



Topological navigation using sensory memory

SLAN versus SLAM

Dassault Aviation, Saint-Cloud, France, December 16th 2009

Professor Philippe Martinet

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<http://robots.lasmea.univ-bpclermont.fr>



Philippe Martinet



Topological navigation using sensory memory: SLAN versus SLAM
LASMEA, Blaise Pascal University, Clermont-Ferrand

Program of the journey

10H	Accueil et présentation de la journée	B. Patin	Dassault Aviation
10H15	Les enjeux et problématiques du SLAM (Survey)	P. Rives	Inria-Sophia Antipolis
11H	Initialisation immédiate d-amers en SLAM monoculaire. Points et lignes	Juan Sola	LAAS
12H	Navigation topologique par mémoire sensorielle: SLAN vs SLAM	P. Martinet	LASMEA
14H	Outils et méthodes d'estimation pour le SLAM - Application au Slam visuel	P. Rives	Inria-Sophia Antipolis
15H	Détection visuelle de fermeture de boucle et applications au SLAM métrique et topologique	D. Filliat	ENSTA ParisTech/UEI Lab
16H		N. Paparoditis	IGN/MATIS
17H	Cloture du séminaire	B. Patin	Dassault Aviation



Philippe Martinet



Topological navigation using sensory memory: SLAN versus SLAM
LASMEA, Blaise Pascal University, Clermont-Ferrand

Outline of the presentation

Introduction

- LASMEA
- Sensor based Control
- Navigation
- SLAN vs SLAM

A generic model

- A unified model for camera
- Case of fisheye cameras
- Partial euclidian reconstruction

Topological navigation system

- Global system
- Case of vision
- Differents Modules
- SOVIN

Illustrations

- Indoor applications
- Outdoor applications

Discussion

- Learning process
- Updating process
- Closing the loop problem



Philippe Martinet



Topological navigation using sensory memory: SLAN versus SLAM
LASMEA, Blaise Pascal University, Clermont-Ferrand

→ Introduction

A generic model

Topological navigation system

Illustrations

Discussion

Lasmea

Director : Michel Dhome

400km south of Paris
200km West of Lyon

CNRS/UBP
Mixed Unit 6602

France

Clermont-Ferrand

Universitary Campus

LASMEA

Philippe Martinet

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MATELEC

GRAVIR

➤ Optoelectronics, microelectronics

➤ Electromagnetism

➤ Gaz sensor

33 teacher/researcher
1 research scientist
25 Phd

➤ Perception System

➤ Computer that See

➤ ROSACE

25 teacher/researcher
2 research scientist,
49 Phd, 2 post-doc

Philippe Martinet

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LASMEA, Blaise Pascal University, Clermont-Ferrand

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Lasmea : GRAVIR-PERSYST

Perception System

PERception SYSTEMs

J.P. Derutin

Multisensor Perception

Smart Sensors

Architecture and methods

Data fusion

Scene understanding

SLAM

Algorithm Architecture Adequation

Cognitive Vision

Parallelism in vision

High speed prototyping tools

Tools for embedded applications

Philippe Martinet

Topological navigation using sensory memory: SLAN versus SLAM
LASMEA, Blaise Pascal University, Clermont-Ferrand

Lasmea : GRAVIR-COMSEE

Artificial Vision *COMputer that SEE*

<http://comsee.univ-bpclermont.fr>

T. Chateau

Geometry for visual perception

Metrology by vision
Automatic rigid scene reconstruction

Vision in Deformable Environments

Modeling and algorithm for deformable environment

Visual Recognition

Real time object tracking
Object recognition

Lasmea : GRAVIR-ROSACE

ROSACE

P. Martinet & Y. Mezouar

Robotics and Autonomous Complex systems

<http://www.lasmea.univ-bpclermont.fr/Control>
<http://robots.lasmea.univ-bpclermont.fr>

VISIR

Visual Servoing of Robots

Omnidirectional visual servoing **15 to 60Hz**

Topological navigation through sensory memory

Multi-sensor-based control

Control design under uncertain dynamics

Hybrid control architecture

Multi-robot-system control

15 to 60Hz

...

AGV *Automatic Guided Vehicles*

MICMAC

*Modeling, Identification and
Control of Complex Machines*

Vision-Based Control of Parallel Robots

Control of redundant robots

Control of High Dynamics System

400Hz

1kHz

...

Lasmea : GRAVIR

People involved in SLAM or near SLAM problems

PERSYST

F. Berry, R. Chapuis, F. Chausse, P. Checchin, J.P. Derutin, L. Trassoudaine
(IMPALA/CITYVIP)

(CITYHOME/EURIPIDE/BRI)

COMSEE

M. Dhôme, M. Lhuillier, E. Royer

(MOBIVIP/CITYVIP/BODEGA)

(FACT/CITYHOME/EURIPIDE/BRI)

ROSACE

Y. Mezouar, P. Martinet, B. Thuilot

(MOBIVIP/CITYVIP/BODEGA/R-DISCOVER/ARMEN)

(SAFEMPOVE, FACT/CITYHOME/EURIPIDE/BRI)

Applications

Autonomous navigation (RTK-GPS, Vision, Multi-sensor)

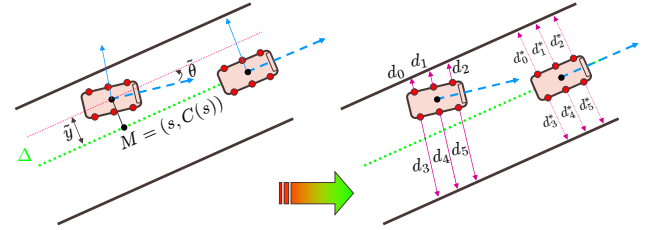
Platoon: Autonomous leader (RTK-GPS, Vision, Multi-sensor)

Platoon: Leader manually driven (RTK-GPS, Vision)

2D/3D maps building (vision, Radar, Range finder, Multi-sensor)

Sensor based control: History

[ESPIAU87]



Lateral control in cartesian space:

Bringing $(\tilde{y}, \tilde{\theta})$ to $(0, 0)$

Explicite declaration of Δ and required cartesian localization

Lateral control in sensor space:

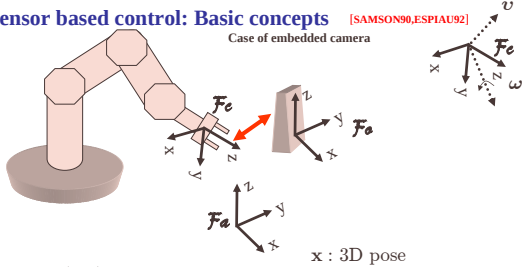
Bringing d to d^*

No explicite declaration of Δ and do not required cartesian localization

Sensor based control: Basic concepts

Case of embedded camera

[SAMSON90,ESPIAU92]



$s = s(x, t)$

$\dot{s} = \frac{\partial s}{\partial x} \frac{dx}{dt} + \frac{\partial s}{\partial t}$

$\dot{s} = \frac{\partial s}{\partial x} v + \frac{\partial s}{\partial t}$

Interaction matrix

If (fixed object) $\frac{\partial s}{\partial t} = 0$

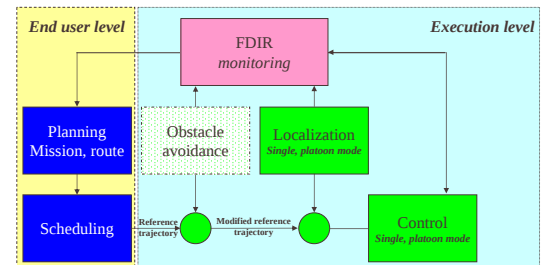
$\dot{s} = L_s v + \frac{\partial s}{\partial t}$

