Self-Positioning Robot Navigation Using Ceiling Image Sequences

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Abstract

This paper presents the analysis of a vision-based homing behavior that provides self-positioning for a mobile robot using ceiling structures as landmarks. This new behavior enters the navigation approach we developed for mobile robots, which basic idea is to represent the robot spatial knowledge in a topological map, where nodes consist of self-positioning sites and edges may be any reactive behavior moving the robot between two nodes.

1. Introduction

The behavioral approach to control robots is inspired to some extent by the animal world, where a behavior may be described as an independent stereotyped action that is maintained by a specific stimulus. Although simple tasks can be achieved very easily with this approach, a common problem is that typical navigation problems requiring spatial knowledge (a map) are difficult to solve, since the robot underlying architecture is based on an interaction of the environment with reactive behaviors that are not mapped in the robot configuration space.

A solution to the spatial knowledge problem is provided by the self-positioning approach we proposed in earlier publications [Facchinetti94, Facchinetti95], which uses a new class of vision-based behaviors that provide the critical link between navigation and control levels. In the self-positioning approach, homing behaviors control the robot by servoing its moves to low-level visual primitives, such as points and segments extracted from image sequences that relate to features and structures of the environment. We understand here self-positioning (or homing) as the action of finding a stable state of the robot pose relatively to the environment in terms of visual primitives in an image or set of images.

An alternative for robot navigation is to use the more traditional positioning approach, which proceeds by finding the robot position in the environment from a match between a map and observations derived from vision, for example by stereoscopy or dynamic vision, a procedure known to be rather complex [Faugeras93]. Self-positioning lends itself better to behavioral architectures and provides means for the robot to learn the spatial structure of unknown environments by building a simple map, with the sole homing sites and paths between them.

We propose in this paper an in-depth study of a vision-based behavior we developed for homing the robot relatively to ceiling structures, in the self-positioning context. In the following section, we briefly describe the robot hardware and software environment. In section 3 we detail the home-on-ceiling behavior vision system and the servoing control algorithm. In section 4 we present and discuss the results of the behavior performances in a navigation evaluation experiment. Finally, section 5 concludes this paper.

2. The MANO environment

The behavioral approach for designing autonomous systems is based on the existence of individual behaviors and on their coordination. It states that autonomy emerges from the co-operative work of various behaviors [Brooks90]. MANO (Mobile Autonomous NOmadic™) is the behavioral architecture we derived from this approach for our Nomadic-200 mobile platform [Tièche94]. It is a physically grounded system, providing advantages such as concurrency of several behaviors, simplicity,

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modularity of design, and abstraction (or time response) hierarchy.

The integration of a vision device in the behavioral architecture requires operations at all three levels: defining the vision system in a physical layer (robot devices), defining the related vision-based behavior in a behavioral layer, and making best use of these resources in the reasoning layer. The latter includes cognitive units that know the behaviours by their status (or stimulus) and proceed by activating/deactivating them. They are built from state automatons in connection with a state machine representation of the robot tasks.

Typical behaviors considered for vision-based navigation are: avoid-obstacle, push-obstacle, follow-odometric-path, follow-wall, follow-landmark, wander-around, home-on-landmarks, home-on-corners [Hügli93] and now home-on-ceiling.

3. Homing on ceiling structures

Vision devices that have been considered so far in our investigations belong to active sensors: back-reflecting landmark tracking and laser line-stripping ranging. The work presented in this paper focuses on a new ceiling vision system we developed for tracking ceiling structures and servoing the robot.

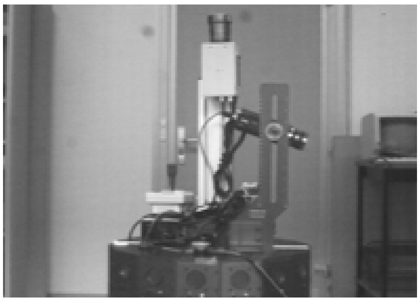

Figure 1: the vertical-mounted ceiling vision system mounted on top of the Nomad-200 mobile platform

3.1 Robot geometry

The robot geometry is illustrated in Figures 1 and 2. It is composed of a three-wheels synchronous drive mechanical system (the base) that allows rotation without translation, and a freely orientable turret supporting the vision system. The parameter θ describes the orientation of the wheels vertical axes, relatively to the absolute frame *0*. Similarly, the parameter ϕ describes the turret orientation relatively to frame *0*.

