On the Adequateness of Emergency Exit Panel and Corridor Identification as Pilot Scheme for a Mobile Robot

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Abstract. There are different approaches to mobile robot navigation. Landmark-based localization has shown to be the alternative to simple dead-reckoning, but often landmarks are environmental specific, and recognition algorithms are computationally very expensive. This paper presents an approach to landmark-based navigation using emergency exit pannels and corridors as cues, without odometric information. Experiments are carried out to verify appart each landmark identification subsystem and both behaviors are combined together in a complete path through the environment.

Keywords: Robot Navigation, Landmark Recognition, Behavior-Based Systems, Neural nets, Autonomous Systems

1 Introduction

Goal-oriented navigation is probably the main problem that needs to be solved for the development of the autonomy of mobile robots. Dead-reckoning can be used to reach the destination from a departure point, but that techique only makes use of propioceptive sensors and thereby, there is no way to confirm the destination location has been reached. It is well known that odometric error accumulation is not acceptable for long travels [5]. Another option is to apply landmark-based navigation. There, landmarks in the environment are used as cues by the robot to identify the different locations and to self-localize in the environment. The robot makes use of exteroceptive sensors to recognize goals.

This paper presents an approach based on the identification of natural landmarks: corridors and emergency exit panels. We consider that corridors are connected by non-corridor places. The landmark identification processes are added to a behavior-based control architecture [6] we are incrementally developing, making use of SORGIN, the software framework specially designed for those kind of systems [3]. All behaviors are combined and, using a finite state automathon (FSA) that connects the different corridors with non-corridors locations, identify at each step the landmarks needed along a predefined path to reach the goal. The outputs of the landmark identification modules are used to change the robot behavior according to the situation. The environment is left unmodified and the experimentation is subject of dynamical changes due to lighting conditions variations and people walking around.

2 Landmarks for navigation

If landmarks are being used for navigation, first what might be considered as a landmark should be clarified. In [9] landmarks are defined as potentially visible real-world objects at known locations. In [14] landmarks are not restricted to real-world objects and are considered as such, features of the environment that are detected by the robot sensors. Within the contents of this paper we will refer as a landmark any property of a location identifiable by the robot sensors.

Landmarks can be predefined by the operator. For example, door crossings, corners and edges. This requires a very good knowledge of the robot sensory system because the robot perception of the environment differs from humans' one. The alternative is to use landmarks learned by the robot. Landmark learning has the main advantage that is the robot who selects the environmental features that can be identified.

Landmarks can also be patterns extracted from visual images. Those patterns can be the result of modifying the environment (bar codes, synthetic signals), or can be properties like color or brightness, or patterns recognized in images (doors, ceiling lights). They also can be parts of images, or complete scenes in images (see [20] for a more detailed categorization of visual landmarks). In the last few years there have been also some trends in using omnidirectional visual systems for landmark recognition instead of the more classical single camara with a limited range of view [16, 8].

References can be found in the literature that tackle landmark-based robot navigation from different points of view. Many approaches combine environmental landmarks with odometric information to reduce the aliasing, to deambiguate different locations with the same sensory perception to the robot [19, 7]. [15] present an application to landmark-based navigation that builds a robust map that allows the robot to plan alternative maps to succed in the assigned task. [12] uses Genetic Algorithms (GA) to correct robot's position and orientation from sonar readings. [10] also use GAs to learn office nameplates and to read the text on them. [17] presents a method for the equalization of landmark description using uniquely visual information for robot homing, and [4] make a theoretical approach for robot localization based on sonar readings scan matching.

In the approach presented in this paper we combine emergency exit panels and corridor identification for navigation. Although human specified landmarks, emergency exit panels can be considered as standard landmarks because they are mandatory in every public building. They also must meet color and location specification and thereby, we make the assumption that they should be identifiable by the robot and, combined with corridor sensor patterns learned, effectively be used for navigation.

