Using and Learning Vision-Based Self-Positioning for Autonomous Robot Navigation

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Abstract

One of the problems autonomous mobile robots are confronting is representing and learning spatial knowledge in order to operate in a physical environment. A proposition for the body of this knowledge is the *cognitive map* [3, 14, 15], which may be analyzed in two ways. From a topological point of view (or reasoning level), a symbolic representation is central to the cognitive map. From the robot resources point of view (or control level), the cognitive map is grounded in the interaction of the robot sensors and actuators with the environment.

In the autonomous architecture we developped for our mobile robot, the control level consists of a multitude of simple behaviours that servo the robot moves to low-level visual primitives of the environment, such as points and segments extracted from image sequences [6, 7]. The behavioral approach 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 perceived stimulus [13]. This approach is already amenable to simple tasks that move the robot along a wall, avoid unexpected obstacles or go towards objects. However, a common problem is that typical navigation problems that require spatial knowledge (a topological map) are difficult to solve, since the robot interacts with the environment with reactive behaviors that are not mapped in the robot parameters space [4].

We propose in this paper a self-positioning strategy based on a new class of vision-based *homing* behaviors that provides the critical link between the reasoning and control levels. The homing behaviours control the robot moves so that they tend to match one (or more) sensed visual primitive(s) against one (or more) predefined reference(s). A reference is an ideal visual primitive with predefined orientation and image coordinates. As a result, *self-positioning sites* are defined in the environment where visual primitives may stimulate one homing behaviour. A main concern is to characterize which visual primitives may be used to define stable self-positioning sites.

The control strategy of the homing behaviours aims

Figure 1: *NOMAD robot homing on a corner site using a horizontal laser line-stripping vision sensor (which trace is visible on the corner of the wall). A second camera is placed vertically for homing on ceiling structures.*

at finding local maxima of the function that describes the transform between the visual primitives and their references. Unlike other approaches for which the maxima can be easily found by means of hill-climbing strategies [3, 10], the vision-based homing behaviours have to face a fairly complex, geometrically constrained parameter space. Hence, we use visual- and position-based servoing techniques for controlling the robot moves [12]. Both control strategies provide robust performance, eliminating the cumulative position error of the sensor and actuator uncertainties at the site center.

At the topological level, the self-positioning sites are symbolized by nodes, whereas all the other reactive behaviours are represented by edges [2, 5]. Nodes and edges form a network that describe the spatial knowledge of the robot about its environment (see Figure 2). This map can be used to plan the robot actions, distinguish ambiguous sites and explore unknown regions of the environment.

Figure 2: *The robot is moving between self-positioning sites (numbered 1 through 3) using homing behaviours to reset the cumulative drift due to the robot sensors and actuators uncertainties.*

The ability to learn the environment structure for an autonomous robot is a critical feature, since manual input of information most natural for humans may not correspond well to data to which the robot has sensory access, especially within our behavioral context. We use learning techniques to find and characterize new self-positioning sites, as well as build the topological map of unknown environments [3, 11].

Our self-positioning approach contrasts with more expensive and fragile traditional positioning (or localizing) approaches [1, 8, 9] that estimate the robot position by matching sensed features against a geometrical model of the environment, using stereoscopy (2 or 3 cameras), dynamic vision (single mobile camera) or similar techniques. These approaches are essentially robot-centric: they aim at reconstructing the environment from the robot sensors point of view. This is a rather complex problem that requires heavy computation and for which most of the efforts while trying to solve it generally aim at coping with the unstable nature of both robot resources and the real world.

Self-positioning may have different aspects depending on the sensor that is used for the implementa-

Figure 3: *Behaviors such as* homing on landmarks, going to a target *and* detect obstacle *are used cooperatively for tidying up chairs in a room.*

tion. We developed three homing behaviours, based on different vision systems, for evaluating the self-positioning concept on a real robot. The selected visual primitives are reflective landmarks, simple ceiling structures and wall corners (see Figure 1). We ran a set of experimental tests that showed good robustness for the *homing on corners* and *homing on landmarks* behaviors [4]. The *homing on ceiling structures* is currently being evaluated. The tests show that self-positioning reduces the cumulative drift due to the actuators and odometric sensors uncertainties to a maximal value of 15 cms, along any path defined in the topological map (a simple example is shown in Figure 2). The homing precision can be reduced up to about 5 cms, which is the limit fixed by sensor resolution, at the cost of a much slower performance. Similarly, the minimum orientation precision is less than 1 degree.

The *homing on landmarks* behaviour has been also supporting navigation for a structured task we developed for tidying up chairs in a room. This task ran succesfully during demonstration sessions of about one hour, showing good autonomy (see Figure 3).

The homing behaviors provide means for the robot to learn the structure of unknown environments by reducing their huge noisy spatial state spaces to a small amount of stable self-positioning sites and paths. With them, navigation is possible in terms that were conceptually reserved so far to positioning-like approaches (using traditional geometric and probabilistic methods). We are currently extending the self-positioning approach in the context of a task that tidies up and moves chairs in a physical environment consisting of offices and hallways.

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