$\dot{s} = L_s v$

x : 3D pose

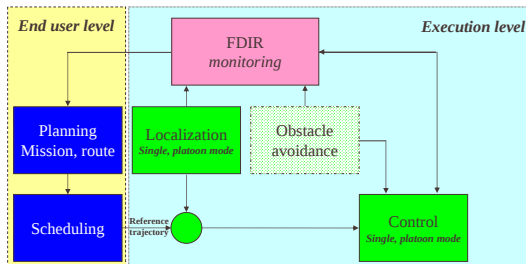
Navigation

Navigation scheme



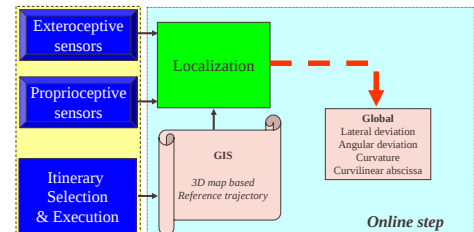
Navigation

Navigation scheme



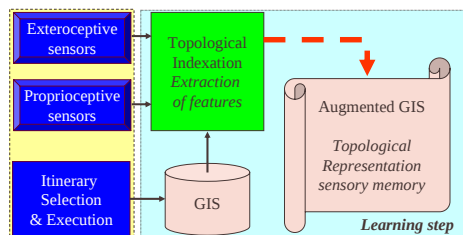
Navigation

3D Map based navigation (absolute navigation)



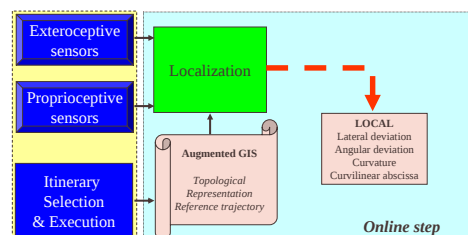
Navigation

Memory based navigation (relative navigation)



Navigation

Memory based navigation (relative navigation)



SLAN vs SLAM

	SLAM	SLAN
MAPS	Metric 2D/3D	Topological Semi-Metric
Localization	Absolute	Relative
Control space	Cartesian	Sensor space Cartesian (relative)

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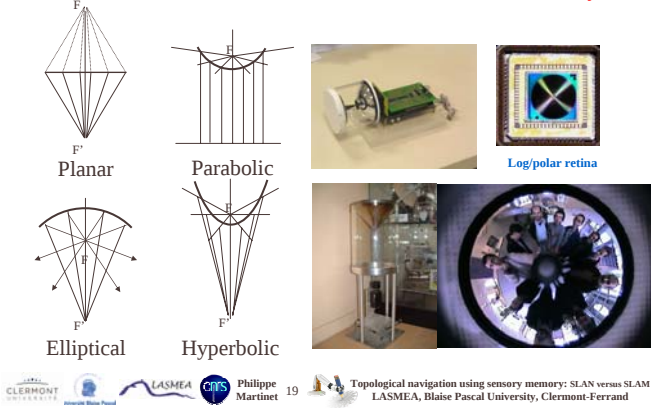
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- Outdoor applications

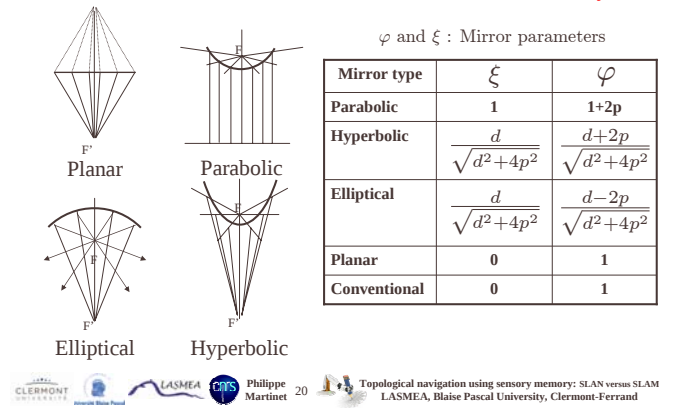
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A unified model for camera *Single view point system : Classification [Geyer00]*



A unified model for camera *Single view point system : Classification [Geyer00]*



A unified model for camera *Single view point system : case of point*

$$\mathbf{m}_m = \frac{1}{\rho} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

$$\rho = \|\mathbf{m}\| = \sqrt{X^2 + Y^2 + Z^2}$$

$$\mathbf{m}_n = [\mathbf{x}^T \beta]^T = \begin{bmatrix} X \\ Z + \xi \rho \\ Y \\ Z + \xi \rho \\ \beta \end{bmatrix}$$

$$\mathbf{m}_p = \mathbf{K}_M \mathbf{m}_n$$

A unified model for camera *Single view point system : case of point*

$$\mathbf{M} = \begin{bmatrix} \varphi - \xi & 0 & 0 \\ 0 & \varphi - \xi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{K} = \begin{bmatrix} f & fs & u_0 \\ 0 & fr & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{f}(\mathbf{m}_{3D}) = \begin{bmatrix} X \\ \frac{\epsilon Z + \xi \sqrt{X^2 + Y^2 + Z^2}}{\epsilon Z + \xi \sqrt{X^2 + Y^2 + Z^2}} \\ 1 \end{bmatrix}$$

Special cases :

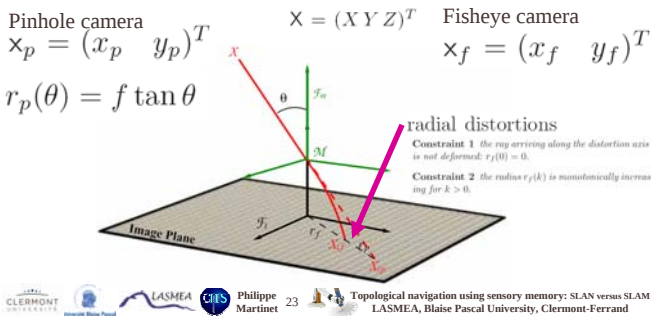
- $\epsilon = 1$ and $\xi = 0 \rightarrow$ perspective projection
- $\epsilon = 0$ and $\xi = 1 \rightarrow$ spherical projection

Generic Projection function

$$\mathbf{m}_p = \underbrace{\mathbf{K}_M \mathbf{M}}_{\mathbf{K}_M} \mathbf{f}(\mathbf{m}_{3D})$$

Case of fisheye camera *Fisheye camera model : definition*

- ★ r = distance between X and the image point
- ★ θ = angle between the incoming ray and the principal axis



Case of fisheye camera *Fisheye camera model : Pinhole based models*

Mapping :

$$r_p \xrightarrow{T_1} r_f$$

$L(r_p, n) = 1 + k_1 r_p^2 + k_2 r_p^4 + \dots + k_n r_p^{2n}$ n parameters

★ $r_f^1(r_p) = r_p L(r_p, n)$ used for perspective cameras [T. Pajdla97, Hartley00, Zhang98, Ma2006...]

★ $r_f^2(r_p) = \frac{r_p}{L(r_p, n)}$ handle high distortion [Fitzgibbon01]

★ $r_f^3(r_p) = \frac{r_p}{1 + k_1 r_p^2}$ one parameter [Fitzgibbon01]

Case of fisheye camera *Fisheye camera model : Pinhole based models*

Mapping :
 $r_p \xrightarrow{T_1} r_f$

★ $r_f^4(r_p) = r_p \frac{L_1(r_p, n_1)}{L_2(r_p, n_2)}$ rational model n1+n2 parameters [Li05]

★ $r_f^5(r_p) = s \log(1 + \lambda r_p)$ logarithmic mapping [Basu95]
 s is a scaling factor and λ a gain to control the amount of distortion

★ $r_f^6(r_p) = \frac{1}{\omega} \arctan(2r_p \tan \frac{\omega}{2})$ Field-of-view (FOV) model [Devenay01]

★ $r_f(r_p) = \lambda r_p$ [Hartley07]

The "distortion function" $\lambda = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$ can be then fitted by a parametric model

Case of fisheye camera *Fisheye camera model : Captured rays based models*

Mapping :
 $\theta \xrightarrow{T_2} r_f$

★ $r_f^1(\theta) = f\theta$ cameras with limited distortions [Kingslake89]

★ $r_f^2(\theta) = 2f \tan(\frac{\theta}{2})$ stereographic projection preserves circularity and thus project 3D local symmetries onto 2D local symmetries [Fleck94, Stevenson95]