3 Robotic platform

The work described in this paper has been performed using an holonomic B21 robot with different sensory capabilities: she is provided with a CCD camera set in a pan/tilt unit, also a ring of 24 sonar sensors surrounds her body, together with infrareds, bumpers and an electronic compass. The robot is provided with two internal Pentiums (120 MHz) and therefore, the computation capabilities are rather poor.

4 Emergency exit panel recognition

Although they can be slightly varying from the one shown in figure 1, emergency exit panels are international landmarks mandatory in every public building that must follow some shape, color and location standards.

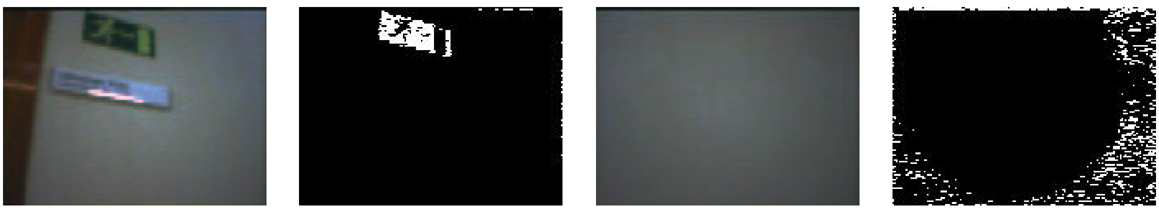
Figure 1: Emergency Exit Panel

According to the European "Council Directive 92/58/EEC of 24 June 1992 on the minimum requirements for the provision of safety and/or health signs at work", [1] they must be put in every juntion or intersection where the wrong way to the exit can be taken. This can be very helpfull for the robot to identify crossroads. An emergency exit panel must be put from every evacuation origin to a location where the emergency exit or the panel that indicates it is clearly visible. They must be clearly visible even when the lighting is off. The norm also indicates that an excessive number of panels is not dessirable because people can be confused.

We claim that those requirements made the signals adequate for being used as landmarks for robot navigation, if the robot posseses the capabilities needed to perceive them.

4.1 Image preprocessing

In order to obtain better segmentation we apply a color enhancing algorithm to the image. The selected algorithm is the one offered by The Gimp image processing GNU tool [1]. This algorithm runs an automatic saturation strength on the 3 channels in the image within HSV color space [18], preserving Hue. For each channel in the image, it finds the minimum and maximum values and uses those values to stretch the individual histograms to the full range. After the image has been enhanced we apply a simple thresholding to segment the green areas of the image. Figure 2 gives an idea of the performance of the segmentation process. Once



A.1 A.2 B.1 B.2

Figure 2: Original and segmented images. The green emergency panel on image A.1 gives a good segmented result as shown in image A.2. Image B.1 is an original image with no panel and B.2 shows the noisy segmented image obtained.

[1]Official Journal L 245 , 26/08/1992 P. 0023 - 0042

the image has been segmented we need a method to classify an image as containing a panel. For the identificacion process we need a mechanism capable to cope with noisy situations.

4.2 Emergency exit panel recognition

Probably, the most intuitive idea to classify an image as containing a panel is to find a white rectangle in the segmented image. However, the distance from the wall and the viewpoint of the robot can distort the segmented image. Thereby, instead of using image correlation functions we choosed to use a multi layer perceptron (MLP) with a single hidden layer, trained with images taken from different view points and distances [11]. The input layer length of the MLP depends on the kind of input vector used. But the real-time performance of the system is heavily affected by the computational load associated to the net. We have made a bunch of experiments in order to find a net configuration that enables good performance/low computation rate. All the nets had 5 neurons in the hidden layer and have been trained for 1000 epochs.

