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Robustness Characteristics of POLLICINO System for Autonomous Robot Self-Localization

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Abstract

POLLICINO is a system for autonomous mobile robot self-localization along previously learned routes in a dynamic environment. The system is based on a conical device that allows an omnidirectional perception of the environment and on a learning system. Robustness tests towards occlusion and robot rotations are presented.

1. Introduction

This paper presents robustness tests that are being carried on the POLLICINO[1] system, developed at the Department of Electronics for Automation, University of Brescia (Italy) and presented last year at EUROBOT 96 [1].

The aim of the tests is to measure system robustness against random occlusions in the perception field, like people walking around the robot and against undetected robot rotations around a vertical axis.

Tests are performed on a simulated system, while the real one is being implemented.

This paper mainly focuses on the problem of evaluating and characterizing system robustness with the aim of controlling and correcting navigation and improving self-localization skills.

2. POLLICINO structure

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 [2][3][4]. The system operation involves two phases: the supervised learning of the working areas and the autonomous navigation of the robot in the learned areas.

A feature of the localization system is the ability to work even if the learned environment changes (e.g. people walking around, objects that were not present in the training phase, etc.) Tests about this capability are presented.

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

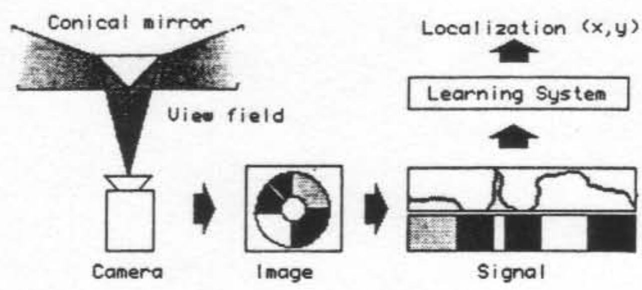


Fig. 1. Structure of the system.

The perception system generates an image of the omnidirectional view of a section of the environment around the robot [4][5]. It is composed of a CCD camera facing upwards, which records the image of a cone-shaped mirror, placed at a known distance, coaxially to the camera lens.

Images obtained by the perception system are pre-processed in order to simplify and enhance useful information that is used in the learning phase.

[1] POLLICINO is the Italian name of the famous tale "Tiny thumb" by Charles Perrault, in which a little boy must find his way back home in a dark wood.

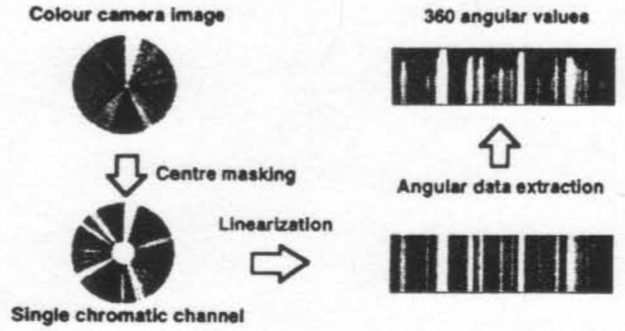


Fig. 2. The image preprocessing.

The conical mirror does not have to be a perfect mirror, because the perception system is not designed to obtain a perfect image of the environment. After the preprocessing phase, only the mean brightnesses for each angular sector and for each chromatic channel are extracted from the grabbed image (Fig. 2). These data, extracted from some images along the path, are then used, during the learning phase, to train the neural network.

In the execution phase, the mobile robot attempts to follow the previously learned path. The localization system takes advantage of the information organised and stored in the neural network to obtain an approximation of the actual robot position.

Long paths are divided into relatively small subsections of the whole path.

Only the perception system (CCD camera + conical mirror) has so far been mounted on POLLICINO, while the image pre-processing and the learning system training were performed off-line.

The tests on the system, limited to only a subsection of a longer path, were performed as follows. First, images were taken corresponding to known position given by a sampling grid of the work area. Then, the input–output patterns for the neural network were obtained by pre-processing the images and associating them with the corresponding coordinates.

Only a subset of these data was used to train the neural network. Data not used for training were then used to check the system ability in self-localization by measuring the mean localization error between the output of the neural network and the actual position.

3. The acquisition scene

A briefing room with tables and chairs has been used as a test scene. 96 images were taken in a rectangular test area, along three asymmetric lines and in random points, as shown in Fig. 3. Total area dimension is 110x70 cm.