★ $r_f^3(\theta) = f \sin \theta$ orthogonal or sine law projection [Ray94]

★ $r_f^4(\theta) = f \sin(\frac{\theta}{2})$ equisolid angle projection [Smith92]

Case of fisheye camera *Fisheye camera model : Captured rays based models*

Mapping :
 $\theta \xrightarrow{T_2} r_f$

★ $r_f^5(\theta) = f(k_1\theta + k_2\theta^3 + \dots + k_n\theta^{2(n-1)+1})$ Improvement of the polynomial model accuracy [xiong97, kannala04, schwalbe05, Scaramuzza06]

★ $r_f^6(\theta) = \alpha \sin(\beta\theta)$ ★ α : scale factor
 ★ β : radial mapping parameter [Kumler00]

★ $r_f^7(\theta) = a \tan(\theta/b) + c \sin(\theta/d)$ Combination of
 - stereographic projection (with parameters a, b)
 - equisolid angle projection (with parameters c, d) [Bakstein02]

Case of fisheye camera *Generic camera model : Unified Spherical Model*

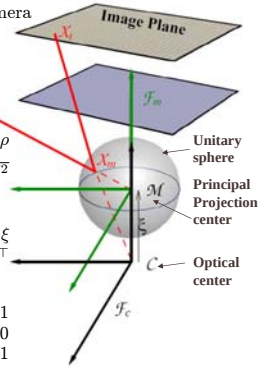
- ★ F_c : frame attached to the conventional camera
- ★ F_m : frame attached to the unitary sphere

$X = [X \ Y \ Z]^T \quad \underline{x} = [x \ y \ 1]^T$

Step 1 : Projection on the unitary sphere
 X_m in F_m : $X_m = X/\rho$
 where $\rho = \|X\| = \sqrt{X^2 + Y^2 + Z^2}$

Step 2 : Perspective projection
 on the normalized image plane $Z = 1 - \xi$

$\underline{x}' = f(X) = \begin{bmatrix} \frac{X}{\varepsilon_s Z + \xi \rho} & \frac{Y}{\varepsilon_s Z + \xi \rho} & 1 \end{bmatrix}^T$
 spherical projection : $\varepsilon_s = 0$ and $\xi = 1$
 pinhole model : $\varepsilon_s = 1$ and $\xi = 0$
 Catadioptric model : $\varepsilon_s = 1$ and $\xi = 1$



Case of fisheye camera *Generic camera model : Unified Spherical Model*

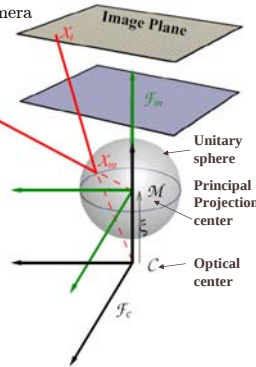
- ★ F_c : frame attached to the conventional camera
- ★ F_m : frame attached to the unitary sphere

$X = [X \ Y \ Z]^T \quad \underline{x} = [x \ y \ 1]^T$

Step 3 : Projection onto image plane

$\underline{x} = M \underline{x}'$
 $M = \begin{pmatrix} f\kappa & 0 & 0 \\ 0 & \delta f\kappa & 0 \\ 0 & 0 & 1 \end{pmatrix}$ f : focal length
 δ is equal to ± 1
 $\kappa > 0$

catadioptric cameras : $\delta = -1$
 perspective camera : $\kappa = 1$ and $\delta = +1$



Case of fisheye camera *Generic camera model : Unified Spherical Model*

- ★ F_c : frame attached to the conventional camera
- ★ F_m : frame attached to the unitary sphere

$X = [X \ Y \ Z]^T \quad \underline{x} = [x \ y \ 1]^T$

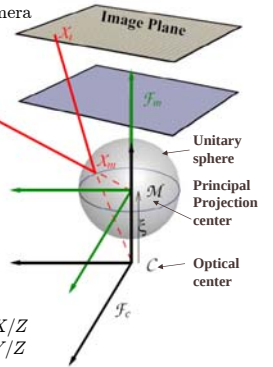
Step 4 : Pixel transformation

$m = K \underline{x}$ plane-to-plane collineation K

$K = \begin{pmatrix} k_u & s_{uv} & u_0 \\ 0 & k_v & v_0 \\ 0 & 0 & 1 \end{pmatrix}$

$(u_0, v_0)^T$: position of the optical center
 k_u and k_v : scaling along the x and y axes
 s_{uv} : skew

Pinhole camera setting $\xi = 0$, $\kappa = 1$ and $\delta = +1$ $\begin{cases} x_p = f_p X/Z \\ y_p = f_p Y/Z \end{cases}$



Partial euclidian reconstruction

Unified model - Case of points

$$m \in \pi$$

$$\bar{\mathbf{m}} = \beta_{x,x^*} \mathbf{H}_\pi \bar{\mathbf{m}}^*$$

$$\text{where } \beta_{x,x^*} = \frac{\eta^{*-1} + \xi}{\eta^{-1} + \xi} \frac{\rho^*}{\rho}$$

Linear form

$$\bar{\mathbf{m}} \times \mathbf{H}_\pi \bar{\mathbf{m}}^* = 0$$

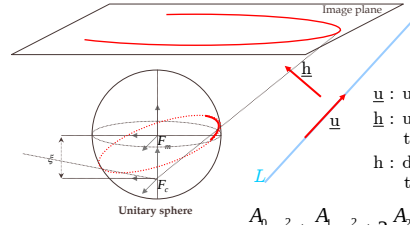
$$\mathbf{H}_\pi \rightarrow \mathbf{R} \text{ and } \mathbf{t}_{d^*} = \frac{\mathbf{t}}{d^*}$$

$$\sigma = \frac{\rho}{\rho^*} = (1 + \mathbf{n}^{*T} \mathbf{R}^T \mathbf{t}_{d^*}) \frac{(\eta^{*-1} + \xi) \mathbf{n}^{*T} \bar{\mathbf{m}}^*}{(\eta^{-1} + \xi) \mathbf{n}^{*T} \mathbf{R}^T \bar{\mathbf{m}}}$$

Partial euclidian reconstruction

Unified model - Case of lines

Similar results are obtained from lines (using polar lines)



Plücker coordinates

$$L = (\underline{u}, \underline{h}, h)^T$$

$\underline{u}$: unitary vector along the line L

$\underline{h}$: unitary vector orthogonal to the interpretation plane

h : distance between the origin of the frame and the line

$$\frac{A_0}{A_3} x^2 + \frac{A_1}{A_3} y^2 + 2 \frac{A_2}{A_3} xy + 2 \frac{A_4}{A_3} x + 2 \frac{A_5}{A_3} y + 1 = 0$$

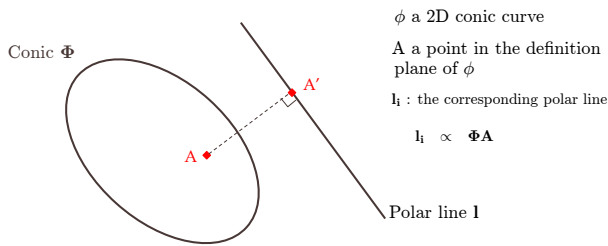
$$B_i(\underline{h}, \xi, K_M) = \frac{A_i}{A_3}$$

Partial euclidian reconstruction

Unified model - Case of lines

Similar results are obtained from lines (using polar lines)

Polar lines



ϕ a 2D conic curve

A a point in the definition plane of ϕ

l_i : the corresponding polar line

$$l_i \propto \Phi A$$

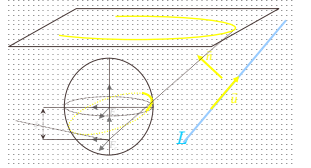
Partial euclidian reconstruction

Unified model - Case of lines

Similar results are obtained from lines (using polar lines)

