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Navigation of a non-holonomic mobile robot with a memory of omnidirectional images

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***Abstract*— This paper extends our vision based navigation framework proposed in [2] to the entire class of central cameras (conventional and catadioptric cameras). During an off-line learning step, the robot performs paths which are sampled and stored as a set of ordered key images acquired by an embedded camera. The robot is then controlled by a vision-based control law along a visual route which joins the current image to the target image in the visual memory. We propose here to use an omnidirectional camera which significantly improves the localisation and navigation steps thanks to its large field of view. Simulations as well as real experimental results with an indoor robot illustrate the validity of the presented framework.**

I. Introduction

Often used among more "traditional" embedded sensors - proprioceptive sensors like odometers as exteroceptive ones like sonars - vision sensor provides accurate localisation methods. The authors of [4] accounts of twenty years of works at the meeting point of mobile robotics and computer vision communities. In many works, and especially those dealing with indoor navigation as in [9], computer vision techniques are used in a landmark-based framework. Identifying extracted landmarks to known references allows to update the results of the localisation algorithm. These methods are based on some knowledges about the environment, such as a given 3D model or a map built online. They generally rely on a complete or partial 3D reconstruction of the observed environment through the analysis of data collected from disparate sensors. The mobile robot can thus be localized in an absolute reference frame. Both motion planning and robot control can then be designed in this space. The results obtained by the authors of [16] leave to be forcasted that such a framework will be reachable using a single camera. However, although an accurate global localisation is unquestionably useful, our aim is to build a complete vision-based framework without recovering the position of the mobile robot with respect to a reference frame. In [4] this type of framework is ranked among qualitative approaches.

The principle of this approach is to represent the robot environment with a bounded quantity of images gathered in a set called visual memory. In the context of mobile robotics, [13] proposes to use a sequence of images, but recorded during a human teleoperated motion, and called View-Sequenced Route Reference. This concept underlines the close link between a human-guided learning and the performed paths during an autonomous run. However, the automatic control of the robot in [13] is not formulated as a visual servoing task. In [2], we propose to achieve navigation task using a conventional camera looking at the ceiling toward recovering features observed during a learning stage.

In this paper, we extend our image-based framework for mobile robots navigation proposed in [2] to the entire class of central cameras *i.e.* to perspective and catadioptric cameras. A sequence of omnidirectional images, acquired during a human-guided learning step, allows to derive paths driving the robot from its initial to its goal locations. In order to reduce the complexity of the image sequences, only key views are stored and indexed on a visual path. The set of visual paths can be interpreted as a visual memory of the environment. A navigation task consists then in performing autonomously a visual route which is a concatenation of visual paths. The visual route connects thus in the sensor space the initial and goal configurations. Section II details more precisely the concept of visual memory as described in [2].

Panoramic views acquired by an omnidirectional camera are well adapted to this approach since they provide a large amount of visual features which can be exploited as well as for localisation than for visual servoing. Moreover, keeping features in the field of view of an omnidirectional camera is easier than in the case of a perspective camera. The Section III deals with the omnidirectional vision-based control scheme designed to control the robot motions along a visual route.

In Section IV, simulations and experiments on a Pioneer AT3 mobile robot illustrate the proposed framework.

II. Omnidirectional vision-based memory

In [4], approaches using a "memorization" of images of the environment taken from an embedded camera are ranked among mapless navigation systems. Indeed, as proposed in [13] or in [10], any notion of map nor topology of the environment appears, neither to build the reference set of images, nor for the automatic guidance of the robot. The first step of our framework proposed in [2] consists on a learning stage to build the visual memory. The visual memory is structured according to the environment topology to reduce the computational cost.

A. Visual Memory Structure

The Visual Memory Structure presented in [2] is briefly summarized hereunder. The learning stage relies on the human experience. The user guides the mobile robot along one or several paths of its workspace. A visual path ${}^{r}\Psi_p$ is then stored and indexed as the p^{th} learnt path in the r^{th} place. It is composed of n key images:

$$ {}^{r}\Psi_p = \{ {}^{r}\mathcal{I}_i^p | i = \{1, 2, \ldots, n\} \} $$

For control purpose (refer to Section III), the authorized motions during the learning stage are assumed to be limited to those of a car-like vehicle, which only goes forward. The following Hypothesis 2.1 formalizes these constraints.

