Contributions to dense visual tracking and visual servoing using robust similarity criteria

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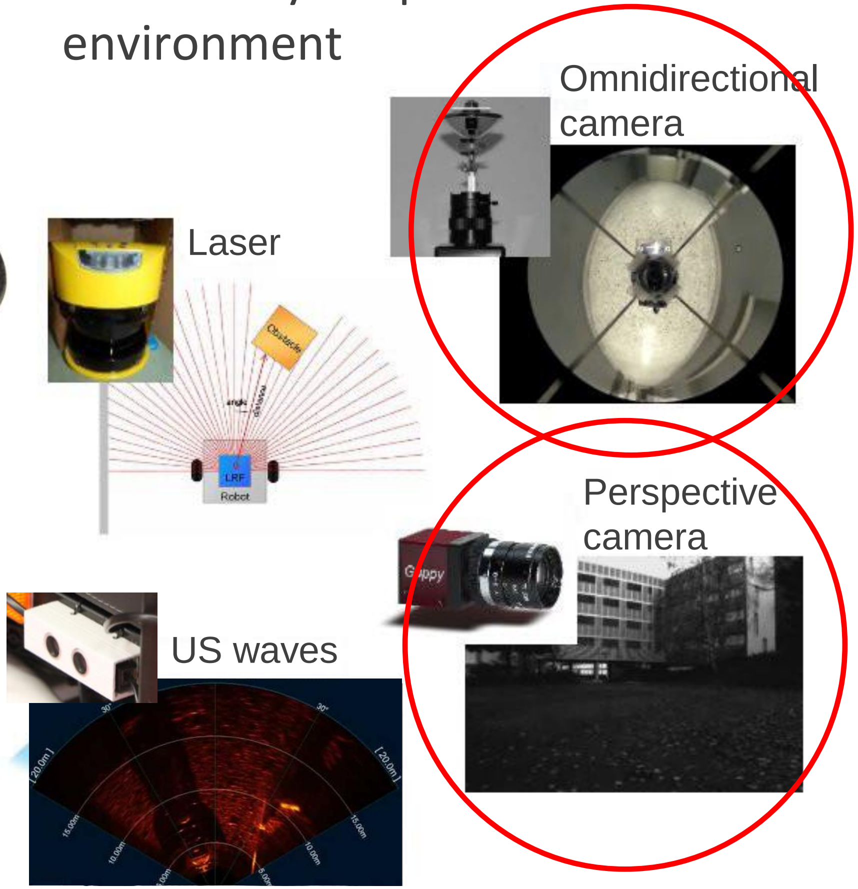
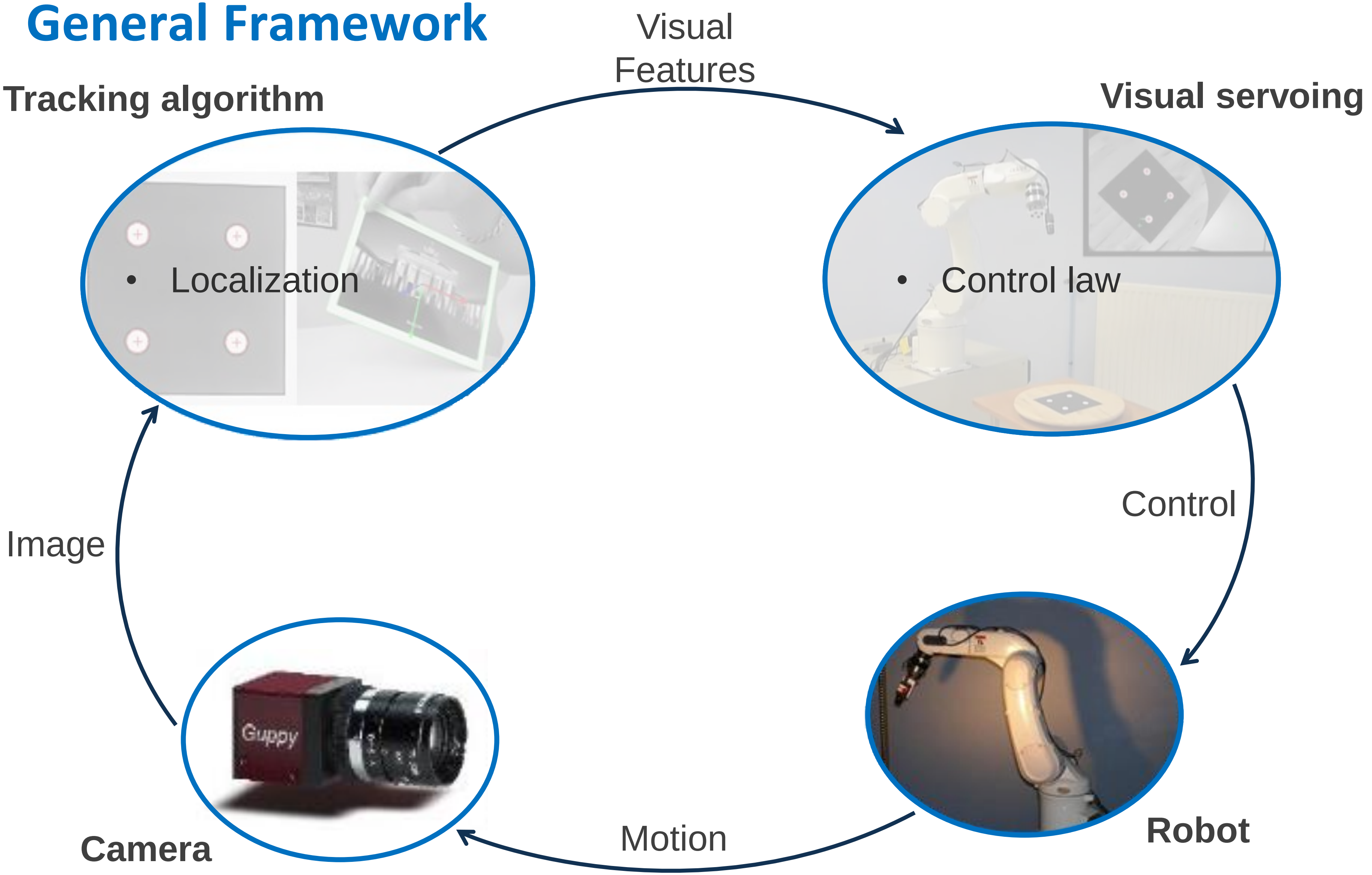
Context | Robotics

- More and more robots

- Lots of ways to perceive the environment



General Framework



Challenges

Tracking algorithm

- **Robustness issue**
  - Global variations
  - Local variations
  - Deformations

BYPASS

Visual servoing

- **Need for accuracy**
- **Can we avoid relying on a tracking algorithm ?**

Camera

Robot

Our contributions

Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- Robust non-rigid dense tracker

Visual servoing

- Use of robust similarity measures (SCV and NMI)
- Robust dense visual servoing
- Adaptation to omnidirectional sensors

DENSE APPROACHES

Camera

Robot

Our contributions

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DENSE APPROACHES

Camera

Robot

(Dis)Similarity functions

- Sum of Squared Differences (SSD)

[Lucas, 81] [Baker, 04] [Gay-Bellile, 10]

Lack of robustness

- Sum of Conditional Variance (SCV)

[Richa, 11]

- Normalized Cross Correlation (NCC)

[Irani, 98] [Scandaroli, 12]

Robustness to global variations

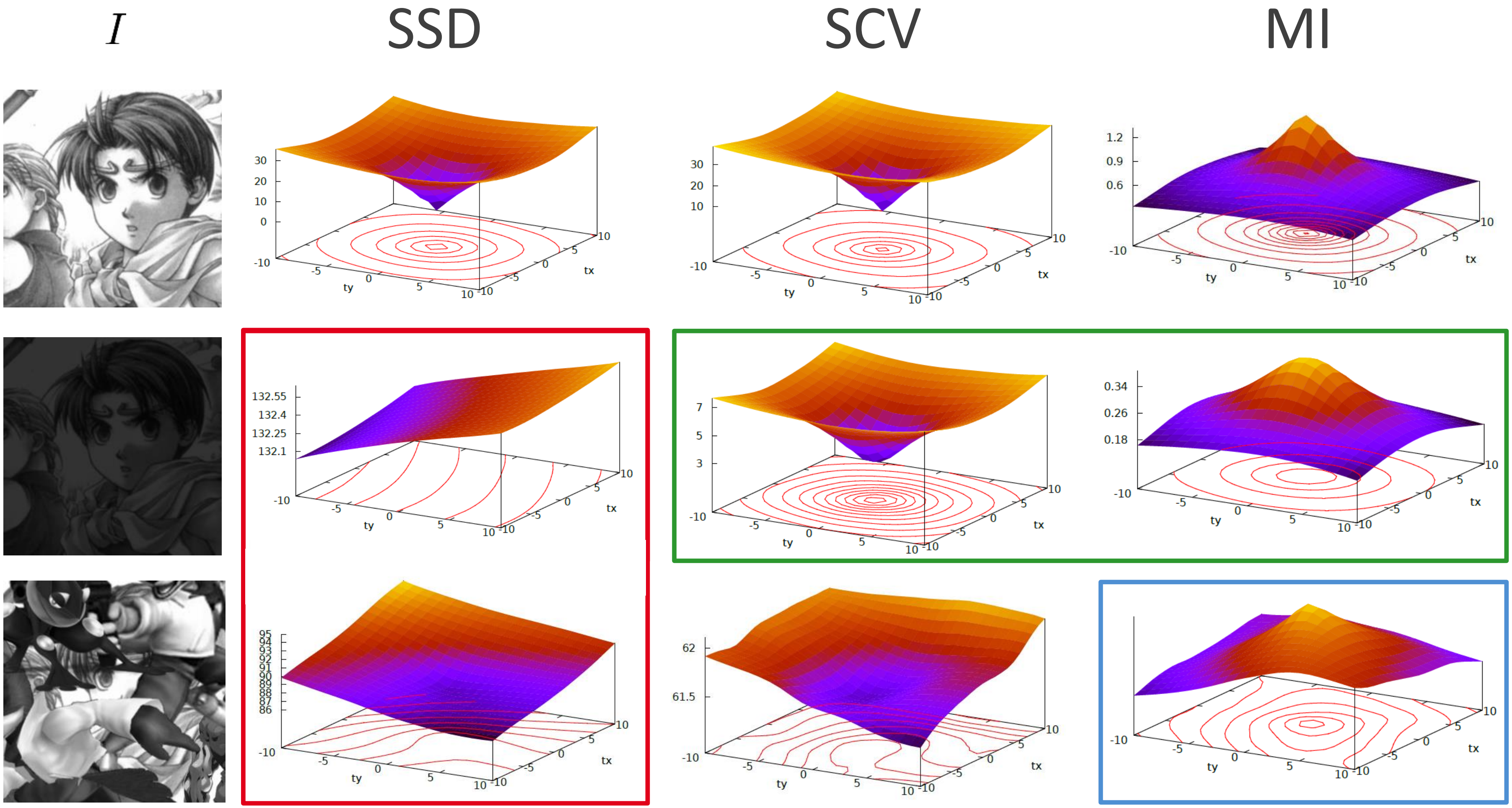
- Mutual Information (MI) [Shannon, 48] [Viola, 97] [Dame, 12]

Robustness to global variations

Robustness to local variations

(Dis)Similarity functions | Robustness analysis

I^*



Tracking algorithm

- **Use of robust similarity measures (SCV and MI)**
- **Robust model-based dense tracker**
- **Robust non-rigid dense tracker**

Visual servoing

- **Use of robust similarity measures (SCV and NMI)**
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DENSE APPROACHES

Camera

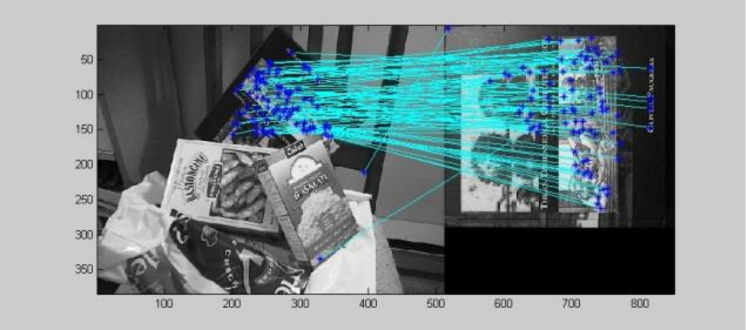
Robot

Differential Template Tracking [Baker, 04]

Dense visual tracking

- No use of geometrical features

[Simon, 00]



[Petit, 13]

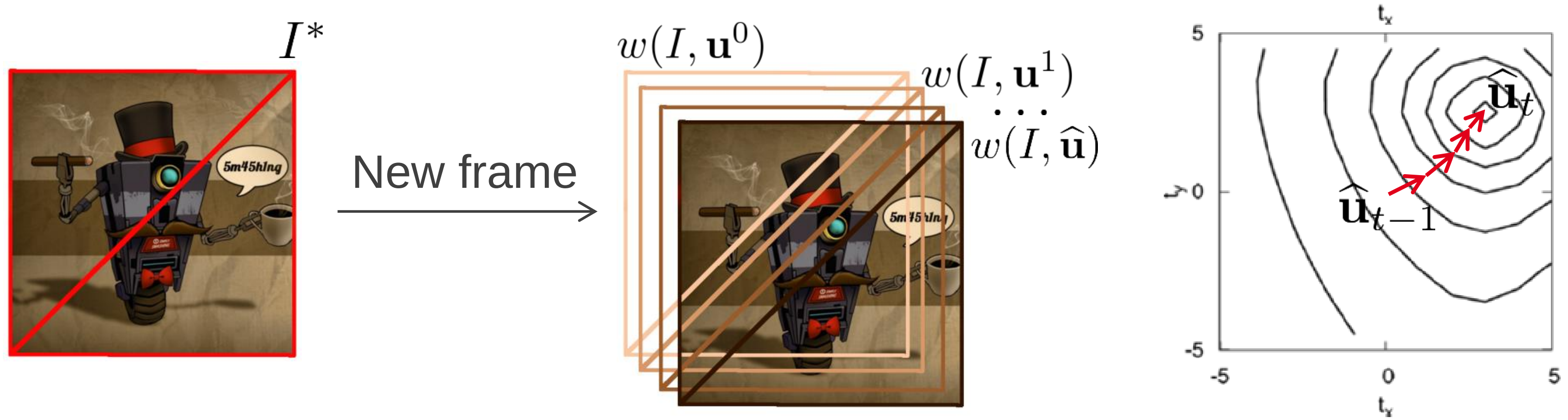
Differential Template Tracking [Baker, 04]

Dense visual tracking

- No use of geometrical features
- Find the displacement that optimizes a (dis)similarity function

$$\widehat{\mathbf{u}} = \arg\min_{\mathbf{u}} \sum_{k=1}^{N_{\mathbf{x}}} f(I^*(\mathbf{x}_k), I(w(\mathbf{x}_k, \mathbf{u})))$$