Polar lines

$$\Omega = \begin{pmatrix} h_x^2 - \xi^2 (1 - h_y^2) & h_x h_y (1 - \xi^2) & h_x h_z \\ h_x h_y (1 - \xi^2) & h_y^2 - \xi^2 (1 - h_x^2) & h_y h_z \\ h_x h_z & h_y h_z & h_z^2 \end{pmatrix}$$



$$\underline{x}_i^T \underbrace{\mathbf{K}^{-T} \Omega \mathbf{K}^{-1}}_{\Omega_i} \underline{x}_i = 0$$

The polar line of the optical center with respect to the conic Ω_i is given by:

$$l_i \propto \Omega_i O_i$$

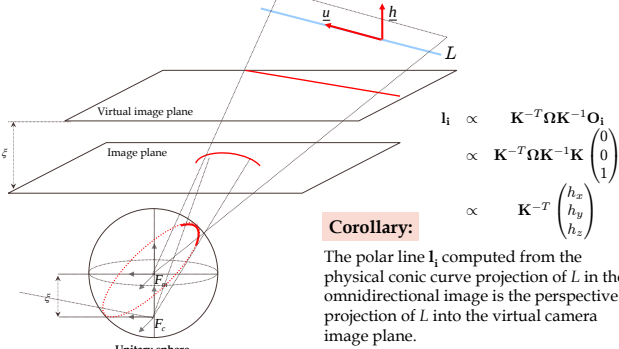
principal point

$$O_i = [u_0 \ v_0 \ 1]^T = \mathbf{K} [0 \ 0 \ 1]^T$$

Partial euclidian reconstruction

Unified model - Case of lines

Similar results are obtained from lines (using polar lines)



$$l_i \propto \mathbf{K}^{-T} \Omega \mathbf{K}^{-1} O_i$$

$$\propto \mathbf{K}^{-T} \Omega \mathbf{K}^{-1} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$\propto \mathbf{K}^{-T} \begin{pmatrix} h_x \\ h_y \\ h_z \end{pmatrix}$$

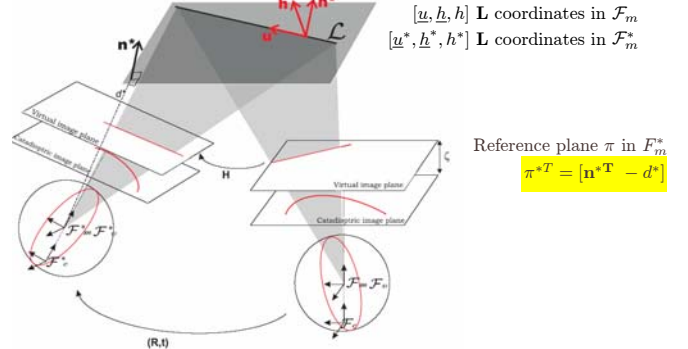
Corollary:

The polar line l_i computed from the physical conic curve projection of L in the omnidirectional image is the perspective projection of L into the virtual camera image plane.

Partial euclidian reconstruction

Unified model - Case of lines

Similar results are obtained from lines (using polar lines)



$$[\underline{u}, \underline{h}, h] \text{ L coordinates in } \mathcal{F}_m$$

$$[\underline{u}^*, \underline{h}^*, h^*] \text{ L coordinates in } \mathcal{F}_m^*$$

Reference plane π in $\mathcal{F}_m^*$

$$\pi^{*T} = [\mathbf{n}^{*T} \ -d^*]$$

Partial euclidian reconstruction

Unified model - Case of lines
Similar results are obtained from lines (using polar lines)

$\mathcal{X}_1$ and $\mathcal{X}_2$ are two points in the 3D space lying on the line $\mathcal{L}$

$$\begin{aligned} \mathbf{h} &\propto \mathbf{H}^{-T} \mathbf{h}^* & \mathbf{l}_i &\propto \mathbf{K}^{-T} \mathbf{h} & \rightarrow & \mathbf{l}_i \propto \mathbf{K}^{-T} \mathbf{H}^{-T} \mathbf{h}^* \\ \mathbf{l}_i^* &\propto \mathbf{K}^{-T} \mathbf{h}^* & \rightarrow & \mathbf{l}_i \propto \mathbf{K}^{-T} \mathbf{H}^{-T} \mathbf{K}^T \mathbf{l}_i^* \\ & & & \mathbf{l}_i \propto \mathbf{G}^{-T} \mathbf{l}_i^* \\ & & & \mathbf{G} = \mathbf{K} \mathbf{H} \mathbf{K}^{-1} \end{aligned}$$

Linear form

$$\mathbf{l}_i \times \mathbf{G}^{-T} \mathbf{l}_i^* = 0 \quad \text{with 4 couples } (\mathbf{l}_i, \mathbf{l}_i^*) \quad \rightarrow \quad \mathbf{H} \quad \rightarrow \quad \mathbf{R} \text{ and } \mathbf{t}_{d^*} = \frac{\mathbf{t}}{d^*}$$

$$\mathbf{H} = \mathbf{R} + \frac{\mathbf{t}}{d^*} \mathbf{n}^* \mathbf{n}^{*T}$$

$$r = \frac{h}{h^*} = (1 + \mathbf{t}_d^* \mathbf{R}^T \mathbf{n}^*) \frac{\|\mathbf{n}^* \times \mathbf{K}^T \mathbf{l}_i^*\|}{\|\mathbf{R} \mathbf{n}^* \times \mathbf{K}^T \mathbf{l}_i\|}$$

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- SLAM vs SLAM

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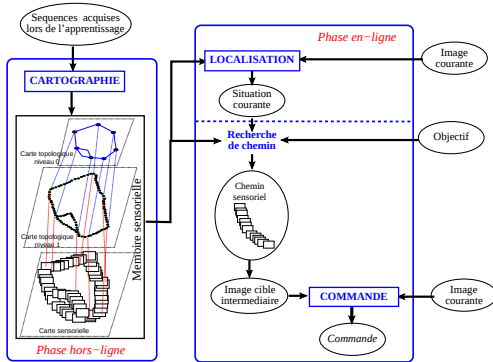
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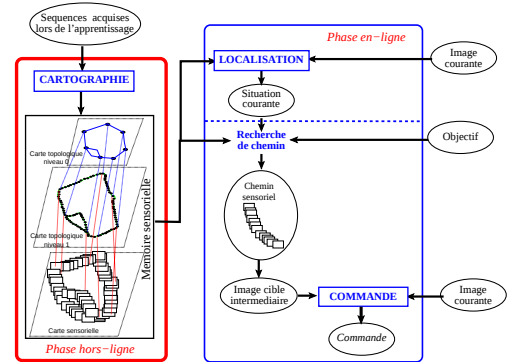
- Learning process
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Global system



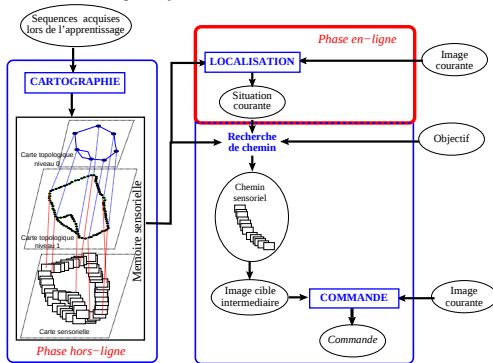
Global system

Supervised learning step: building of the sensory memory



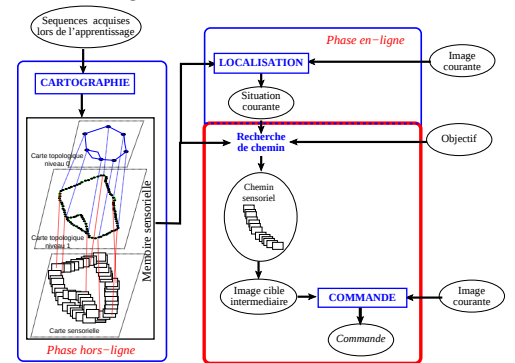
Global system

Initialization: primary localization

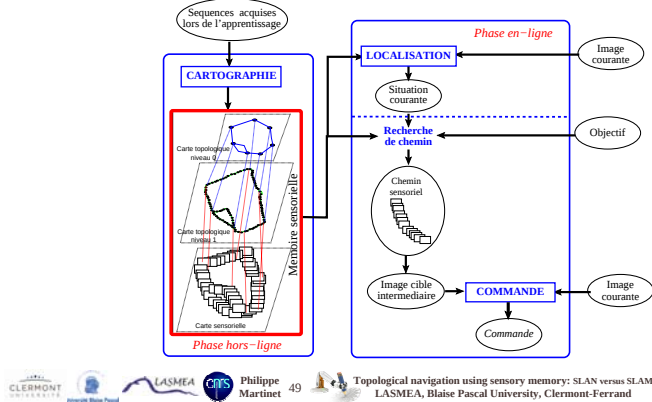


Global system

One line navigation and control



Case of vision



Case of vision

Topological map level 0 (CT0)

- ✓ High level representation : corridor, routes, ..