Hypothesis 2.1: Given two frames ${}^{R}\mathcal{F}_i$ and ${}^{R}\mathcal{F}_{i+1}$, respectively associated to the mobile robot when two successive key images $\mathcal{I}_i$ and $\mathcal{I}_{i+1}$ of a visual path Ψ were acquired, there exists an admissible path ψ from ${}^{R}\mathcal{F}_i$ to ${}^{R}\mathcal{F}_{i+1}$ for a car-like vehicle whose turn radius is bounded, and which only moves forward.

Moreover, because the controller is vision-based, the robot is controllable from ${}^{r}\mathcal{I}_i^p$ to ${}^{r}\mathcal{I}_{i+1}^p$ only if the hereunder Hypothesis 2.2 is respected.

Hypothesis 2.2: Two successive key images $\mathcal{I}_i$ and $\mathcal{I}_{i+1}$ contain a set $\mathcal{P}_i$ of matched visual features, which can be tracked along a path performed between ${}^{R}\mathcal{F}_i$ and ${}^{R}\mathcal{F}_{i+1}$.

During the acquisition of a visual path, the Hypothesis 2.2 constrains the choice of the key images.
In order to connect two visual paths, the terminal extremity of one of them and the initial extremity of the other one must be constrained as two consecutive key images of a visual path.

B. Omnidirectional Visual Memory

In [2], ceiling images are used for two purposes. First, conditions of visibility of features in the ceiling plane are similar during the learning and the navigation stages. Secondly, a good approximation of the normal to the reference plane can be obtained. Unfortunatly, localisation using only ceiling images is a hard task since images taken at two positions can be very similar. As the image acquired by an omnidirectional camera is able to cover a large part of the environment, the localisation is easier. Localisation may be realized using a global image matching (see [14] for example where the image's Fourier Signature is used) or a local feature matching (as proposed [18] using an Iterative SIFT descriptor). The method proposed in [14] requires to unwarp the omnidirectional images into a panoramic cylinder whereas the matching is directly obtained from the omnidirectional image in [18]. Matching directly from the omnidirectional images better suit our framework.

If a perspective camera is used, a visual path should contain many images to satisfy Hypothesis 2.2. When using omnidirectional cameras this hypothesis is easily verified, using only few images. The tracking is possible too in the case of unpredicted large movements as it may occur during an obstacle avoidance behaviour. Moreover, the inversion of the graph is possible when using omnidirectional images: if Hypothesis 2.1 and 2.2 are respected between ${}^{R}\mathcal{F}_i$ and ${}^{R}\mathcal{F}_{i+1}$, there are also respected between ${}^{R}\mathcal{F}_{i+1}$ and ${}^{R}\mathcal{F}_i$.
Thus using an omnidirectional camera highly increases the navigation capacities of the robot compared to the same framework using a perspective camera. Moreover, with a field of view of 360°, a surveillance task may be realized by the omnidirectional camera as well.

C. Visual route

A visual route describes the robot's mission in the sensor space. Given two key images of the visual memory $\mathcal{I}_c$ and $\mathcal{I}_g$, corresponding respectively to the current and goal locations of the robot, a visual route is a set of key images which describes a path from $\mathcal{I}_c$ to $\mathcal{I}_g$.

The visual route describes a set of consecutive states that the image has to reach in order that the robot joins the goal configuration from the initial one. The robot motions are controlled along the visual route using the data provided by the embedded camera. The next section deals with this issue.

III. Routes following using an omnidirectional camera

Visual-servoing is often considered as a way to achieve positioning tasks. Classical methods, based on the task function formalism, are based on the existence of a diffeomorphism between the sensor space and the robot's configuration space. Due to the nonholomic constraints of most of wheeled mobile robots, under the condition of rolling without slipping, such a diffeomorphism does not exist if the camera is rigidly fixed to the robot. In [20], the authors add extra degrees of freedom to the camera. The camera pose can then be regulated in a closed loop.
In the case of an embedded and fixed camera, the control of the camera is generally based on wheeled mobile robots control theory [17]. In [11], a car-like robot is controlled with respect to the projection of a ground curve in the image plane. The control law is formalized as a path following problem. More recently, in [3], a partial estimation of the camera displacement between the current and desired views has been exploited to design vision-based control laws. The camera displacement is estimated by uncoupling translation and rotation components of an homography matrix. A trajectory following task is achieved. The trajectory to follow is defined by a prerecorded video and the control law is proved stable using Lyapunov-based analysis.
In [8], *homing* strategy is used to control a wheelchair from a memory of omnidirectional images but the control is not a part of the presented framework. A memory of omnidirectional images is also used in [6] where localisation and navigation are realized in the bird's eye (orthographic) views obtained

