Difficulties :
  - Tiring gestures
  - Indirect visual feedback, lack of depth information
  - Inverted motions limited to 4 DOF
  - Poor haptic feedback

LSiiT

Classical robotic control of the endoscope

AESOP (Computer Motion/Intuitive Surgical)

Voice controlled

EndoAssist (Armstrong-Healthcare)

Controlled with head motions

"The surgeon's third hand"

Vision-based control of the endoscope

R. Taylor (95), A. Casals (95), G. Wei and G. Hirzinger (97), S. Voros and Ph. Cinquin (2006), etc.

More vision guided systems than real visual servoing

- Centering the image on marked instruments
- Tracking of instruments
- Centering the image on specific physiological markers

Laparoscopic surgery

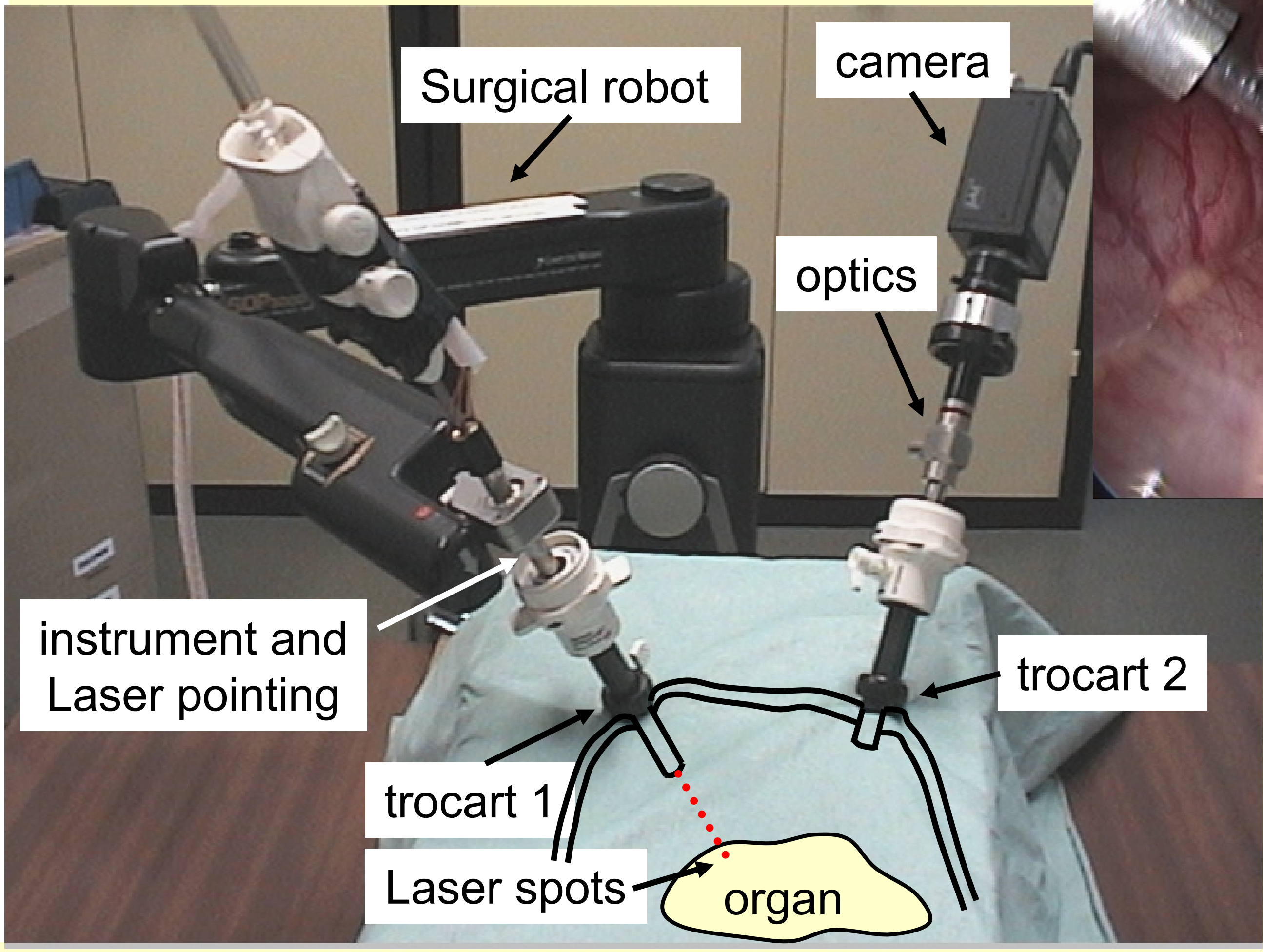
Visual servoing based control of the instrument (Krupa 2003)

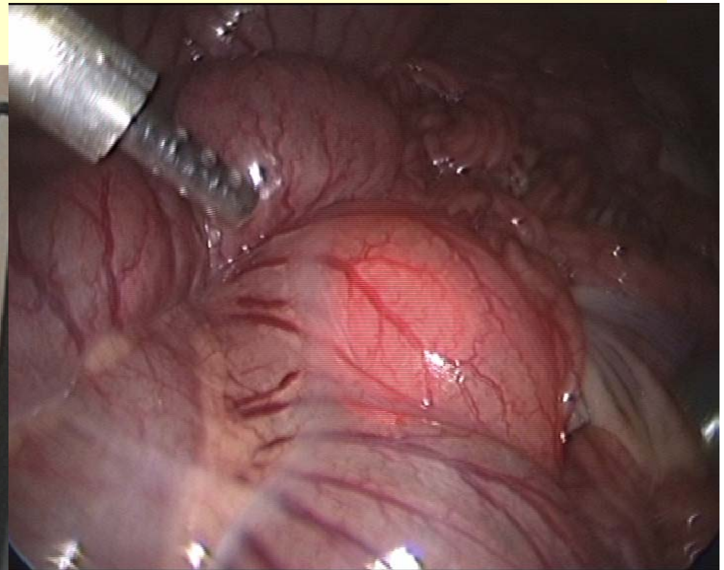
- Goal : surgical instrument guidance
  - Autonomous recovery of the instruments
    - Bring the instrument in the field of view
    - Centering of the instrument in the image
  - Automatic positionning
    - Put the instrument at a desired location w.r.t to tissues
    - Provide depth informations

Motivations : - increase safety
- improve ergonomy
- speed up surgical procedures

LSiiT

Experimental setup





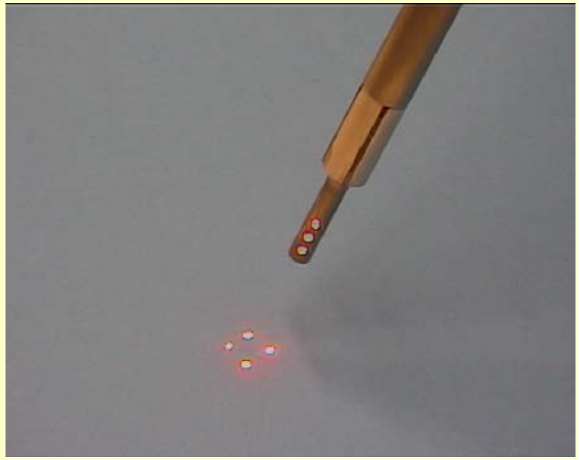
External camera configuration

Laser projection to add information to the scene

Experimental setup

- laser pointing device





  - 4 laser spots
  - To be used with standard instruments (4 mm) and standard trocarts (10 mm)

