ACTIVE STRUCTURE ESTIMA-TION FROM KNOWN MOTION

Spica R.*, Robuffo Giordano P.** Chaumette F.***

*Univ. de Rennes I at IRISA/Inria Rennes, riccardo.spica@irisa.fr, **CNRS at IRISA/Inria Rennes, prg@irisa.fr, ***IRISA/Inria Rennes, francois.chaumette@inria.fr



Structure estimation from motion is a classical topic in computer/robot vision. We propose an active strategy that enforces an estimation dynamics equivalent to that of a linear 2nd-order system with desired poles by suitably acting on the estimation gains and on the inputs applied to the system. This can also be combined with execution of a visual servoing task exploiting a novel projection operator to increase robot redundancy. The theory is experimentally validated in various case studies.

Observer design

Let $(oldsymbol{s},oldsymbol{\chi})\in\mathbb{R}^{m+p}$ with $egin{array}{c} \dot{oldsymbol{s}}=oldsymbol{f}_m(oldsymbol{s},oldsymbol{u},t)+oldsymbol{\Omega}^T(t)oldsymbol{\chi} \ \dot{oldsymbol{\chi}}=oldsymbol{f}_u(oldsymbol{s},oldsymbol{\chi},oldsymbol{u},t) \end{array}$

with input $u, s \in \mathbb{R}^m$ measurable and $\chi \in \mathbb{R}^p$ unmeasurable. The observer

$$\begin{cases} \dot{\hat{\boldsymbol{s}}} = \boldsymbol{f}_m(\boldsymbol{s}, \, \boldsymbol{u}, \, t) + \boldsymbol{\Omega}^T(t) \hat{\boldsymbol{\chi}} + \boldsymbol{H} \boldsymbol{\xi} \\ \dot{\hat{\boldsymbol{\chi}}} = \boldsymbol{f}_u(\boldsymbol{s}, \, \hat{\boldsymbol{\chi}}, \, \boldsymbol{u}, \, t) + \alpha \boldsymbol{\Omega}(t) \boldsymbol{\xi} \end{cases}$$

with $\xi = s - \hat{s}$, H > 0, $\alpha > 0$ (gains) is (locally) exponentially stable iff [1] the Persistence of Excitation (PE) holds

$$\int_{t}^{t+T} \mathbf{\Omega}(\tau) \mathbf{\Omega}^{T}(\tau) d\tau \ge \gamma \mathbf{I}_{p} > 0 \ \forall t \ge t_{0}$$
or (when $m \ge p$) if $\mathbf{\Omega}(t) \mathbf{\Omega}^{T}(t) \ge \frac{\gamma}{T} \mathbf{I}_{p}$

The active strategy

- Eigenvalues σ_1^2 of $\Omega\Omega^T$ determine convergence rate
- ullet in SfM $oldsymbol{\Omega} = oldsymbol{\Omega}(oldsymbol{s},oldsymbol{u} = (oldsymbol{v},oldsymbol{\omega}))$ and

$$\dot{(\sigma_i^2)} = oldsymbol{J}_{u,i} \dot{oldsymbol{u}} + oldsymbol{J}_{oldsymbol{s},i} \dot{oldsymbol{s}}$$

