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

Bertrand Delabarre
Lagadic Team
Inria Rennes Bretagne Atlantique & Irisa

http://www.irisa.fr/lagadic
December 23rd, 2014
Context | Robotics

- More and more robots
- Lots of ways to perceive the environment

- Laser
- Omnidirectional camera
- Perspective camera
- US waves
General Framework

Tracking algorithm

- Localization

Visual Features

- Control law

Visual servoing

Robot

Control

Motion

Camera

Image
Challenges

Tracking algorithm
- Robustness issue
- Global variations
- Local variations
- Deformations

Camera

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

Robot

BYPASS

• Can we avoid relying on a tracking algorithm?
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
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
(Dis)Similarity functions

- Sum of Squared Differences (SSD)
  
  [Lucas, 81] [Baker, 04] [Gay-Bellile, 10]  

- Sum of Conditional Variance (SCV)
  
  [Richa, 11]  

- Normalized Cross Correlation (NCC)
  
  [Irani, 98] [Scandaroli, 12]  

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

Lack of robustness

Robustness to global variations

Robustness to local variations
(Dis)Similarity functions | Robustness analysis

\[ I \quad \text{SSD} \quad \text{SCV} \quad \text{MI} \]
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
- Adaptation to omnidirectional sensors

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

$$\hat{\mathbf{u}} = \arg\min_{\mathbf{u}} \sum_{k=1}^{N_x} f(I^*(x_k), I(w(x_k, \mathbf{u})))$$

• Hypothesis: the displacement between two images is small

• The previous estimated parameters $\mathbf{u}$ are refined to estimate the new parameters

\[ I^* \rightarrow \text{New frame} \]
Differential template tracking | Classical SSD approach

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

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

- Simple optimization over the parameters of a displacement function

\[
\hat{u} = \arg\min_{u} \sum_{l=1}^{N} \left[ I(w(x_k, u)) - I^*(x_k) \right]^2
\]

+ Easy to use

- Very poorly robust to perturbations
Sum of conditional variance | Template adaptation [Richa, 11]

- Sum of conditional variance
  \[ SCV = \sum_{l=1}^{N} \left[ I(w(x_k, u)) - \hat{I}^*(x_k) \right]^2 \]

- Template histogram adaptation
  \[ \hat{I}^*(j) = \sum_i i \frac{p_{II^*}(i,j)}{p_{I^*}(j)} \]

- Probability density functions
  - \( p_{II^*}(i,j) = p(I(x) = i, I^*(x) = j) \)
    \[ = \frac{1}{n \times m} \sum_x \alpha(I(x) - i) \alpha(I^*(x) - j) \]
  - \( \alpha(u) = 1 \) if and only if \( u = 0 \)

  + Easy to use
  + Robust to global perturbations
  - Poorly robust to local perturbations
Mutual information | MI

- Quantity of information shared by two signals
  \[ MI(I, I^*) = H(I) + H(I^*) - H(I, I^*) \]  
  [Shannon, 1948]

- Entropy computation
  \[ H(I) = - \sum_{r=0}^{N_x} p_I(r) \log (p_I(r)) \]

- Histogram binning

- Multimodality

Very robust to both global and local variations

Complex to use
Computationally expensive
Visual Tracking | Displacement model

<table>
<thead>
<tr>
<th>Reference</th>
<th>Translation</th>
<th>sRt</th>
<th>Affine</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Reference" /></td>
<td><img src="image2.png" alt="Translation" /></td>
<td><img src="image3.png" alt="sRt" /></td>
<td><img src="image4.png" alt="Affine" /></td>
</tr>
</tbody>
</table>

- **Reference**
- **Translation**
- **sRt**
- **Affine**

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

**More accuracy**

**More freedom**

- **Homography**
  - $x \in SL(3)$ (2D)
  - $x \in SE(3)$ (3D)

- **More accuracy**
- **More freedom**

**Thin Plate Splines**

- $x \propto N_c$
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
- Adaptation to omnidirectional sensors

[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

\[
\hat{r} = \arg \min_r \sum_{l=1}^{N} [I(w(x_k, r)) - I^*(x_k)]^2
\]

• 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
Model-based tracking

- 3D model initialization

\[ H_l(T(r)) = \frac{cR_o + c_{o}t_o + c_{n\text{'} n_{l}^{t}}}{c_{d_{l}}} \]

where \( c_{n} = c_{R_{o}o_{n}} \), sim. \( c_{d} \)

- 3D pose estimation

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

- Dynamic adaptation to model changes
Sum of conditional variance | Adapting the current view

- Differential tracking
  \[ \hat{r} = \arg \min_r \sum_{l=1}^{N_l} \sum_{k=1}^{N_x} \left[ I^*(x_k) - \hat{I}(w_l(x_k, r)) \right]^2 \]

- Image adaptation
  - \( \hat{I} \) is the current view seen in the same conditions as \( I^* \)
  \[ \hat{I}(x) = \mathcal{E}(I^*(x) \mid I(x)) \quad \text{where} \quad \hat{I}(j) = \sum_i i \frac{p_{I^*}(i,j)}{p_I(j)} \]