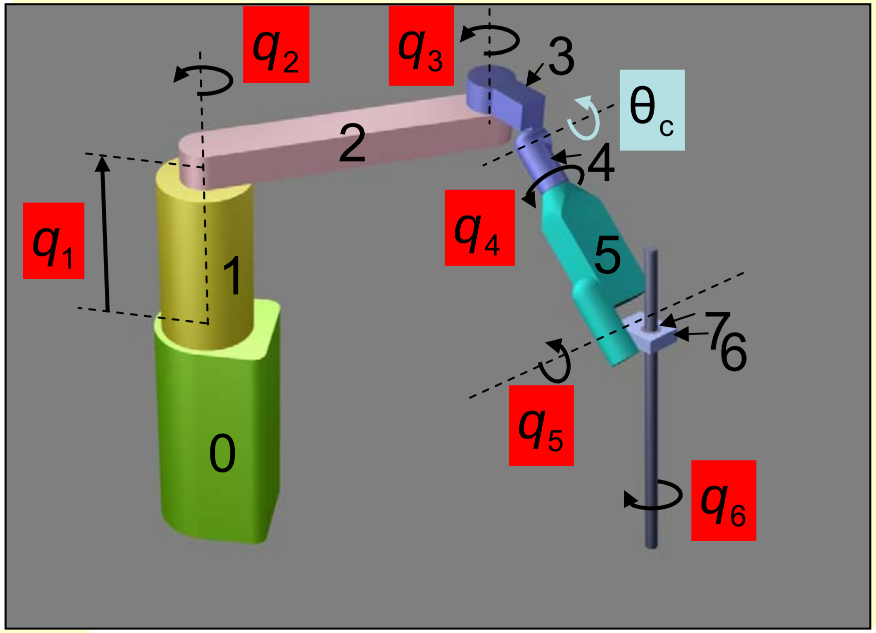
- 3 optical markers (detection of the instrument)

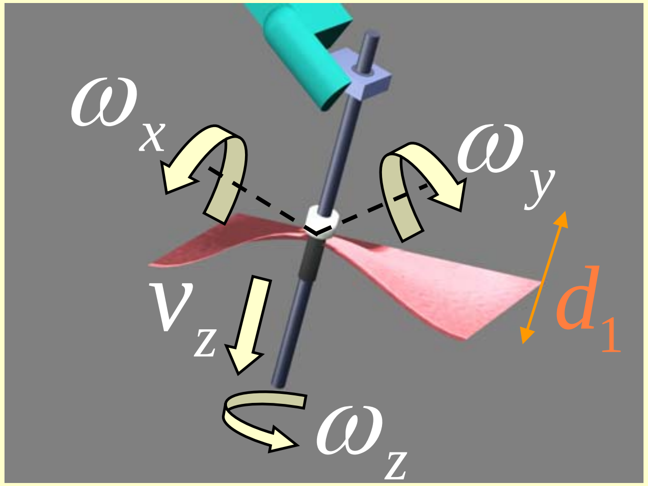
Kinematics in laparoscopic surgery

- constraints: 4 DOF

$$\dot{\mathbf{W}}_{op} = \left(\omega_x \quad \omega_y \quad \omega_z \quad v_z\right)^T$$

- AESOP: 6 DOF (2 passive joints)





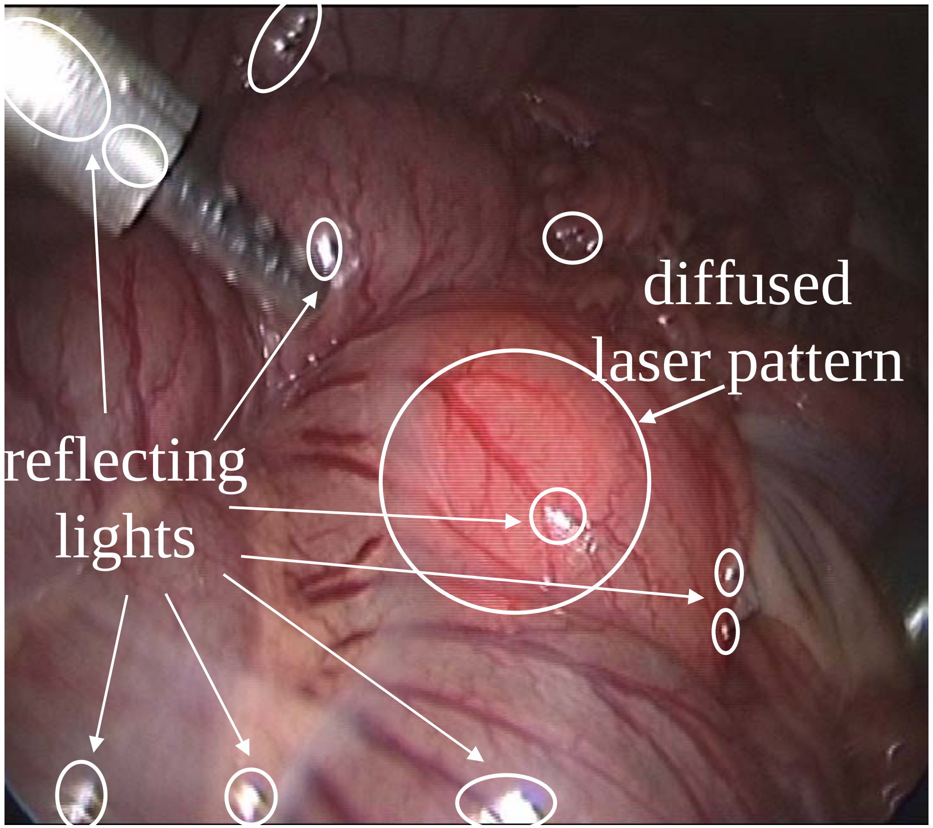
– kinematic model :

$$\dot{\mathbf{W}}_{op} = \mathbf{J}_{op}(\mathbf{q}, d_1)\dot{\mathbf{q}}_c$$

$$\dot{\mathbf{q}}_c^{\ *} = \mathbf{J}_{op}(\mathbf{q}, \hat{d}_1)^{-1}\dot{\mathbf{W}}_{op}^{\ *}$$

