SOME RESULTS IN THE EVALUATION OF A SONAR SYSTEM FOR RECOGNITION OF THE ENVIRONMENT BY MOBILE ROBOTS

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Abstract: The objective of the work is to present some results in the evaluation of the SONAR system of a mobile robot. As environment a corner of our lab is considered. Based on some reference positions, where the robot is making a complete rotation, some test positions are considered with the task of recognition of the environment, to estimate the position and the initial orientation. Using similarity measures based on Euclidian distance, similarities maps are defined and estimated. The results are useful in defining more complex strategies of navigation based on SONAR systems.

Keywords: SONAR systems, Pattern recognition, Similarity measures, Navigation, and Mobile Robots.

1. INTRODUCTION

The objective of the work is to evaluate the performance of the built-in SONAR system of ATRV-Jr mobile robot, (iROBOT 2002), in order to have a reference for a new generation of SONAR head, which is being built under EU project CIRCE - *Chiroptera Inspired Robotic Cephaloid: a Novel Tool for Experiments in Synthetic Biology*, (CIRCE 2002).

The context and the main steps in processing of the SONAR data are presented in section 2. In section 3 a short description of the used SONAR system is presented together with the set-up of the experiment.

Later, in section 4, the main signal processing steps are presented, as well as filtering of the outliers and segmentation of the environment. In section 5 some results of the classification are presented using a simple classifier based on Euclidean distance. Section 6 is for conclusions and proposals in improving the performance of the classifier.

2. DESCRIPTION OF THE CONTEXT

The analysis and the path work are under the structure presented in Fig. 1. First, the mobile robot is inspecting the workspace and information about environment collected using echolocation. The range measurements from environment are pre-processed by filtering (removing of the outliers) and segmentation (environment codification by ranges and angles). In the context of navigation, it is important to estimate the position and the orientation of the robot in the environment, and to decide on the best path to follow in moving in the environment, from a start to a goal position.

As the robot's SONAR sensors fire off pings and receive echoes, they continuously update a data structure. Each SONAR sensor detects obstacles in a cone-shaped region that starts out, close to the robot, with a half-angle of about 15 degrees, and spreads outwards. An obstacle's surface characteristics, as well as the angle at which an obstacle is placed relative to the robot, significantly affect how and even whether that obstacle will be detected. Rather than assuming that SONAR sensor data is infallible, we look at multiple readings and do appropriate cross checking.

The SONAR sensors can be fooled for a number of reasons, (iROBOT 2002):

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Figure 1 - The structure for the estimation of the position, using SONAR data

- The SONAR sensor has no way of knowing exactly where, in its fifteen-degree and wider cone of attention, an obstacle actually is.
- The SONAR sensor has no way of knowing the relative angle of an obstacle.
- Obstacles at steep angles might bounce their echoes off in a completely different direction, leaving the SONAR sensor ignorant of their existence, as it never receives an echo.
- The SONAR sensor can be fooled if its ping bounces off an obliquely-angled object onto another object in the environment, which then, in turn, returns an echo to the SONAR sensor. This effect, called specular reflection, can cause errors; the SONAR sensors overestimate the distance between the robot and the nearest obstacle.
- Extremely smooth walls presented at steep angles, and glass walls, can seriously mislead the SONAR sensors.

These facts generate hard constraints in the generation of a navigation strategy and in the correct recognition of the environment. A way to avoid some of the presented problems is to build SONAR systems with multiple SONAR sensors, as the ATRV-Jr robot does, and presented in Fig.2, providing redundancy and enabling cross checking. More details on SONAR errors and solutions to correct them are described, e.g. in (Akbarally and Kleeman 1995; Budesnske and Gini, 1994; Peremans et al 1993).

Having as input the SONAR measurements, the following questions will be considered mainly:

- What is the performance of the SONAR system in terms of the estimated distances between robot and the environment's obstacles?
- Can the robot estimate the shape of the environment?
- Define ways to improve the obtained performance of the built-in SONAR system.