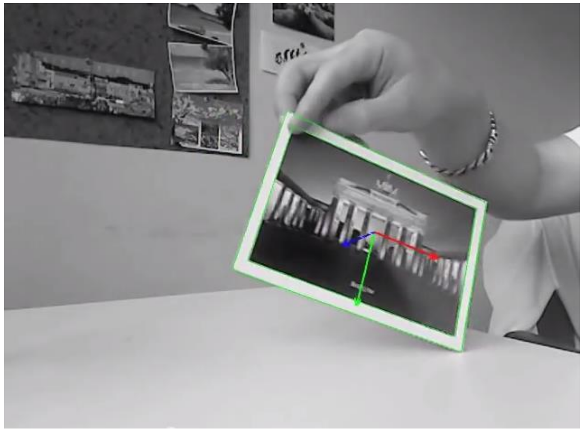
- Hypothesis: the displacement between two images is small
    - The previous estimated parameters $\mathbf{u}$ are refined to estimate the new parameters



Differential template tracking | Classical SSD approach

[Baker, 04]

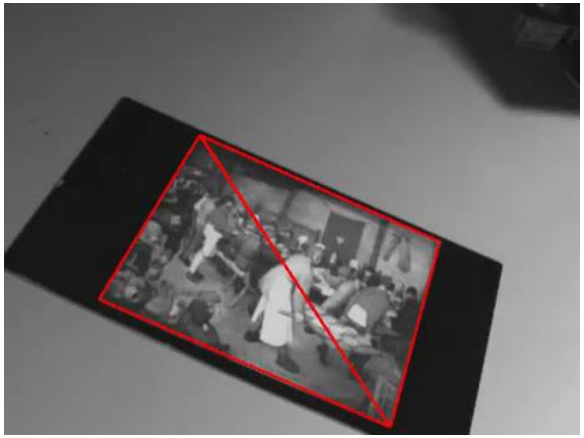
- Sum of Squared Differences (SSD)
  - Difference between two sets of pixels



$$SSD = \sum_{l=1}^{N} \left[I(w(\mathbf{x}_k, \mathbf{u})) - I^*(\mathbf{x}_k) \right]^2$$

  - Simple optimization over the parameters of a displacement function

$$\widehat{\mathbf{u}} = \arg\min_{\mathbf{u}} \sum_{l=1}^{N} \left[I(w(\mathbf{x}_k, \mathbf{u})) - I^*(\mathbf{x}_k) \right]^2$$



+ Easy to use

− Very poorly robust to perturbations

Sum of conditional variance | Template adaptation

[Richa, 11]

- Sum of conditional variance

$$SCV = \sum_{l=1}^{N} \left[I(w(\mathbf{x}_k, \mathbf{u})) - \widehat{I^*}(\mathbf{x}_k) \right]^2$$

- Template histogram adaptation

$$\widehat{I^*}(j) = \sum_i i \frac{p_{II^*}(i,j)}{p_{I^*}(j)}$$

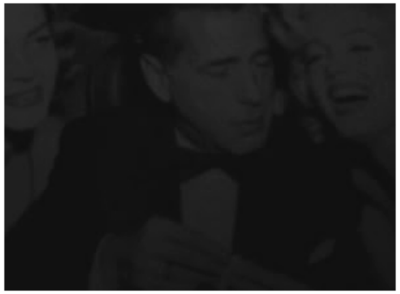
- Probability density functions
  - $$\begin{aligned} p_{II^*}(i,j) &= p(I(x) = i, I^*(x) = j) \\ &= \frac{1}{n \times m} \sum_{\mathbf{x}} \alpha(I(\mathbf{x}) - i)\alpha(I^*(\mathbf{x}) - j) \end{aligned}$$

$\alpha(u) = 1 \text{ if and only if } u = 0$

\+ Easy to use

\+ Robust to global perturbations

− Poorly robust to local perturbations



Current view

Reference template

Adapted template

Mutual information | MI [Dame, 11]

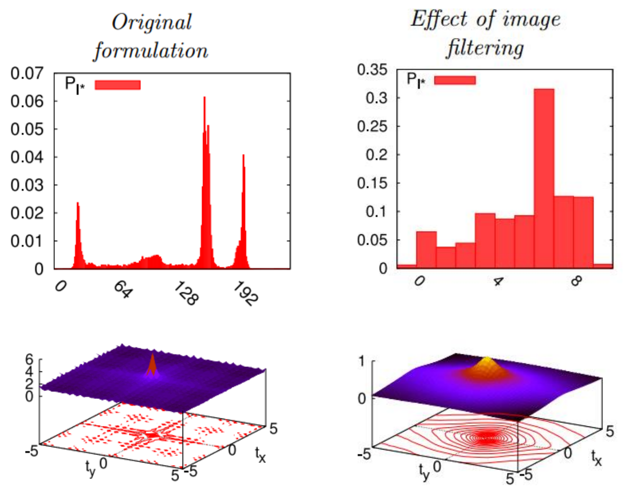
- Quantity of information shared by two signals

$$\mathrm{MI}(I, I^*) = \mathrm{H}(I) + \mathrm{H}(I^*) - \mathrm{H}(I, I^*)$$ [Shannon, 1948]

- Entropy computation

$$\mathrm{H}(I) = -\sum_{r=0}^{N_{\mathbf{x}}} p_I(r) \log\left(p_I(r)\right)$$

- Histogram binning



- Multimodality

Map

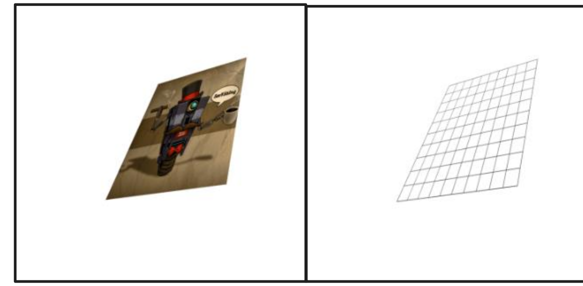
Satellite images

➕ Very robust to both global and local variations

➖ Complex to use
Computationally expensive

Visual Tracking | Displacement model

Homography



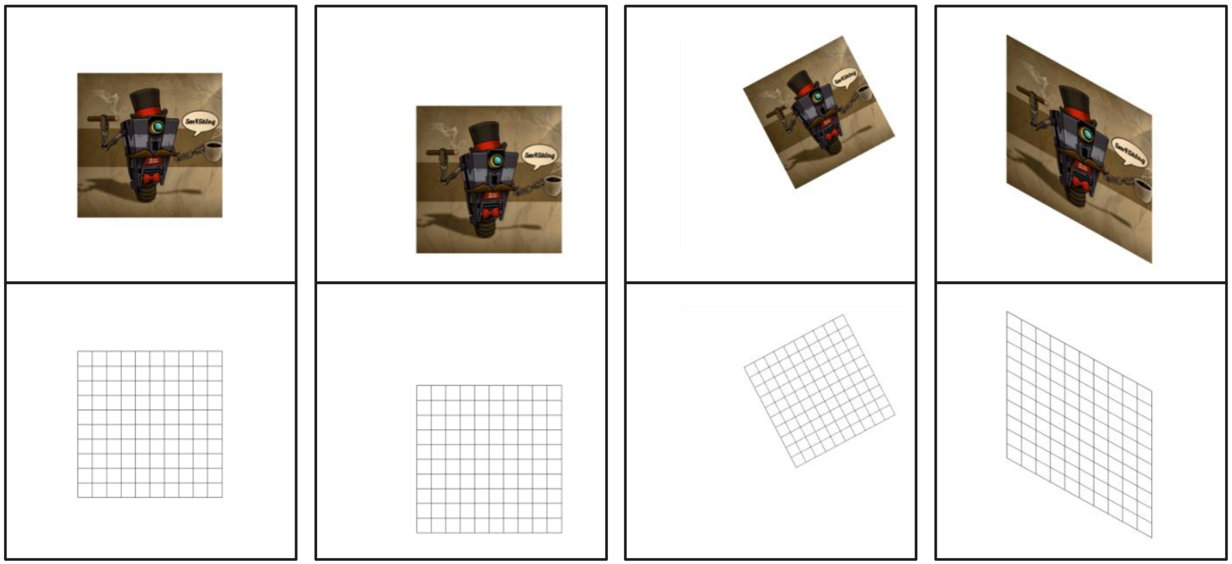
$\mathbf{x} \in \mathrm{SL}(3)\ \ (2\mathrm{D})$

$\mathbf{x} \in \mathrm{SE}(3)\ \ (3\mathrm{D})$

More accuracy

More freedom

Reference | Translation | sRt | Affine

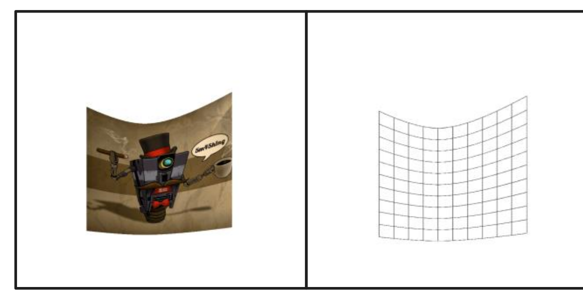


$\mathbf{x} \in \mathbb{R}^2 \quad \mathbf{x} \in SL(2) \times \mathbb{R}^2 \quad \mathbf{x} \in \mathbb{R}^6$

More accuracy

More freedom

Thin Plate Splines



$\mathbf{x} \propto N_c$

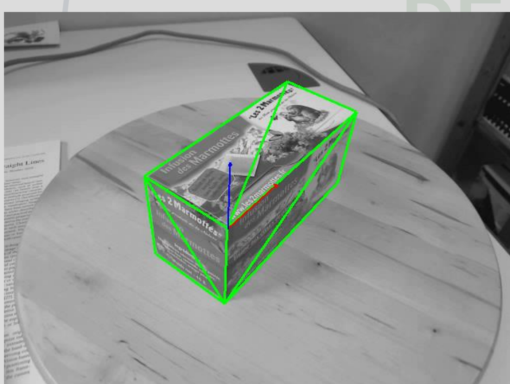
Tracking algorithm

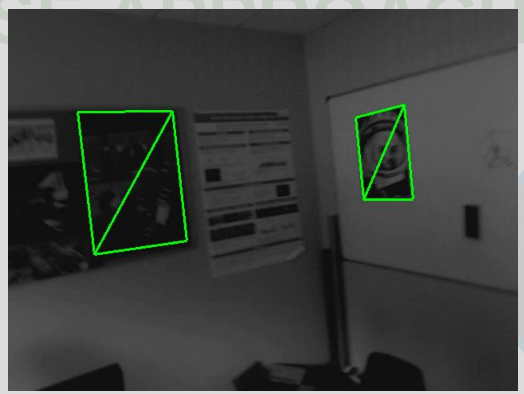
Visual servoing

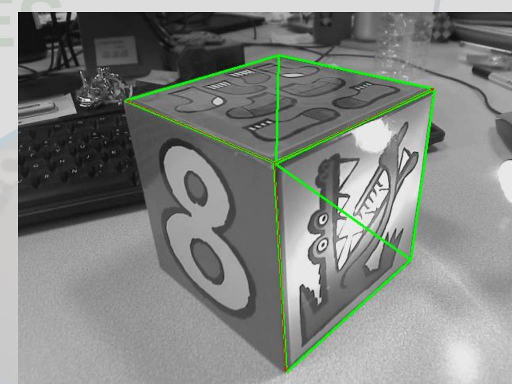
- Use of robust similarity measures (SCV and MI)
- **Robust model-based dense tracker**
- Robust non-rigid dense tracker

- Use of robust similarity measures (SCV and NMI)
- Robust dense visual servoing
- Adaptation to omnidirectional sensors

DENSE APPROACHES







Camera

Robot

[Delabarre, IEEE IROS' 13]

Tracking planes [Benhimane, 06]

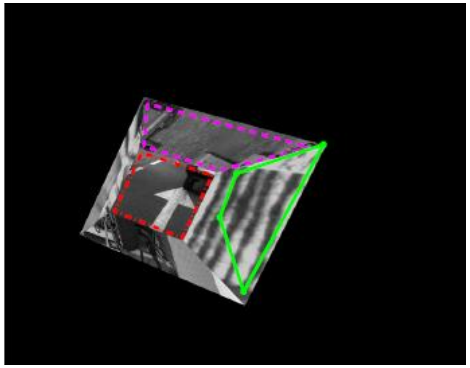
- From a camera pose, homographies are computed for every planes considered

- Minimization of the Sum of Squared Differences

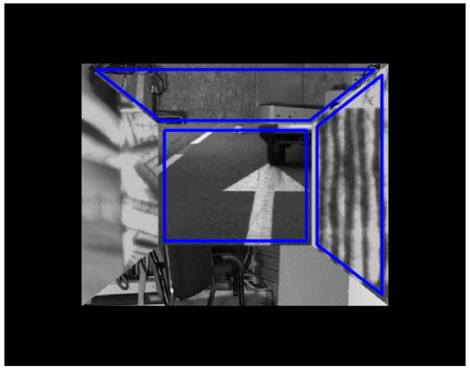
$$\hat{\mathbf{r}} = \arg\min_{\mathbf{r}} \sum_{l=1}^{N} \left[I(w(\mathbf{x}_k, \mathbf{r})) - I^*(\mathbf{x}_k) \right]^2$$

- Including Euclidean constraints allows to add several planes to the same optimization loop

- Several drawbacks
  - No adaptation to a dynamic model
  - No robustness of the SSD