Table 1: Input vector types and performance of the living-one-out crossvalidation for the MLP

type	Explanation	L.O.O performance
1	Normalized Column sum and row sum of green pixels	$\%93.36$
2	Weighted colum sum and row sum of green pixels. The weighting algorithm is very simple: just consider as weight the number of green pixels in the 3×3 surrounding of a green pixel. $$i^{th}input = pixel * \frac{num\_green\_pixels}{8} \quad (1)$$	$\%95$
3	Quadratic weighted colum sum and row sum: $$i^{th}input = pixel * \frac{(num\_green\_pixels)^2}{8^2} \quad (2)$$	$\%96.36$
4	4th power weighted colum sum and row sum $$i^{th}input = pixel * \frac{(num\_green\_pixels)^4}{8^4} \quad (3)$$	$\%98.18$
5	Normalized sum of 10×5 sized blocks.	$\%91.81$
6	Normalized sum of 20×10 sized blocks.	$\%93.36$
7	Normalized sum of 20×20 sized blocks.	$\%96.36$
8	Weighted sum of 20×20 sized blocks.	$\%95.45$
9	Quadratic weighted sum of 20×20 sized blocks.	$\%97.27$
10	4th power of weighted sum of 20×20 sized blocks.	$\%95$

Table 1 shows the performace of the nets obtained using the different kinds of input vectors. Because the image database was relatively small (220 images), the leaving-one-out (L.O.O) crossvalidation has been used to obtain the nets accuracy estimation. The best performance is obtained for the quadratic weighted sum of 20×20 sized blocks and for the 4th power of the column and row sums – rows 9 and 4 respectively.

Input type corresponding to row numbered 9 is the one choosen to be tested on the robot. The reason is that a 1% loose in accuracy is compensated with the substantially lower number of calculations needed to classify a single pattern.

5 Corridor identification

We do agree with Nehmzow [13] when affirming that nominal paths are better suited for landmark identification than just wandering behaviors, arguing that robust robot navigation is feasible if the environment has cues that can be used as landmarks while the robot follows cannonical paths: “If landmarks are known that describe the desired path, piloting can be used instead of the more unreliable dead-reckoning”.

Having that idea on mind, we defined a nominal path for the robot that allowed her to go from the lab to the library hall and come back to the lab. The robot global behavior was the result of the adequate combination of two main behaviors: compass following and corridor following, and therefore, it was mainly the result of the motor fusion due to sonars and compass readings (infrared and bumper managing behaviors are designed to activate only in emergency situations). That combination turned out in a wall following behavior out of corridors. We made a bunch of trials and reported the sonars and compass readings during that nominal path. The data collected was for about two hours of robot moving along the path, and posterior analysis of the data showed that corridors presented very strong properties that make them identifiable. We consider the same physical corridor as being different depending on the way the robot is following it. Corridors can be followed in the environment from North to South (NS) or from South to North (SN). The compass allows to deambiguate those situations. Equation (4) shows the single rule applied for corridor identification. The i subindex stands for NS or SN direction.

$$corridor\_id_i(t) = \begin{cases} 1 & \text{if } \theta \in [\theta^i_{min}, \cdots, \theta^i_{max}] \text{ and } \textit{sonars} < TH \\ 0 & \text{else} \end{cases} \tag{4}$$

To make the corridor identification more robust, instead of trusting just on a single sonar and compass reading, we mantain a belief value of being in each corridor using a fixed size FIFO buffer that contains the results of the corridor identification behavior for the last BSIZE readings[2]:

$$Bel(corridor_i) = \sum_{k=(t-BSIZE)}^{t} corridor\_id_i(k) \times w_k$$

where w_k is an increasing weighting parameter that gives more importance to the recent values of *corridor_id*. Figure 3 shows an example of the output of the corridor behavior traversing the way from the lab to the first hall. Neither open doors and presence of irregularities, nor variations in the robot path due to dinamical obstacles should affect the identification. Next section explains how we coped whith confidence level variations to avoid perturbances in the recognition processes.