Visual features detection

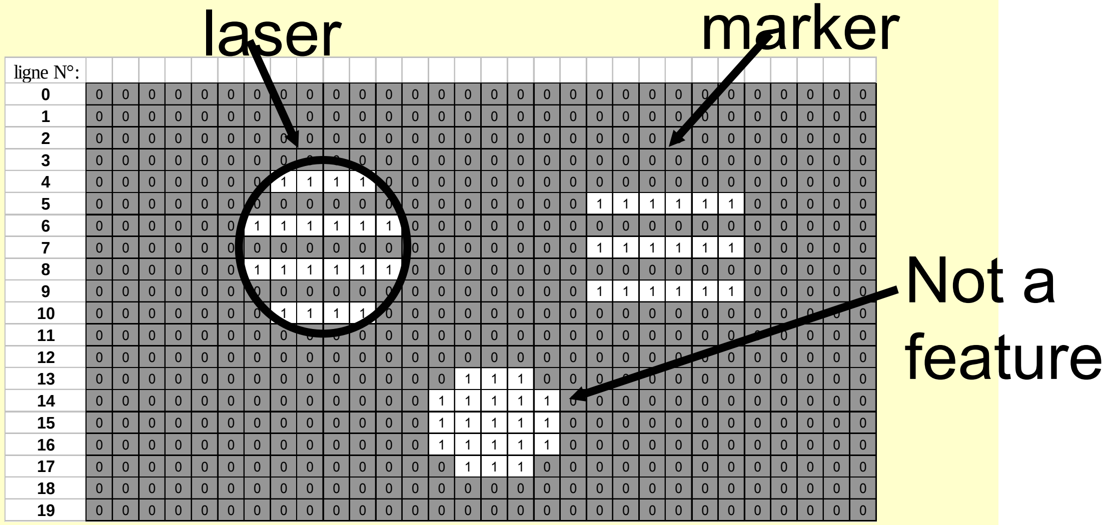
- Goal: to obtain the image coordinates of the centers of laser spots and optical markers



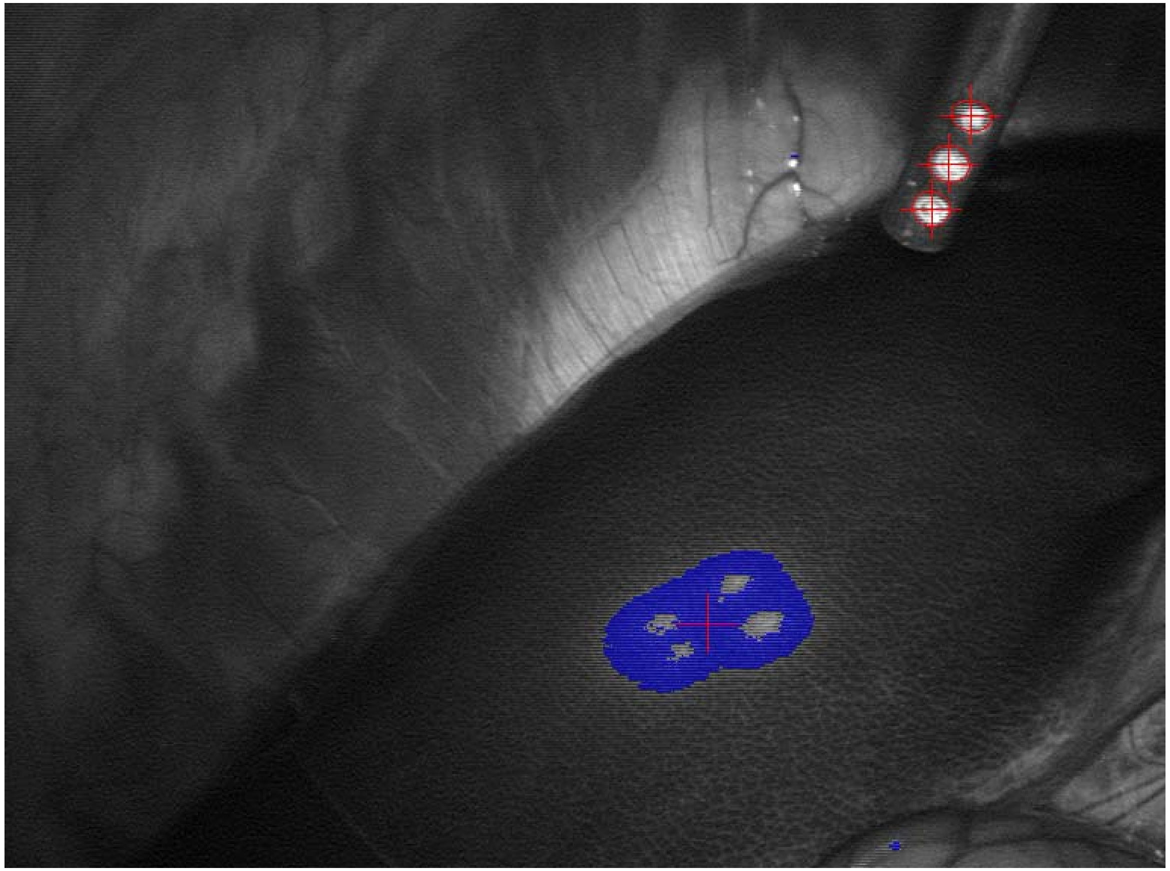
Robust detection

- Blinking laser spots and optical markers synchronized with frame acquisition
  - Even frames : laser on – markers off
  - Odd frames : markers on – laser off

- Selection by high-pass filtering

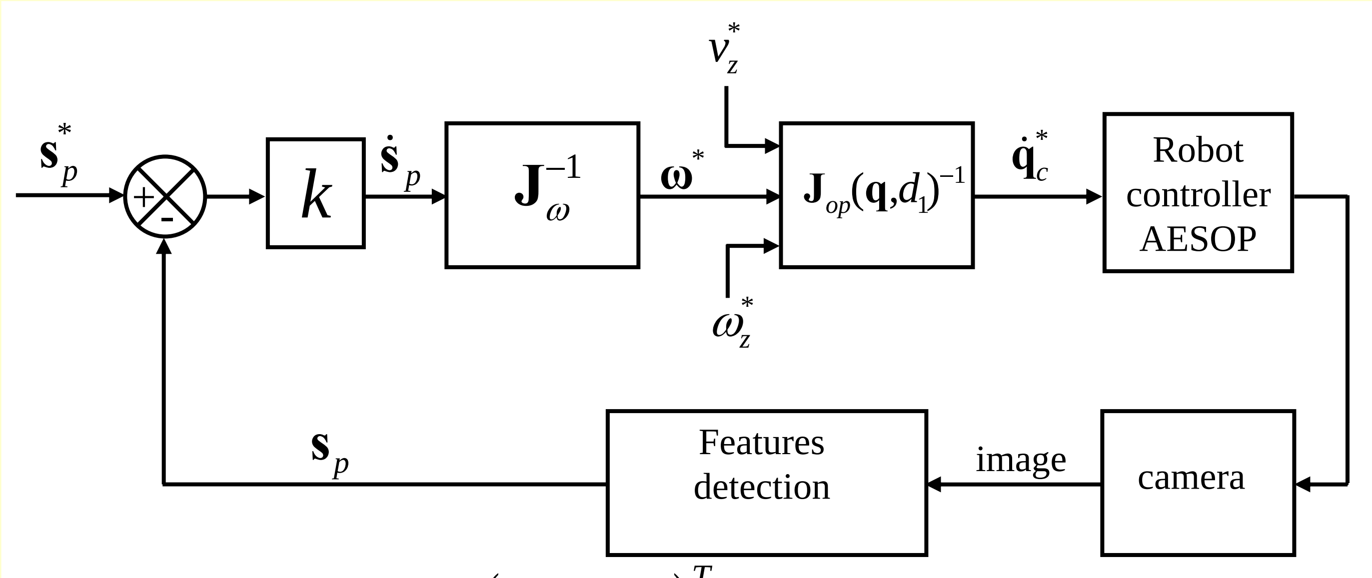


Robust detection



Control of the position of the spot

- 2D direct visual servoing scheme (Image-based)