- Inverse compositional optimization scheme \[ \text{[Baker, 04]} \]
  \[ \Delta \hat{r} = \arg \min_{\Delta r} \sum_{l=1}^{N_l} \sum_{k=1}^{N_x} \left[ I^*(w_l(x_k, \Delta r)) - \hat{I}(w_l(x_k, r)) \right]^2 \]

- Computation of the displacement update
  \[ J(\Delta r) = \frac{\partial I^*}{\partial w_l} \frac{\partial w_l}{\partial T} \frac{\partial T}{\partial x} \frac{\partial x}{\partial \Delta r} = J_{I^*} J_{w_l} J_T J_x (\Delta r) \]
  \[ \Delta \hat{r} = - (J_{I^*} J_{w_l} J_T J_x (0))^{+} SCV(0) \]
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)

\[
\hat{\Delta r} = \arg \max_{\Delta r} MI(I(w)(x, \Delta r)), I^*(x))
\]

- Computation of the gradient and Hessian

\[
G_{MI} = \sum_{r,t} \frac{\partial p_{II^*}}{\partial \Delta r} \left( 1 + \log \left( \frac{p_{II^*}}{p_I} \right) \right)
\]

\[
H_{MI} = \sum_{r,t} \frac{\partial p_{II^*}}{\partial \Delta r} \frac{\partial p_{II^*}}{\partial \Delta r} \left( \frac{1}{p_{II^*}} - \frac{1}{p_{I^*}} \right) + \frac{\partial^2 p_{II^*}}{\partial \Delta r^2} \left( 1 + \log \frac{p_{II^*}}{p_I} \right)
\]

- Minimizing the gradient \( \hat{\Delta r} = -H_{MI}^{-1}G_{MI}^{\top} \)
Convergence analysis | SSD vs SCV vs MI

- Nominal conditions:

\[
\begin{align*}
\sigma_t &= 0 \\
\sigma_t &= 0.002 \\
\sigma_t &= 0.02 \\
\sigma_t &= 0.05
\end{align*}
\]
Convergence analysis | SSD vs SCV vs MI

- Global variations:

\[ \sigma_t = 0 \quad \sigma_t = 0.002 \quad \sigma_t = 0.02 \quad \sigma_t = 0.05 \]
Convergence analysis | SSD vs SCV vs MI

- Local variations:
  \[ \sigma_t = 0 \quad \sigma_t = 0.002 \quad \sigma_t = 0.02 \quad \sigma_t = 0.05 \]
Experiments

Nominal conditions
No perturbation
MI and SCV very effective

Light Variations
Global perturbation
MI and SCV not impacted

Specular spots
Local perturbation
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
- Adaptation to omnidirectional sensors

[Delabarre, IEEE ICIP’ 14]
Non-rigid displacement | Thin-Plate Splines [Arad, 95]

\[ w(x, u) = \begin{pmatrix} a_0 & a_1 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} a_2 \\ a_5 \end{pmatrix} + \text{Affine warp} + \text{Deformation term} \]
Non-rigid displacement | Thin-Plate Splines

- Thin-Plate Spline:
  \[ w(x, u) = \begin{pmatrix} a_0 & a_1 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} a_2 \\ a_5 \end{pmatrix} + \sum_{k=1}^{N_p} \begin{pmatrix} w^k_x \\ w^k_y \end{pmatrix} \phi(d^2(x, c_k)) \]
  
  **Affine warp**
  
  **TPS kernel**

- Kernel function:
  \[ \phi(x) = \frac{x^{(4-p)} \log(x)}{\alpha} \]
  \[ \alpha = 2 \]
  \[ p = 2 \]
  \[ \phi(x) = \frac{1}{2} x^2 \log(x) \]

- Warp parameters:
  \[ u^\top = \begin{pmatrix} a_0 & a_1 & a_2 & a_3 & a_4 & a_5 \end{pmatrix} \begin{pmatrix} w_x^\top \\ w_y^\top \end{pmatrix} \]
  
  **Affine warp**
  
  **Deformation**
Thin-Plate Splines | Derivation

- Warp parameters: \( \mathbf{u}^\top = \begin{pmatrix} a_0 & a_1 & a_2 & a_3 & a_4 & a_5 \\ w_x^\top & w_y^\top \end{pmatrix} \)

Affine warp  Deformation

- Derivation with relation to the parameters:

\[
\frac{\partial \mathbf{w}}{\partial \Delta \mathbf{u}} = (\mathbf{J}_A \mathbf{J}_\Omega)
\]

with:

\[
\mathbf{J}_A = \begin{pmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{pmatrix}
\]

Affine parameters  Deformation

\[
\mathbf{J}_\Omega = \begin{pmatrix} \phi(d^2(x, c_1)) & \ldots & \phi(d^2(x, c_{N_T})) & 0 & \ldots & 0 \\ 0 & \ldots & 0 & \phi(d^2(x, c_1)) & \ldots & \phi(d^2(x, c_{N_T})) \end{pmatrix}
\]
Differential template tracking | SCV and MI