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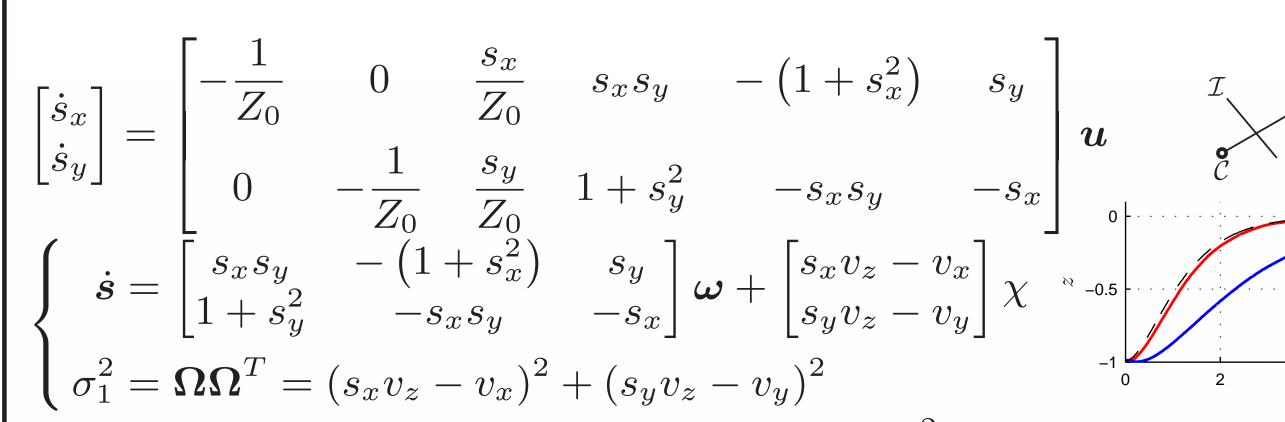
we can *optimize* the behavior by actively choosing u with, e.g.

$$\dot{u} = \frac{k_1 u}{\|u\|^2} \left(\|u_0\|^2 - \|u\|^2 \right) + k_2 \left(I - \frac{u u^T}{\|u\|^2} \right) \left(J_{u,1}^T - J_{u,1}^{\dagger} J_{s,1} \hat{\dot{s}} \right)$$
Result:

- ullet fastest convergence ullet speed for a given limited $\|u\|$
- predictability of $z = \chi \hat{\chi}$ transient (approximates a 2-nd order system)
- online strategy (no pre-planning)

Case studies

• Point feature [2]: let $s=(\frac{X_0}{Z_0},\,\frac{Y_0}{Z_0})$ and $\chi=\frac{1}{Z_0}$ with m=2>p=1



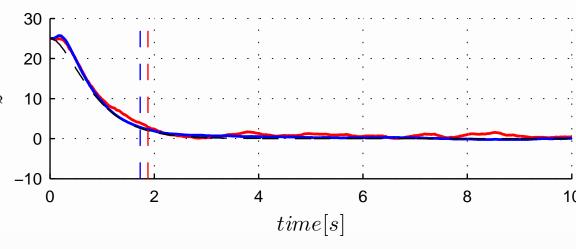
note: in all cases only linear velocity ${m v}$ enters in σ_1^2

Estimation error for "active" (red) and constant (blue) $oldsymbol{v}$ (same norm)

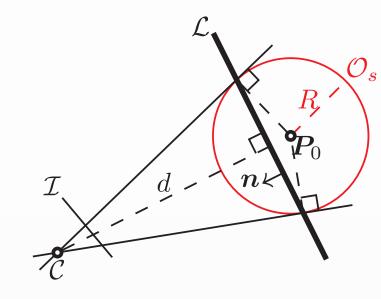
• Spherical target [2]: $s = \frac{P_0}{B}$ and $\chi = \frac{1}{B}$ with m = 3 > p = 1

$$\left\{egin{array}{l} \dot{oldsymbol{s}} = \left[oldsymbol{s}
ight]_{ imes} oldsymbol{\omega} - oldsymbol{v}\chi \ \sigma_1^2 = oldsymbol{\Omega} oldsymbol{\Omega}^T = \left\|oldsymbol{v}
ight\|^2 \end{array}
ight.$$

note: direction of motion doesn't matter in this case



Estimation error for different $oldsymbol{v}$ (same norm)