- controlled variable : $\mathbf{S}_p = \begin{pmatrix} u_p & v_p \end{pmatrix}^T$

- control input : $\boldsymbol{\omega}^* = \begin{pmatrix} \omega_x^* & \omega_y^* \end{pmatrix}^T$

- control law : $\dot{\mathbf{S}}_p = k\left(\mathbf{S}_p^* - \mathbf{S}_p\right) = \mathbf{J}_\omega \boldsymbol{\omega}^*$

Estimation of interaction matrix

Open loop estimation of $\mathbf{J}_\omega$

Hypothesis : standstill camera $\hat{\mathbf{J}}_\omega = \begin{bmatrix} \hat{J}_{\omega 11} & \hat{J}_{\omega 12} \\ \hat{J}_{\omega 21} & \hat{J}_{\omega 22} \end{bmatrix}$

$$\Delta T \quad \begin{cases} \omega_x^* = cst \\ \omega_y^* = 0 \end{cases} \Rightarrow \quad \hat{J}_{\omega 11} = \frac{\Delta u_p}{\omega_x^* \Delta T} \qquad \hat{J}_{\omega 21} = \frac{\Delta v_p}{\omega_x^* \Delta T}$$

$$\Delta T \quad \begin{cases} \omega_x^* = 0 \\ \omega_y^* = cst \end{cases} \Rightarrow \quad \hat{J}_{\omega 12} = \frac{\Delta u_p}{\omega_y^* \Delta T} \qquad \hat{J}_{\omega 22} = \frac{\Delta v_p}{\omega_y^* \Delta T}$$

Stability if $\mathbf{J}_\omega \hat{\mathbf{J}}_\omega^{-1} > \mathbf{0}$

Laparoscopic surgery

Autonomous retrieval and positioning of a surgical tool in robotized laparoscopic surgery using automatic visual servoing

A. Krupa C. Doignon J. Gangloff
M. de Mathelin G. Morel

Strasbourg I University, Louis Pasteur - ENSPS
LSIIT/GRAViR (UPRESA CNRS 7005)
Bd. S. Brant, 67400 Illkirch, France
e-mail: alexandre.krupa@ensps.u-strasbg.fr

Laparoscopic surgery

Autonomous complex gestures (F. Nageotte 2005)

- Automatic stitching in laparoscopic surgery
- Trajectory planning in the camera frame
- Trajectory following using the endoscopic camera

⇨ Avoid registration procedure between sensors

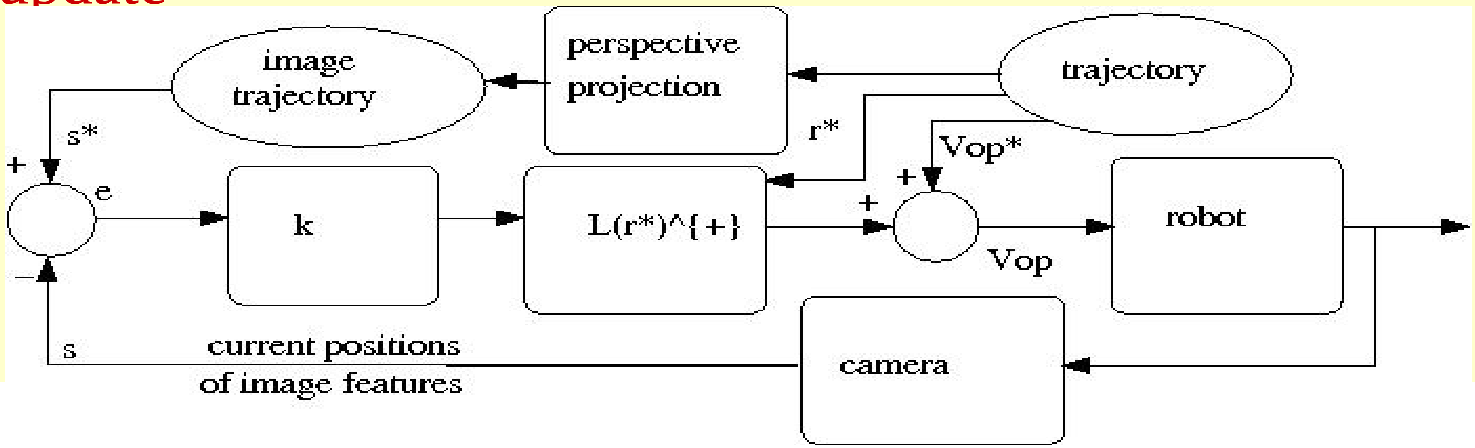
Autonomous complex gestures (F. Nageotte 2005)

- 2D visual servoing :
  - Marked instrument
  - Reference images : projection of the needle-holder in the endoscopic image

    ⇒ fine camera calibration required
  - Controlled variables : marker points + cylinder (10 to 16)
  - Control input : 4 DOFs of end-effector