by radial distortion correction of the omnidirectional images. The control of the robot is formulated in the bird's eye view of the ground plane which is similar to a navigation in a metric map. The View-Sequenced Route presented in [13] has been applied to omnidirectional images in [12]. The control is not formulated as a visual servoing task and images are unwarped for the localisation step.
In our framework, omnidirectional images do not need to be unwarped and the control is directly formulated as a visual servoing task.
A visual route following can be considered as a sequence of visual-servoing tasks. A stabilization approach could thus be used to control the camera motions from a key image to the next one. However, a visual route is fundamentally a path. In [15], the authors propose to plan the trajectories of image features directly in the sensor space from the first image to the last one. These trajectories are then used as references to control a robotic arm.
To design the controller, described in the sequel, the key images of the reference visual route are considered as consecutive checkpoints to reach in the sensor space. The control problem is formulated as a path following to guide the nonholonomic mobile robot along the visual route.

A. Model and assumptions

Let $\mathcal{I}_i, \mathcal{I}_{i+1}$ be two consecutive key images of a given visual route to follow and $\mathcal{I}_c$ be the current image. Let us note $\mathcal{F}_i = (O_i, \mathbf{X_i}, \mathbf{Y_i}, \mathbf{Z_i})$ and $\mathcal{F}_{i+1} = (O_{i+1}, \mathbf{X_{i+1}}, \mathbf{Y_{i+1}}, \mathbf{Z_{i+1}})$ the frames attached to the robot when $\mathcal{I}_i$ and $\mathcal{I}_{i+1}$ were stored and $\mathcal{F}_c = (O_c, \mathbf{X_c}, \mathbf{Y_c}, \mathbf{Z_c})$ a frame attached to the robot in its current location. Figure 1 illustrates this setup. The origin O_c of $\mathcal{F}_c$ is on the axle midpoint of a cart-like robot, which evolutes on a perfect ground plane.

The control vector of the considered cart-like robot is $\mathbf{u} = [V, \omega]^T$ where V is the longitudinal velocity along the axle $\mathbf{Y_c}$ of $\mathcal{F}_c$, and ω is the rotational velocity around $\mathbf{Z_c}$. The hand-eye parameters (*i. e.* the rigid transformation between $\mathcal{F}_c$ and the frame attached to the camera) are supposed to be known.

According to Hypothesis 2.2, the state of a set of visual features $\mathcal{P}_i$ is known in the images $\mathcal{I}_i$ and $\mathcal{I}_{i+1}$. Moreover $\mathcal{P}_i$ has been tracked during the learning step along the path ψ between $\mathcal{F}_i$ and $\mathcal{F}_{i+1}$. The state of $\mathcal{P}_i$ is also assumed available in $\mathcal{I}_c$ (*i.e* $\mathcal{P}_i$ is in the camera field of view). The task to achieve is to drive the state of $\mathcal{P}_i$ from its current value to its value in $\mathcal{I}_{i+1}$.

B. Principle

Consider the straight line $\Gamma = (O_{i+1}, \mathbf{Y}_{i+1})$ (see Figure 2). The control strategy consists in guiding $\mathcal{I}_c$ to $\mathcal{I}_{i+1}$ by regulating asymptotically the axle $\mathbf{Y}_c$ on Γ. The control objective is achieved if $\mathbf{Y}_c$ is regulated to Γ before the origin of $\mathcal{F}_c$ reaches the origin of $\mathcal{F}_{i+1}$. This can be done using chained systems. Indeed in this case chained system properties are very interesting. A chained system results from a conversion of a mobile robot non linear model into an almost linear one [17]. As long as the robot longitudinal velocity

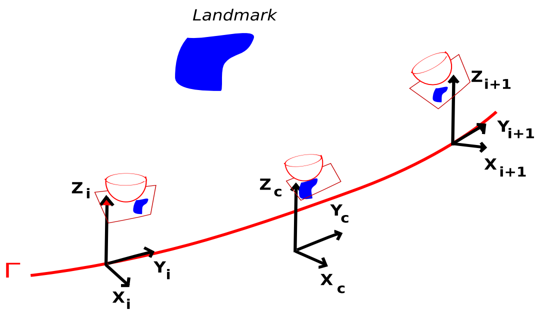

Fig. 1. Frames $\mathcal{F}_i$, $\mathcal{F}_{i+1}$ and $\mathcal{F}_c$. Images I_i and I_{i+1} are two consecutive key images of the visual route Ψ. I_c is the current image. Γ (in red) is the path to follow.