[2] For the experimental done $BSIZE = 100$

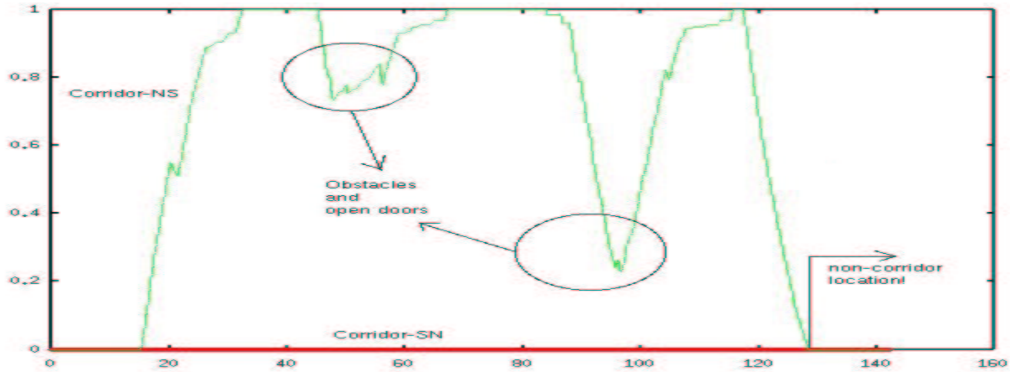


Figure 3: Capture of the corridor identification state during a NS corridor. The thick line around 0 value represents the identification state of the SN corridor. Circles underline perturbances.

6 Integration of landmark identification processes in the control architecture

Our goal was to present emergency exit panel and corridor identification for robot navigation. Non-corridor locations are easier to manage because the robot feels compfortable in wide places. However, it becomes harder to force the robot to enter narrow corridors. Emergency exit panels can be used to chage the followed compass orientation to the adequate corridor orientation.

In order to test the adequacy of the selected landmarks for navigation, we defined a specific task that consisted of going from the laboratory to the library hall and coming back again after visiting Otzeta's office, placed in the corridor parallel to the laboratory's one (see figure 4-a. The landmark identification processes were added to the previously defined behaviors for wandering in a priviledged compass orientation. These processes should act as perceptual triggers and change the desired compass orientation and the camera's pan and tilt angles to look for the exit panels. Summarizing, we have built a control architecture consisting of the following three competences integrated into SORGIN behavior-based framework:

1. *Collision-free navigation:* The basic navigation competency was designed to perform safe-wandering in a priviledged compass orientation, avoiding collisions with objects and people in a semi-structured office environment. The main behaviors are: *Corridor-follower*, *Compass-follower*, *Obstacle-avoider* and *Stop*. Because each behavior is aiming at its own objective, it is essential to carry out a coordination task. For the work described here, we used a cooperative strategy, in which the global response is a weighted sum of different motor responses. This was the control architecture initially built up to collect data for the corridor recognition.

2. *Landmark detection:* The landmark identification processes, explained in sections 4 and 5, were added to our behavior-based control architecture, that consists of *exit_panel_id*, for exit panel identification, and *corridor*$\_id_i$ for corridor identification (again, the i subindex stands for NS or SN).

3. *Finite state automata (FSA) based landmark detection for navigational purposes:* The top level task is constructed combining all the above explained behaviors using a finite state automata. The landmark detection subsystems continuously search their inputs looking for new landmarks. If a landmark is detected, the robot executes actions that guide herself

to the direction of the goal. The FSA receives inputs from *corridor_id* and *exit_panel_id* behaviors. Information from landmark identification modules is used to change the robot behavior according to the situation. To follow the stablished path, two kind of outputs are taken into consideration by the FSA: at one hand, when the operating state changes, that is, when the robot reaches a new location, a new compass orientation is given to guide the robot through the location. The camera is re-positioned according to the location in order to identify a new exit panel. On the other hand, when the robot identifies a new exit panel, a new compass heading is given that makes the robot look for a new location.