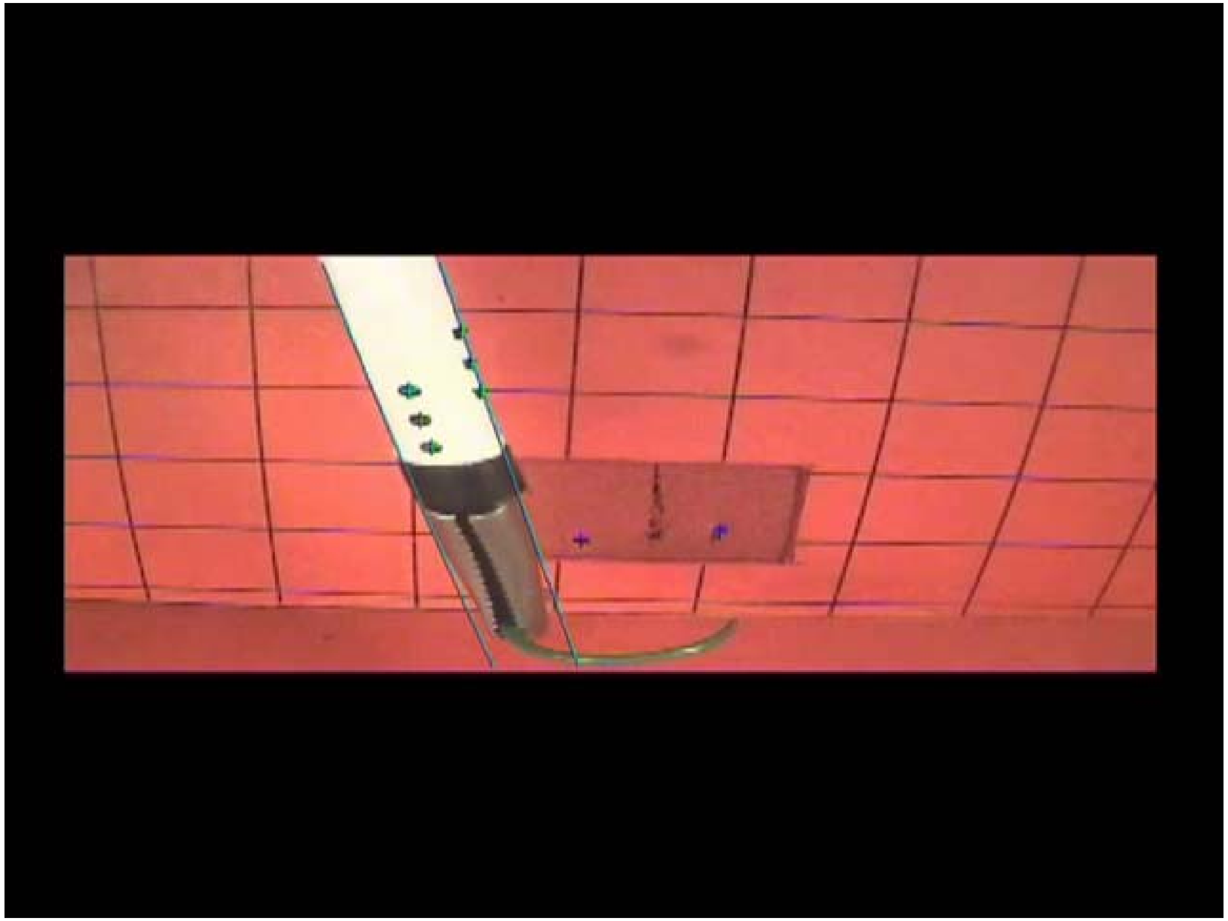
Autonomous complex gestures (F. Nageotte 2005)

- Complex interaction matrix with varying size.
- Hypothesis : small tracking error ⟹ matrix computed using known reference pose ⟹ no pose estimation required
- Prediction of feature appearance and disappearance for update



LSiiT

Automatic suturing



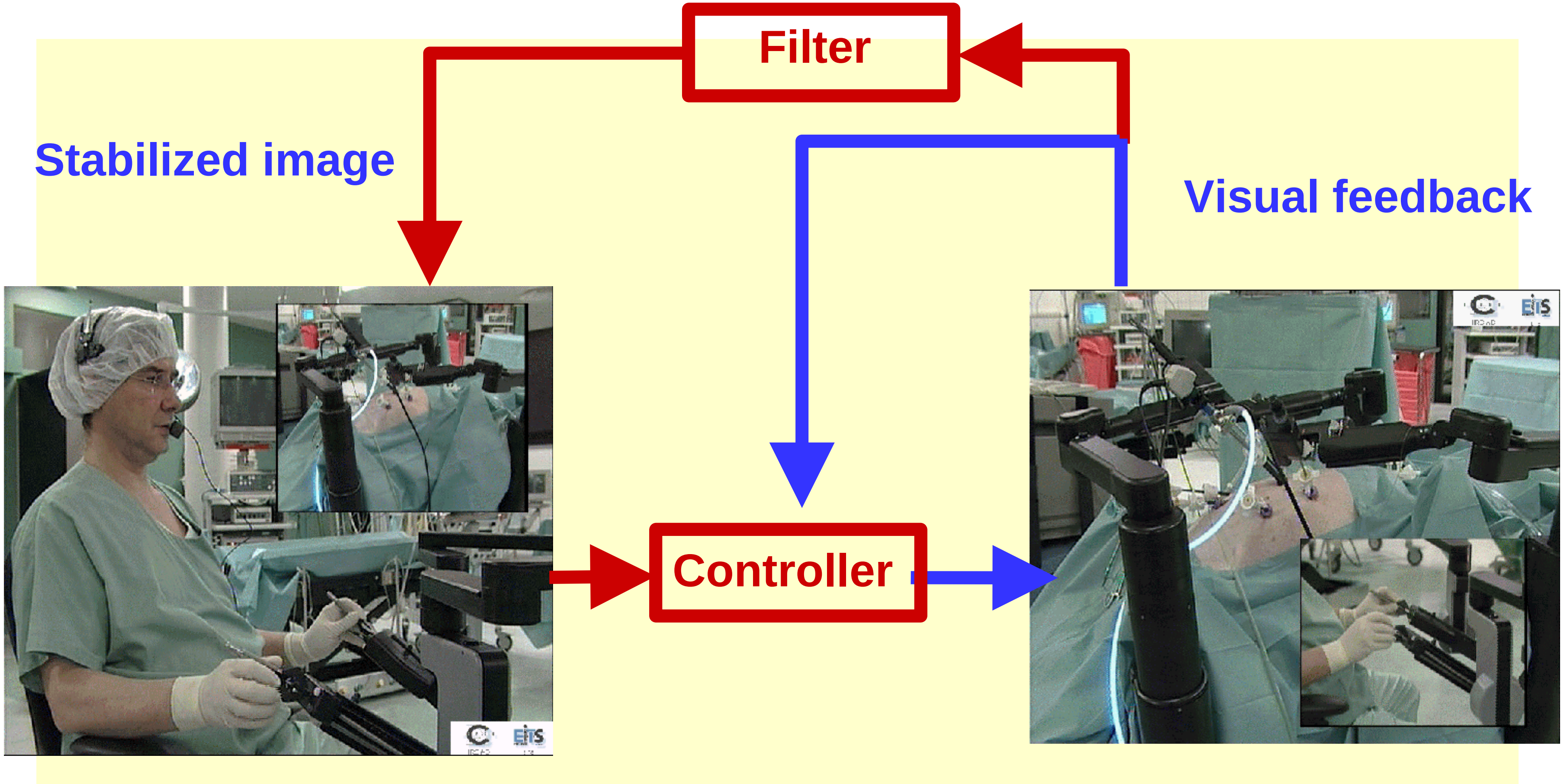
Overview

- Part I : Fundamentals of visual servoing
  - Background and definitions
  - Servoing architectures and classification
  - Position-based visual servoing
  - Image-based visual servoing
  - Visual servoing without feature extraction

- Part II : Medical robotics applications
  - Laparoscopic surgery
  - Internal organ motion tracking

LSiiT

Objectives



LSiiT

Breathing motion compensation (R. Ginhoux 2003)

Predictive control law : take into account periodic disturbance
GPC control law with periodic output perturbation model

- Dynamic model of the robot is required : linearized model obtained by pseudo-random excitation
- Controlled variable : distance to the organ
- Control input : first axis of the robot (particular configuration)

