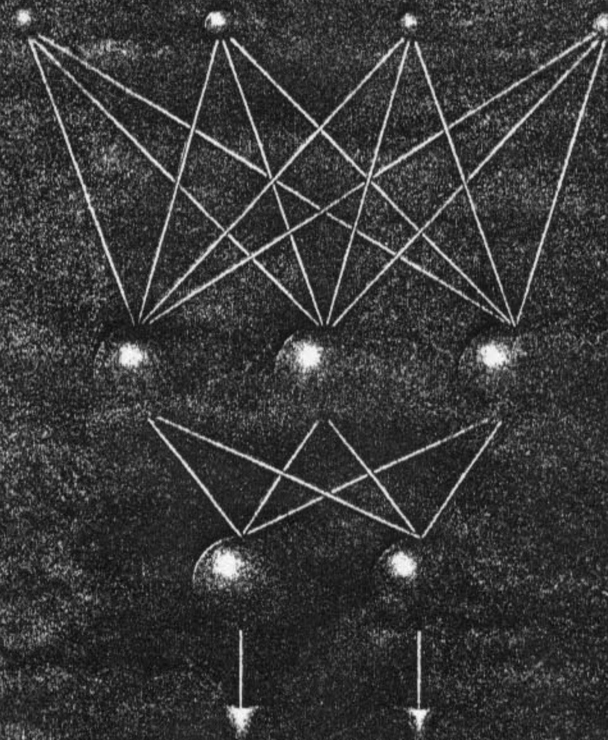
MACHINE LEARNING AND PERCEPTION



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Contents

A PERCEPTION SYSTEM FOR MOBILE ROBOT LOCALIZATION

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Abstract

A localization system for mobile robots is presented. The system enables an autonomous mobile robot to locate itself along learned routes in a dynamic environment. The localization is based on data provided by an omnidirectional visual perception system that makes use of optical pre-processing and of neural network learning.

1. Introduction

A key feature for a mobile robot is the ability to accomplish its tasks in a dynamic, uncertain and unstructured environment, carrying out at least autonomous navigation tasks. Such feature is required both in industrial [6] and military [7] fields of application; although, different degrees of robot autonomy, flexibility and reliability are needed.

Research in Artificial Intelligence has shown that autonomous capabilities involving perception and motion control are much more difficult to automate than "classical" intelligent activities, such as logic reasoning [8]. Great problems are encountered in mobile robotics, such as in the design of perception systems aiming to describe a dynamic world wich is extremely complex and rich in details. Besides being hard to manage, a detailed description of the world could quickly become useless if the world can evolve to unpredictable configurations [9].

The proposed system is being developed in the context of a joint research program among the Department of Electronics for Automation, University of Brescia (Italy) and the Laboratory of Automation, University of Besançon (France)[3] This paper focuses on the overall structure of the perception device, and describes research and application perspectives.

2. Aim of the system

The aim of the system is the localization of a mobile robot moving autonomously in a working area in which it has been previously trained. The localization system is devised to take advantage of natural, pre-existent fixed reference-objects in the environment (walls, openings...), without requiring their explicit identification. Hence, neither conditioning of the environment around the working area nor accurate distance measurements are required.

Another feature of the localization system is its ability to work even if the learned environment changes. This holds true, provided that changes affect only limited portions of the whole omnidirectional vision field: this allows the perceived images to appear globally similar to the learned images. The system operations involve two phases: the supervised learning of the working areas, and the autonomous navigation of the robot in the learned areas. During the learning phase the mobile robot is guided along a route in the operating area. While moving, the perception system collects images and associates them with the corresponding position in the environment, related to a previously chosen coordinate reference system.