In order to ensure that transitions occur effectively, preserve the system from noise and make it more robust, we have applied the previously explained landmark identificators in the following manner:

- *exit_panel_id*: The emergency exit panel recognition based on the MLP gives as output the mean value of the last 10 images. This value gives a measure of the confidence level (cl) of the recognition process. Therefore, it will send an output 1 indicating that a new landamark has been detected only after 10 positive identifications. When this occurs the proper actions would be taken. This confidence level also affects the global translational velocity of the robot according to the following expression:

$$v' = (1 - cl).v$$

  The aim of this velocity reduction is to slow down the robot when a panel is being recognized so that she does not loose it. This approach follows latest trends in what is called *purposive vision* [2].

- *corridor_id:* The corridor identification processes also make use of a confidence level (see equation (5)). But to act as perceptual triggers the output is defined as:

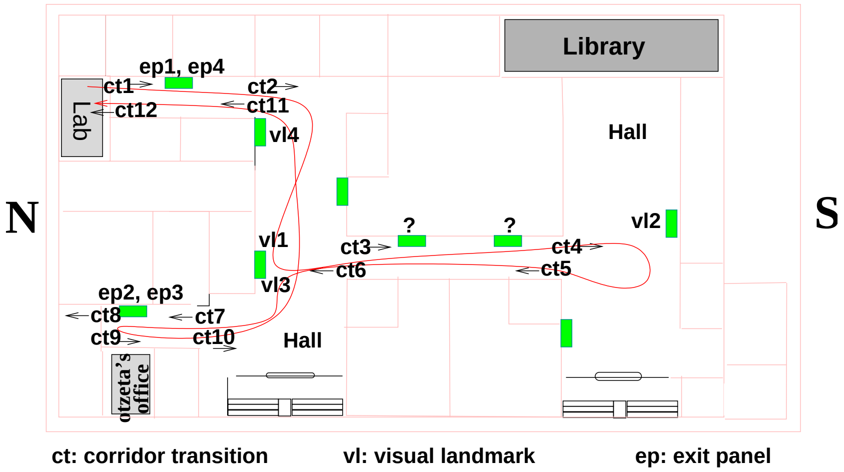
$$\begin{cases} 1 & \text{if } Bel_i > 0.6 \quad \text{in corridor} \\ 0 & \text{if } Bel_i < 0.1 \quad \text{not in corridor} \\ 0.5 & \text{else} \quad \text{uncertainty} \end{cases} \tag{5}$$

  Only when they send the value 1 as output the automata will consider being in a corridor. There is an uncertainty range due to transitions and perturbances and it is indicated by a 0.5 output. There is no change in the global state while uncertainty remains.

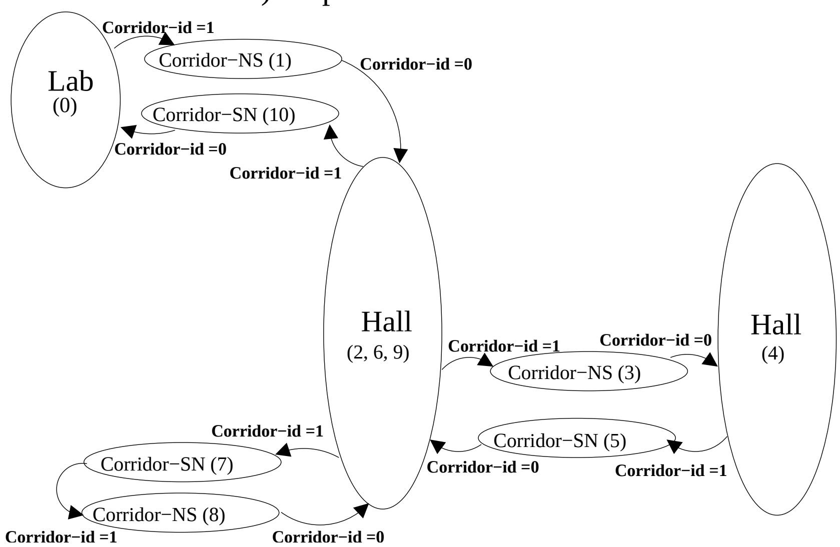
Figure 4-a) shows the map of the environment in which we made the experiments and the path followed by the robot. Figure 4-b) is a graphical representation of an FSA for such a robotic task. The circles represent the possible operating states with the label indicating the localisation of the robot. The arcs are labeled with the perceptual triggers causing the transitions.