- Identification of the interaction gain

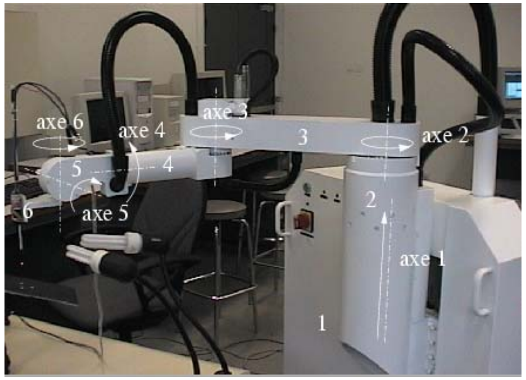
LSiiT

In vivo experiment

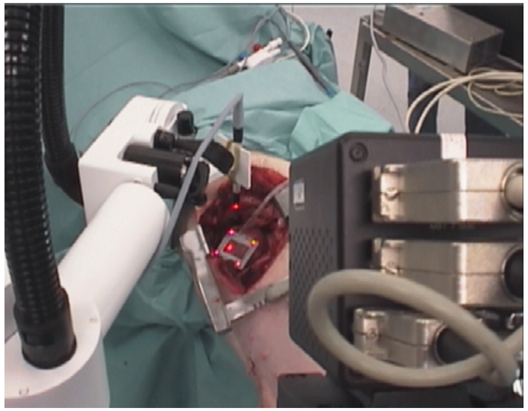
LSiiT

Physiological motions compensation

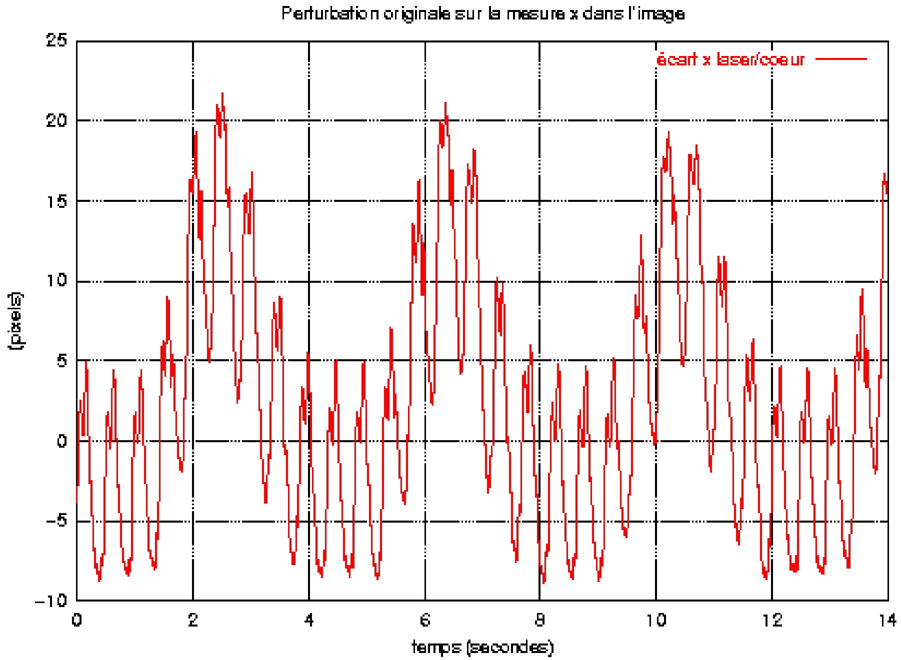
Beating heart motion compensation (R. Ginhoux 2003)



Fast robot



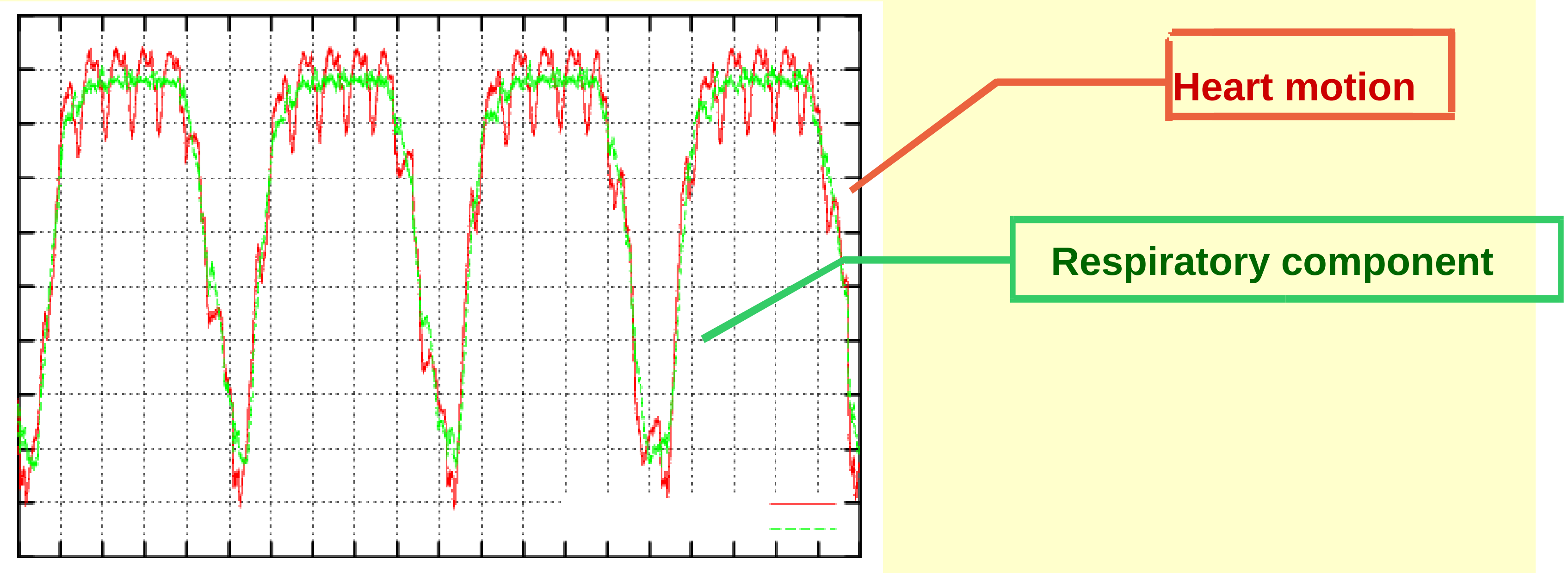
Fast camera (500hz)



2 types of motion: - slow (~0.25 Hz)
- fast (~1.5 Hz)