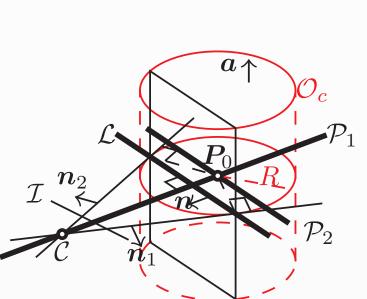


• Cylindrical target [2]: $s = \frac{P_0}{R}$ and $\chi = \frac{1}{R}$ with m = 3 > p = 1

$$\left\{egin{array}{l} \dot{oldsymbol{s}} = [oldsymbol{s}]_{ imes} oldsymbol{\omega} + (\mathbf{a}\mathbf{a}^T - oldsymbol{I}) oldsymbol{v} \chi & egin{array}{c} & \mathbf{0} & \mathbf{0} \ \sigma_1^2 = oldsymbol{\Omega} oldsymbol{\Omega}^T = \|oldsymbol{v}\|^2 - (\mathbf{a}^T oldsymbol{v})^2 & \mathbf{0} \end{array}
ight.$$

Estimation error for "active" (blue and green)

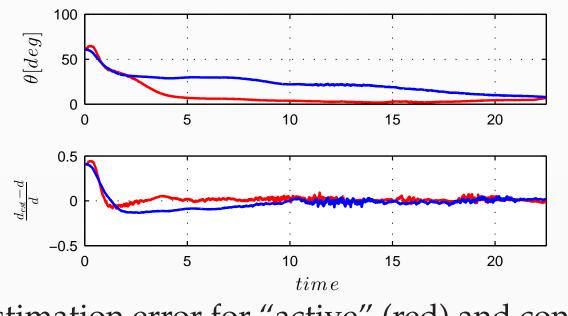
and constant (blue) \boldsymbol{v} (same norm)



• Planar scene [3]: $s = (m_{ij})$ with $m_{ij} = \sum_{k=1}^{N} x_k^i y_k^j$ (discrete points) or $m_{ij} = \iint_{\mathcal{O}_n} x^i y^j dx dy$ (dense patch) and $\chi = -n/d$ with $m \ge p = 3$

$$egin{aligned} \dot{m}_{ij} &= f_{m_{ij}}(m_{kl},oldsymbol{\omega}) \ &+ oldsymbol{f}_{\Omega_{ij}}(m_{kl},oldsymbol{v})oldsymbol{\chi} \ \sigma_{1,2,3}^2 &= \sigma_{1,2,3}^2(m_{kl},oldsymbol{v}) \end{aligned}$$

expression depends on chosen moments but can always be computed in closed form



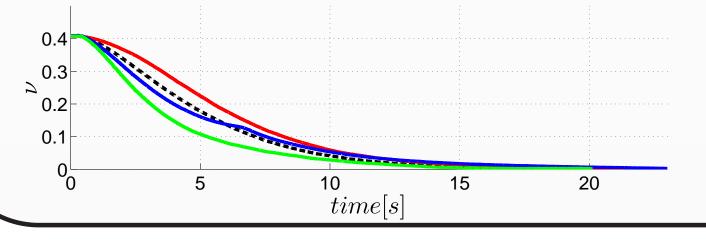
Estimation error for "active" (red) and constant (blue) $oldsymbol{v}$ (same norm)

Multitask coupling [4]

In visual servoing we often have:

$$\frac{d}{dt}(ask) = \dot{m{r}} = m{J}(m{s},\,m{q},\,m{\chi})m{u}$$

- ullet estimating χ while executing the task can improve performance
- redundancy can be exploited for active estimation
- redundancy can be maximized controlling task error norm ν (one quantity) instead of task error



References

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- [2] R. Spica, P. Robuffo Giordano, and F. Chaumette, "Active Structure from Motion: Application to Point, Sphere and Cylinder," *IEEE Trans. on Robotics*, conditionally accepter.
- [3] —, "Experiments of Plane Estimation by Active Vision from Point Features and Image Moments," in *submitted to 2014 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Chicago, IL, Sep 2014.
- [4] —, "Coupling Visual Servoing with Active Structure from Motion," in 2014 IEEE Int. Conf. on Robotics and Automation, Hong Kong, China, May 2014.