Real-time analysis of the robustness of the navigation strategy of a visually guided mobile robot

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Abstract. This paper describes a method that is able to analyze in real-time the robustness of a pattern-driven guidance strategy for mobile robots. The robot computes its next step towards the goal by considering visual patterns which have been previously selected through a biologically-inspired phase. Starting from the analysis of the navigation vector field the system generates in the environment, formal aspects related to the concept of convergence can be considered. In this paper we show how the convergence analysis can be effectively addressed in real time, though not in the whole environment but along the path the robot has traveled. A Nomad200 is the agent used for the experiments.

1 Introduction

A key problem in robotics is the development of robust visual navigation strategies [3]. Interestingly, animals, including insects, are robustly able to achieve visual navigation that offer valuable ideas for robot navigation [13]. In biological navigation systems, the selection of relevant visual features, their use in visual navigation models and the applicability to practical solutions has been widely addressed in literature (e.g. [4, 1]).

Starting from biological bases, recently we have presented a theory that studies two of the main aspects related to the concept of *robustness* [2]: i.e. *repeatability* and *convergence*. The latter is concerned with the *visual potential function* that represents the driving principle to perform visual guidance. This is proven to be a *Lyapunov* function and therefore it can state about the convergence of the navigation system to the goal. The former is the *conservativeness* of the navigation vector field. This deals with the concept of repeatability of the trials and provides key information to perform pattern learning [7].

In the previous work, despite the fact that movements are computed in real-time, assessing the robustness of the strategy on the environment all the computations had to be exploited off-line, after the whole set of navigation vectors has been collected from the environment.

The main contribution of the present paper is concerned with the real-time computation of issues related to the concept of converge. By considering the visual patterns surrounding the robot, a real-time computation of the navigation vector leading to the goal is exploited. This data can be suitably considered to assess the robustness of the trajectory that has been followed by the robot. Critical situations can thus be adequately recognized and solved.

The method operates with a color camera and a *Nomad200* robot, which includes a Fujitsu real-time tracking card.

2 Theory

Let vector $\vec{V} = [V_x \; V_y]$ represent the next movement the robot has to perform with a module and a direction relative to the actual robot position. The system dynamical model to perform guidance with a two D.O.F. agent is:

$$\begin{cases} x(k+1) = x(k) + V_x(x(k), y(k)) \\ y(k+1) = y(k) + V_y(x(k), y(k)) \end{cases} \tag{1}$$

where $x(k)$ and $y(k)$ represent the coordinates of robot at step k; $x(k+1)$ and $y(k+1)$ represent the new positions the robot will move to. An equilibrium point (x^*, y^*) for the system is given by the coordinates of the goal position.

The computation over the whole environment of vector $\vec{V}$ defines a vector field $\mathbf{V}$. Equivalent statements about a generic vector field $\mathbf{V}$ are [10].

- any oriented simple closed curve c: $\oint_c \mathbf{V} \cdot d\mathbf{s} = 0$
- $\mathbf{V}$ is the gradient of some function U: $\mathbf{V} = \nabla U$

The former is related to the concept of *conservativeness* of the field. The latter is concerned with the existence of a *potential function* that uniquely generates the field.

From another point of view, the former is concerned with the repeatability of the experiments, the latter is concerned with their convergence to the goal. The following Section addresses the first aspect.

2.1 Convergence

Supposing that all the necessary hypotheses hold, the dynamic system presented in Equation 1 can be considered continuous-time with the following (omitting the vector notations):

$$\dot{x}(t) = V(x(t)) \tag{2}$$

where x represents the generic coordinates of a point and x^* is an equilibrium located at the goal position.

When a dynamic system can be represented by $\dot{x} = f(x)$ with a fixed point x^*, and it is possible to find a *Lyapunov function*, i.e. a continously differentiable, real-valued function $U(x)$ with the following properties [10]:

1. $U(x) > 0$ for all $x \neq x^*$ and $U(x^*) = 0$
2. $\dot{U}(x) < 0$ for all $x \neq x^*$ and $\dot{U}(x^*) = 0$ (all trajectories flow *downhill* toward x^*)

then x^* is globally stable: for all initial conditions $x(t) \rightarrow x^*$ as $t \rightarrow \infty$.