In vivo experiments

Beating heart motion compensation



- Adaptive filtering of 12 harmonics of the heart beat rate

Beating heart motion compensation

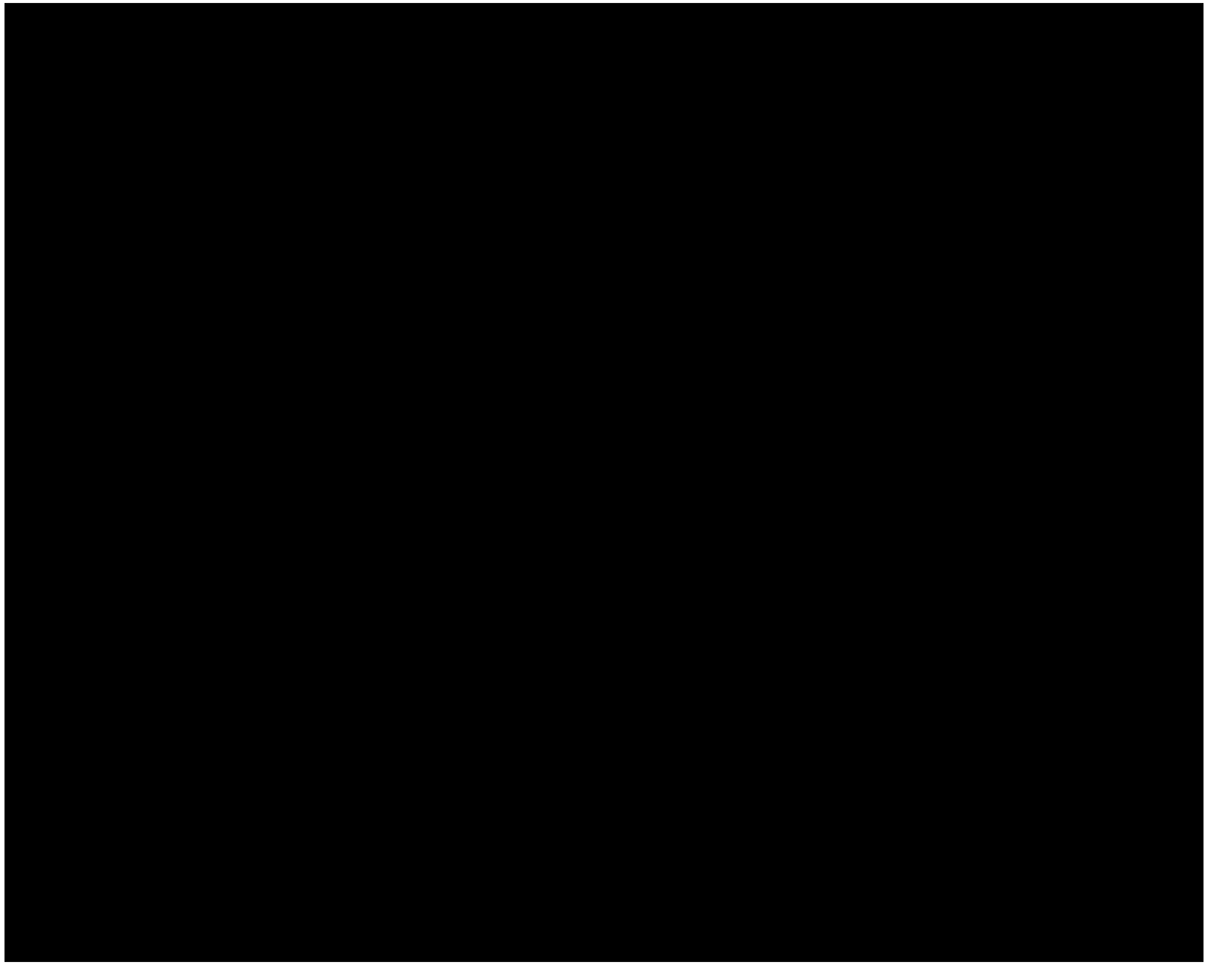
- Prediction of the perturbation ⇨ reference correction
- GPC control law
- 3 controlled variables : distance to the organ in the image z, spot position on the organ surface (x,y)
- Control input : 3 axes of the robot (q1, q2, q3)
- Linearized dynamic model of the axes of the robot considered as dynamically decoupled
- Hypothesis : interaction matrix partly decoupled

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} 0 & L_{12} & L_{13} \\ 0 & L_{22} & L_{23} \\ L_{31} & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix}$$

Estimated around working position in open loop

Physiological motions compensation

In vivo experiment



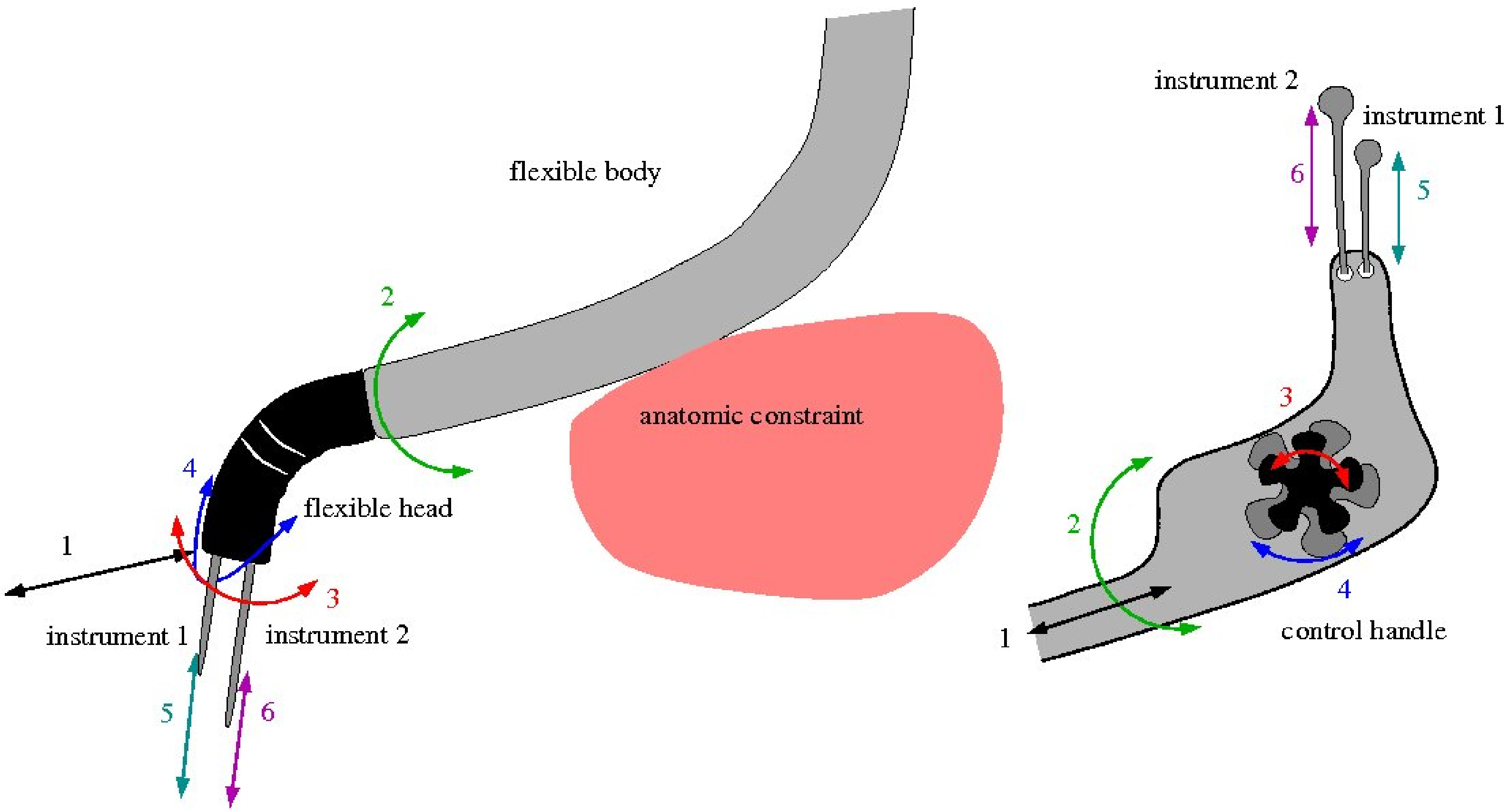
Physiological motions compensation

Breathing motion compensation with a flexible endoscope

- Flexible endoscopes : gastroscopy, coloscopy, transluminal operations
- Hard to manually control, orientation and translation coordination very complex
- Backlashes, dead zones