For the training phase only a subset of the regularly sampled images has been used: 48 images in "high density", 16 in "mid density" and 9 in "low density".

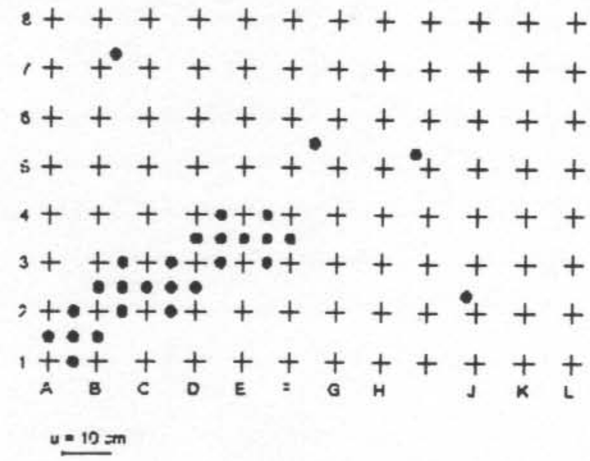


Fig. 3. Sampling grid in the test area.

4. The learning systems

A modified version of the neural network used for the previous test [6] has been used as learning system.

It is called STD3BP and it is a feed-forward neural network trained with a back-propagation algorithm [8]. This network, as shown in Fig. 4, has two hidden layers and an output layer consisting of two output units that encode the position of the robot in the chosen reference system (i.e. as X, Y co-ordinates).

Each hidden layer is completely connected to the following layer and is composed of units with a sigmoidal activation function.

Each unit in the first hidden layer gets its inputs only from a group of units of the input layer, thus forming a cluster. Moreover, input clusters are partially superposed. This improves the robustness of the system. In this way, small pattern rotations or moderate changes in the perceived environment can be tolerated.

The input layer is composed by 360x3 units, one for each degree and for each chromatic channel. This structure is shown in Fig. 4.

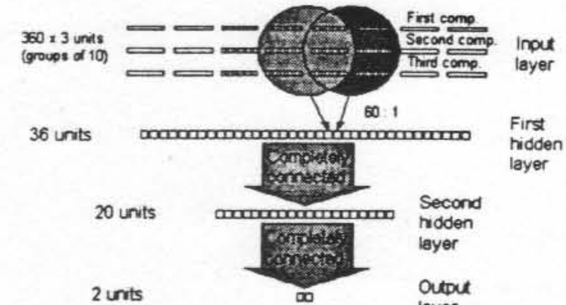


Fig. 4. STD3BP structure.

5. Test results

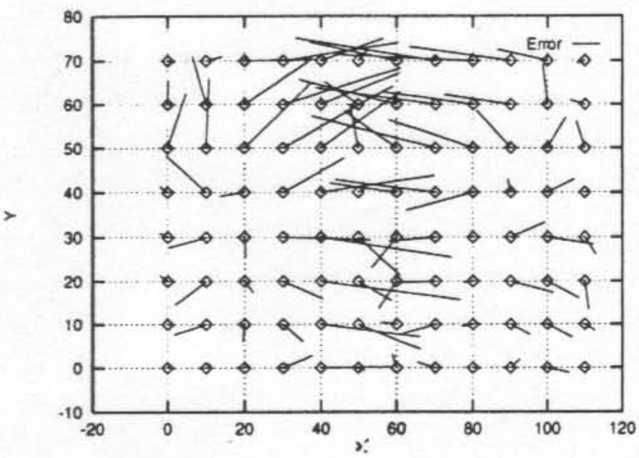
POLLICINO has been tested with STD3BP in normal condition and the results with different density are visible in Tab. 1.