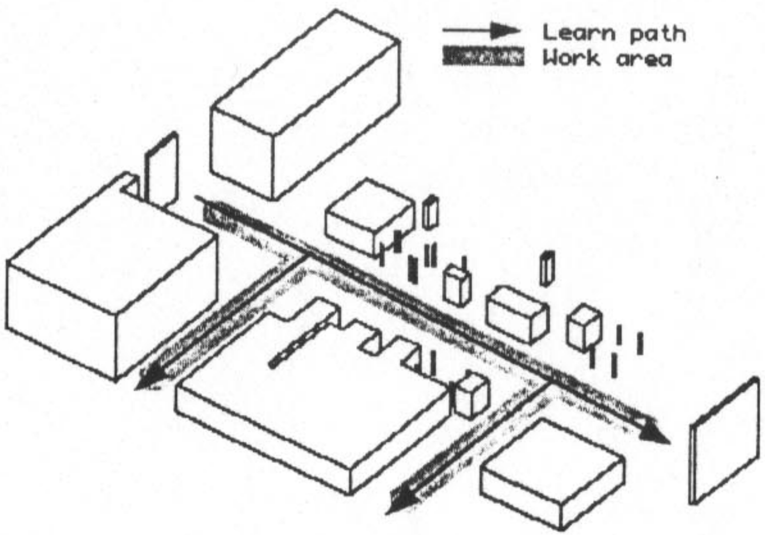

Fig. 1 Working area and learning paths

In order to have usable data, they have to be collected not only along the path to be followed, but also in its surroundings. To do this, different methods can be used. A first solution is to drive the mobile robot along several, but not identical, learning paths, to obtain a sampled grid of the working area. Another approach, that avoids the long and probably inaccurate execution of many similar paths is having the perception system move on the robot, shifting transversally with respect to the path direction. It's also possible to mount more than one perception system on the robot: the geometric pattern of the perception systems fixed on the robot, repeated in the space as the robot moves will result in a quite regular sampling grid.

3. System description

The localization system is composed of the following sub-systems:

- an omnidirectional visual perception system (CCD camera / conical mirror);
- an image pre-processing system;
- a learning system based on a neural network.

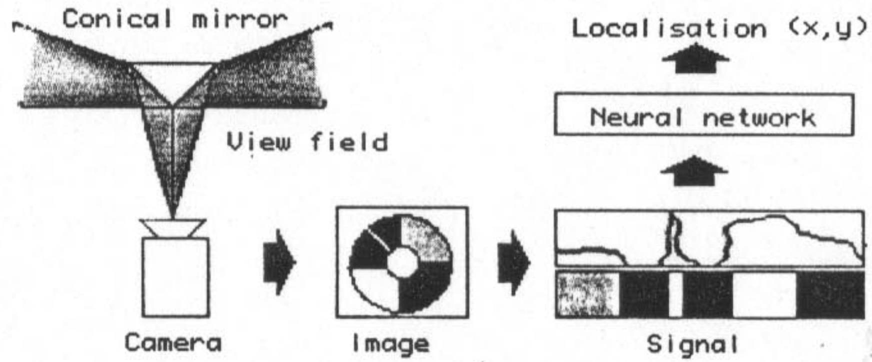

Fig. 2 Block structure of the system.

During the learning phase, the neural network is trained using the signals obtained by the pre-processing of the images acquired along the learning path and the associated positions. Position information could be obtained either by an external control system or by an operator, or from an actual position estimate based on odometric sensing.

During the execution phase, the mobile robot will attempt to follow the previously learned path. Given the actual perceived image of the environment, the localization system will take advantage of the information organised and stored in the neural network to obtain the actual position and use it as an error signal to correct the trajectory of the robot. Obviously, the output of the neural network is an approximation of the robot's position, and it is based only on the actual perceived image. To achieve a better localization, position data supplied by the network output could then be fused with data coming from other sensors.

4. The perception and pre-processing systems

The perception system generates an image of the omnidirectional view of the environment around the robot. It is composed of a CCD camera facing upwards, which records the image of a cone-shaped mirror. The mirror is placed at a known distance, coaxially to the camera lens.

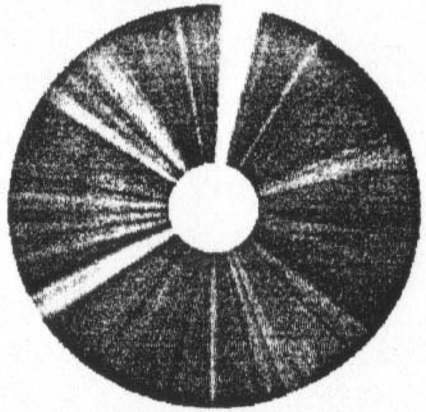

Fig. 3 An environment image from the conical mirror.