The result of the present investigation will be used as a reference in the evaluation of a new SONAR head based on biological principles (bat echolocation).

3. DESCRIPTION OF THE SONAR SYSTEM

The distribution of the SONAR transducers is presented in Fig. 2. The horizontal axis is considered as *x*-axis. There are 17 transducers of POLAROID type, (Polaroid, 2003), with a relatively large angle beam (15 degrees) using a carrier frequency of 50 KHz.

The considered environment is – in fact - a corner of our laboratory, with 35 marked positions. From those, the positions from 1 to 21 are reference positions. The remaining ones, from 22 to 35 positions are considered test positions. The distribution of the considered positions is presented in Fig. 3. In every position, from 1 to 35, the robot is rotating around its axis in steps of 30 degrees. For one position this result in 12 orientations. For every orientation of the robot, 11 measurements are performed with each of the 17 range sensors. From every set only one is considered using a median filtering, i.e. sorting the set of 11 measurements and keeping the 6th one.

The initial orientation of the robot is neglected in this experiment. To be able to compare the set of obtained measurements with the real environment all the measurements are reported at the horizontal axis of the environment. This is obtained by adding the initial angles to all the theta angles which correspond the all orientations of one position (site). In Fig. 4 the results of measurements for the position 2 are presented, for different modes of representations (polar and Cartesian). All range measurements are limited to a maximum value of 5 meters, in order to increase the readability of the map. This is equivalent of saying that we are not interested on what is more then 5 meters away, from the center of the robot. The measurements are from all 12 orientations, and this is the explanation of the 'star' configuration. It is interesting to see that the targets are correctly located in the field, at the small range. There are also some outliers, obtained from multiple reflections of echoes on the walls of the environment. Looking at all the positions a first conclusion can be drawn: the SONAR system reports fairly accurate measurements for close by objects but produces quite a lot of outliers.



Figure 2 - Distribution of the SONAR transducers. The beam angle is about 15 degrees





Figure 3 - The environment and the distribution of the reference positions (1:21) and test positions (22:35)



Figure 4 – A SONAR image from position 2

4. PRE-PROCESSING OF THE RAW MEASUREMENTS

By pre-processing is understood filtering of the outliers and the segmentation of the environment. In Fig. 5 is presented a SONAR image of the environment from position 8, in polar coordinates, with and without outliers. By outlier is understood a spike in the representation of the SONAR range.

Taking out the outliers is equivalent with a noise filtering operations. It is obtaining a more accurate picture (or map) of the environment. The filtering process should be tuned to the number of outliers which should be removed. The outliers were filtered by using a median filter on a window of 5 elements.



Figure 5 – Segmentation of the environment. Polar coordinates. Robot in position #8

5. RESULTS IN THE RECOGNITION OF THE ENVIRONMENT

From the 21 reference positions a data base is obtained with vectors of $(17*12) \times 21$ size, with elements ordered on theta angle. Every position has a pattern vector of $(17*12) \times 1$ size. The problem is to decide, for an arbitrary (test) position in the field, e.g. from 22 to 35, which reference positions are closest; i.e. to recognize its location within the environment. For this task a classifier based on minimum distance is used. For every test position, a distance is computed. After comparison with all the reference positions a vector of 21 distances is obtained. Sorting in ascending order of distance values and taking the first *k*-distances we can obtain an estimation of the position inside of the considered environment. In fact, this is a multi-winner problem in the sense that for each test position it is possible to have more than one solution, i.e. it is possible to have more then one reference position at equal distance from the considered test position.

In the case of a single winner position than we can go to the next problem: the estimation of the orientation with reference to the winning reference position. If there is more then one winner then putting a problem of orientation estimation it seems to not have immediately a sense. In such cases with more than one winner, the first one will be considered as reference for estimation of the orientation.