The robot base moves are controlled by the rotation speed of the wheels η_1 (which results in a velocity $\dot{X}_r$ in the heading direction) and the angular velocity of the wheels vertical axis $\eta_2 = \dot{\theta}$. The turret angular velocity is controlled by $\eta_3 = \dot{\phi}$. Despite the three-dimensional control vector formed by the η_i's, the robot movement control space is only two-dimensional (η_1, η_2) and hence ruled by non-holonomic constraints [Campion93].

3.2 Tracking ceiling structures

As shown in Figure 2, the optical axis of the grayscale camera stands vertical and perpendicular with respect to the ground (and the ceiling). As a result, the geometry of objects in the image is unaffected in size when the robot is translating or rotating, which greatly simplifies image processing operations.

The goal of the ceiling vision system is to track the position *X,Y* and orientation γ (with respect to the image frame) of a predefined template image in a sequence of images. The tracking algorithm is based on two powerful *C* functions supported by the vision system hardware:

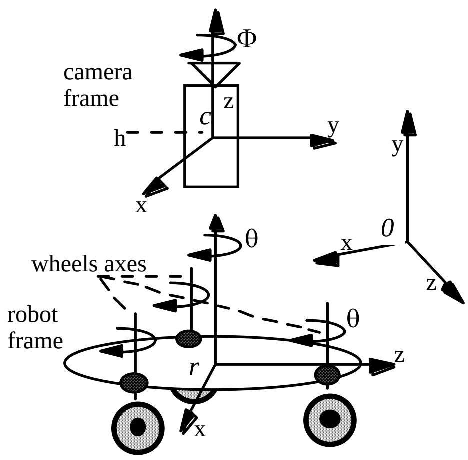

Figure 2: Nomad robot geometry with a vertical-mounted camera

The FindOrientation [Matrox93] function yields the major orientation (not position) of a whole image. A single orientation value γ' is calculated between –45° and +45°.

The FindModel [Matrox93] function finds occurrences of a specified template in the current image by template matching. It does not allow for changes in image orientation since the template was defined, with about ±7° of tolerance.

To account for changes of orientation, we define a collection of predefined templates taken 11.25° apart

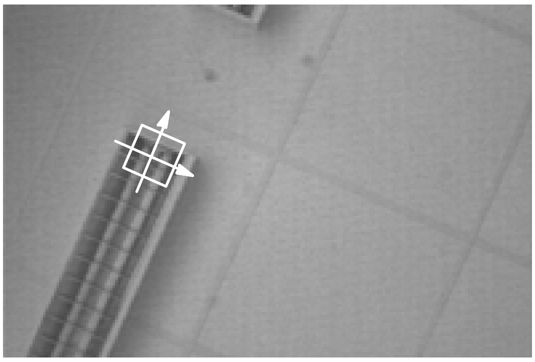

Figure 3 : snapshot taken from a sequence of video images while performing the homing

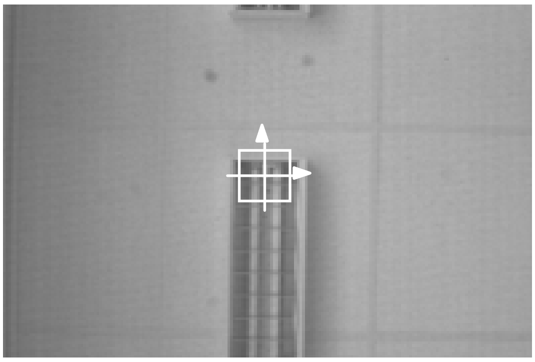

Figure 4 : snapshot taken from a sequence of video images at the homing site: the model is positioned at the image center and its orientation is 0°

(for a total of 8 templates per quadrant). A third function, LoadModel, is used to load the template into memory.