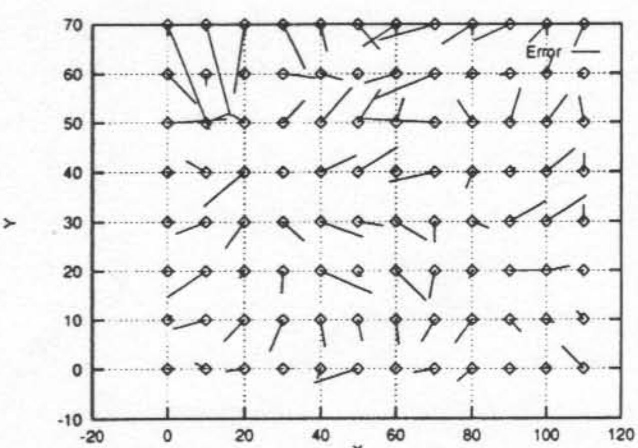
Avg			Dev		
High	Mid	Low	High	Mid	Low
4	7.77	13.61	2.64	4.45	9.98

Tab. 1. STD3BP test results. Localization errors in cm.

The best localization error, related to the length of the path was less than 4% in high density, while the maximum localization error was around 12% in low density.

Error spatial distribution can be seen in Fig. 5a. 5b, 5c. The lines indicate the error for each image in both the learning and the testing set. These lines connect the actual position with the estimated one.





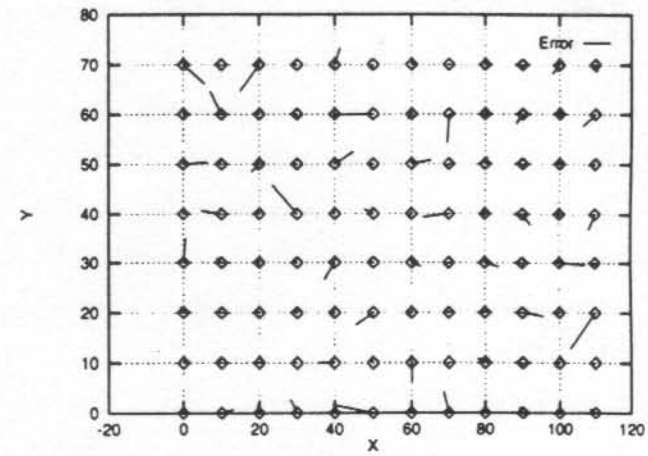
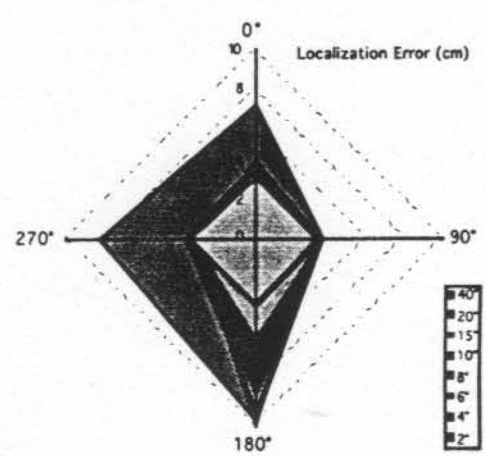
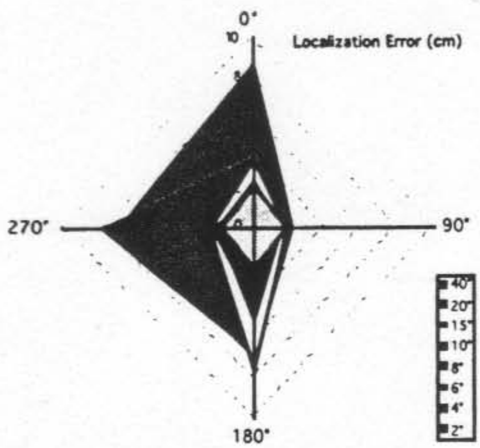


Fig. 5a, 5b, 5c. Error distribution in the test area obtained with low (a), mid (b) and high (c) learning density.

6. Test results with occlusions

The robustness of the system against "occlusions" of the omnidirectional view field, due to the presence of unlearned objects in the environment, has been tested. A simple approximation of occlusion effects has been simulated introducing noise in the original image extracted data. This noise is supposed to simulate the presence of a size varying, high saturated red coloured object. The effect of the noise has been evaluated simulating the variation both of the size of the object and its direction in the omnidirectional view field. Four main directions have been chosen (0, 90, 180, 270 degrees) and also different noise sizes (2, 4, 6, 8, 10, 15, 20, 40 degrees). The localization error obtained at low, mid and high density on two randomly chosen points can be seen in Fig. 6a, 6b, 6c and the relative data in Tab. 2, Tab. 3 and Tab. 4.