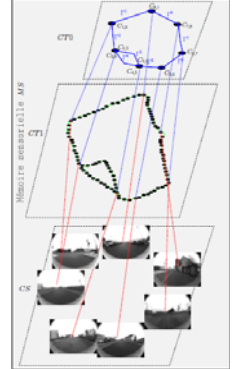
Topological map level 1 (CT1)

- ✓ Image network representation
- ✓ Navigability
- ✓ Commandability
- ✓ Plannification

Sensory map (CS)

- ✓ Initial localization
- ✓ Sensor based control
- ✓ Visualization of the environment
- ✓ Human interface

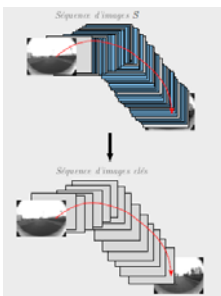
Sensory memory



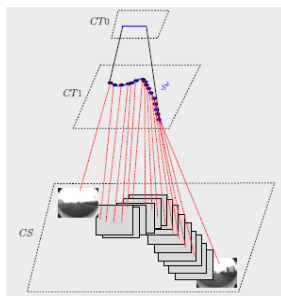
Different modules

Learning step (first arc, first two nodes)

Key images selection

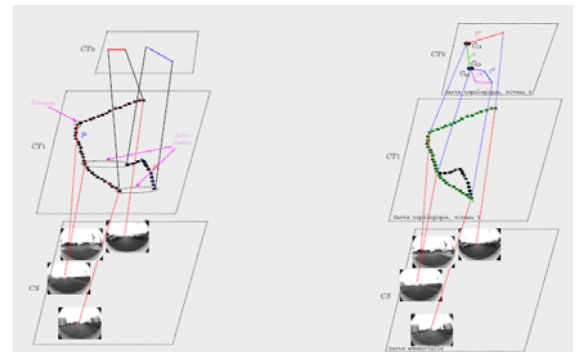


Building the sensory memory



Different modules

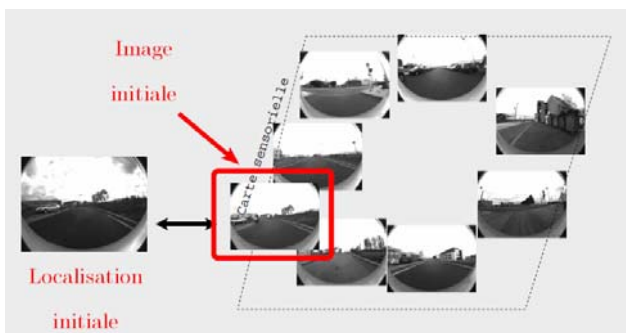
Learning step (expanding the processus...)



Differents modules

Initial localization

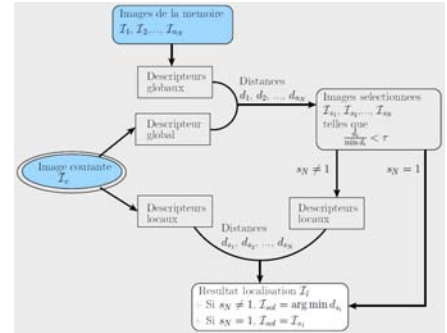
How to find the closest image in the database ?



Differents modules

Initial localization

How to find the closest image in the database ?

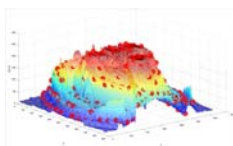
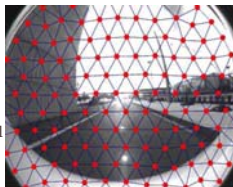


Differents modules Initial localization

How to find the closest image in the database ?

Use of a regular mesh [PERSSON04]
Cubic interpolation of the image surface

Global descriptor : vector of the interpolated grey level
pixels at the position of the control point



Control point distribution (one example)

Differents modules Initial localization

How to find the closest image in the database ?

Local descriptor : interest points detected by
Harris Stephen detector

Use of patches 11x11



Matching done by using the centered cross correlation score ZNCC

Use of the number of matched point to compute the similarity between 2 images

Differents modules Initial localization

How to find the closest image in the database ?

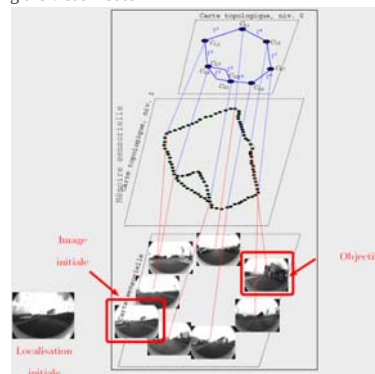
Evaluation of the approach [ICRA08] using three image databases regarding 3 main criteria:
Used memory size, percentage of success, computation time for localization

Camera	Taille image	Nb images	Images
Catadioptrique	1024 × 768	978	
Fisheye 110 deg	384 × 288	188	
Fisheye 190 deg	640 × 480	445	

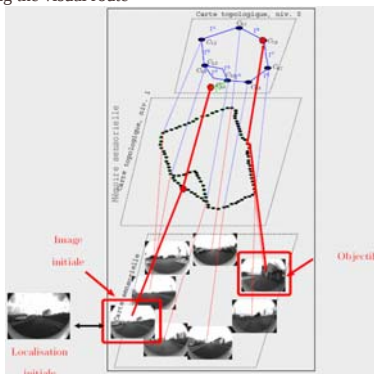
Several approaches were compared : GONZ [GONZALES02], PHLAC [LINAKER04],
CUB, SURF, SIFT, HARRIS, **CUBHAR**

Differents modules Planifying the visual route

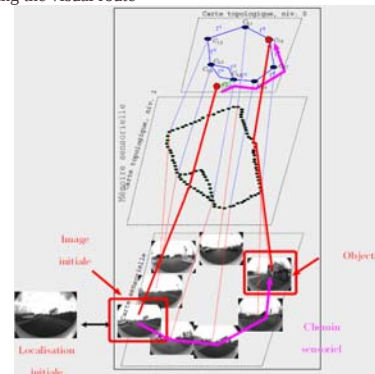
How to find the optimal path ?

**Differents modules** Planifying the visual route

How to find the optimal path ?

**Differents modules** Planifying the visual route

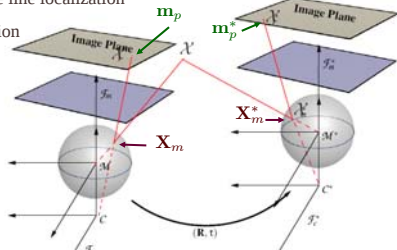
How to find the optimal path ?