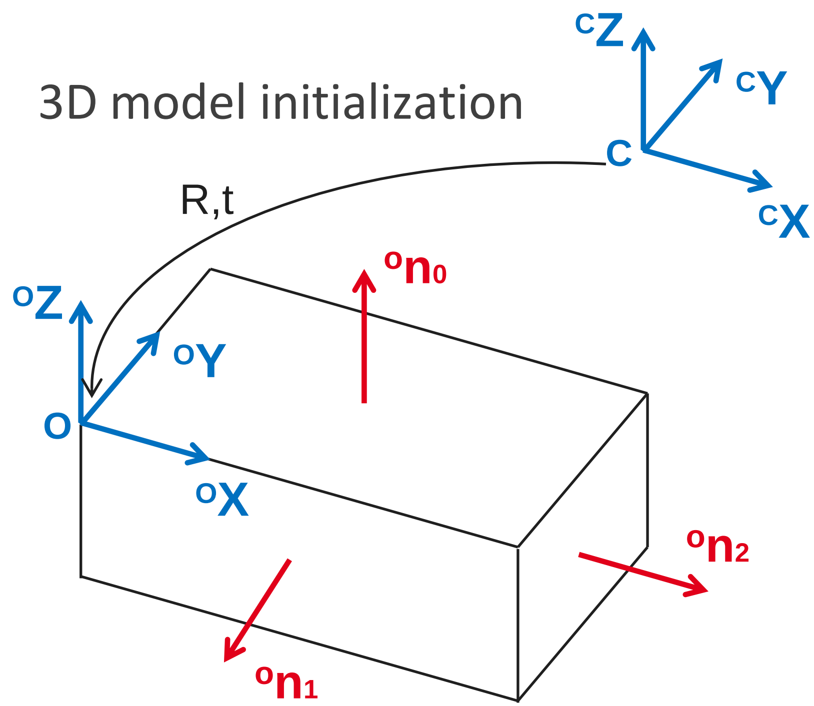
3 trackers



1 tracker

Model-based tracking

- 3D model initialization

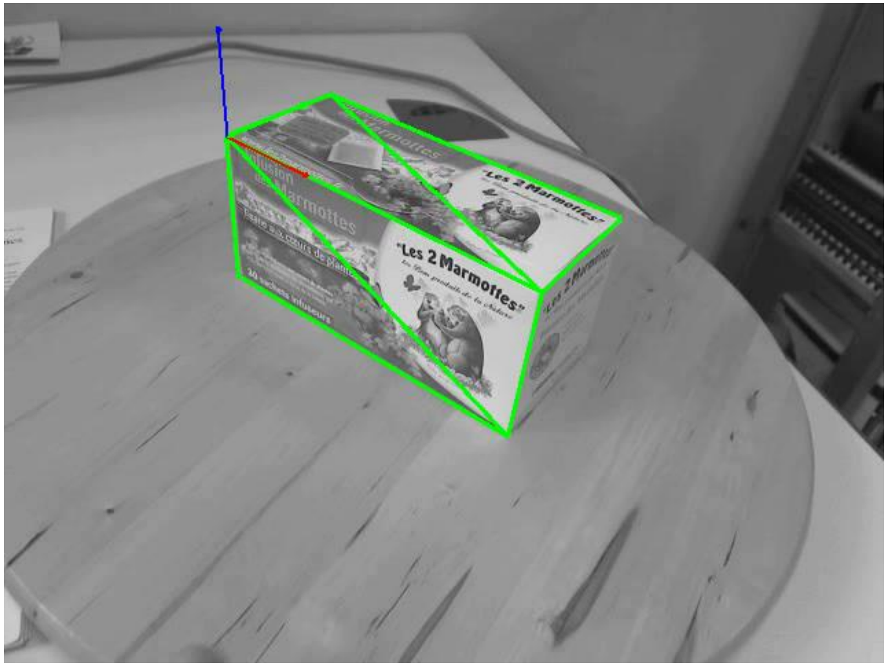


Common for every plane in the model

$$\mathbf{H}_l(\mathbf{T}(\mathbf{r})) = {}^{\mathbf{c}}\mathbf{R}_{\mathbf{o}} + {}^{\mathbf{c}}\mathbf{t}_{\mathbf{o}} \frac{{}^{\mathbf{c}}\mathbf{n}_l^{*\top}}{{}^{\mathbf{c}}\mathbf{d}_l}$$

Different for each plane in the model

where ${}^{\mathbf{c}}\mathbf{n} = {}^{\mathbf{c}}\mathbf{R}_{\mathbf{o}}{}^{\mathbf{o}}\mathbf{n}$, sim. ${}^{\mathbf{c}}\mathbf{d}$



- 3D pose estimation

$$\hat{\mathbf{r}} = \arg\min_{\mathbf{r}} f(I^*, w(I, \mathbf{r}))$$

- Dynamic adaptation to model changes

Sum of conditional variance | Adapting the current view

- Differential tracking

$$\widehat{\mathbf{r}} = \arg\min_{\mathbf{r}} \sum_{l=1}^{N_l} \sum_{k=1}^{N_{\mathbf{x}}} \left[I^*(\mathbf{x}_k) - \widehat{I}(w_l(\mathbf{x}_k, \mathbf{r})) \right]^2$$

Different for each plane in the model

Common for every plane in the model

- Image adaptation
  - $\hat{I}$ is the current view seen in the same conditions as I^*

$$\hat{I}(\mathbf{x}) = \mathcal{E}(I^*(\mathbf{x}) \mid I(\mathbf{x})) \qquad \text{where} \qquad \hat{I}(j) = \sum_i i \frac{p_{II^*}(i,j)}{p_I(j)}$$

- Inverse compositional optimization scheme [Baker, 04]

$$\widehat{\Delta\mathbf{r}} = \arg\min_{\Delta\mathbf{r}} \sum_{l=1}^{N_l} \sum_{k=1}^{N_{\mathbf{x}}} \left[I^*(w_l(\mathbf{x}_k, \Delta\mathbf{r})) - \widehat{I}(w_l(\mathbf{x}_k, \mathbf{r})) \right]^2$$

- Computation of the the displacement update

$$\mathbf{J}(\Delta\mathbf{r}) = \frac{\partial I^*}{\partial w_l} \frac{\partial w_l}{\partial \mathbf{T}} \frac{\partial \mathbf{T}}{\partial \mathbf{x}} \frac{\partial \mathbf{x}}{\partial \Delta\mathbf{r}} = \mathbf{J}_{I^*} \mathbf{J}_{w_l} \mathbf{J}_{\mathbf{T}} \mathbf{J}_{\mathbf{x}}(\Delta\mathbf{r})$$

$$\widehat{\Delta\mathbf{r}} = -\left(\mathbf{J}_{I^*} \mathbf{J}_{w_l} \mathbf{J}_{\mathbf{T}} \mathbf{J}_{\mathbf{x}}(\mathbf{0})\right)^+ SCV(\mathbf{0})$$

Mutual information | MI

- Quantity of information shared by two signals

$$MI(I, I^*) = H(I) + H(I^*) - H(I, I^*)$$

- Complete formulation

$$MI = \sum_{r,t} p_{II^*}(r,t) \left(\frac{p_{II^*}(r,t)}{p_I(r) p_{I^*}(t)} \right)$$

- Maximization over SE(3)

$$\widehat{\Delta \mathbf{r}} = \arg\max_{\Delta \mathbf{r}} MI\left(I(w_l(\mathbf{x}, \Delta \mathbf{r})), I^*(\mathbf{x})\right)$$

  - Computation of the gradient and Hessian

$$\mathbf{G}_{MI} = \sum_{r,t} \frac{\partial p_{II^*}}{\partial \Delta \mathbf{r}} \left(1 + \log \left(\frac{p_{II^*}}{p_{I^*}} \right) \right)$$

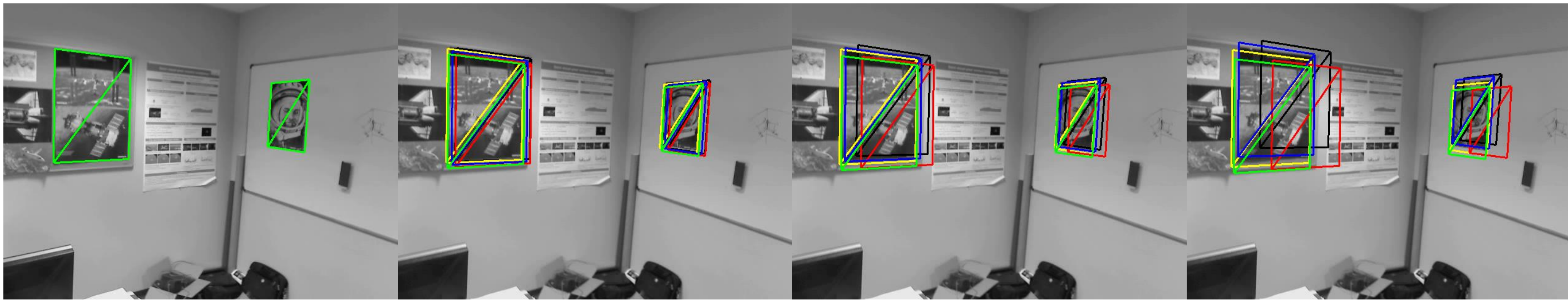
$$\mathbf{H}_{MI} = \sum_{r,t} \frac{\partial p_{II^*}}{\partial \Delta \mathbf{r}}^\top \frac{\partial p_{II^*}}{\partial \Delta \mathbf{r}} \left(\frac{1}{p_{II^*}} - \frac{1}{p_{I^*}} \right) + \frac{\partial^2 p_{II^*}}{\partial \Delta \mathbf{r}^2} \left(1 + \log \frac{p_{II^*}}{p_{I^*}} \right)$$

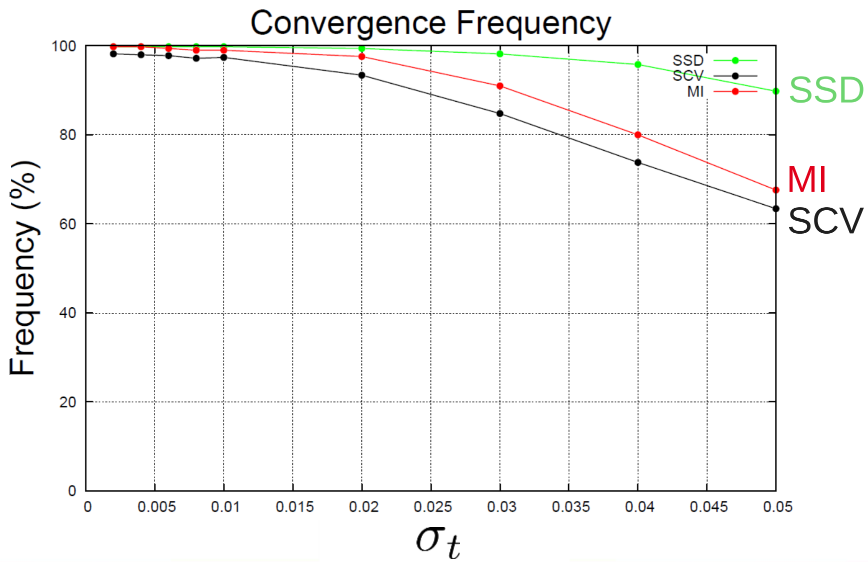
  - Minimizing the gradient $\widehat{\Delta \mathbf{r}} = -\mathbf{H}_{MI}^{-1} \mathbf{G}_{MI}^\top$

Convergence analysis | SSD vs SCV vs MI

- Nominal conditions:

$\sigma_t = 0$ $\sigma_t = 0.002$ $\sigma_t = 0.02$ $\sigma_t = 0.05$





Convergence analysis | SSD vs SCV vs MI

- Global variations:

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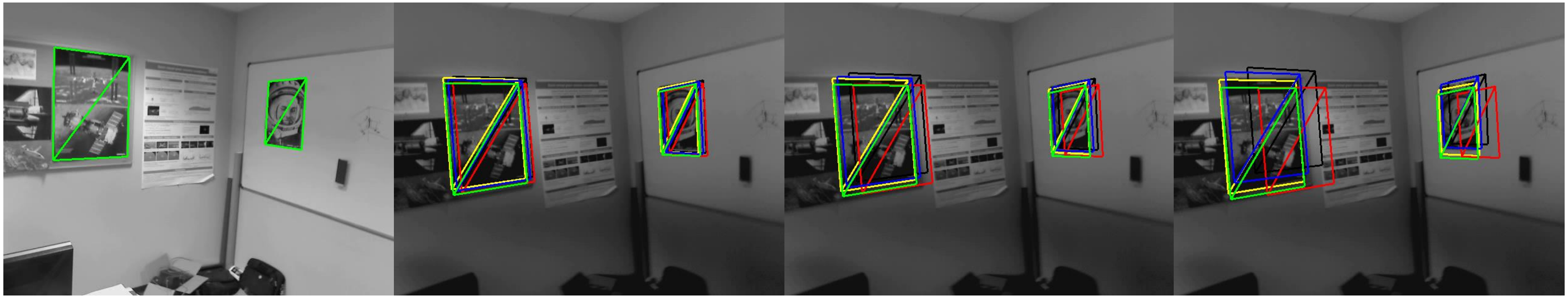
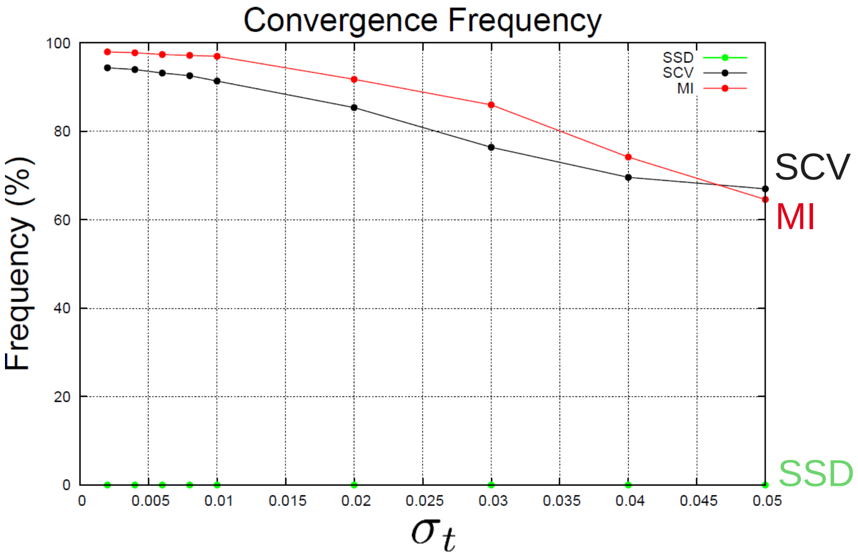
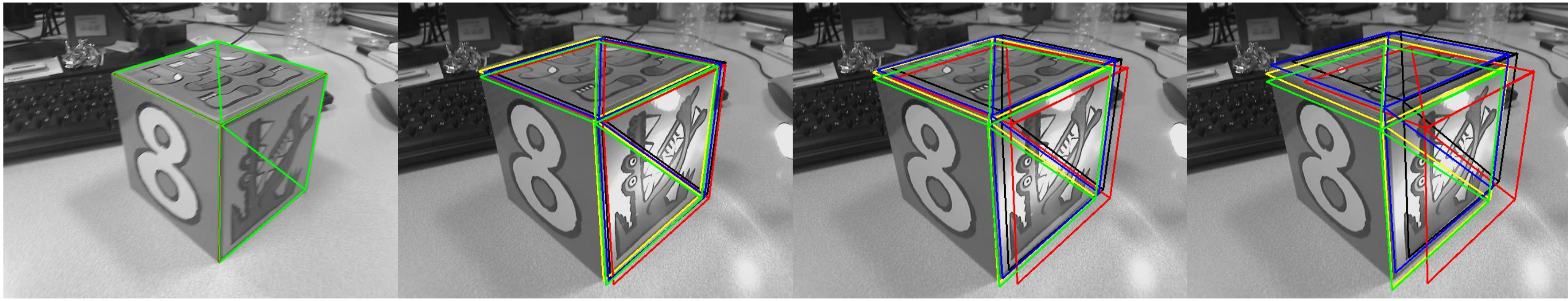


