RECOGNITION OF CONTEXTS WITH SCANNER-LASER FOR MOBILE ROBOT NAVIGATION

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Abstract

The paper proposes the use of a scanner laser rangefinder for context detection in mobile robotics. Contexts are particular situations perceived along the execution of a task, which trigger specific actions, such as navigation behaviors. Scanner laser sensors offer accurate and comprehensive data for context detection. In particular, the approach considers range distributions for a number of sectors around the robot. This can be seen as an extension of typical sonar ring approaches, where only a range is available for each sensor. Imprecisions originated by the knowledge of the actual position and orientation of the vehicle are coped with by a fuzzy processing of the sensor data.

Keywords: Mobile robotics, laser rangefinder, perception, navigation, pattern recognition, fuzzy logic.

1 INTRODUCTION

Mobile robot applications in the real world usually involve a strong reliance on perception. The achievement of autonomy for the execution of planned tasks implies dealing with the dynamic aspects of the environment, the presence of unexpected obstacles, and the issue of self-localization.

Apart from proprioceptive devices, that provide valuable information about the vehicle's internal state (e.g., odometry), several types of sensors have been used for external perception [1]. In particular, the application of range sensors (such as ultrasonic transducers) and CCD cameras have been widely studied. Moreover, a combination of external sensors is generally necessary to compose a useful picture of the robot's surroundings.

The paper proposes an application of scanner-laser rangefinders. Although laser sensors have been used in mobile robotics for more than twenty years [3], they are currently becoming increasingly competitive in price with respect to traditional lower cost range sensors (especially, sonar rings). In intrinsically structured environments, laser rangefinders are suitable since they can provide abundant, readily available and highly reliable data in frequent scans. These are usually referred to local polar coordinates on a bidimensional plane parallel to the ground, with wide angular sweeps (of 180º or even 360º). Thus, scanner lasers have recently been used for accurate vehicle localization [4] and avoidance of both static and moving obstacles [2].

The paper addresses the problem of context recognition with range scanner-laser data. Contexts correspond to crucial points in the task of an autonomous robot, and can be determined by the perception of external and internal conditions. For instance, behavior based navigation can rely on context detection for switching behaviors. Contexts can also be used to detect points in the task where a particular action has to be performed.

Context recognition with scanner laser data consists in trying to match the set of ranges obtained by the current scan with one of several pre-recorded sets. One way to compare the scans is by using crosscorrelation between the scans but it is difficult to match scans when the position from which they were taken are not exactly the same. The problem is that reading two identical scan sets is not possible in practice. The robot can reach the context with small variations in position and orientation, which will render different, although similar, scan sets. Moreover, in a dynamic environment the current scan and the recorded scan may not be exactly the same even if obtained from the same localization. To avoid these problems histograms of scanner readings can be employed, angle histograms [5], or range histograms. The method exposed in this work is based on fuzzy range histograms**.**

2 CONTEXT RECOGNITION

While executing a task, a mobile robot may have to recognize particular localizations in the task that provide the context for associated actions to be performed. For instance, behavior based tasks consist of a sequence of control schemes that have to be activated and deactivated as context conditions are detected. Thus, a turning behavior could be activated after following a wall when a corner context is detected. Contexts may also correspond to exceptions, such as the presence of an unexpected obstacle.

Contexts can be detected by combining odometry and external sensors. Consider the example presented on Fig.1, where the robot has to turn left after finding corner B. If an ultrasonic sensor ring is used, a corner can be found by failing to read anything on the left side. But, as can be seen on the figure, similar corners exist along the path (A and B). Two solutions are possible. The first one is counting corners, so the robot would have to turn left at *the second* corner. But what if A is a door that is usually closed and has not been considered? What if specular reflections of the sonar fail to detect a portion of the wall from A to B? The second solution, in which odometry is considered, avoid those problems by specifying that the turn would have to take place at the first corner *after 7 meters*. These two solutions can be efficient for execution, but they complicate task specification.