The image of the environment as it is reflected by the conical mirror has a characteristic circular structure with many different bright or coloured angular sectors. Geometrically, each cone generating line determines an infinitesimally small plane mirror, coincident with the tangent plane. These infinitesimally small plane mirrors are directed all around the cone-camera axis and enable us to collect information related to the whole environment in a single omnidirectional image.

The perception system is derived from the COPIS system, used by Yagi [1, 2] for obstacle avoidance or map based mobile robot navigation. In our system we do not however require the construction of an explicit and detailed map of the world surrounding the robot.

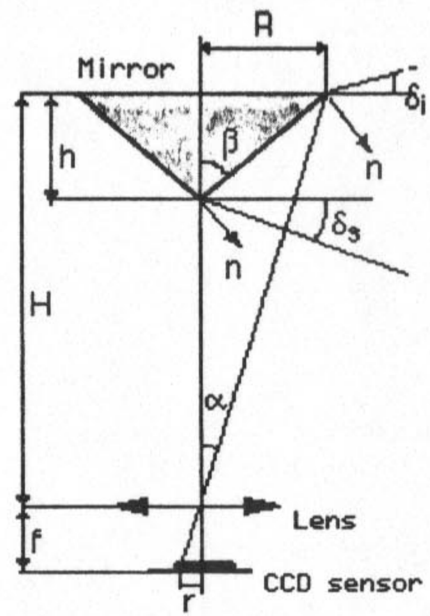

Fig. 4 Conical mirror geometry and camera view field.

Let us consider a vertical symmetry plane for the cone-camera system, as shown in figure 4. Let 2β be the cone angle and 2α the camera view angle. The direction and the angle of the vision field are then easily determined. The bisecting line of the vision field has an inclination with the horizontal equal to $2\beta - \pi/2 + \alpha/2$, while the vision field angle is α. By choosing different cone angles we can obtain vision fields directed in different directions; i.e. with $2\beta = 90°$ the vision field never intercepts the floor, as δ_s is $0°$.

The perception system is not designed to obtain a perfect image of the environment. Large amount of detail in the image obtained by a perfect mirror would increase the image elaboration complexity. As high spatial frequencies are less influent on the performance of the learning system, it is convenient to enhance the image blur. The increased diffusion acts as a low-pass filter and is responsible of the loss of the information related to those objects in the environment that are small or far away from the robot. To obtain a diffusion effect on the image we can take advantage of the conical mirror surface roughness, instead of applying diffusion algorithms on the pixel matrix of the image, because one of the effects originated by the surface roughness is an increased diffuse reflection component [5]. The information obtained enhances the colour and the brightness of large surfaces in the environment. Large surfaces are more useful than small ones in determining robot localization.

The main goal of the pre-processing of the images obtained by the perception system is simplify and enhance useful information. In fact information related to the angular position of objects around the robot is circularly distributed in the omnidirectional image. Thus, a reference system transformation is applied, from rectangular to polar coordinates. A selected ring of the circular image maps into a rectangle. Each vertical stripe of the rectangle contains pixels representing the chromatic characteristics perceived in the related direction.

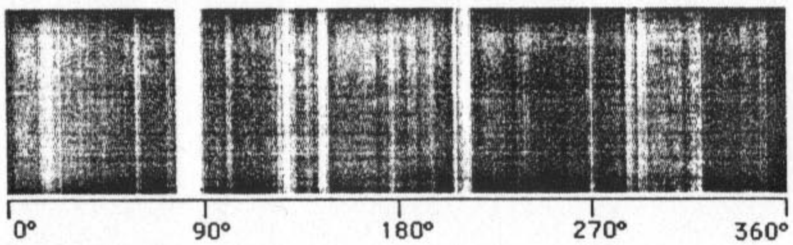

Fig. 5 The image obtained transforming the ring of Fig. 3

For a b/w CCD sensor the value for each pixel is the brightness, scaled on the available grey-level range. For a colour CCD we obtain more information, wich can be used to increase the performance of the learning system.