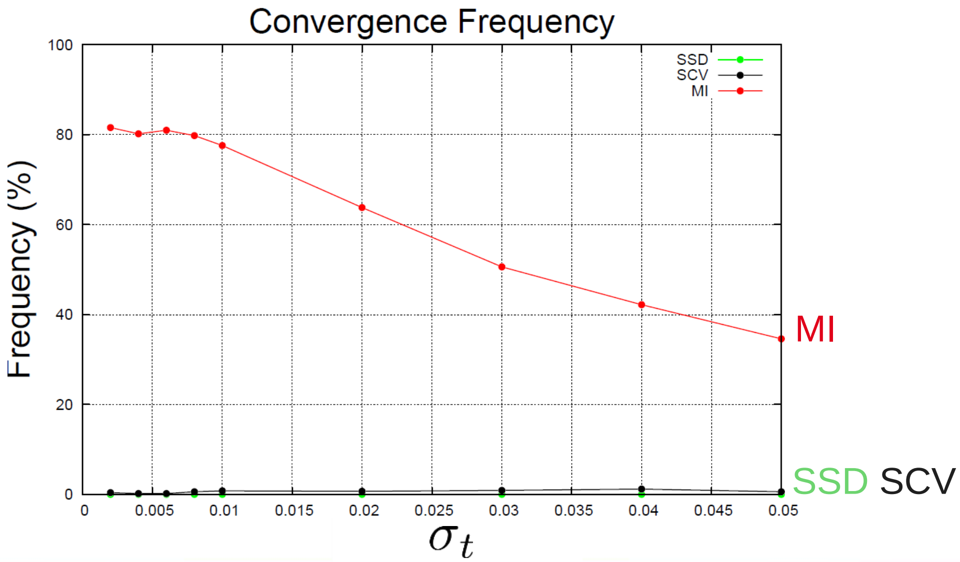


Convergence analysis | SSD vs SCV vs MI

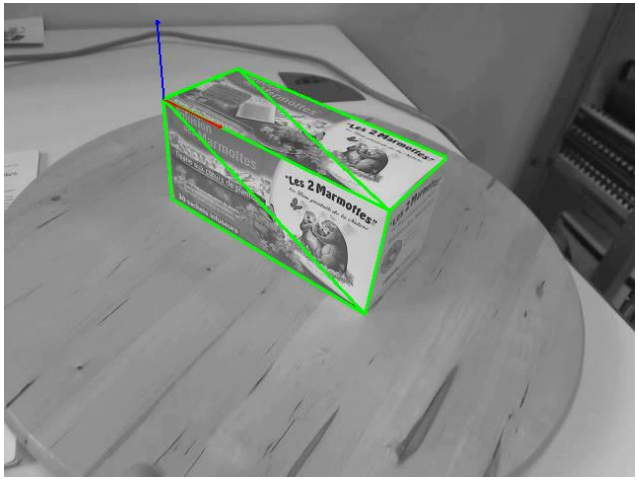
- Local variations:

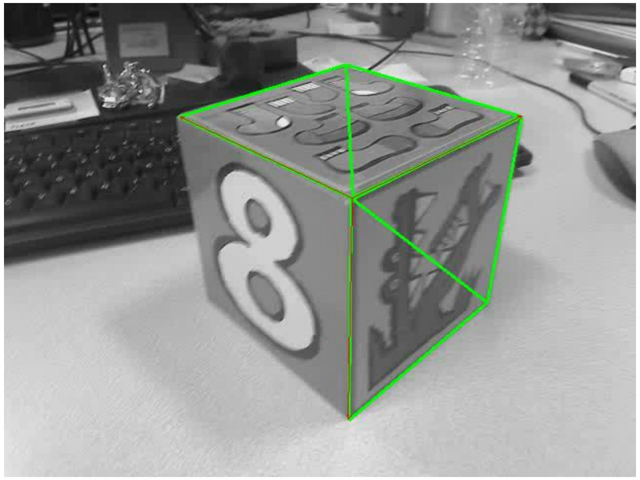
$\sigma_t = 0$ $\sigma_t = 0.002$ $\sigma_t = 0.02$ $\sigma_t = 0.05$





Experiments





Nominal conditions	Light Variations	Specular spots
No perturbation	Global perturbation	Local perturbation
MI and SCV very effective	MI and SCV not impacted	MI not impacted SCV impacted and fails

Part I | Visual Tracking

Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- **Robust non-rigid dense tracker**

Visual servoing

- Use of robust similarity measures (SCV and NMI)
- Robust dense visual servoing
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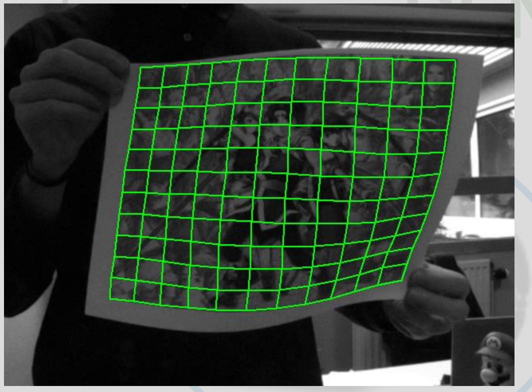
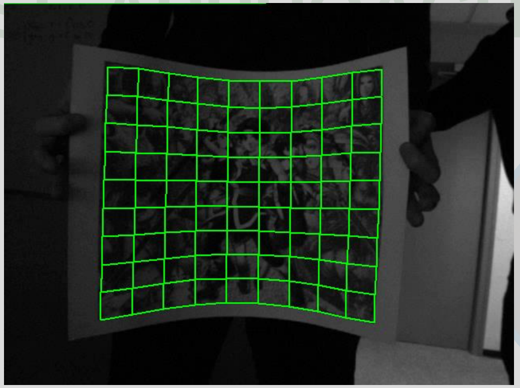
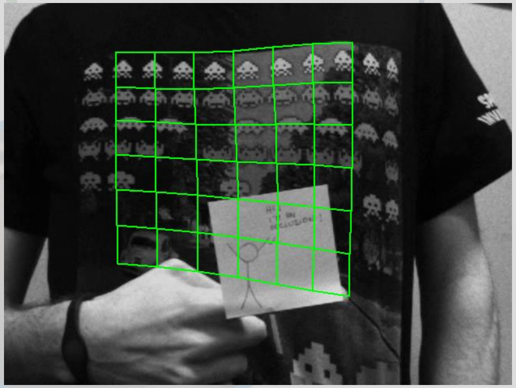
DENSE APPROACHES





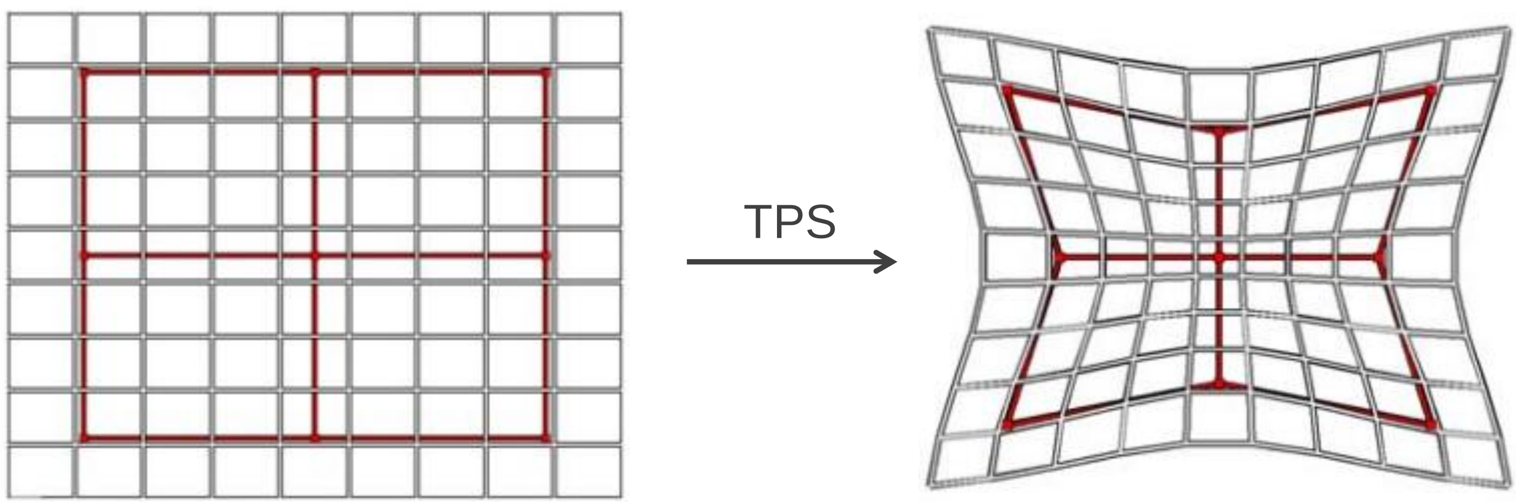


Camera

Robot

[Delabarre, IEEE ICIP' 14]

Non-rigid displacement | Thin-Plate Splines [Arad, 95]



[Gay-bellile, 2008]

$$w(\mathbf{x}, \mathbf{u}) = \underbrace{\begin{pmatrix} a_0 & a_1 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} a_2 \\ a_5 \end{pmatrix}}_{\text{Affine warp}}$$ + Deformation term

Non-rigid displacement | Thin-Plate Splines

- Thin-Plate Spline:

$$w(\mathbf{x}, \mathbf{u}) = \underbrace{\begin{pmatrix} a_0 & a_1 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} a_2 \\ a_5 \end{pmatrix}}_{\text{Affine warp}} + \underbrace{\sum_{k=1}^{N_p} \begin{pmatrix} w_x^k \\ w_y^k \end{pmatrix} \phi(d^2(\mathbf{x}, \mathbf{c}_k))}_{\text{TPS kernel}}$$

- Kernel function:

$$\phi(x) = \frac{x^{(4-p)} \log(x)}{\alpha} \xrightarrow[p \; = \; 2]{\alpha \; = \; 2} \phi(x) = \frac{1}{2} x^2 \log(x)$$

- Warp parameters:

$$\mathbf{u}^\top = \begin{pmatrix} a_0 & a_1 & a_2 & a_3 & a_4 & a_5 & \mathbf{w}_x^\top & \mathbf{w}_y^\top \end{pmatrix}$$

Affine warp Deformation

Thin-Plate Splines | Derivation

- Warp parameters: $$\mathbf{u}^\top = (a_0\ a_1\ a_2\ a_3\ a_4\ a_5\ \mathbf{w}_x^\top\ \mathbf{w}_y^\top)$$

  Affine warp Deformation

- Derivation with relation to the parameters:

$$\frac{\partial w}{\partial \Delta \mathbf{u}} = (\mathbf{J_A} \mathbf{J_\Omega})$$

Affine parameters Deformation

with:

$$\mathbf{J_A} = \begin{pmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{pmatrix}$$

$$\mathbf{J}_\Omega = \begin{pmatrix} \phi(d^2(x, c_1)) & \dots & \phi(d^2(x, c_{N_p})) & 0 & \dots & 0 \\ 0 & \dots & 0 & \phi(d^2(x, c_1)) & \dots & \phi(d^2(x, c_{N_p})) \end{pmatrix}$$

Differential template tracking | SCV and MI

- Differential template tracking
  - SCV

$$\hat{\mathbf{u}} = \arg\min_{\mathbf{u}} \sum_{i=1}^{N_{\mathbf{x}}} \left[I^*(\mathbf{x}_i) - \widehat{I}(w(\mathbf{x}_i, \mathbf{u})) \right]^2$$

$$\widehat{\Delta\mathbf{u}} = -\mathbf{J}^+(\mathbf{u}) \left[I^* - w(\hat{I}, \mathbf{u}) \right] \quad \text{where} \quad \mathbf{J}(\mathbf{u}) = \nabla I^* \frac{\partial w}{\partial \mathbf{u}}$$

  - MI

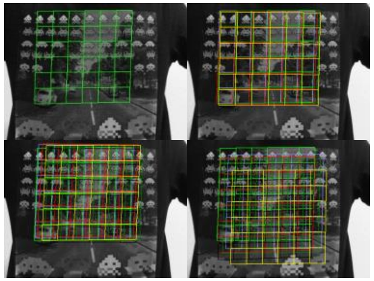
$$\hat{\mathbf{u}} = \arg\max MI(I^*, w(I, \mathbf{u}))$$

$$\widehat{\Delta\mathbf{u}} = -\mathbf{H}_{MI}^{-1} \mathbf{G}_{MI}^{\top}$$

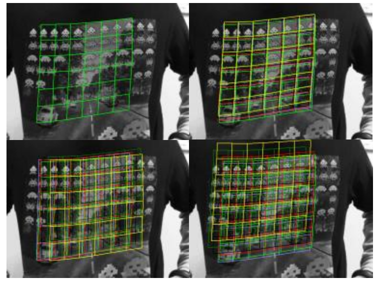
- Same optimization schemes (here shown in forward form for clarity)
- Only one plane considered
- Computational differences lie in the warp derivations

Convergence domain analysis

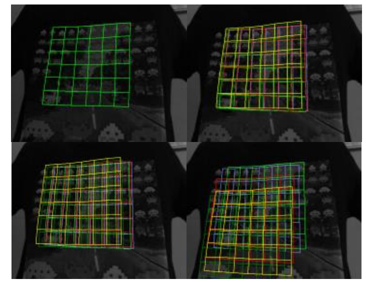
- No deformation:



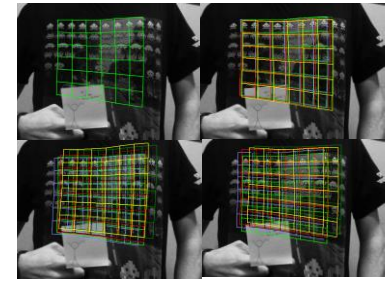
- Extension:

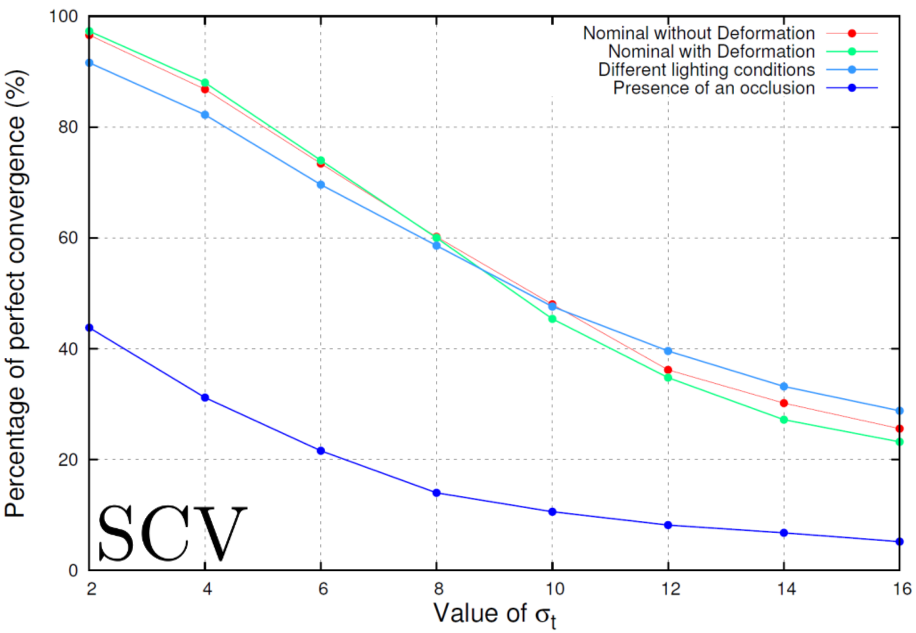


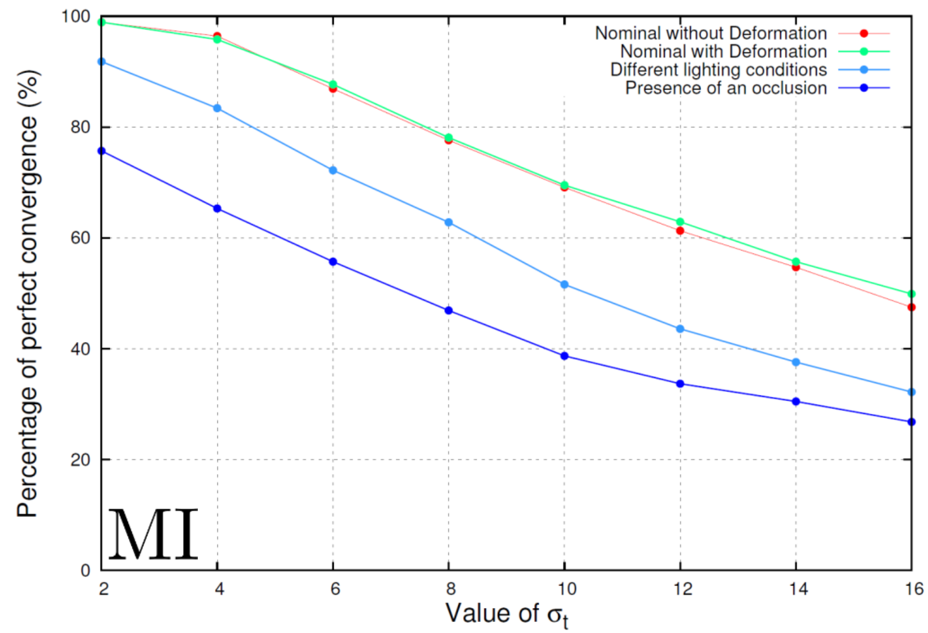
- Light changes:



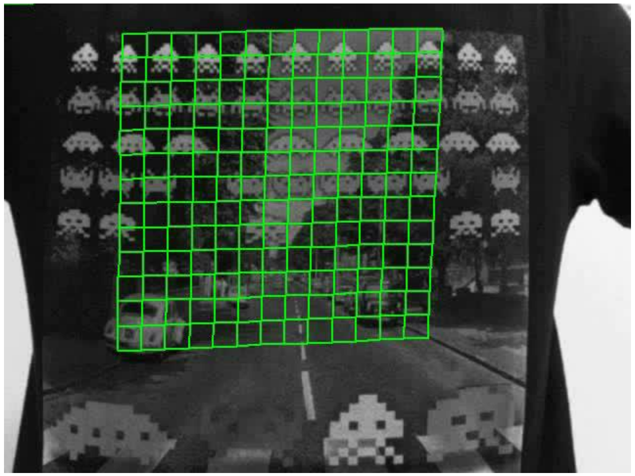
- Occlusion:







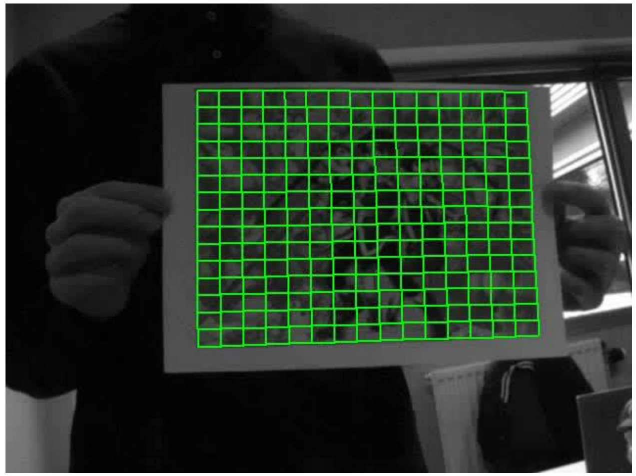
Experiments | A few examples



Nominal conditions

Extension of the template

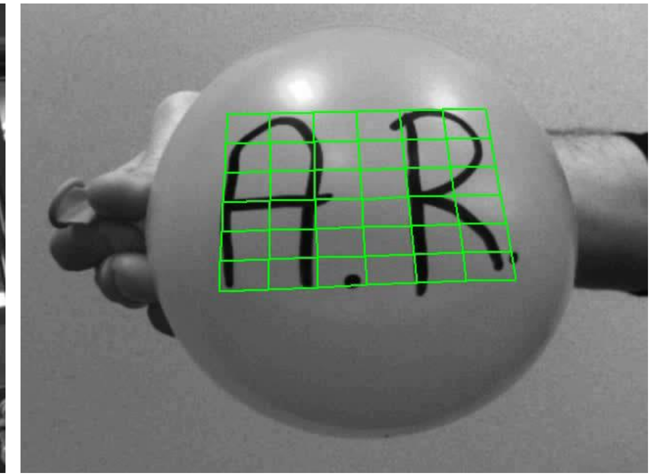
MI and SCV very effective



Nominal conditions

Compression of a paper with template

MI and SCV very effective



Depth approximation (original idea from [Malis, 07])

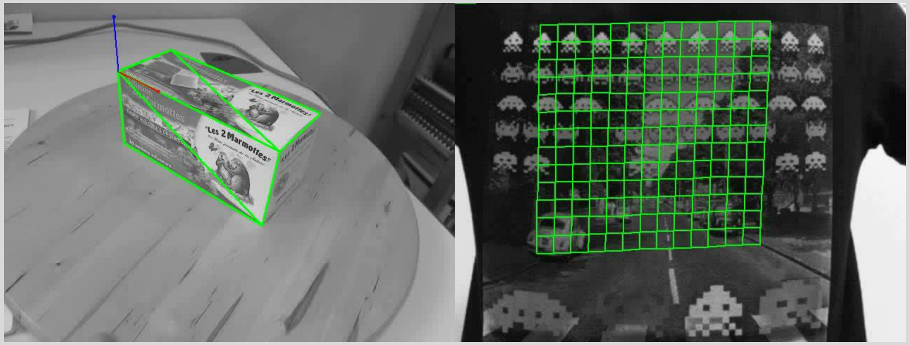
Low texture + specularity

MI not impacted

SCV fails to register properly

Tracking algorithm

- **Use of robust similarity measures (SCV and MI)**
- **Robust model-based dense tracker**
- **Robust non-rigid dense tracker**



- Dense algorithms
  - SCV-based
    - + Simple to use (close to the SSD, few parameters)
      Robust to global perturbations
    - − Impacted by local perturbations
  - MI-based
    - + Robust to global and local perturbations
    - − More complex to use (more parameters)

Part II | Visual Servoing

Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- Robust non-rigid dense tracker

Visual servoing

- Use of robust similarity measures (SCV and NMI)
- Robust dense visual servoing
- Adaptation to omnidirectional sensors

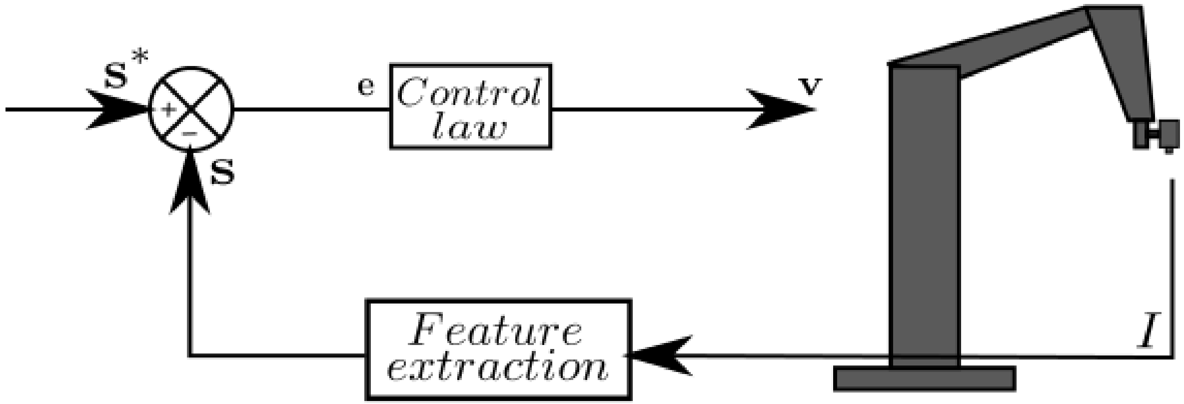
DENSE APPROACHES

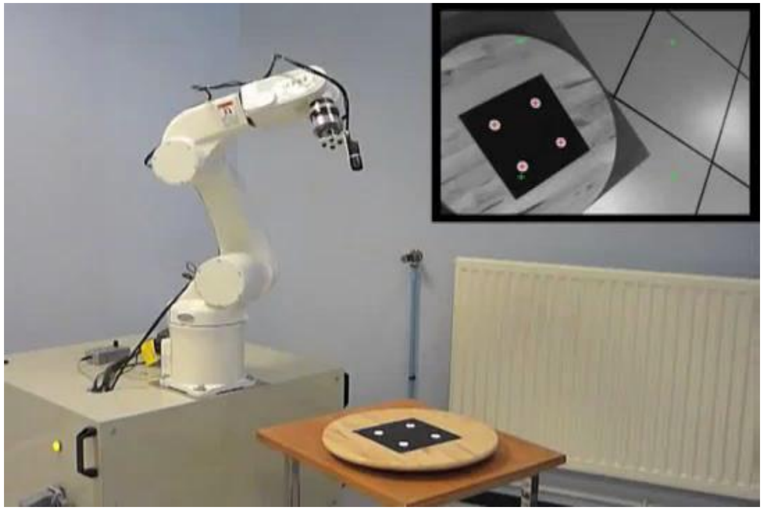
Camera

Robot

Visual Servoing | Classical feature-based servoing

[Chaumette, Hutchinson, 06]





- Similarity function

$$\mathbf{e} = \mathbf{s}(\mathbf{r}) - \mathbf{s}^*$$

- Control law

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

- $\mathbf{L_s}$ is the interaction matrix linking the variations of $\mathbf{s}$ in the image to the camera velocity

Part II | Visual Servoing

Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- Robust non-rigid dense tracker

Visual servoing

- Use of robust similarity measures (SCV and NMI)
- Robust dense visual servoing
- Adaptation to omnidirectional sensors

BYPASS

DENSE APPROACHES

Camera

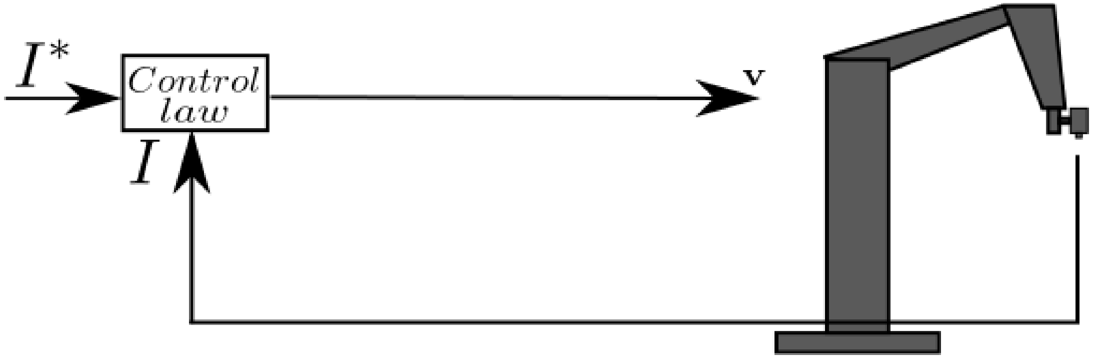
Robot

Visual Servoing | Photometric visual servoing

[Collewet, Marchand, 11]

Current view

Error Image



- Similarity function: SSD

$$\mathbf{e} = \mathbf{I}(\mathbf{r}) - \mathbf{I}^*$$

- Control law

$$\mathbf{v} = -\lambda \widehat{\mathbf{L_I}}^{+} (\mathbf{I}(\mathbf{r}) - \mathbf{I}^*)$$

- $\mathbf{L_I}$ is the interaction matrix linking the variations of intensities of $\mathbf{I}(\mathbf{r})$ to the camera velocity

Photometric visual servoing | Luminosity issue

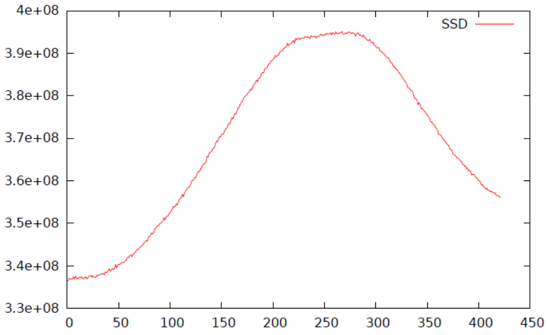
- When conditions change, the reference is not relevant anymore

$\mathbf{I}^*$

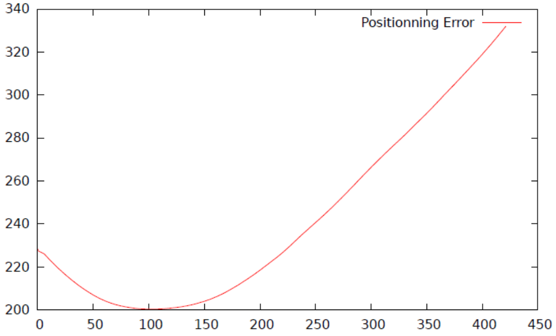
$\mathbf{I}(\mathbf{r})$

$\mathbf{I}(\mathbf{r})$

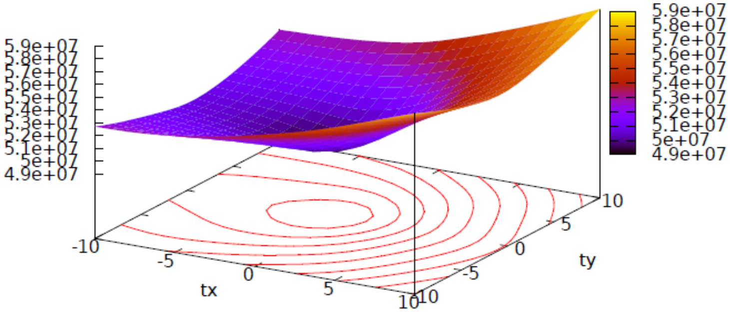
- Servoing fails if no robustness scheme is added



Value of SSD



Distance to the goal



Shape of the cost function

Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- Robust non-rigid dense tracker

Visual servoing

- Use of robust similarity measures (**SCV** and NMI)
- **Robust dense visual servoing**
- Adaptation to omnidirectional sensors

Camera

Robot

[Delabarre, IEEE IROS' 12]

Visual servoing | Adapting SSD-based VS to SCV

- Minimizing the SCV:

$$\widehat{\mathbf{r}} = \arg\min_{\mathbf{r}} \sum_{i=1}^{n\times m} \left[\widehat{I}(\mathbf{r})(\mathbf{x}_i) - I^*(\mathbf{x}_i)\right]^2$$