V is non zero, the performances of path following can be determined in terms of settling distance [19]. The settling distance has to be chosen with respect to robot and perception algorithm performances.
The lateral and angular deviations of $\mathcal{F}_c$ with respect to Γ to regulate can be obtained through partial Euclidean reconstructions as described in the next section.

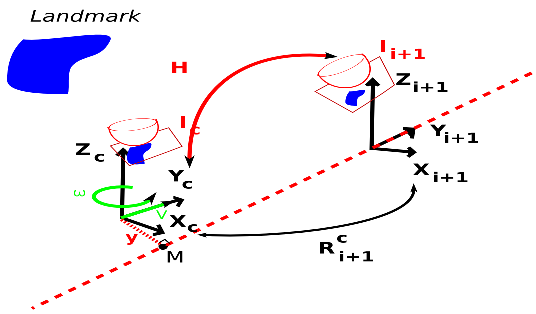

Fig. 2. Control strategy using the homography matrix

C. State estimation from central catadioptric camera

Many applications in vision-based robotics, such as mobile robot localisation can benefit from panoramic field of view provided by omnidirectional cameras. In the literature, there have been several methods proposed for increasing the field of view of cameras systems. One effective way is to combine mirrors with conventional imaging system. The obtained sensors are referred as catadioptric imaging systems. The resulting imaging systems have been termed central catadioptric when a single projection center describes the world-image mapping. From a theoretical and practical view point, a single center of projection is a desirable property for an imaging system. In our application, a central catadioptric camera has been used to obtain omnidirectional views. First, the model of such a sensor is briefly described and then an homographic mapping is exploited to extract the state of the robot.

1) Camera model: A central catadioptric projection can be modeled by a central projection onto a virtual unitary sphere followed by a perspective projection onto an image plane [7] (cf Figure 3). This generic model is parametrized by the couple $(\xi\,,\,\psi)$ describing the type of sensor and the shape of mirror.

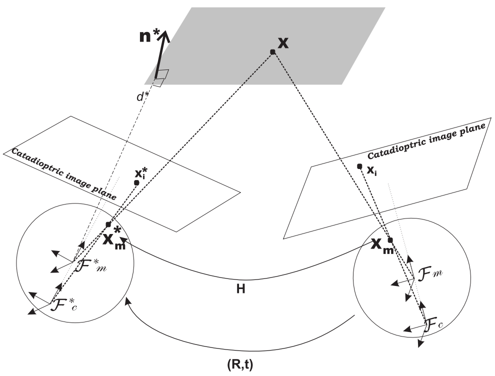

Fig. 3. Central catadioptric projection

The coordinates x_i of the point in the image plane corresponding to the 3D point $\mathcal{X}$ are obtained after three steps:

Step 1 : Projection of the 3D point $\mathcal{X}$ of coordinates $\mathsf{X} = [X\ Y\ Z\ ]^T$ on the unit sphere: $\mathsf{X_m} = \mathsf{X}/\|\mathsf{X}\|$

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

$$\underline{\mathsf{x}} = f(\mathsf{X}) = \begin{bmatrix} \frac{X}{Z+\xi\|\mathsf{X}\|} & \frac{Y}{Z+\xi\|\mathsf{X}\|} & 1 \end{bmatrix} \qquad (1)$$

Step 3 : Finally, the coordinates $\underline{\mathsf{x}}_\mathsf{i}$ in the image plane is obtained after a plane-to-plane collineation $\mathbf{K} = \mathbf{K}_c\mathbf{M}$ of the 2D projective point $\underline{\mathsf{x}}$: $\underline{\mathsf{x}}_i = \mathbf{K}\underline{\mathsf{x}}$ ($\mathbf{K}_c$ contains the usual intrinsic parameters of the perspective camera and $\mathbf{M}$ contains the mirror intrinsic parameters).