Differents modules

One line localization

Scaled euclidian reconstruction



Epipolar constraint can be expressed by:

$$X_m^T R (t \times X_m^{*T}) = X_m^T R [t]_{\times} X_m^{*T} = 0$$

$$\text{For pinhole model } X_m^T E X_m^{*T} = 0$$

From five couples of points E can be estimated

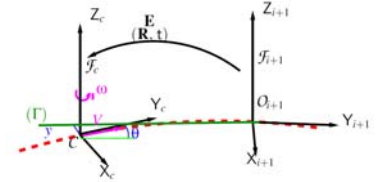
Outliers are rejected by using RANSAC

Differents modules

State estimation and control (one example)

State model of the mobile robot

$$(s, y, \theta)$$



$$\mathcal{F}_i = (O_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{Z}_i)$$

$$\mathcal{F}_{i+1} = (O_{i+1}, \mathbf{X}_{i+1}, \mathbf{Y}_{i+1}, \mathbf{Z}_{i+1})$$

$$\begin{cases} \dot{s} = v \frac{\cos \theta}{1 - c(s)y} \\ \dot{y} = v \sin \theta \\ \dot{\theta} = \omega \left(\frac{\tan \delta}{l} - \frac{c(s) \cos \theta}{1 - c(s)y} \right) \end{cases}$$

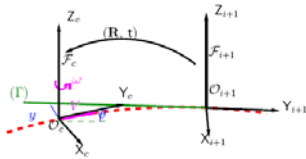
Chained System theory [IAV04]

Kinematic model of the mobile robot

Differents modules

State estimation and control (one example)

Path following approach



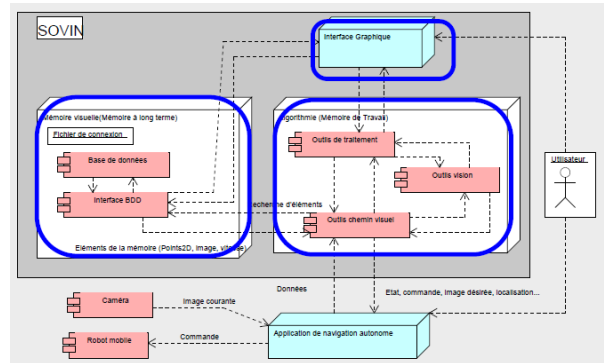
Goal: $y \rightarrow 0, \theta \rightarrow 0$ before $\mathcal{F}_c$ reaches $\mathcal{F}_{i+1}$

Asymptotically stable guidance control law based on the chain system approach:

$$\delta(y, \theta) = \arctan(-l [\cos^3 \theta (-K_d \tan \theta - K_p y)])$$

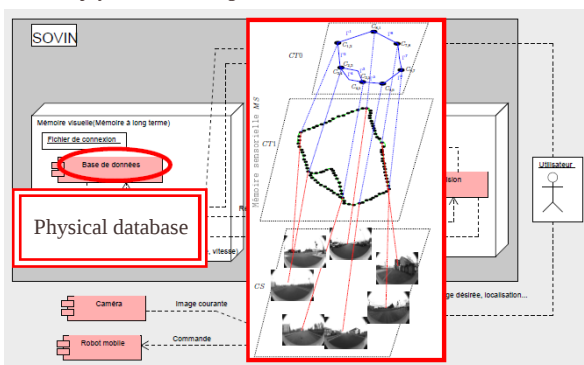
SOVIN

A global software environment for topological navigation in wide spaces



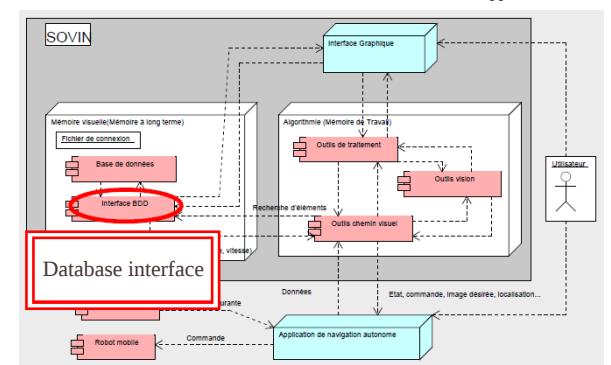
SOVIN

A physical database organized in three levels

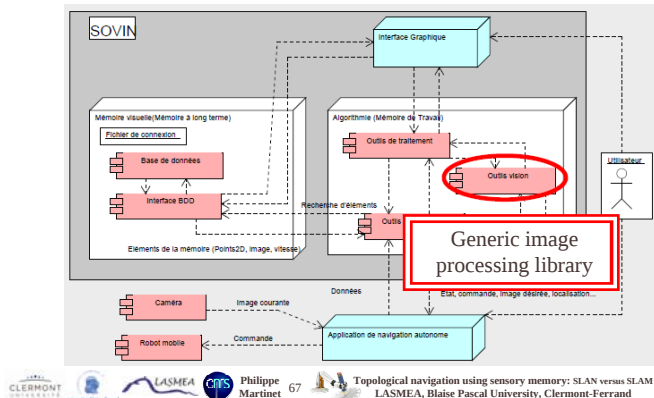


SOVIN

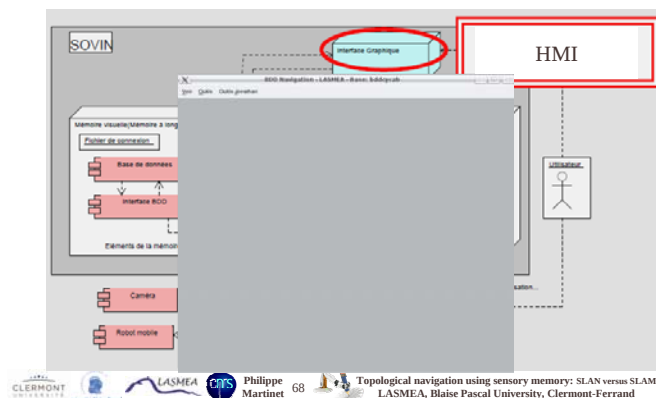
An efficient database interface for on line and real time applications



SOVIN A generic library (generic visual sensor) for visual algorithm processing



SOVIN An efficient Human Machine Interface for managing applications



Outline of the presentation

Introduction

- LASMEA
- Sensor based Control
- Navigation
- SLAN vs SLAM

A generic model

- A unified model for camera
- Case of fisheye cameras
- Partial euclidian reconstruction

Topological navigation system

- Global system
- Case of vision
- Differents Modules
- SOVIN

Illustrations

- Indoor applications
- Outdoor applications

Discussion

- Learning process
- Updating process
- Closing the loop problem

Applications and projects in LASMEA AGV using visual memory



Indoor applications : WACIF project (2002-2005)

Autonomous Robot for Telepresence navigation, localization, learning, warning and communication capabilities



- Study and development of a demonstrator like a personal robot fully integrated in the context of « wireless home »

- An innovant domotic HMI dedicated for software useful for human, family and home applications



Wireless communication and services

- Telepresence and telesurveillance tasks home supervision through any wireless point, abnormal event detection in family environment (intrusion, noise, ...)



Autonomous navigation strategy

Indoor applications : WACIF project (2002-2005)

Global navigation strategy

Topological representation

Predefined trajectory

Graph representation

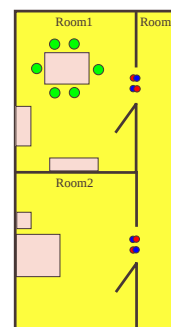
Visual memory concept

Hypothesis : knowledge

HS = HOME Space

RS_i = Room Space i

$HS = \sum_i RS_i$



- Starting point
- Ending point

Topological representation step is a part of the knowledge we get from the HOME environment

Introduction

A generic model

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Indoor applications : WACIF project (2002-2005)

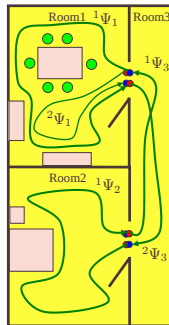
Global navigation strategy

Topological representation

Predefined trajectory

Graph representation

Visual memory concept



Predefined trajectory step is totally supervised using robot teleoperation

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Indoor applications : WACIF project (2002-2005)

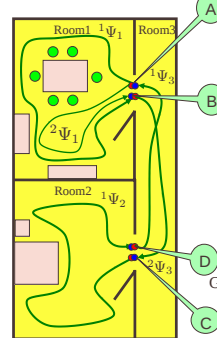
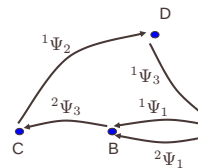
Global navigation strategy