In our case, by considering the vector field the guidance system produces, a Lyapunov function can be constructed by integrating the right-hand side of the system Equation 2 as reported in [9].

Our approach consists of calculating the shape of U *a posterior*, starting from the vector field $\mathbf{V}$ whilst, classically, U is given *a priori* [6].

By integrating the conservative field $\mathbf{V}$ in question (by following a *particular* curve c) the result of the integration process is [10, 1, 7]:

$$U(x,y) = -\int_c \mathbf{V} \cdot d\mathbf{s} = -\int_{p_x}^{x} V_x(X, p_y) \cdot dX - \int_{p_y}^{y} V_y(x, Y) \cdot dY \tag{3}$$

where $U(x,y)$ is the potential function and the path of integration is along the semi-perimeter of the rectangle connecting (p_x, p_y) to (x, y). This method assumes the goal position being considered to as the reference point (p_x, p_y). Every other point is thus referred to in terms of potential in reference to the goal position.

If the visual potential function has a basin of attraction where the minimum is at the goal position then for the considerations expressed above the guidance strategy is intrinsically stable, when starting navigating from part of the environment. See figure 6 where examples of visual potential function and path followed by the robot are reported.

3 The model for guidance

A pattern must be reliable for accomplishing a task and patterns which appear to be appropriate for human beings are not necessarily appropriate for robots because of the completely different sensor apparatus and matching systems [12]. Following the biological argument, one key point is that once the meaning of reliability has been established then the problem of selecting patterns is automatically solved. Therefore, stating what is meant by *reliability of patterns*, once given the specific sensor and matching apparatus, is a mandatory step.

Good patterns can be adequately selected following a learning phase where the agent follows a set of stereotyped movements. Navigation movements are subsequently produced by taking into account that the agent needs to restore the original position and size of every pre-learnt pattern. The data can then be fused together by weighed addition. Further details can be found in [1].

3.1 Choosing reliable visual patterns

The *Fujitsu Tracking Card (TRV)* which performs real-time tracking of full color templates at a NTSC frame rate (30Hz). Basically, a template is a rectangular region of a frame which can be identified by two parameters m_x and m_y representing the sizes along X and Y axes respectively.

The card can simultaneously track many templates which have been previously stored in a video RAM. For each stored template the card performs a match in a sub-area of the actual video frame adopting the block matching method [5]. This introduces the concept of *correlation* between the template and a sub-area of the actual video frame. The correlation measure is given by the sum of the absolute differences between the values of the pixels.

The sub-area is composed of 16×16 positions in the frame. The whole set of computed correlation measures is known by the term *correlation matrix*. To perform the tracking, the matching system supplies as an output the coordinates of the position which represents the global minimum in the correlation matrix. This approach strongly resembles the *region-based optical flow* techniques [8].

Mori *et al.* have taken advantage of the correlation matrix to generate attention tokens from scenes [11]. Therefore, by reliable patterns we mean *templates which are uniquely identifiable.*

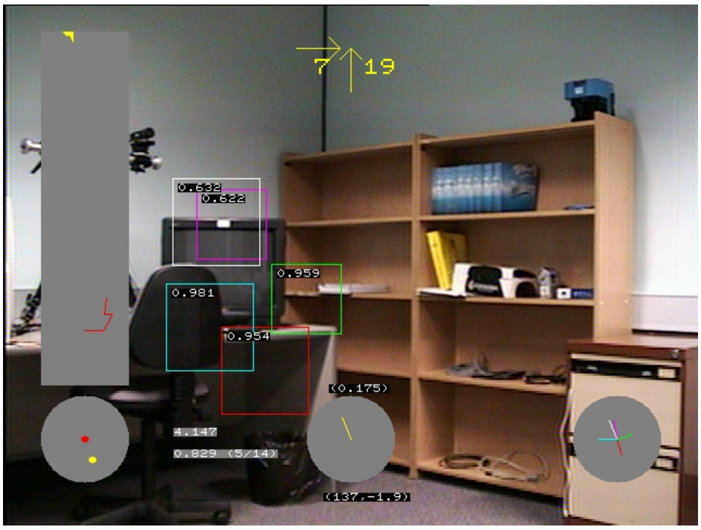

Figure 1: A frame taken by a real navigation

The patterns which have been *statically* chosen are used for navigation tasks. We found that it was necessary to *test* them in order to verify whether they represent good guides for navigation tasks [7]. In particular, through a phase called *turn back and look*, composed by a set of movements that lead the robot away from the goal, we tested whether the patterns we chose are visible and well tracked during the backward path. Interestingly, the selection phase influences the conservativeness of the navigation field thus influencing the robustness of the navigation system as well [2, 7].