- Image adaptation:
  - $\widehat{I}$ is the current image seen in the same conditions as the template I^*

$$\widehat{I}(\mathbf{x}) = \mathcal{E}(I^*(\mathbf{x}) \mid I(\mathbf{x})) \quad \text{where} \quad \widehat{I}(j) = \sum_i i \frac{p_{II^*}(j,i)}{p_I(j)}$$

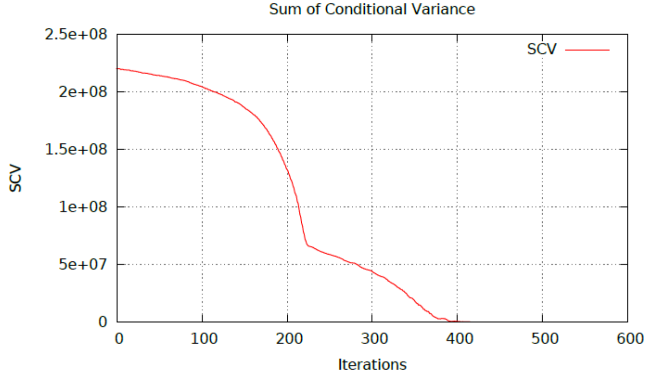
- Interaction matrix of the task evaluated at the desired position:

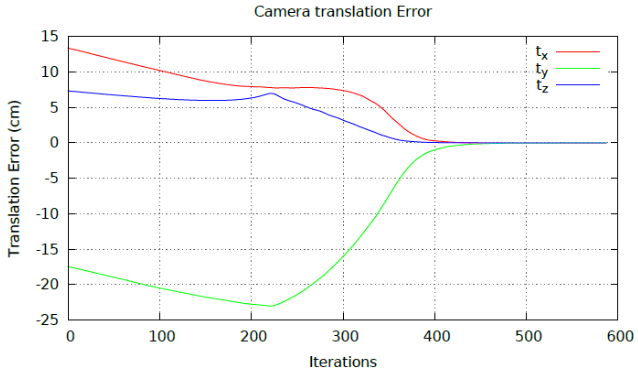
$$\begin{aligned} \frac{\partial I^*}{\partial t} &= \mathbf{L}_{I^*}\mathbf{v} \\ &= -\nabla I^* \mathbf{L}_{\mathbf{x}}\mathbf{v} \end{aligned}$$

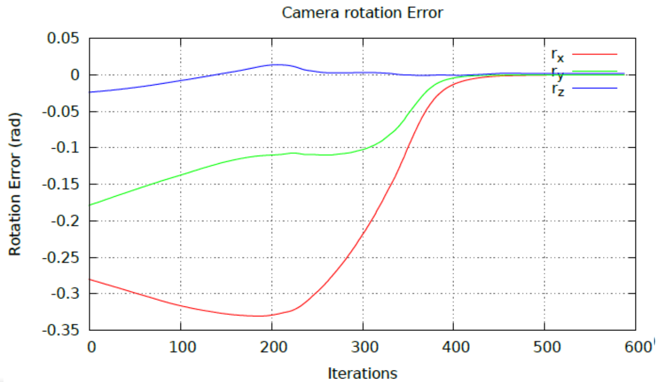
- Control law (exponential decrease of the error):

$$\mathbf{v} = -\lambda\, \mathbf{L_{I^*}}^+ (\widehat{\mathbf{I}}(\mathbf{r}) - \mathbf{I}^*)$$

SCV | Nominal conditions



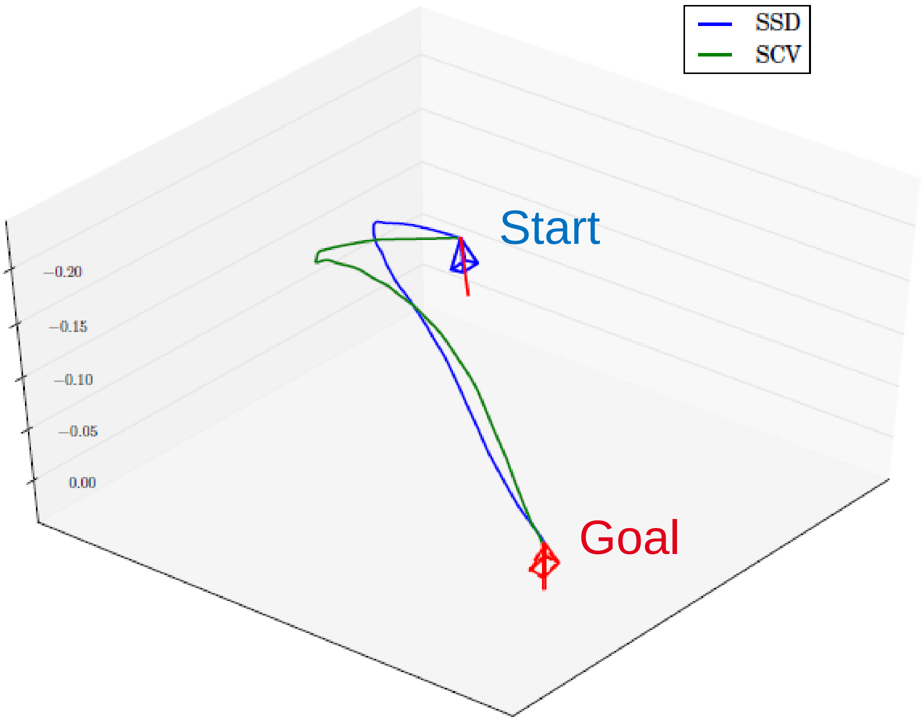




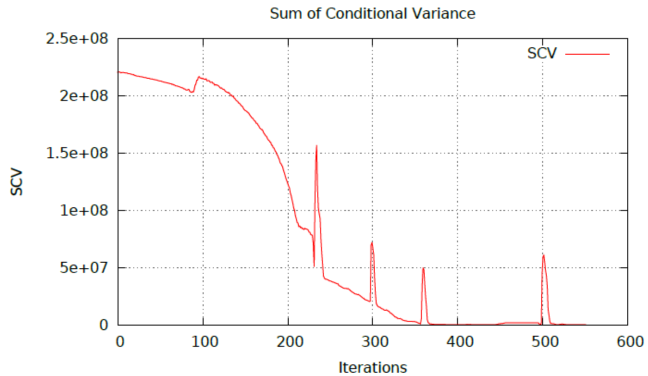
$\mathbf{I}(\mathbf{r})$

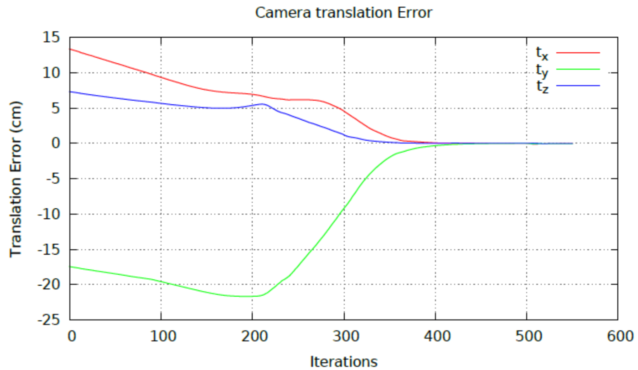
$\mathbf{I}^*$

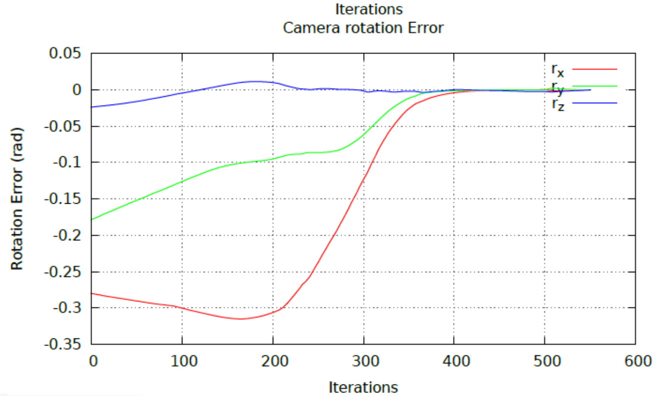
$\mathbf{I}(\mathbf{r}) - \mathbf{I}^*$

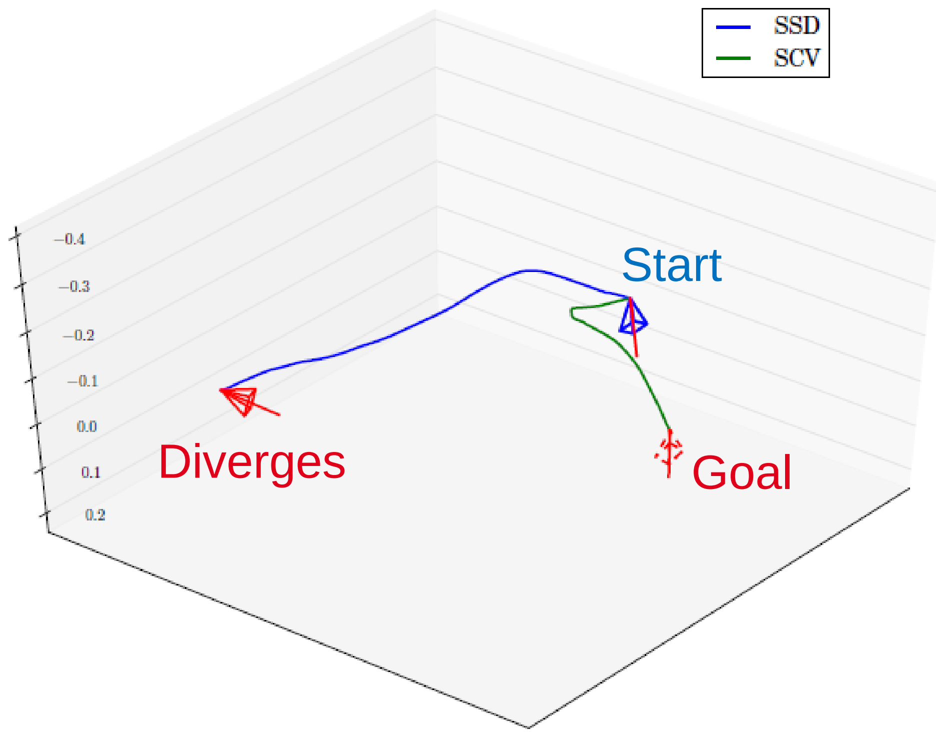


SCV | Light Variations









Tracking algorithm

- Use of robust similarity measures (SCV and MI)
- Robust model-based dense tracker
- Robust non-rigid dense tracker

Visual servoing

- Use of robust similarity measures (SCV and **NMI**)
- **Robust dense visual servoing**
- Adaptation to omnidirectional sensors

DENSE APPROACHES



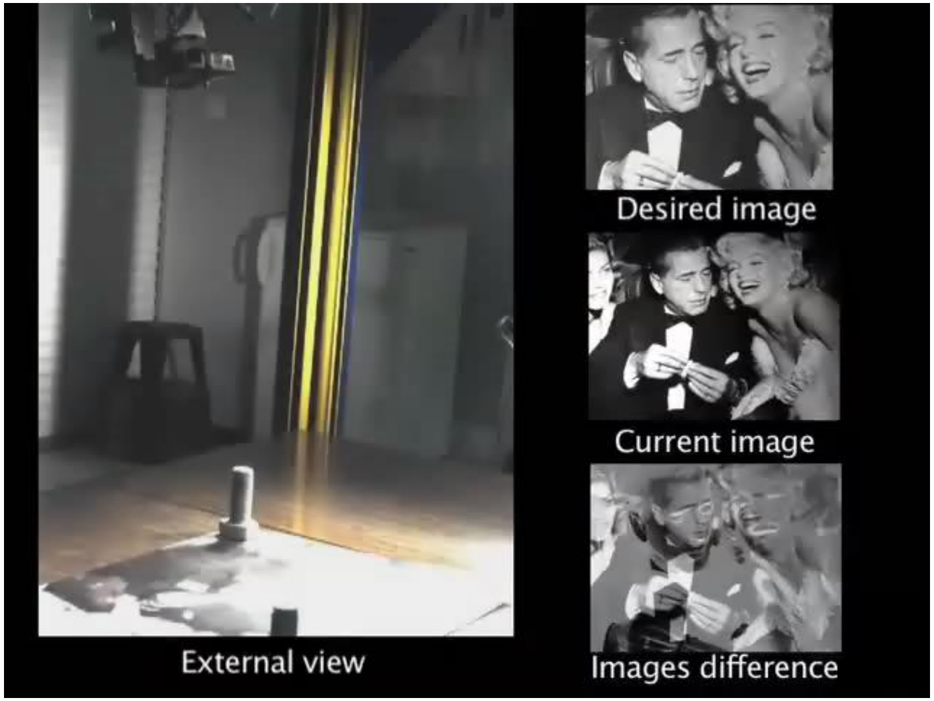
Camera

Robot

[Delabarre, IFAC SYROCO’ 12]

Visual Servoing | Using the mutual information

[Dame, 11]



- Mutual information:
  Quantity of information shared by two signals. [Shannon, 1948]

- Similarity measure:
  - Difference of entropies

$$\mathrm{MI}(I(\mathbf{r}), I^*) = \mathrm{H}(I(\mathbf{r})) + \mathrm{H}(I^*) - \mathrm{H}(I(\mathbf{r}), I^*)$$

- Task:

$$\arg\min_{\mathbf{r}} \mathbf{L}_{MI} = \arg\min_{\mathbf{r}} \frac{\partial MI(I(\mathbf{r}), I^*)}{\partial \mathbf{r}}$$

- Control law:

$$\mathbf{v} = -\lambda \mathbf{H}_{MI}^{-1} \mathbf{L}_{MI}$$

Visual servoing | From MI to NMI

- Classical mutual information: $MI(I(\mathbf{r}), I^*) = H(I(\mathbf{r})) + H(I^*) - H(I(\mathbf{r}), I^*)$
- Problem: No fixed upper bound
- Our solution: use a normalized version (NMI)

$$NMI(I(\mathbf{r}), I^*) = \frac{H(I) + H(I^*)}{H(I(\mathbf{r}), I^*)}$$

[Studholme, 99]