As the structure of the ceiling is often made of homogeneously oriented perpendicular features (as visible in Figures 3 and 4), the tracking algorithm first estimates the major orientation of the whole current image. A 90° ambiguity induced by the FindOrientation function is then solved by loading four predefined templates (one per quadrant) which orientations are closest to that of the current image, searching them (using the FindModel function) and keeping the template with the highest matching score. As a result, the values of X,Y and γ (calculated between 0° and 360° from γ') for the best match are returned by the tracking algorithm. A simpler form of this algorithm is detailed in Section 4.

3.3 Visual servoing

The control law used for the homing behaviors, including the home-on-ceiling behavior, are derived from the task function approach [Khadraoui95, Espiau92, Samson91]. The emphasis in this paper is only on application and we refer to these sources for a complete study of the control method.

In the case of the home-on-ceiling, the control algorithm uses two successive servoing steps that reduce their respective control laws to the one dimensional linear form

$$\eta_i = -\lambda_i \cdot e(t)$$

where η_i (i=1,3) is one of the robot control parameters, λ_i is the associated adaptive gain, and the error function (or visual primitive) $e(t)$ is derived from the current template pose (X, Y, γ). The robot control parameter η_2 is not visually servoed, but used instead to make the robot base point towards the center of the ceiling feature. The two servoing steps are then

i) servo the control parameter η_1 so that the robot ends up exactly underneath the center of the ceiling feature. In the image, the template final position is the image center. The error function is simply given by

$$e(t) = \sqrt{X^2(t) + Y^2(t)}$$

ii) servo the control parameter η_3 so that the robot ends up with the same orientation as the ceiling feature. In the image, the template final position is the image center (from the previous step) and the final orientation is φ=0°. The error function is given by

$$e(t) = \gamma(t)$$

3.4 The capture zone

Consider a four-dimensional hyper-map of the robot configuration space, for which each element $s_i(\bar{x})$, $\bar{x} = (x, y, \theta, \Phi)$, takes a Boolean value representing the stimulus state of a homing behavior H_i. More formally we have

$$s_i(\bar{x}) = \begin{cases} 1 & \text{stimulated} \\ 0 & \text{not stimulated} \end{cases}$$

The set of robot poses satisfying

$$\Omega_i = \{\bar{x} \mid s_i(\bar{x}) = 1\}$$

represents the region of the robot configuration space for which the homing behavior H_i will be stimulated. We call this region the capture zone.

The size and shape of the capture zone depends mostly on internal parameters of the vision system and the associated homing behavior, but also depends on variable external parameters bound to the environment (such as lighting, obstacles, etc.),

```
GrabImage(image);
γ = FindOrientation(image);
if (-15° < γ ≤ -5°)
        model = LoadModel(1);
elseif (-5° < γ ≤ +5°)
        model = LoadModel(2);
elseif (+5° < γ ≤ +15°)
        model = LoadModel(3);
FindModel(model, image);
return (X, Y, γ)
```

Figure 5: Template tracking algorithm

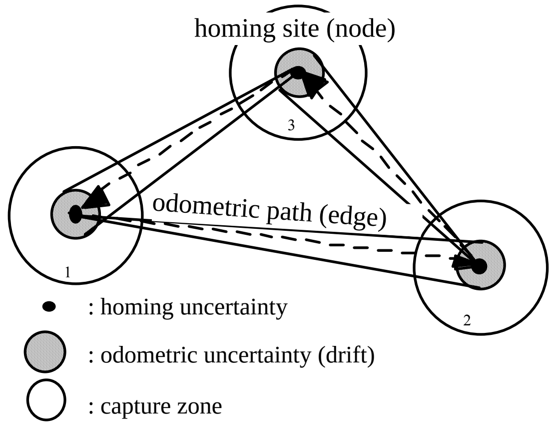

Figure 6: A triangle race navigation using visual homing sites and odometric paths between them

and may hence vary between homing sites [Facchinetti94]. In the case of the home-on-ceiling behavior, we use a simpler model: the capture zone is projected on the ground plane and Σ_{cz} describes its size.