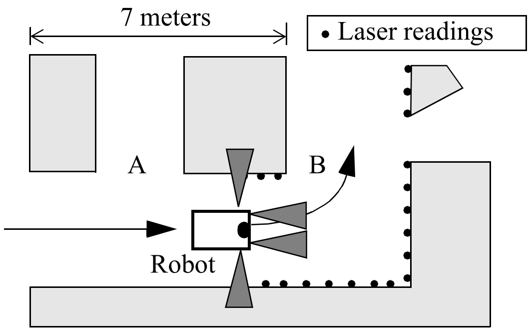


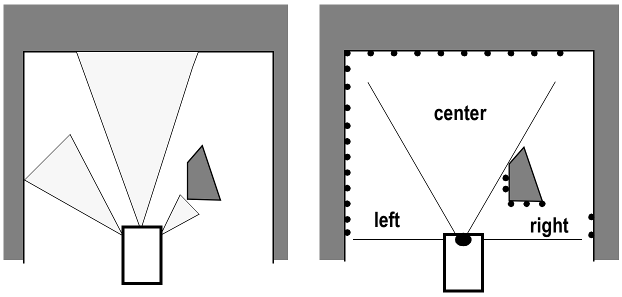
Figure 1: Similar contexts for "turning left" are discriminated with laser scanner readings.

In this sense, scanner-laser rangefinder readings offer comprehensive information about the robot's surroundings. The pattern of laser readings shown in the example of fig. 1 clearly and accurately identifies spot B. However, a geometric interpretation of the vector of scan points is not always necessary for context identification [6]. The following section describes an approach for identifying distributions of ranges aimed at the problem of context recognition.

3 RANGE DISTRIBUTIONS

The use of a distribution of ranges around the robot can be considered as an extension of the ultrasonic sensor approach. With a sonar ring, the robot can make use of a range for each transducer in the ring, which corresponds to the nearest object within the ultrasonic cone, as shown on Fig.2.a. If a scanner range-finder is used instead (for instance a 180º scan, as in fig. 2.b) the whole scan can be divided into sectors around the robot. Each of these sectors provides not only the distance to the closest object but a distribution of distances for the sector. The information contained in the distribution for each sector can be used to recognize particular contexts in the robot's path.

Consequently, an important design parameter is the number of sectors to be defined around the robot. A greater number of sectors is helpful to differentiate different contexts. However, it must be taken into account that resolution is small enough to provide a meaningful distribution for each sector.



(a) (b)

Figure 2: Range perception. a) with ultrasonic sensors.
b) with a 180º laser scan.

In any case, it must be taken into account that in practice the robot will reach a particular context with imprecision about position and orientation. Fuzzy logic can be an useful tool to process data with such imprecision.

By way of example, examine the case of Fig. 2.b. Let's consider that the target distribution of distances for all sectors has been learned as shown in the figure. What would happen when the robot arrives to that position in execution time with a slight variation in angle and position? The sensor readings for the central sector may then include a number of ranges corresponding to the obstacle close to the robot on the right. The center sector of the real and the original distributions will then be difficult to match, even if the robot localization is reasonably close to that of the target context.

This problem can be overcome by assigning a fuzzy degree of membership to each measured range, in such a way that ranges corresponding to the border of two sectors are actually considered for both of them, as shown by the membership functions in Fig. 3.