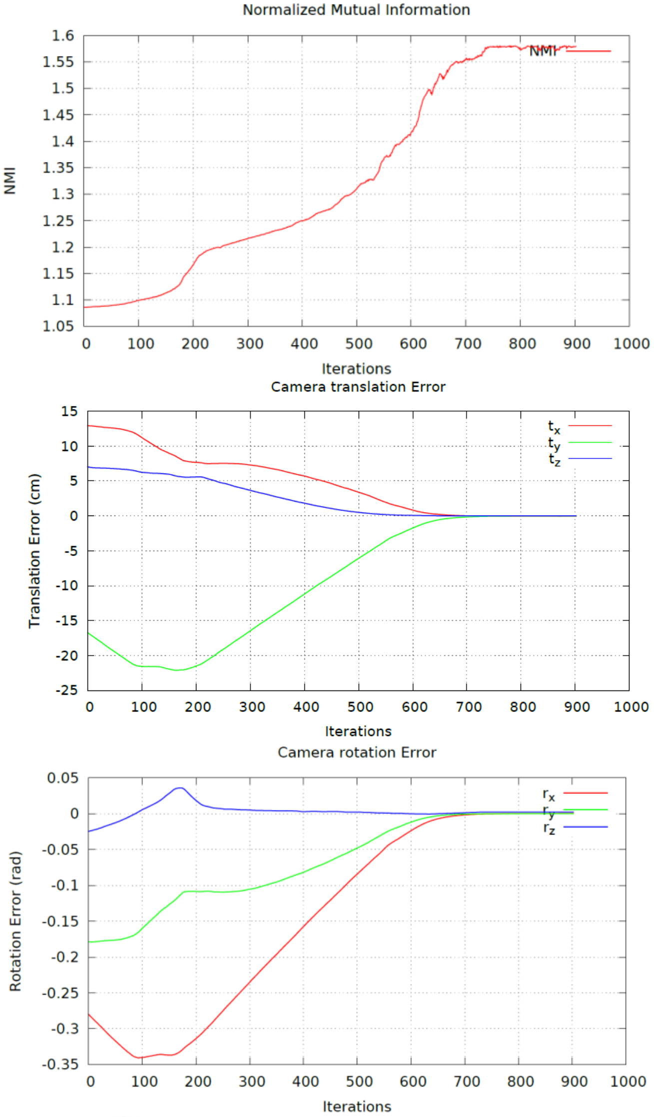
- Fixed bounds: 1 < NMI < 2
- More complexity induced by the division of entropies
- More robustness to overlapping situations
- Task:

$$\arg\min_{\mathbf{r}} \mathbf{L}_{NMI} = \arg\min_{\mathbf{r}} \frac{\partial NMI(I(\mathbf{r}), I^*)}{\partial \mathbf{r}}$$

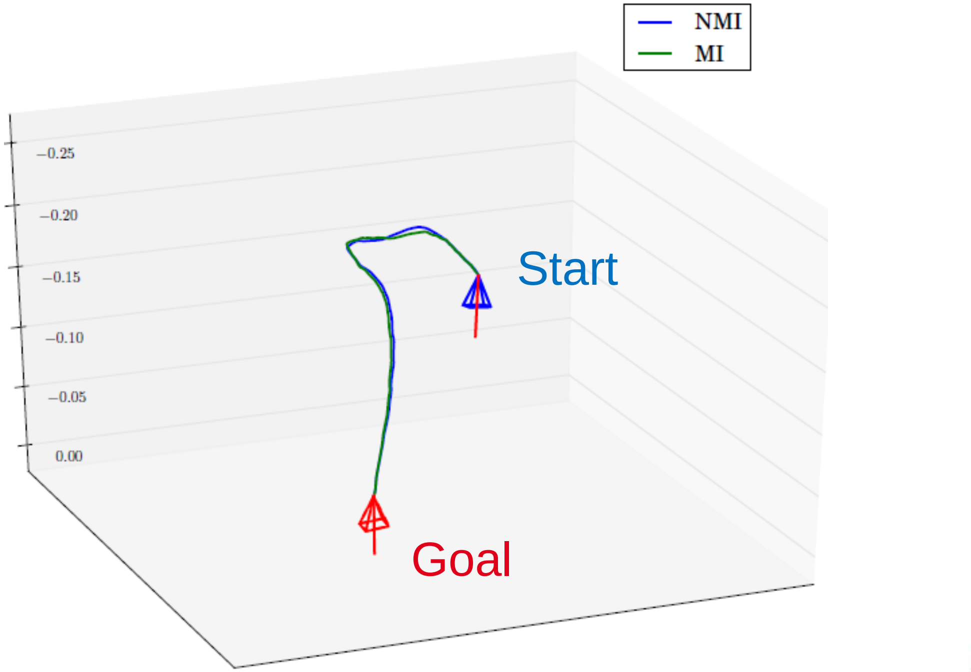
- Control law:

$$\mathbf{v} = -\lambda \mathbf{H}_{NMI}^{-1} \mathbf{L}_{NMI}$$

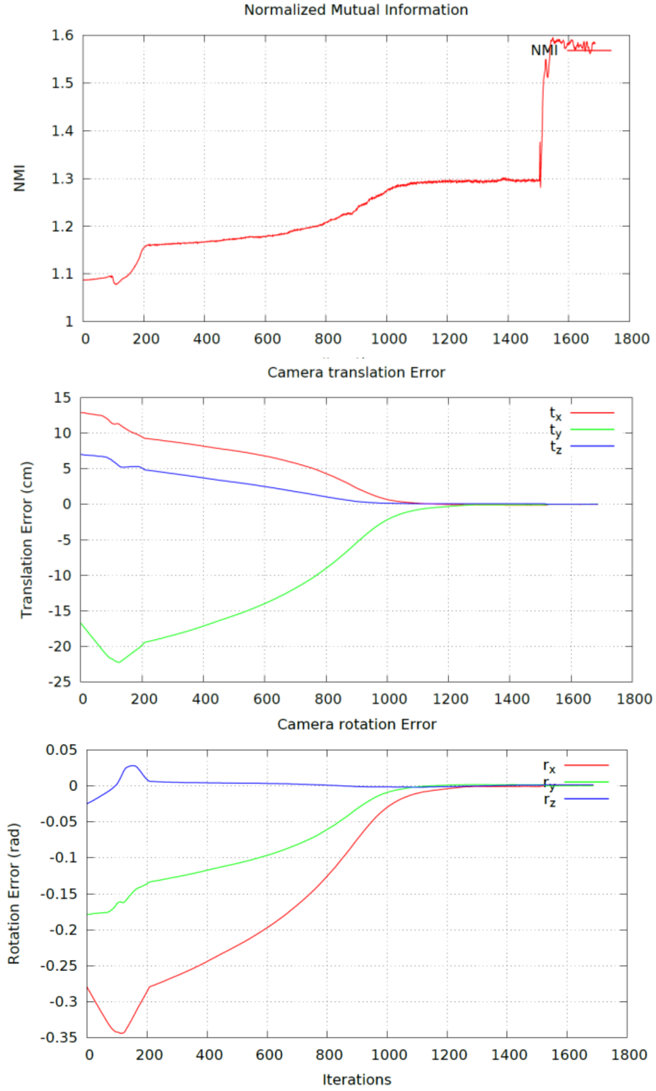
NMI | Nominal conditions

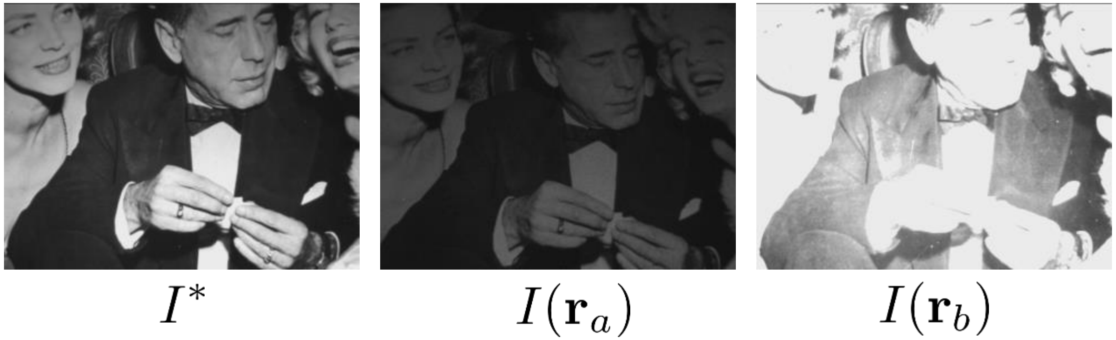


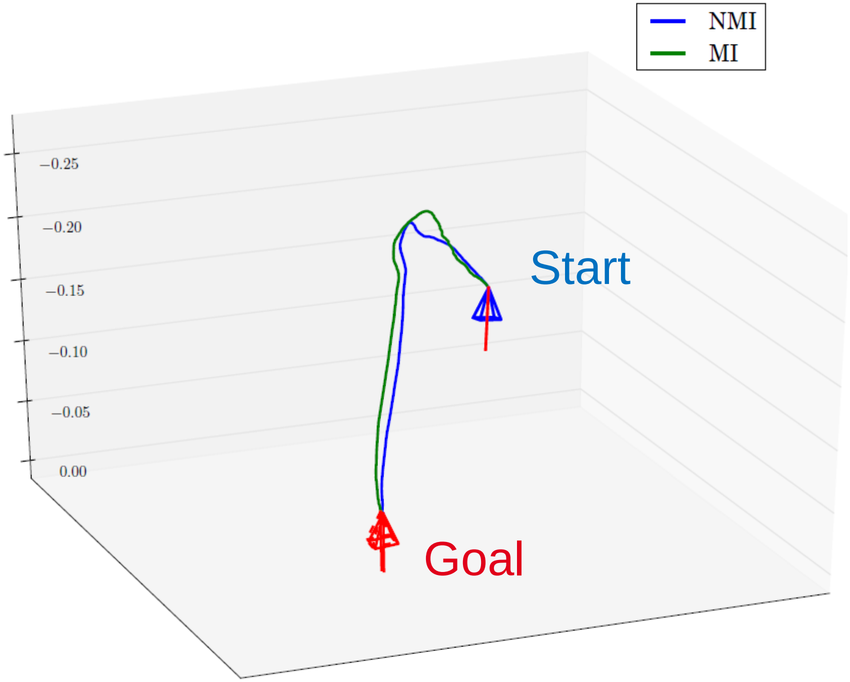
$I(\mathbf{r})$ I^* $I(\mathbf{r}) - I^*$



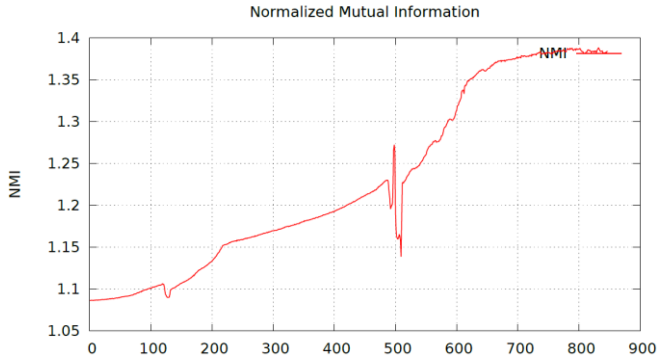
NMI | Light variations

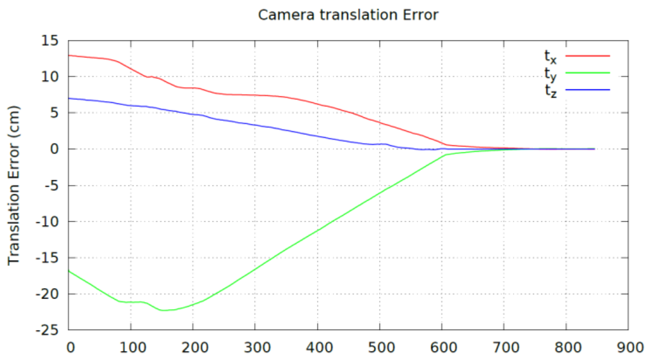


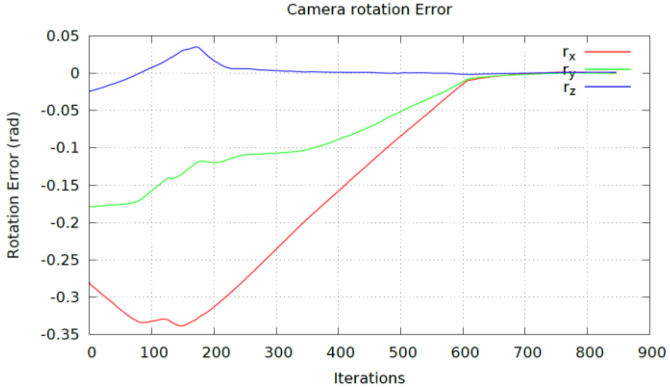




NMI | Large occlusions

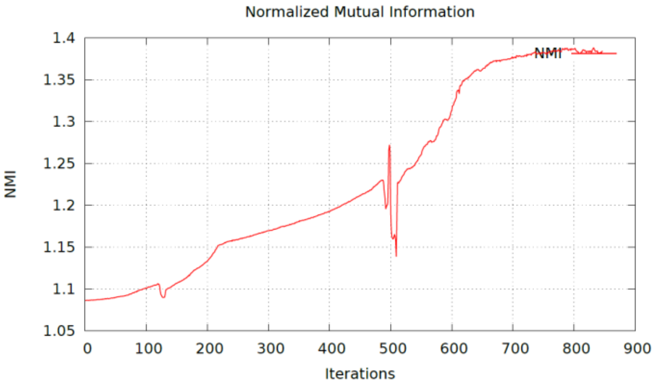




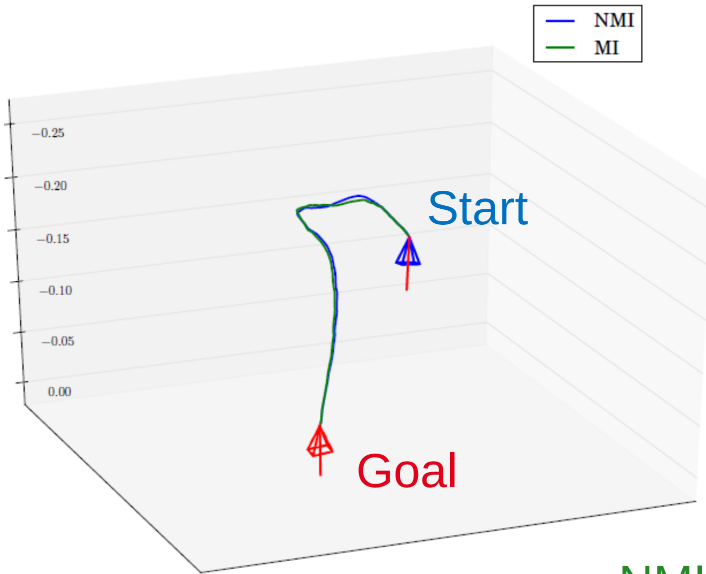


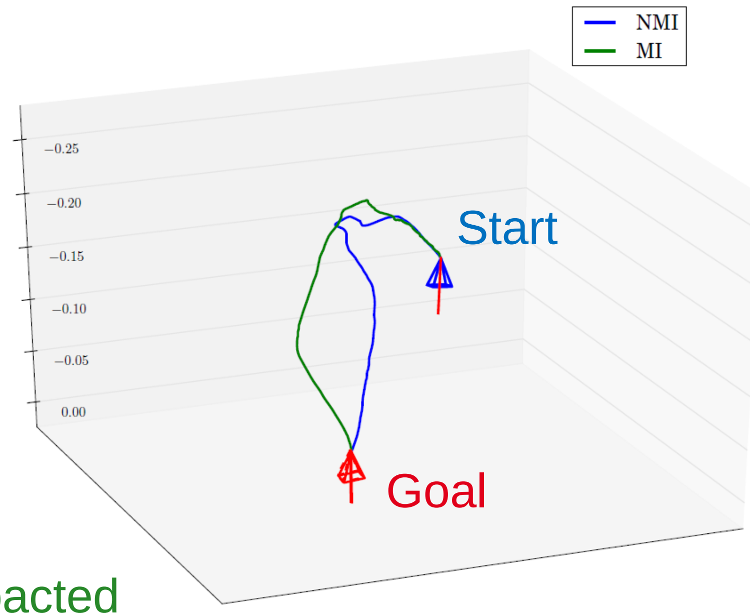
I^* $\quad I(\mathbf{r}_a)$ $\quad I(\mathbf{r}_b)$