For simplicity reasons the first considered distance function was the Euclidian distance. The inputs to the classifier are the segmented range vectors, ordered on theta values. The result is a matrix of size 14×21 , which corresponds to the 14 test cases and 21 reference positions. A graphical result is presented in Fig. 6 for 4 test cases. In Table 1 the results of the classification are presented.



for some test cases

In Table 1 are shown the minimum geometric distances from the test position to the reference positions (first four).

Table 1 - Quantitative results of the classification

Case	Increasing				Increasing			
test	geometric distance				perceptual distance			
22.	2	1	3	9	2	3	8	1
23.	16	14	11	13	14	6	8	13
24.	17	13	15	14	13	21	10	18
25.	9	16	8	11	9	8	14	7
26.	3	2	4	8	2	3	4	7
27.	5	4	6	7	4	5	3	8
28.	18	7	10	6	18	13	6	14
29.	19	12	21	10	19	16	20	6
30.	2	3	8	9	2	22	3	8
31.	8	3	2	7	8	3	2	4
32.	8	9	16	11	8	14	7	9
33.	8	9	2	16	8	3	2	9
34.	16	11	14	8	14	11	10	12
35.	7	8	16	18	7	31	8	3

The results of the classifiers are slightly different and could be quantized in some coefficients, called e.g. classification rates coefficients.

The rate of absolute classification is defined as ratio of correct classifications over the number of all test cases

$$r_a = \frac{no_of_correct_answers}{no_test_cases}$$
(1)

A value of 9/14 = 0.64 is obtained. For a relative ratio of classification, defined by taking into account the correct answer from a sequence (set) of two, three and four consecutive answers from the perceptual distances, is

$$r_{r2} = \frac{13}{14} = 0.93 \tag{2}$$

These performances can be accepted as more than satisfactory. Depending on the application other rate classification definitions can be considered and evaluated.

Having such results we can say that the classification is accurate and can be used later, for other purposes like navigation. More, the estimation of orientation will be performed later.

Using quantitative results can be difficult in some cases. Another way to represent the results of classification is to draw a map of similarity, using equi-distance curves. The importance of having right similarities can be found details, e.g., (Veltkamp and Hagedoorn, 2000) and (Veltkamp 2001). Such a result is presented in Fig. 7. The representation is obtained by using the contour of the similarity function defined by

$$S(x,y) = \sum_{i} w_{i} \cdot exp\left(-\frac{(x-x_{C})^{2}(y-y_{C})^{2}}{\sigma^{2}}\right)$$
(3)

with

$$w_i \approx \frac{1}{dist(pos_ref, pos(x, y))}$$
(4)

being the weights coefficients. They are defined to be in inverse ratio with the distance from actual position of coordinates (x,y) till the reference position *pos_ref*.

These kinds of maps are good qualitative instruments for evaluating of the results of the classification based on Euclidean distance. For example, in Fig. 7, for the test case 24, the similarities in the environment are very strong. That is correctly reflected by the evolution of the distance in the corner of the environment on the right side. This is true also for the test case 27, where the similarity map reflects the similarity of the environment.

6. CONCLUSIONS

The objective of the paper was to present some results from the performance evaluation of a SONAR system, with multiple transducers. For the purpose of navigation, every site in field has two parameters: the position and the orientation of the robot in that point. In this work only positions were considered. Two kinds of representations were used: a quantitative, based on the discrete results of the classifier, and a qualitative one based on a similarity map.

ACKNOWLEDGEMENTS

The work was supported by the project CIRCE -Chiroptera-Inspired Robotic Cephaloid: a Novel Tool for Experiments in Synthetic Biology, IST-2001-35144, as a collaborative EU-project within the Proactive Initiative 2001 in Bionics entitled LIFE-LIKE PERCEPTION SYSTEMS (LPS). Financial assistance is gratefully acknowledged.



Figure 7 – Similarity maps for the test positions from 22-27

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