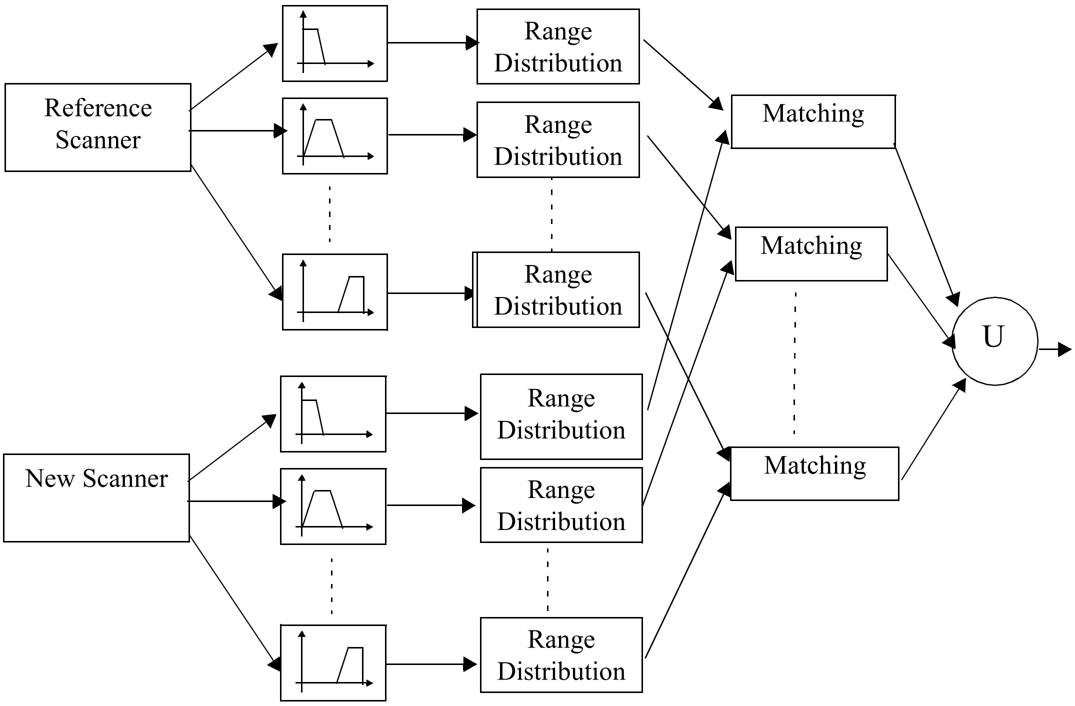


Figure 3: Membership functions for scanner data according to viewing sectors are used to match contexts.

Then, for each sector, a vector is defined whose elements represent the fuzzy occurrences for consecutive distance intervals. A set of target vectors, which represents all considered contexts, is then to be compared with actual readings during task execution.

In order to match the actual scan with a set of possible contexts, the shape of actual vector A and that of a target context T have to comply with the following condition, which is true when A and T are the same:

$$A \cup T = A \cap T$$

Where $\cup$ stands for the *max* operator and $\cap$ is implemented as the *min* operator. Then, a normalization in the range [0 1] becomes necessary for both members of the condition so that a comparison is possible.

Since exact matching is not possible on account of robot motion and odometric imprecisions, an estimation of mean square error can be computed between the maximum and the minimum. Consequently, a threshold value has to be introduced as a design parameter in order to determine if the actual position is sufficiently close to one of the target contexts. The mean square error of all sectors should be under that threshold so that the context can be recognized.

4 EXPERIMENTAL RESULTS

The method presented in the article has been tested on *Auriga*-α, an autonomous vehicle that has been designed and built by the Robotic Research Group of the System Engineering and Automation Department of the University of Málaga (Spain) for outdoor applications (see Fig 4). Auriga-α has compact dimensions: 1.23 x 0.75 x 0.84 m and its locomotion system consists of tracks instead of wheels. The vehicle movement is obtained by two independent DC motors, which provide differential steering.

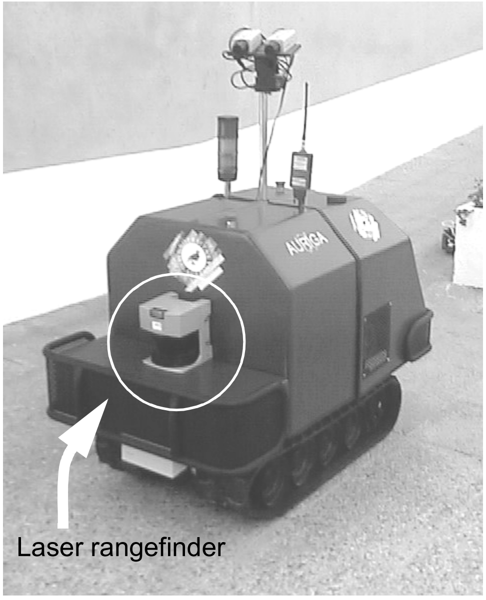


Figure 4: The *Auriga*-α mobile robot.

The mobile platform incorporates the on-board laser scanner PLS-100, which produces a two dimensional description of the environment in polar coordinates over a 180º field of view. The sensor uses reflex flight time and returns data through an RS232 interface. The sensor can reach up to 50 meters, but only measurements under 10 m have been considered. For the experiments, a resolution of 1º (that is 180 ranges) has been obtained with a scan period of 0.3 seconds.

This section presents results from three different experiments. The first one illustrates how the actual scan is matched to the target context. The second experiment consists on detecting a target context while the robot follows a planned path. The third one was made to estimate the best selection for the histogram resolution and number of sectors, as well as to make a comparative with other methods.