NMI | Large occlusions



I^* $I(\mathbf{r}_a)$ $I(\mathbf{r}_b)$





NMI less impacted

Nominal conditions

Presence of occlusions

Part II | Visual Servoing

Tracking algorithm

- **Use of robust similarity measures (SCV and MI)**
- **Robust model-based dense tracker**
- **Robust non-rigid dense tracker**

Visual servoing

- **Use of robust similarity measures (SCV and NMI)**
- **Robust dense visual servoing**
- **Adaptation to omnidirectional sensors**

DENSE APPROACHES

Camera

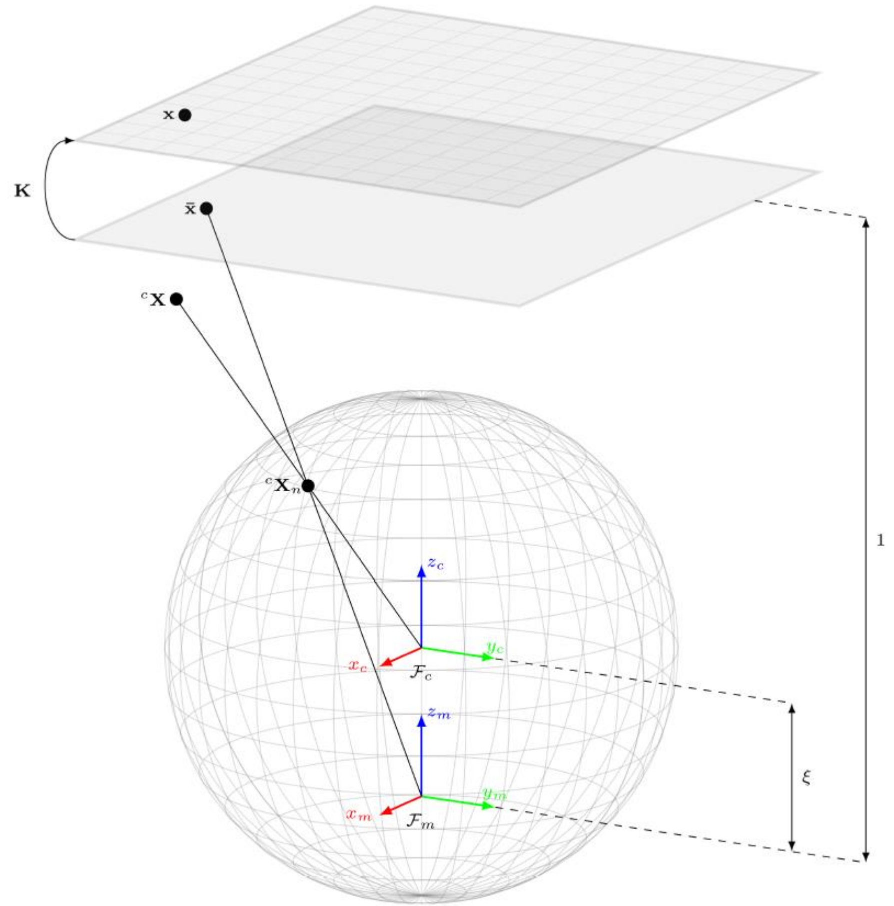
Robot

[Delabarre, IFAC SYROCO' 12]

Omnidirectional cameras | Another way to see the world

- Different types of omnidirectional sensors but one unified projection model [Barreto, 01]

- Computations done on the sphere
- Result: CSVS (Cartesian Spherical VS)
  - Better behaviour of the control law
  - Better estimation of the Jacobians
  - More accuracy
- Closer to the projection model
- More adapted image processing



Omnidirectional cameras | Another way to see the world

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[Barreto, 01]

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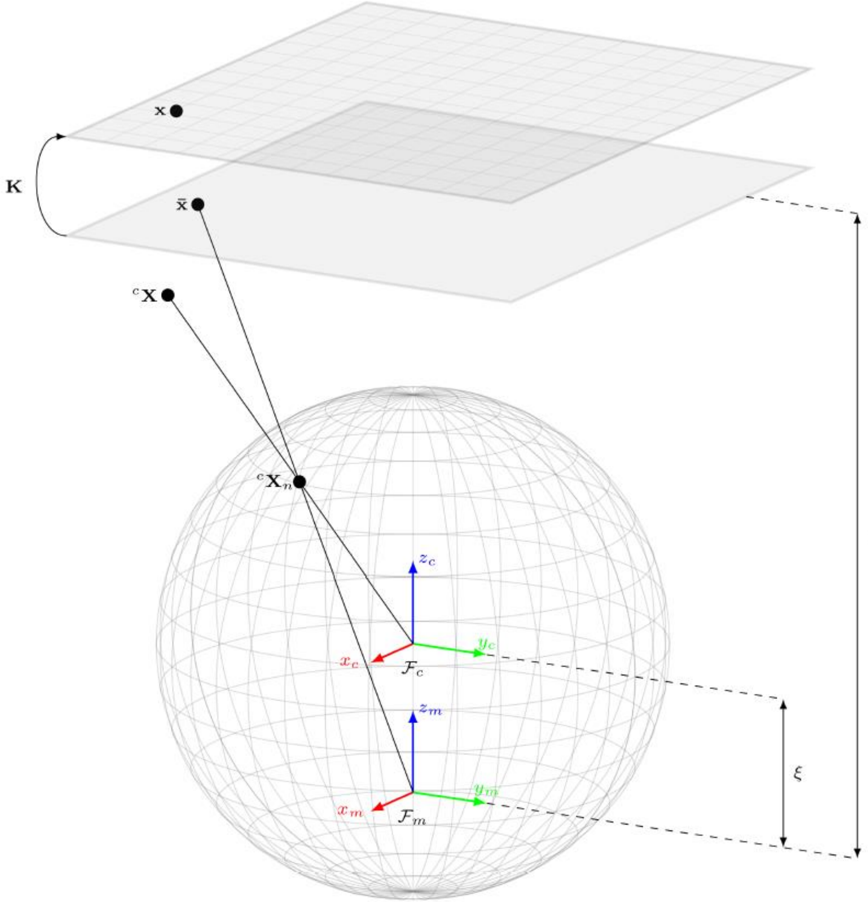
- Result: CSVS (Cartesian Spherical VS)
  - Better behaviour of the control law
  - Better estimation of the Jacobians
  - More accuracy
- Closer to the projection model
- More adapted image processing
  - Gradient example

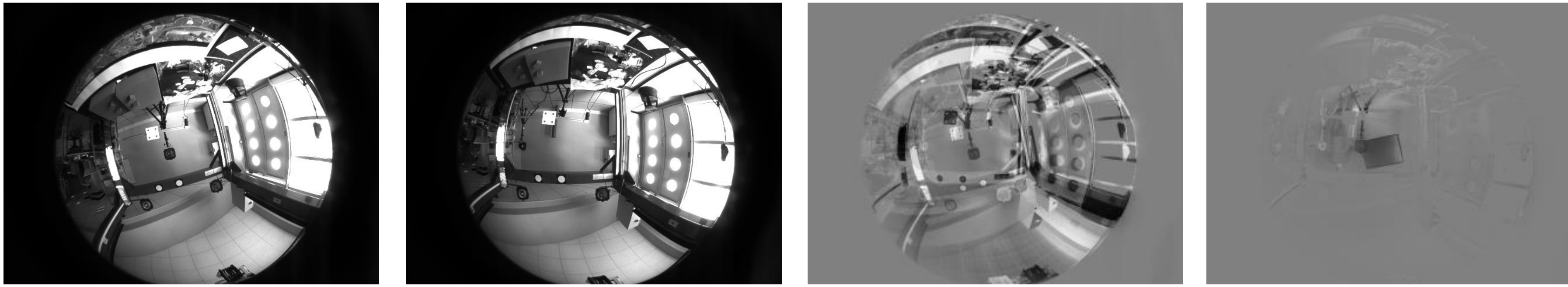
IPVS

CSVS

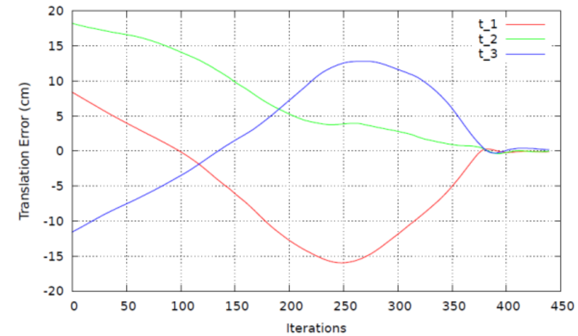
[Caron, 10]

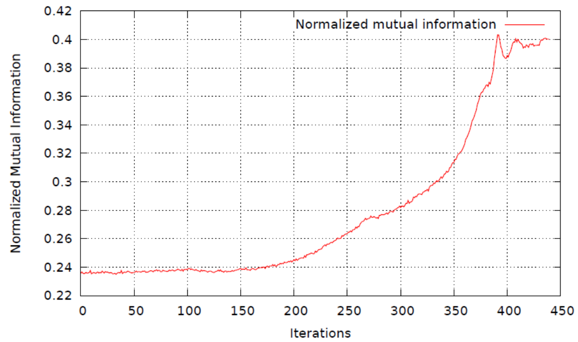


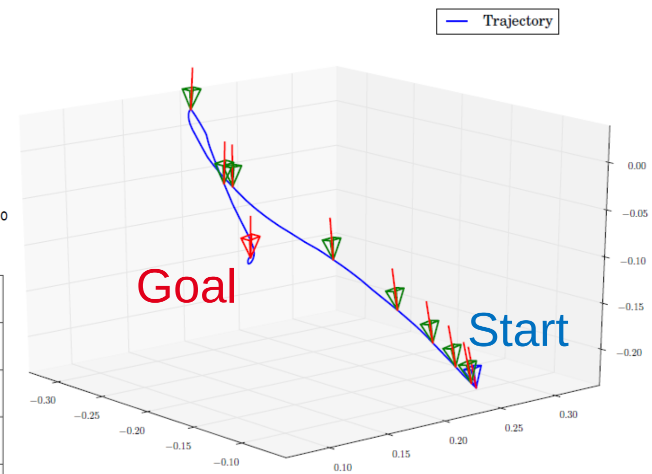
Results | Perturbed conditions

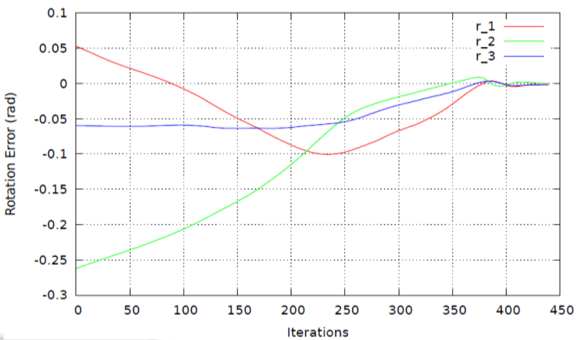


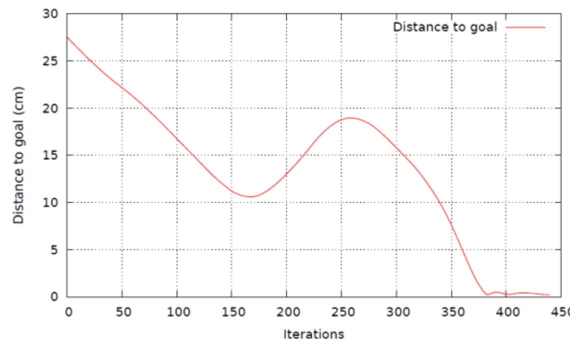
$I(\mathbf{r})$ $\qquad$ I^* $\qquad$ $I(\mathbf{r}) - I^*$











Visual servoing

- **Use of robust similarity measures (SCV and NMI)**
- **Robust dense visual servoing**
- **Adaptation to omnidirectional sensors**

- Dense visual servoing processes
  - SCV-based
    - + Simple to use (close to the SSD, few parameters)
    - Robust to global perturbations
    - − Impacted by local perturbations
  - NMI-based
    - + Robust to global and local perturbations
    - − More complex to use (more parameters)

Conclusion

Tracking algorithm

Visual servoing

- **Use of robust similarity measures (SCV and MI)**
- **Robust model-based dense tracker**
- **Robust non-rigid dense tracker**

- **Use of robust similarity measures (SCV and NMI)**
- **Robust dense visual servoing**
- **Adaptation to omnidirectional sensors**

- Dense algorithms, with no specific robustness schemes
- Robust (dis)similarity functions to achieve natural robustness
- Redefinition of the SCV to have a constant reference
- Model-based and non-rigid tracking algorithms
- Definition of a SCV-based visual servoing control scheme
- Adaptation of the MI-based visual servoing process to a normalized MI
- Extension of that technique to omnidirectional sensors

Perspectives

- Visual tracking:
  - Detect automatically models from a model bank
  - Study more adapted control points localizations for TPS displacement model
  - Extend the TPS warp to take into account more complex motions
  - Code optimizations (real-time tracking)
- Visual servoing:
  - Using the model-based tracker to perform visual servoing
  - Create a visual servoing process with relation to a deformable object
- Navigation:
  - Use of the SCV and NMI algorithms to perform navigation based on visual paths
  - UAV localization and control [Yol, Delabarre, IEEE IROS' 14]

Publications

- **Omnidirectional Visual Servoing using the Normalized Mutual Information**
  - *10th IFAC Symposium on Robot Control, Syroco 2012*, Dubrovnik, Croatia, Septembre 2012
- **Visual Servoing using the Sum of Conditional Variance**
  - *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, IROS'12*, Pages 1689-1694, Vilamoura, Portugal, Octobre 2012
- **Camera Localization using Mutual Information-based Multiplane Tracking**
  - *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, IROS'2013*, Pages 1620-1625, Tokyo, Japon, Novembre 2013
- **Vision-based Absolute Localization for Unmanned Aerial Vehicles**
  - *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, IROS'14*, Pages 3429-3434, Chicago, IL, Septembre 2014
- **Dense non-rigid visual tracking with a robust similarity function**
  - *IEEE Int. Conf. on Image Processing, ICIP'14*, Pages 4942-4946, Paris, France, Octobre 2014

Contributions to dense visual tracking and visual servoing using robust similarity criteria

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December 23rd, 2014