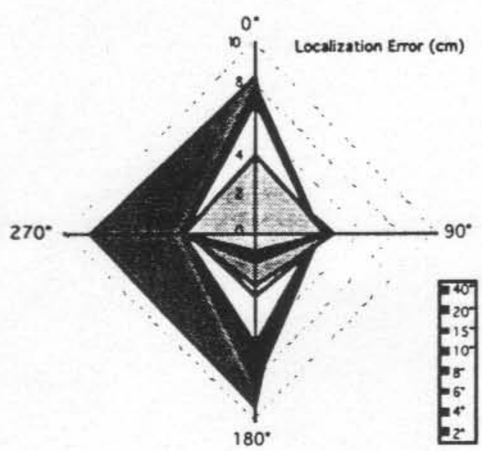


Fig. 6a, 6b, 6c. Localization error with different occlusion size and direction obtained with low (a), mid (b) and high (c) learning density.

	2°	4°	6°	8°	10°	15°	20°	40°
0°	1.9	1.76	1.76	1.93	4.09	7.13	13.5	8.76
90°	1.36	1.42	5.31	1.9	2.03	2.59	2.84	5.03
180°	4.04	3.45	3.62	5.26	5.41	7.52	9.55	9.05
270°	1.11	1.16	1.49	1.6	1.31	1.33	2.95	9.84

Tab. 2. High density occlusion test results (cm).

	2°	4°	6°	8°	10°	15°	20°	40°
[illegible]	2.16	1.63	1.55	1.45	2.34	3.49	3.49	8.5
90°	1.83	1.64	1.5	1.55	1.52	1.76	1.67	2.12
180°	2.11	2.06	2.27	4.06	4.8	7.38	6.5	6.77
270°	1.7	1.74	2.11	2.16	1.89	2.34	7.88	7.04

Tab. 3. Mid density occlusion test results (cm).

	2°	4°	6°	8°	10°	15°	20°	40°
0°	3.25	3.65	3.58	3.55	3.86	4.04	3.93	7.16
90°	3.38	3.48	3.62	3.6	3.65	3.38	3.4	3.54
180°	3.51	3.7	5.3	8.44	9.25	9.83	9	9.69
270°	3.49	3.44	3.38	3.25	3.31	3.28	3.7	8.36

Tab. 4. Low density occlusion test results (cm).

7. Sensitivity to robot rotation

POLLICINO does not measure the robot rotation in the fixed reference system defined in the learning phase. Tests were made to investigate the sensitivity of the system to rotations.

As it can be seen in Tab. 5 and Tab. 6, small rotations are well tolerated. Higher rotations could be managed if the robot keeps track of its heading in the reference system. If the robot heading is known, then a simple circular shift of the pre-processing output data could take into account the rotation effects.

Also in this case the tests have been performed in two randomly chosen points in the test area and the localization errors are measured at low, mid and high density with clockwise and counterclockwise pattern rotations. Results are shown in Tab 5 and Tab. 6.

	Low	Mid	High
0	10.55	5.30	4.11
2	12.43	8.46	4.56
4	17.08	10.84	6.73
6	17.49	13.66	12.03
8	22.46	17.76	15.73
10	24.89	20.21	14.28
15	30.67	23.90	15.24
20	27.44	29.37	17.02
45	43.79	38.20	44.29

Tab. 5. Clockwise rotation test results (cm).

	Low	Mid	High
0	10.55	5.30	4.11
2	9.69	11.25	5.10
4	19.20	17.16	6.82
6	17.37	13.46	7.14
8	17.74	22.15	17.50
10	26.89	30.16	18.53
15	28.27	21.46	24.77
20	21.19	30.16	19.31
45	30.67	37.84	40.01

Tab. 6. Counterclockwise rotation test results (cm).

8. Conclusions

POLLICINO has been tested under noisy conditions.

Two kinds of noise have been considered: occlusions and rotations.

Occlusion tests simulate people walking around robot or any not previously learned object that hides part of the omnidirectional view field. Results have shown that the localization error increases slowly with respect to the occlusion width. The position of the occlusion is very important for the performance degradation, but this fact depends heavily on environment data and thus is hardly predictable.

Rotations tests simulate robot skidding out of dead reckoning control. Results have shown that the localization error increases linearly with respect to the rotation.

9. Bibliography

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