4. Experimental results

4.1 Template tracking implementation

As the task of a homing behavior in the self-positioning navigation is to reduce only the relatively small drift of the robot pose induced by the odometric sensors, image processing speed can be improved considerably by considering only a fraction of the full [0°, 360°] interval for the template orientation g. Figure 5 presents the tracking algorithm limited to only 3 predefined templates taken 10° apart (instead of 32 taken 11.25° apart).

We use a vision system based on the Matrox Image Series™ IM-640 (with real-time processor RTP). The size of the template is 64x64 pixels by 8 bits, and the vision processing time for a 384x256x8 search window does not exceed 170 ms.

4.2 Homing uncertainty region

Normally, when the homing is finished, the robot does not end up exactly at the homing site center $\overline{x}_c$, for which the template is centered and aligned in the image, but rather in an uncertainty region in the robot configuration space centered on $\overline{x}_c$.. This uncertainty region is identical for different ceiling homing sites and can be estimated once for a given ceiling height h, tracking positional accuracy Δe and camera focal length f (assuming a simple pinhole perspective transformation).

For the evaluation experiment presented in this paper, we have f=1.2 cm, Δe=2 pixel and h=350 cm.. A simple calibration calculated from a set of couples $[(X,Y,\gamma)\ ;\ (x,y,\theta,\Phi)]$ measured for different poses of the robot yields

$$\sigma_{\Sigma cz} = 2.696\,cm$$
$$\sigma\gamma = 2^o$$

where $\sigma_{\Sigma cz}$ models the uncertainty region size (within Σ_{cz}), centered on the ground projection of $\overline{x}_c$, and σ_γ the robot orientation uncertainty. Error distribution within these bounds is assumed uniform.

4.3 Triangle race navigation

We present an evaluation of the home-on-ceiling behavior validity in the self-positioning navigation context. The experimental test bench consists in running our mobile robot in the triangle race shown in Figure 6.

The "task" consists in moving the robot in a loop consisting of a sequence of follow-odometric-path

loop #	site 1	site 2	site 3
1	20	11	28
2	7	4	15
3	18	22	9
4	21	12	18
5	6	25	26
6	23	5	12
7	4	17	8

Table 1: position errors [mm] measured after each homing is performed. The robot goes through the homing sites 1,2,3,1,2,… and moves along predefined odometric paths between them

(between two homing sites) and home-on-ceiling behaviors. Running the same loop without self-positioning inevitably results in the robot drifting away from the correct path [Takeda94]. The outer bound of the robot position uncertainty region induced by the odometric sensors, when moving the robot, is modeled by

$$\sigma_o = 2.012 \cdot 10^{-2} \cdot d$$

where d is the traveled distance.

The capture zone projection on the ground plane of the home-on-ceiling behavior has a measured radius of

$$\Sigma_{cz} = 115\,cm$$

Hence, we have $\Sigma_{cz} >> \sigma_{\Sigma cz}$ and $\Sigma_{cz} >> \sigma_o$, as long as the length of the odometric path between two sites d is kept under 54 m (the robot size is 70 cm), which is very reasonable for indoors navigation. Typically, the traveled distance d is smaller than 5 m.

The results reported in Table 1 show robot positions (without orientation) measured after each homing is performed. Clearly, our estimation of $\sigma_{\Sigma cz}$ is correct. Furthermore, we have $\sigma_h << \sigma_o$, which validates the use of the home-on-ceiling behavior to reduce the robot odometric drift.

5. Conclusion

We proposed and developed an new vision-based home-on-ceiling behavior that enhances the self-positioning capabilities of our autonomous mobile robot architecture. Evaluations performed on a real robot showed that high autonomy and good navigation accuracy goals were reached. With this new behavior, and the other vision-based homing behaviors we already implemented (home-on-corners and home-on-landmarks), navigation is possible in terms that were reserved so far to positioning-like approaches, using geometric and probabilistic methods. Furthermore, the option of recording various models in the home-on-ceiling behavior provides an easy way to learn the structure of unknown environments.

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