Topological representation

Predefined trajectory

Graph representation

Visual memory concept



Graph representation step is deduced from the previous step

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Indoor applications : WACIF project (2002-2005)

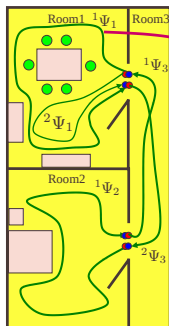
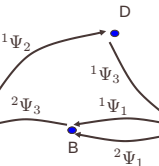
Global navigation strategy

Topological representation

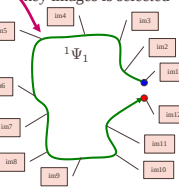
Predefined trajectory

Graph representation

Visual memory concept



Along the teleoperated trajectories a set of key images is selected



Visual memory concept is used for navigation

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Indoor applications : WACIF project (2002-2005)

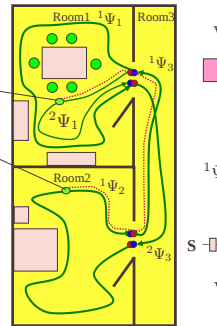
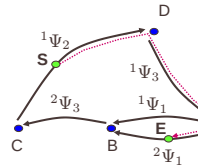
Global navigation strategy

Topological representation

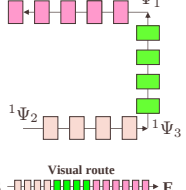
Predefined trajectory

Graph representation

Visual memory concept



From the graph a Visual route is generated



Visual route is used for navigation

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Indoor applications : WACIF project (2002-2005)

Global navigation strategy

Functional decomposition

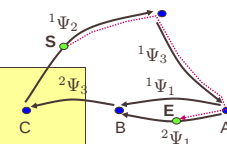
Learning Off line

Define each $i\Psi_j$: learn the trajectory

- ★ Robot teleoperation
- ★ Models features extraction and selection
- ★ Mosaic construction

Re-run of trajectory : On line

- ★ Extract the reference model from the visual route
- ★ Select and track models in current images
- ★ Localization in the mosaic
- ★ Lateral control of the non holonomous robot



Ait Ader [04]
Blanc [04]
Blanc [05]

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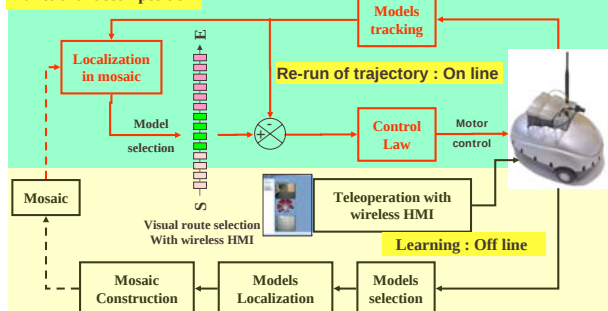
Discussion

Indoor applications : WACIF project (2002-2005)

Global navigation strategy

Ceiling images are used

Functional decomposition



Introduction

A generic model

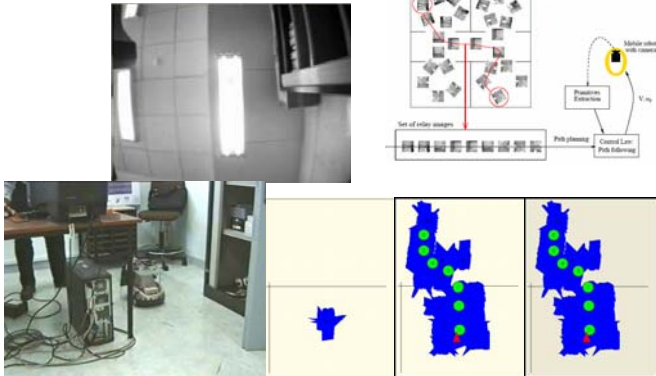
Topological navigation system

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Indoor applications : WACIF project (2002-2005)

Navigation using visual memory



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Topological navigation system

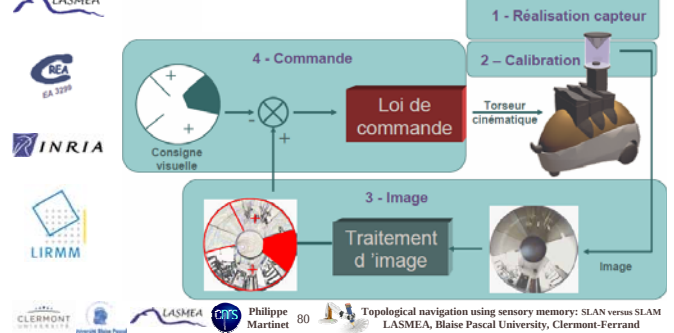
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Indoor applications : OMNIBOT project

From omnidirectional vision to mobile robot control

Development of a complete perception and control approach for mobile robot using omnidirectional vision



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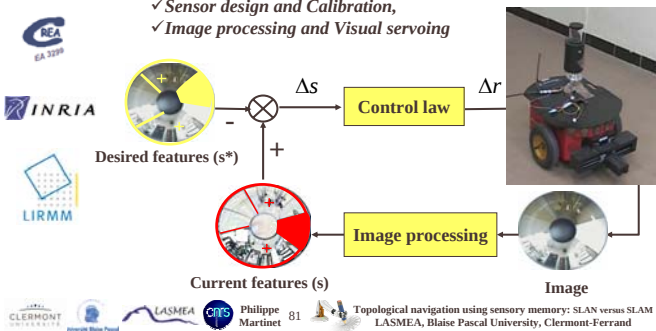
Discussion

Indoor applications : OMNIBOT project

From omnidirectional vision to mobile robot control

Development of a complete perception and control approach for mobile robot using omnidirectional vision :

- ✓ Sensor design and Calibration,
- ✓ Image processing and Visual servoing



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Topological navigation system

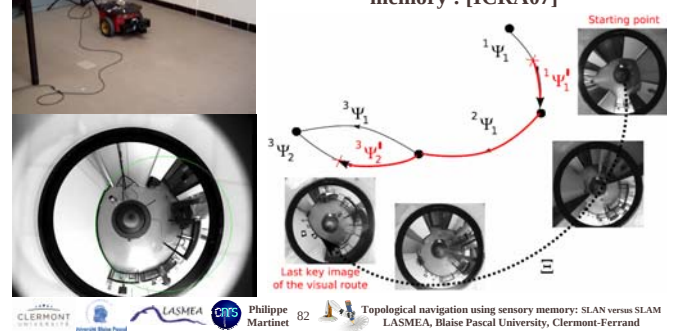
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Indoor applications : OMNIBOT project

H. Hadj Abdelkader [05]

Navigation with omnidirectional visual memory : [ICRA07]



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A generic model

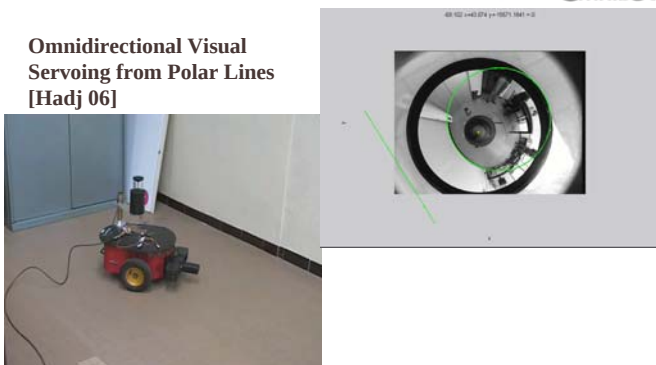
Topological navigation system

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Indoor applications : OMNIBOT project

Omnidirectional Visual Servoing from Polar Lines [Hadj 06]



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Indoor applications : ROSACE project