3.2 Real-time computation of $\vec{V}$

Starting from information computed from landmarks, the overall navigation vector can be thus calculated as (see Equation 1):

$$\vec{V} = [V_x \; V_y] = \frac{\sum_{l=1}^{L} \vec{v}_l \cdot s(r_l)}{\sum_{l=1}^{L} s(r_l)} \tag{4}$$

where L is the number of patterns chosen after the selection phase, $s(r_l)$ is a confidence value continuously associated to pattern l and $\vec{v}_l$ is the attraction force *felt* by pattern l. Details of the computation can be found in [1, 7].

Figure 1 summarizes the situation where the picture represents a typical frame taken during a navigation test. In particular, the circle at the bottom-center represents the overall attraction exerted by the goal. Above the circle the variance of that attraction is reported and under the circle the attraction vector is broken down into a magnitude and an angle.

In the circle on the right the single attraction exerted by each landmark (box-shaped) is drawn. Each landmark has a number associated with it given by the value of the

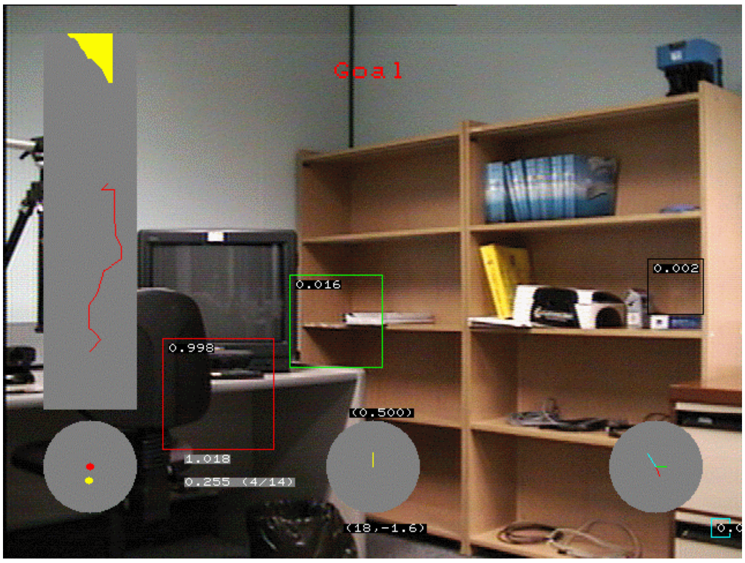

Figure 2: A successful navigation

sigmoid function applied on its reliability measure. The arrows at the top-center of the Figure represent the motion commands given to the robot. In the rectangle on the left the visual potential field profile which has been followed so far is drawn.

3.3 Real-time computation of U

By taking into account the considerations expressed in section 2 and by discretizing equation 3 we can roughly calculate in real-time the potential function along the path traveled by the robot with the following:

$$U(x,y) \approx - \sum_{(X,Y) \in c} (V_x(X,Y) + V_y(X,Y)) \tag{5}$$

where c is the path that has been followed by the robot and (x, y) is the end point of c (i.e. the actual position of the robot) and (X, Y) is the generic point that belongs to c. Considering a parameter t for the trajectory followed by the robot, the profile of the potential function along the whole path followed by the robot can be roughly calculated as:

$$U(t) \approx - \sum_{t \in c} (V_x(t) + V_y(t)) \tag{6}$$

This computation leads to the graph in figure 2 where the profile which was followed by the robot is shown. Taking into account the considerations expressed in section 2, the profile of the potential function can be analyzed in terms of a Lyapunov function as detailed in the following section.

Figure 3: A failed navigation and the potential profile which was followed

4 Experiments

In the following figures, the goal is located at the right of the profile and the starting point is located at one third of the rectangle width. The following frames show a plain view of the room, with start position and final position, along with the trajectory that has been followed.

The first experiment is concerned with a succesfull navigation (see figure 2). The profile of U shows the descendant path towards the minimum, which is the goal.