We notice that X_m can be computed as a function of the coordinates in the image $\overline{\mathsf{x}}$ and the sensor parameter ξ:

$$\mathsf{X}_m = (\eta^{-1} + \xi)\overline{\mathsf{x}} \qquad (2)$$
$$\overline{\mathsf{x}} = \begin{bmatrix} \mathsf{x}^T & \frac{1}{1+\xi\eta} \end{bmatrix}^T$$

with: $\begin{cases} \eta = \frac{-\gamma - \xi(x^2+y^2)}{\xi^2(x^2+y^2)-1} \\ \gamma = \sqrt{1+(1-\xi^2)(x^2+y^2)} \end{cases}$.

2) Homography matrix: Let $\mathcal{X}$ be a 3D point with coordinates $\mathsf{X_c} = [X_c\ Y_c\ Z_c]^T$ in the current frame $\mathcal{F}_c$ and $\mathsf{X}^* = [X_{i+1}\ Y_{i+1}\ Z_{i+1}\ ]^T$ in the frame $\mathcal{F}_{i+1}$. Using the homogenous coordinates $\underline{\mathsf{X}}_\mathsf{c} = [X_c\ Y_c\ Z_c\ H_c]^T$ and $\underline{\mathsf{X}}^* = [X_{i+1}\ Y_{i+1}\ Z_{i+1}\ H_{i+1}]^T$, we can write:

$$\rho(\eta^{-1} + \xi)\overline{\mathsf{x}}_\mathsf{c} = [\ \mathbf{I_3} \quad \mathsf{0}\ ]\,\underline{\mathsf{X}} = [\ \mathbf{R} \quad \mathsf{t}\ ]\,\underline{\mathsf{X}}^* \qquad (3)$$

Given a 3D reference plane (π), $d(\mathcal{X}, \pi)$ is the distance from the world point $\mathcal{X}$ to the plane (π). The plane may be defined by the vector: $\pi^{*T} = [\ \mathsf{n}^* \quad -d^*\ ]$ where n^* its unitary normal in $\mathcal{F}_{i+1}$ and d^* the distance from (π) to the origin of $\mathcal{F}_{i+1}$. After some algebraic manipulation, we obtain:

$$\rho(\eta^{-1} + \xi)\overline{\mathsf{x}}_\mathsf{c} = \rho^*(\eta^{*-1} + \xi)\mathbf{H}\overline{\mathsf{x}}^* + \alpha\mathsf{t} \qquad (4)$$

with:

$$\mathbf{H} = \mathbf{R} + \frac{\mathsf{t}}{d^*}\mathsf{n}^{*T}$$
$$\alpha = -\frac{d(\mathcal{X}, \pi)}{d^*}$$

$\mathbf{H}$ is the Euclidean homography matrix, function of the camera displacement and of the plane coordinates in $\mathcal{F}_{i+1}$. It has the same form as in the conventional perspective case. Note that the camera has to be calibrated to compute the homography matrix but a .

If the point $\mathcal{X}$ belongs to the reference plane (π) (*i.e* $\alpha = 0$), then equation (4) becomes:

$$\overline{\mathsf{x}}_\mathsf{c} \propto \mathbf{H}\overline{\mathsf{x}}^* \qquad (5)$$

That equation (5) can be turned into a linear homogeneous equation $\overline{\mathsf{x}} \times \mathbf{H}\overline{\mathsf{x}}^* = 0$ where $\times$ denotes the cross-product. As usual, the homography related to (π) can be estimated up to a scale factor with at least four couples of coordinates $(\mathsf{x_k}; \mathsf{x}^*_\mathsf{k}), k = 1...n$. From the $\mathbf{H}$-matrix, the camera motions parameters (the rotation matrix $\mathbf{R}$ and the scaled translation $\mathsf{t_d}* = \frac{\mathsf{t}}{d^*}$) and the structure of the observed scene (for example n^*) can be estimated (for more details refer to [5]).

In our case, the mobile robot is supposed to move on a perfect ground plane. Then an estimation of the angular deviation (around the axle Z) θ between $\mathcal{F}_c$ and $\mathcal{F}_{i+1}$ can be extracted directly from $\mathbf{R} = \mathbf{R}^c_{i+1}$ and we can determine the lateral deviation y (*i.e* the distance between the origin of $\mathcal{F}_c$ and Γ) up to a scale factor from $\mathsf{t}/d^* = \mathsf{t}^c_{i+1}/d^*$.