7 Results

Figure 5 shows the plot of the outputs of the different landmark recognition behaviors together with the changes in the state of the FSA during a complete path. The panels in the corridor that connects both halls, marked with a question mark in figure 4-a) are completely missed by the robot, in almost every trial we made. This is due to the extreme lighting condition variations



a) Map of the environment.



b) The associated FSA.

Figure 4: a): rectangles in walls represent the whole set of emergency exits. The subset of those green panels labeled as VL will be used to force the robot to go through the narrow corridors. b): non-corridor places are connected through corridors. State transitions would be activated by corridor to non-corridor and non-corridor to corridor transitions. Numbers in nodes represent state identificators.

in the corridor. However, the robot is capable of catching the visual landmarks needed to force the robot to go into the corridor. Concerning the corridor identification behaviors, the uncertainty range helps to have robust state transitions and the robot is capable of completing the full path without getting lost in spite of corridor width irregularities.

8 Conclusions and further work

The results show that the landmark identification system can be used to tell the robot the task to be fulfilled. We think that the presented system could be adopted to many environments and hence, it is not particular to our environment. But of course, many facts should be improved. Concerning to the visual landmark identification, a zoomed camera could help to adjust the image according to the distance to the wall. We also need to add the identification of the non-corridor places within the cannonical path of the robot in the same manner as cor-

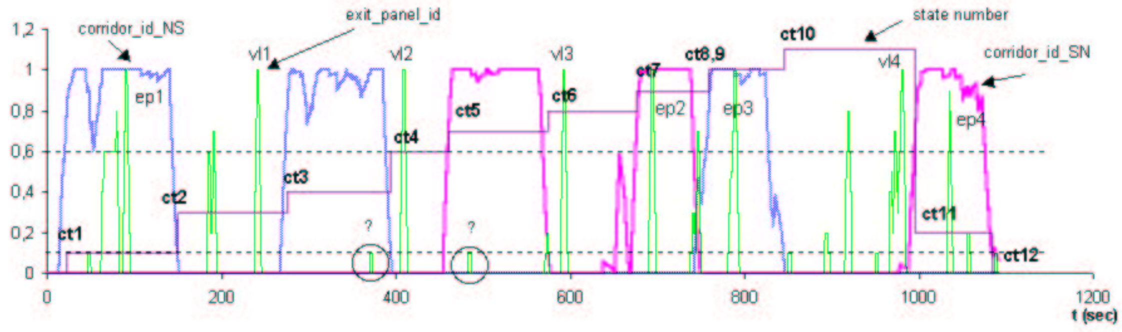


Figure 5: Landmark identification state of a complete path that amounts to 149.5 meters. The circles show the missed exit pannels in that corridor. The stairs-like line displays changes in the state number (multiplied by 0.1 for scale purposes). These changes show that the complete state sequence that corresponds to the defined full path, has been met. The state numbers are those drawn in the FSA.

ridors are recognized in order to deambiguate parallel corridors. Higher granularity is needed for the localization. Door identification must be added as landmark recognition subsystem. We do need to emphasize the developed automathon has been defined only to measure the adecuatedness of the selected landmarks for navigation and as such, the control mechanism needs improvements and a state belief should be mantained. Keeping in mind the above mentioned improvements, a future application of our system could be, like a postman, transfer and deliver envelopes and packages to the members of other laboratories, based on an automathon that changes dinamically according to the task the robot has to perform at each moment. Of course, more experimentation is mandatory, in different environments and with more complicated tasks.

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