In figure 3 the path being followed does not lead to the goal. The robot is attracted by a false goal (the minimum on the left of the profile). In Lyapunov terms, the starting point of the robot is placed between two *valleys*. The robot is attracted from the left valley, which represents a false goals. There the robot gets stuck.

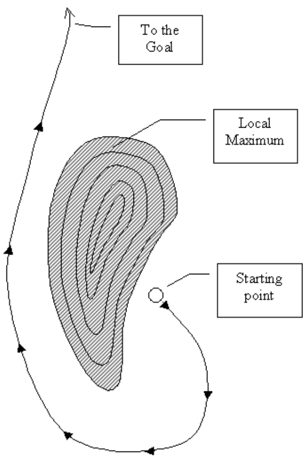

Figure 4: The robot circumnavigates a local maximum along the path to the goal as shown in the frame of figure 5

A different situation is reported in the next example.

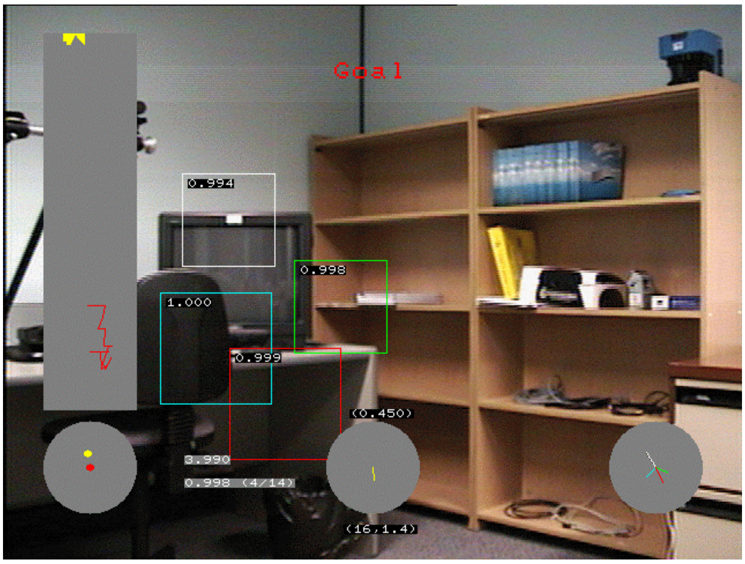

Figure 5: A navigation where the robot gets initially back and then reaches the goal site by circumnavigating a local maximum (see figure 4)

Along the path reported in figure 5 the robot gets initially back instead of approaching the goal site. The profile drawn in figure 4 shows the path followed by the robot. At the beginning, the path circumnavigates a local maximum to reach the goal.

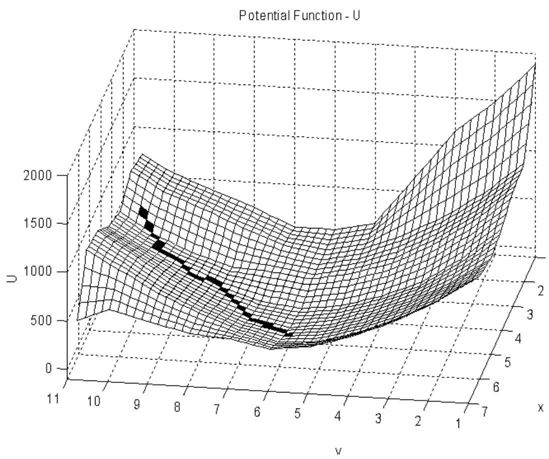

Figure 6: Two-dimension potential function and an example of path (which is the potential profile shown in the frames of the figures)

Basically, the Lyapunov functions that have been computed in the previous experiments, are *slices* taken from the two-dimension potential function U made up off-line (see figure 6). The actual path followed by the robot determines the uni-dimension Lyapunov function shown in the frames as reported in the previous figures.

5 Conclusions

The development of visual navigation strategies have been widely addressed in the robotics literature. An important issue to consider is the robustness of a strategy.

In this paper it has been shown how to take advantage of real-time navigation information to study the converge of a guidance mechanism. The visual potential function can be regarded to as the *engine* of the visual guidance method, and the visual potential function itself can be regarded to as a summarizing function (specifically, a Lyapunov function) to assess the stability of the strategy.

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