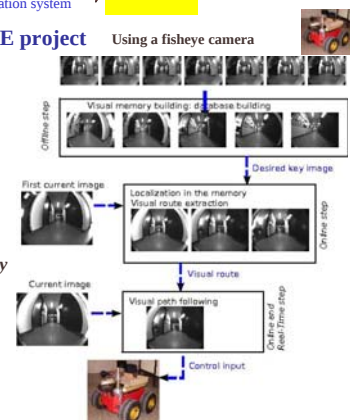
Using a fisheye camera

General framework :

Vision based memory navigation strategy :

3 steps :

1. Visual memory building
2. Localization into the visual memory
3. Navigation into the visual memory



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Indoor applications : ROSACE project

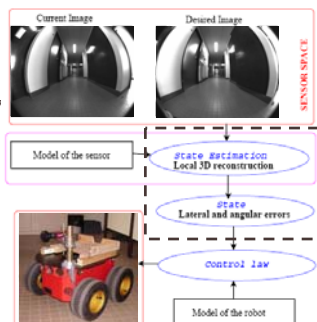
Localization

Vision based memory
navigation strategy :

Localization into the visual memory

- a- Global localization
- b- Selection of key images
- c- Relative pose computation

(y, θ) evaluation



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model

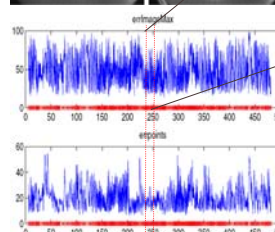
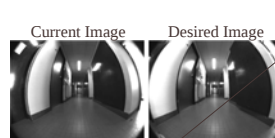
Topological
navigation system

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Indoor applications : ROSACE project

Using a fisheye camera



Global localisation (6.5s) 306 matchings
Visual route (280 key images) – Matching mean=108
- ErrImageMax: longest distance between an
image point and its position in desired image
- Errpoints: Mean distance between those points

When errImageMax reaches 20
we decide to change key image

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Indoor applications : ROSACE project

Using a fisheye camera



[Courbon08]

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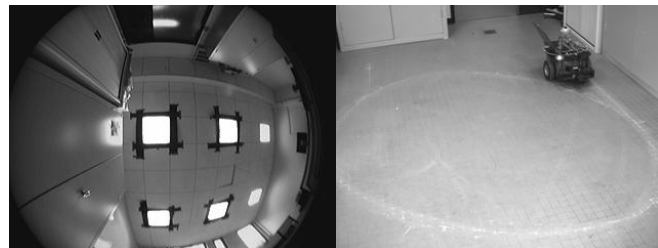
Using a fisheye camera



J. Courbon [07]

Automatic Guided Vehicles
robot control using a fisheye lens

Autonomous navigation using a visual memory



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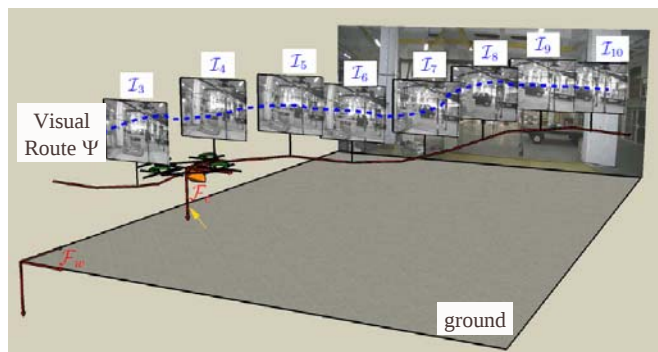
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Indoor applications : µdrone project

Flying robot
[IROS09]

cea list



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Indoor applications : µdrone project

Flying robot
[IROS09]

cea list

Topological
navigation
using
visual memory

CEA 2009
Fontenay-aux-Roses

Using vision only
Clermont-Ferrand
LASMEA-GRAVIR

Visual navigation of
a quadrotor aerial vehicle

J.Courbon, Y.Mezouar
N.Guénard, P.Martinet



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Outdoor applications : MOBIVIP project

urban context [Royer04]

Visual memory

Reference Trajectory and Image features (3D points)

Experimental data Compiegne city center (BODEGA/MOBIVIP)

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Blaise Pascal

LASMEA

CPRS

Philippe Martinet 91

Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

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Outdoor applications : MOBIVIP project

urban context [Royer04]

Perception Localization using monocular camera

Reference Trajectory and localization

Key images And features

Current images and features

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Philippe Martinet 92

Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

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Outdoor applications : MOBIVIP project

urban context [Royer06]

Perception and control

2006: Les Cezeaux Campus CFd

2006: Inner city of Clermont-Fd

Navigation autonome et en convoy par vision monocular

Projet Mobivip

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Philippe Martinet 93

Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

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Outdoor applications : CITYVIP project [ICRA09]

urban context

General framework :

Vision based memory navigation strategy :

3 steps :

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2. Localization into the visual memory
3. Navigation into the visual memory

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Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

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Outdoor applications : CITYVIP project [ICRA09]

urban context

Localization

Vision based memory navigation strategy :

Localization into the visual memory

a- Global localization
b- Selection of key images
c- Relative pose computation

(y, θ) evaluation

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CPRS

Philippe Martinet 95

Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

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Outdoor applications : CITYVIP project [ICRA09]

urban context

Testbed

Experimental robot is a Robucab from Robosoft

Algorithms are implemented in $C++$ language on a laptop using RTAI-Linux OS with a 2GHz Centrino processor

Fujinon fisheye lens, mounted onto a Marlin F131B camera
Field-of-view of 185 deg
Image resolution in the experiments was 800×600 pixels
Frame rate of 15fps

Longitudinal velocity V has been fixed to 1 ms^{-1}
 K_p and K_d are tuned regarding a double pole located at value 0.3

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LASMEA

CPRS

Philippe Martinet 96

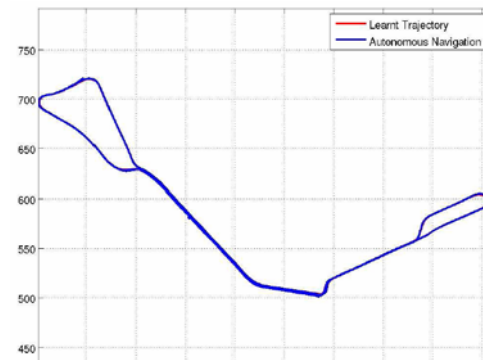
Topological navigation using sensory memory: SLAM versus SLAM LASMEA, Blaise Pascal University, Clermont-Ferrand

Outdoor applications : CITYVIP project [ICRA09] urban context
Experiment Loop 1200 m – 35 edges
 Navigation 1700m (26 minutes, 1400 frame images, 54 edges)

Navigation 1700m (26 minutes, 1400 keys images, 54 edges)



Outdoor applications : CITYVIP project [ICRA09] urban context



Lateral error:
- mean: 23 cm
- standard deviation: 30 cm

Navigation stops after 1700m for security reasons (small number of matched points)

Outdoor applications : CITYVIP project [ICRA09] urban context

Topological
navigation
using
visual memory
Cityvip
Clermont-Fd 2008

Using vision only
Clermont-Ferrand
LASMEA-GRAVIR



Outline of the presentation

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- **LASMEA**
- *Sensor based Control*
- *Navigation*
- *SLAN vs SLAM*

A generic model

- A unified model for camera
- Case of fisheye cameras
- Partial euclidian reconstruction

Togological navigation system

- *Global system*
- *Case of vision*
- *Differents Modules*
- *SOVIN*

Illustrations

- Indoor applications
- Outdoor applications

Discussion

- Learning process
- Updating process
- Closing the loop problem

Learning process

Part of the next step: R-DISCOVER project
Automatic discovering & learning the environment

Updating process

Part of the next step: R-DISCOVER project
Automatic updating the environment

Closing the loop problem

No a priori needs for closing the loop.
Can be useful for improving topological maps



Thanks for your attention

Any questions



<http://www.lasmea.univ-bpclermont.fr/Control>
<http://www.lasmea.univ-bpclermont.fr/Personnel/Philippe.Martinet>



martinet@lasmea.univ-bpclermont.fr