D. Control law

Exact linearization of nonlinear models of wheeled mobile robot under the assumption of rolling without slipping is a well known theory, which has already been applied in many vehicle guidance applications, as in [19] for a car-like vehicle, and in our previous works (see [1]). The used state vector of the robot is $\mathsf{X} = [\ s \quad y \quad \theta\ ]^\top$, where s is the curvilinear coordinate of a point $\mathcal{M}$, which is the orthogonal projection of the origin of $\mathcal{F}_c$ on Γ. The derivative of this state give the following state space model:

$$\begin{cases} \dot{s} = V\cos\theta \\ \dot{y} = V\sin\theta \\ \dot{\theta} = \omega_c \end{cases} \qquad (6)$$

The state space model (6) may be converted into a 3-dimensional chained system: $[\ a_1 \quad a_2 \quad a_3\ ]^T$. Deriving this system with respect to a_1 provides an almost linear system. As proposed in [2] and thanks to classical linear automatics theory, an asymptotically stable guidance control law can be designed by choosing $a_1 = s$ and $a_2 = y$:

$$\omega(y, \theta) = -V\cos^3\theta K_p y - |V\cos^3\theta| K_d \tan\theta \qquad (7)$$

The control law (7) is theorically independant to the longitudinal velocity V. K_p and K_d are two positive gains which set the performances of the control law. Their choice determine a settling distance for the control, *i. e.* the impulse response of y with respect to the covered distance by the point $\mathbf{M}$ on Γ. However, as y is estimated up to a scale factor $\frac{1}{d^*}$, this modifies the performances of the control law (7). In practice, to alleviate this difficulty, we choose K_p and K_d for a given d^* that we though maximum. As said before, the control performances are independent to V. Then V can be fixed or tuned by a supervisor. However, V has to be non-null to allow the regulation. Then, in practice, V is controlled in an open loop at the first and the last image of the visual route.

IV. Results

A. Simulation

The goal is to drive a car-like robot from an initial position to a desired position. In that aim, 4 key images have been memorized. The key images contain 6 points situated at different heights (3m, 3m, 2.5m, 3.5m) according to the key image. The control law (7) is defined with a longitudinal velocity V set to 2m/s. The position of the camera is at $(0.05; -0.05; 0.1)$ (m) of the center of the robot. For the computation of the homography, it is supposed that the plane is situated at 3m on the horizontal axis whereas a rotation of 5° around X-axis was applied to the camera. The trajectory resulting from the simulation is shown in Figure 4. Errors and

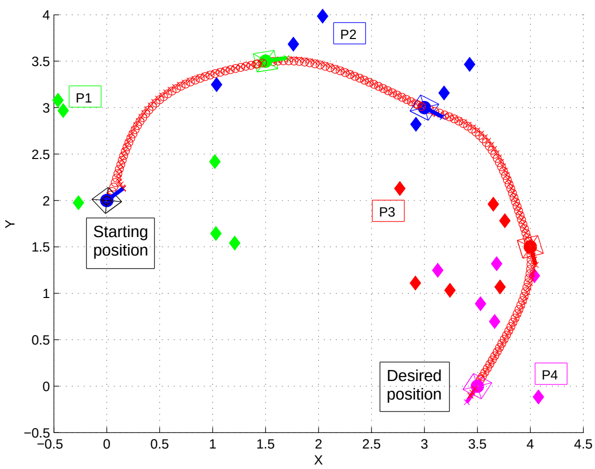

Fig. 4. Absolute plane trajectory of the robot seen from the top view. The 4 memorized sets of features at different heights are represented by full diamonds. The crossed squares are the positions of the camera where the images where acquired. The key views are reached.

control outputs are represented Fig. 5. The discontinuities on the different axes are due to the transitions between two key images. As it can be noticed, lateral and angular errors are well regulated to zero for each key views.