⇨ Autonomous following of the organs

Breathing motion compensation with a flexible endoscope



Breathing motion compensation with a flexible endoscope

• Controlled variables : position of an interest area in the image (u, v)

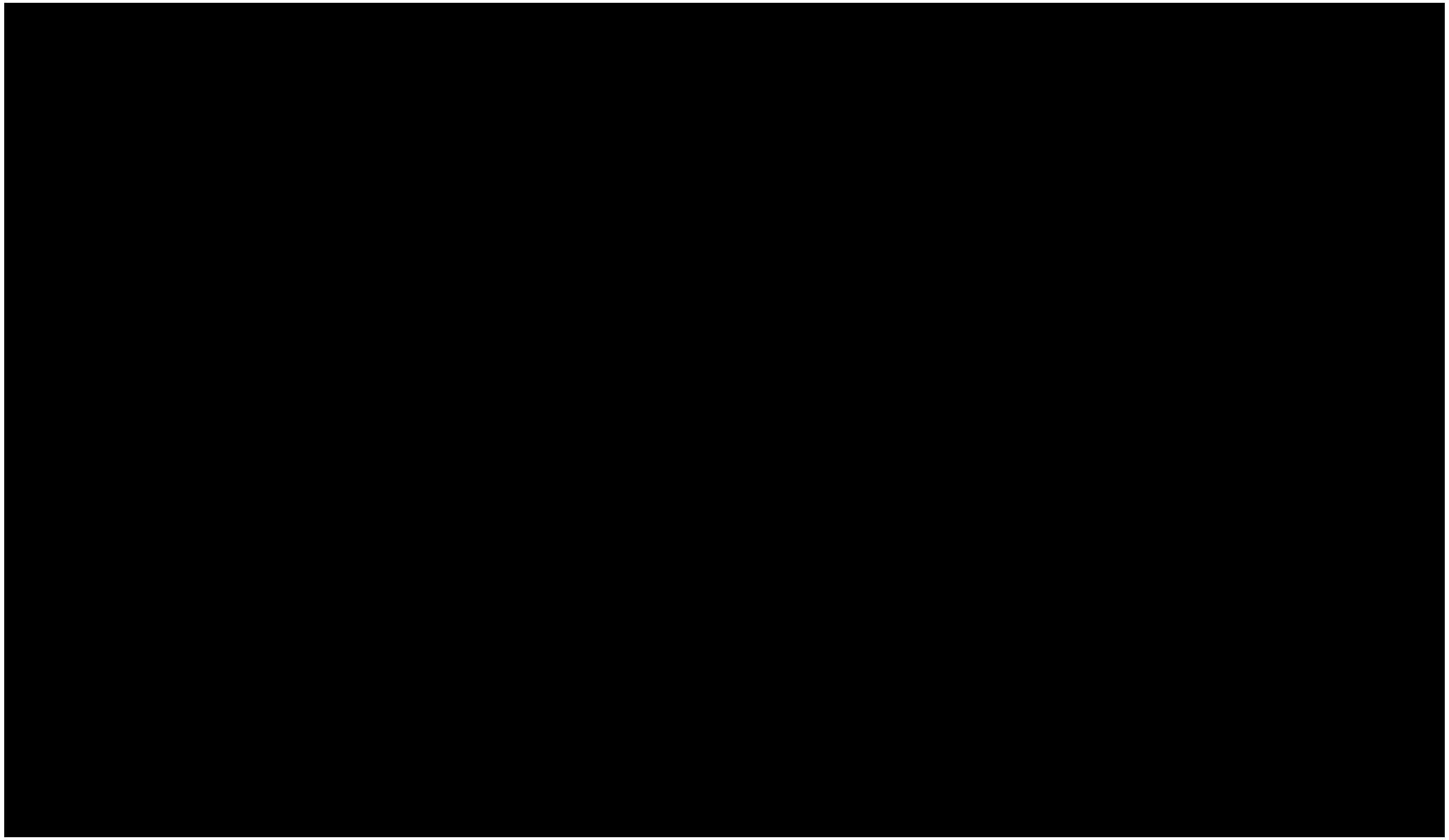
• Control input : $\dot{q}_1$ and $\dot{q}_2$

• Interaction matrix estimated beforehand

$$\begin{bmatrix} \dot{u} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} L_{11} & L_{12} \\ L_{21} & L_{22} \end{bmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix}$$

• Repetitive control law ⇒ rejection of breathing disturbance and model errors after some disturbance periods

Breathing motion compensation with a flexible endoscope



Bibliography

A. Krupa. Visual servoing in laparoscopic surgery. Ph.D. thesis, University Louis Pasteur, Strasbourg I, june 2003

R. Ginhoux. *Compensation des mouvements physiologiques en chirurgie robotisée par commande prédictive*. Ph.D. Thesis, Strasbourg University, december 2003

F. Nageotte. *Contributions à la suture assistée par ordinateur en chirurgie mini-invasive.* Ph.D. Thesis, Strasbourg University, november 2005

A. Krupa, J. Gangloff, C. Doignon, M. de Mathelin, G. Morel, J. Leroy, L. Soler, J. Marescaux. Autonomous 3D positioning of surgical instruments in robotized laparoscopic surgery using visual servoing. *IEEE Transactions on Robotics*, vol 19, no 5, pages 842-853, 2003

R. Ginhoux, J. Gangloff, M. de Mathelin, L. Soler, M. Arenas Sanchez and J. Marescaux. Active Filtering of Physiological Motion in Robotized Surgery Using Predictive Control. *IEEE Transactions on Robotics*, vol 21, no 1, pages 67-79, 2005

L. Ott, Ph. Zanne, F. Nageotte and M. De Mathelin, Problematic of transluminal operations, Surgetica 2007

F. Nageotte, Ph. Zanne, M. De Mathelin and Ch. Doignon, Visual servoing based tracking for endoscopic path following, IROS 2006

Perspectives

- New sensors (visual servoing under CT scan ?)
- Servoing without features extraction on deformable objects
- High speed visual servoing with high resolution

LSiiT