- Differential template tracking
  - SCV
    \[ \hat{u} = \arg\min_u \sum_{i=1}^{N_x} \left[ I^*(x_i) - \hat{I}(w(x_i, u)) \right]^2 \]
    \[ \Delta u = -J^+(u) \left[ I^* - w(\hat{I}, u) \right] \quad \text{where} \quad J(u) = \nabla I^* \frac{\partial w}{\partial u} \]
  - MI
    \[ \hat{u} = \arg\max MI(I^*, w(I, u)) \]
    \[ \Delta u = -H_{MI}^{-1} G_{MI}^T \]

- 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:**

![Images of grid patterns under different conditions]

**Graphs showing percentage of perfect convergence**

- **SCV**
- **MI**
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
Contributions | Visual Tracking

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
Visual Servoing | Classical feature-based servoing

[Chaumette, Hutchinson, 06]

- Similarity function
  \[ e = s(r) - s^* \]

- Control law
  \[ v = -\lambda \hat{L}_s (s(r) - s^*) \]

- \( \hat{L}_s \) is the interaction matrix linking the variations of \( S \) 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

**DENSE APPROACHES**
Visual Servoing | Photometric visual servoing

[Collewet, Marchand, 11]

- Similarity function: SSD
  \[ e = I(r) - I^* \]

- Control law
  \[ v = -\lambda L_I^+ (I(r) - I^*) \]

- \( L_I \) is the interaction matrix linking the variations of intensities of \( I(r) \) to the camera velocity.
Photometric visual servoing | Luminosity issue

- When conditions change, the reference is not relevant anymore
- Servoing fails if no robustness scheme is added
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

[Delabarre, IEEE IROS’ 12]
Visual servoing | Adapting SSD-based VS to SCV

- Minimizing the SCV:
  \[
  \hat{r} = \arg \min_r \sum_{i=1}^{n \times m} \left[ \hat{I}(r)(x_i) - I^*(x_i) \right]^2
  \]

- Image adaptation:
  - \( \hat{I} \) is the current image seen in the same conditions as the template \( I^* \)
  \[
  \hat{I}(x) = \mathcal{E}(I^*(x) \mid I(x)) \quad \text{where} \quad \hat{I}(j) = \sum_i i \frac{p_{II^*}(j,i)}{p_I(j)}
  \]

- Interaction matrix of the task evaluated at the desired position:
  \[
  \frac{\partial I^*}{\partial t} = L_{I^*} v
  \]
  \[
  = -\nabla I^* L_x v
  \]

- Control law (exponential decrease of the error):
  \[
  v = -\lambda L_{I^*}^+(\hat{I}(r) - I^*)
  \]
SCV Nominal conditions

- Sum of Conditional Variance
- Camera translation error
- Camera rotation error

Graphs showing iterations and errors with start and goal points marked.

I(r) I* I(r) − I*
SCV | Light Variations

Sum of Conditional Variance

- SCV

Camera translation error

- Translation Error (cm)
- Iterations

- Camera rotation error

- Rotation Error (rad)
- Iterations

I*

I(r)

I(r)

Start

Diverges

Goal
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

[Delabarre, IFAC SYROCO’ 12]
**Visual Servoing | Using the mutual information**

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

- **Similarity measure**: Difference of entropies

\[
\text{MI}(I(r), I^*) = H(I(r)) + H(I^*) - H(I(r), I^*)
\]

- **Task**: \[
\arg \min_r L_{MI} = \arg \min_r \frac{\partial \text{MI}(I(r), I^*)}{\partial r}
\]

- **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:

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

- Control law:

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

Start

Goal

$I(r)$

$I^*$

$I(r) - I^*$
NMI | Light variations

Normalized Mutual Information

Start

Goal

$I^*$

$I(r_a)$

$I(r_b)$
NMI | Large occlusions

Normalized Mutual Information

Camera translation Error vs NMI

Translation Error (cm)

Camera rotation Error vs NMI

Rotation Error (rad)

Start

Goal

$I^*$

$I(r_a)$

$I(r_b)$
NMI | Large occlusions

Normalized Mutual Information

NMI

Iterations

0 100 200 300 400 500 600 700 800 900

1.05 1.1 1.15 1.2 1.25 1.3 1.35

$I^*$

$I(r_a)$

$I(r_b)$

Nominal conditions

NMI less impacted

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

[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

- 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
  - Gradient example

IPVS  CSVS  [Caron, 10]
Results | Perturbed conditions

$I(r)$

$I^*$

$I(r) - I^*$

Goal

Start
Part II | Visual Servoing

- 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)

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

Visual servoing
Conclusion

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 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

Bertrand Delabarre
Lagadic Team
Inria Rennes Bretagne Atlantique & Irisa

http://www.irisa.fr/lagadic

December 23rd, 2014