B. Experiments

The proposed framework is implemented on an external standard PC which wireless controls a Pioneer 3AT robot. An omnidirectional camera is embedded on the robot and its principal axis is approximately confounded with the rotation

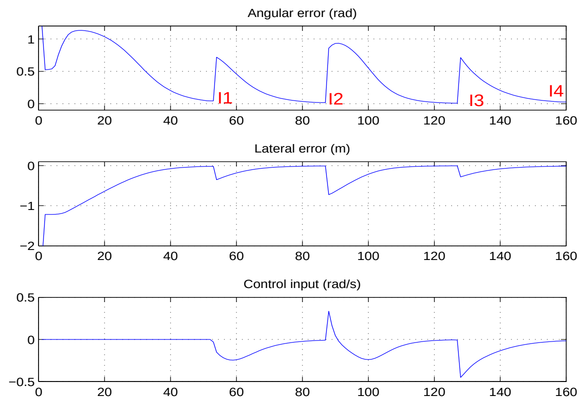

Fig. 5. Evolution of the lateral (in m) and the angular (in rad) errors during the simulation. The control input (angular speed of the robot, in rad/s) is represented bottom.

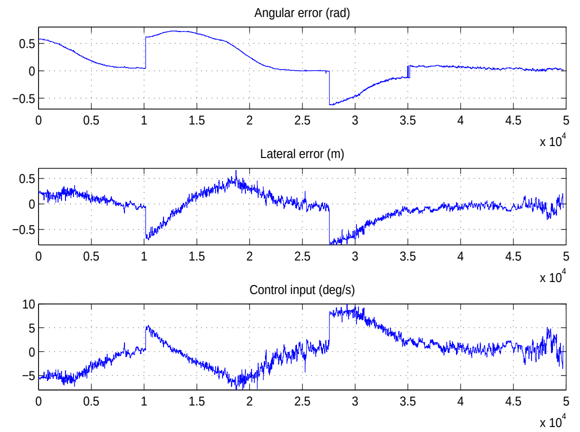

Fig. 6. Evolution of the lateral (in m) and the angular (in rad) errors and of the control input (angular speed in deg/s) during the experimentation.

axis of the robot (see Figure 7).

A learning stage has been conducted off-line and images have been memorized as proposed in Section II. Three key views (cf Fig.8) have been selected to drive the robot from its initial configuration to the desired one. For this experiments, the positions of four planar points are memorized and then tracked. The control is realized using the homography matrix from the projection of the patterns onto the equivalence sphere as explained in III-C.2. Parameters of the camera are known (a calibration step has been done) and the calibration between camera and robot frames is approximative. Note that distances from the optical center at the desired position to the reference plane have been overestimated and that the directions of the normals of the plane are inaccurate. The results of the experimentation (Figure 6) are similar to the simulation: the lateral and the angular errors are regulated to zero before reaching a key image, even with a not accurate calibration. Distances to the plane are been overestimated.

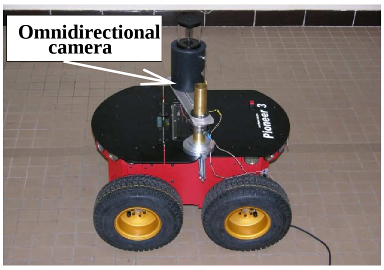

Fig. 7. Mobile robot Pioneer 3 equipped with an omnidirectional camera

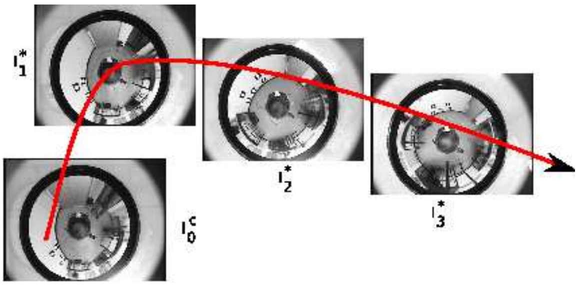

Fig. 8. Initial image I_c^0 and desired images the robot has to reach $I_j^*, j = 1:3$.

V. Conclusion and future works

In this paper a sensor-based navigation framework for a non-holonomic mobile robot has been presented. The framework is presented in the context of an indoor navigation and using as sensor a central catadioptric camera. The navigation mission consists in following a visual route in a visual memory composed of panoramic key-images. The visual-servoing control law is realized in the sensor space, and it is adapted to the robot non-holonomy.

Even if this framework was applied in indoor environment, the principles of our method can be used outdoor (omnidirectional vision-based memory and control law). This last application will require to adapt the matching and the tracking of visual features.

Future improvements will deal first with these issues and second with the analysis of the transitions between key views to manage the discontinuities of the control law.

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