5. The learning system.

The learning system is based on a feed-forward neural network, trained with a back-propagation algorithm [4]. A b/w CCD sensor is used and the network has an input layer composed of 360 input units, each one corresponding to a 1° angular sector. The network has two hidden layers and an output layer made of two output units that encode the position of the robot in the chosen reference system (i.e. as x, y coordinates). The hidden layers are completely connected to the following layer and are made up of units with a sigmoidal activation function. Using a neural network as a learning system enables the localization system to work correctly, even if is used in a dynamic, changing environment, although with degraded performance [4].

6. Results and perspectives

The system has been verified both in real and computer modelled environments. In the first experimental set a b/w camera has been used to take images at pre-determined positions in a sampling grid. The neural network has been simulated on a workstation using the neural network simulator software SNNS (version 3.1), developed at IPDHS, Stuttgart University. The tests have shown the following.

The transformation on the camera view field performed by the conical mirror has revealed its efficiency. The images obtained represent the whole environment and the circular structure makes pre-elaboration processes very efficient.

The neural network is able to learn and take advantage of the information selected by the pre-processing. The network perfectly learns signals corresponding to the images in the learning set. Moreover, the network is able to determine the position of images not included in the learning set, but acquired in the same working area, with a limited average error. On a 5 m^2 working area, the average error was 20 cm. However, while some images not belonging to the learning set were correctly localized, some other test images were associated to a position very far from the expected result. This is the reason for the high network output variance.

In addition there is the need to split the complete learning path into sections. This is because very far elements in the environment could appear as fixed characteristics, thus completely uncorrelated with the robot motion. Splitting the learning path into sections with carefully chosen lengths will reduce the effects of the farthest objects. A dependency on environment lighting exist. Some images were incorrectly localized due to different lighting conditions.

The system is now being tested with a colour camera and different network structures with the aim of reducing the average localization error and of taking into account lighting conditions. In fact, the colour of each pixel from the conical mirror image is determined by a chromatic mix of the hues received by the CCD into the solid angle corresponding to that pixel [10]. In each stripe considered we could find pixels with a variety of hue, brightness and saturation. Many similar but different colours will be detected, because of the spatial sampling. The number of different colours could be reduced generating a false-coloured image; e.g. by clustering techniques in the RGB chromatic space.

References

1. Y. Yagi and M. Yachida, "Real-time generation of environment map and obstacle avoidance using omnidirectional image sensor with conic mirror", in Proceedings of the IEEE Conference on Computer Vision & Pattern, pp 160-165, 1991
2. Y. Yagi, Y. Nishizawa and M. Yashida, "Map based navigation of a mobile robot using omindirectional vision system COPIS", in *Proceedings of the IEEE Int. Conference on Robotics & Automation*, Nice, France, may 1992
3. E. Bideaux, P. Baptiste, C. Day and D. Harwood, "Mapping with a backpropagation neural network", in *Proceedings of the IMACS-IEEE/SMC Symposium*, Lille, France, April 1994
4. D.E. Rumelhart and J.L. McClelland, "Un quadro generale del processamento distribuito in parallelo", "L'apprendimento di rappresentazioni interne attraverso la propagazione dell'errore", in PDP. Microstruttura dei processi cognitivi, Bologna, Il Mulino 1991
5. S.K. Nayar, K. Ikeuchi and T. Kanade, "Surface reflection: physical and geometrical perspectives", in *IEEE Trans. Pattern Anal. Machine Intell.* , vol. 13, 7, Luglio 1991
6. R.K. Miller, *Automated Guided Vehicles and Automated Manufacturing*, pp. 1-8, 33-42, American Society of Manufacturing Engineers 1987
7. R. Finkelstein, *Unmanned Vehicle Systems: Military and Civil Robots For The Coming Millenium*, pp. -, Arlington, Pasha 1994
8. T. Poggio, *L'occhio e il cervello*, pp. 44-45, Roma, Theoria 1991
9. G. Gini and M. Terribile, "Comportamenti emergenti in una flotta di robot autonomi", in *Atti del gruppo di lavoro su percezione e robotica AIIA*, pp. 21-22, 1994
10. G.E. Healey and R. Kondepudy, "Radiometric CCD Camera Calibration and Noise Estimation", in *IEEE Trans. Pattern Anal. Machine Intell.* , vol. 16, 7, March 1994