For the first experiment, it seems interesting to reproduce a context similar to that on the example presented in the previous section, since it is a difficult case. Figure 5 shows that target context (represented in local polar coordinates) together with an actual reading, which slightly differs in position and orientation to the target context. This scan should be matched to the context despite those imprecisions. Note how the close obstacle on the right (which was intentionally kept on the border at the right sector of the target context) lies partially on the center sector of the actual reading.

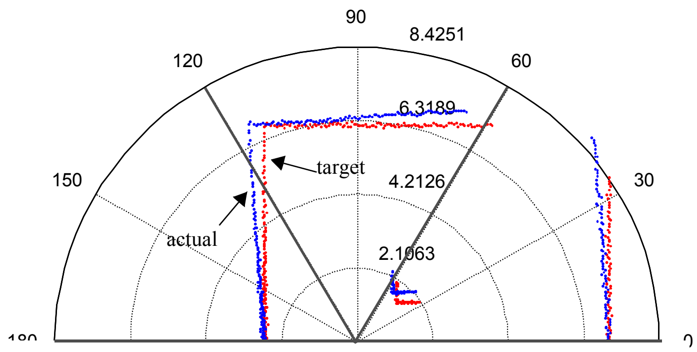


Figure 5: Actual perception is close to the target context in local polar coordinates.

Vectors of fuzzy occurrences are shown in Fig. 6 for each sector, with increments of 0.5 meters along a total distance of 10 meters. By making the sectors to be fuzzy, readings around bounds are considered for both sectors. Thus, the fuzzy distribution for the center sector has non-zero occurrences for distances of about 2 meters (the obstacle) in the target context (upper row), despite the fact that this obstacle does not actually lie on the center sector.

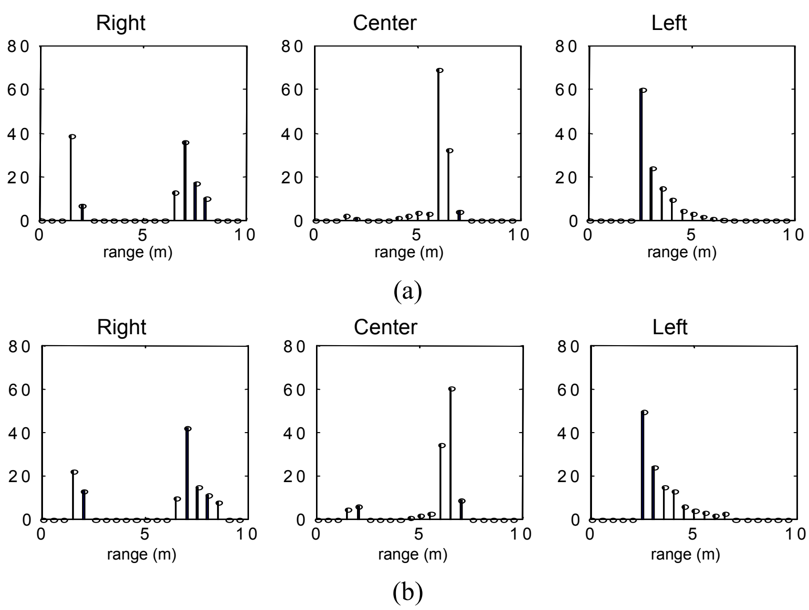


Figure 6: Range distribution for (a) target context, and (b) actual context.

Fuzzy distributions for actual readings are obtained in the same way (Fig. 6.b). Then, intersection and union are used to compare both sets of fuzzy distribution. This is implemented by applying the max and min operations to each pair of elements in the distribution vectors. The resulting min and max vectors are then normalized, as shown in Fig. 7 before they can be compared with the mean square error. It is clear from Fig. 7 that there is a close matching for the actual and target contexts in all three sectors.

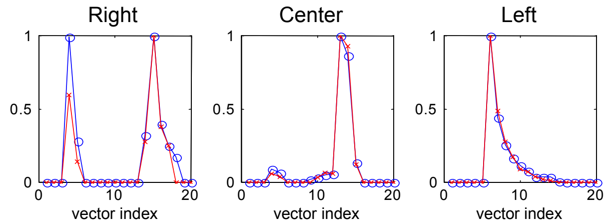


Figure 7: Normalized union (o) and intersection (x) for each fuzzy sector.

The second experiment consists on the execution of a whole path by the robot, from *A* to *B* as shown in Fig. 8. A target context has been obtained beforehand at coordinates (-5.05, 2.35) and orientation 1.43 (the corresponding localization has been represented as a circle o in Fig. 8).

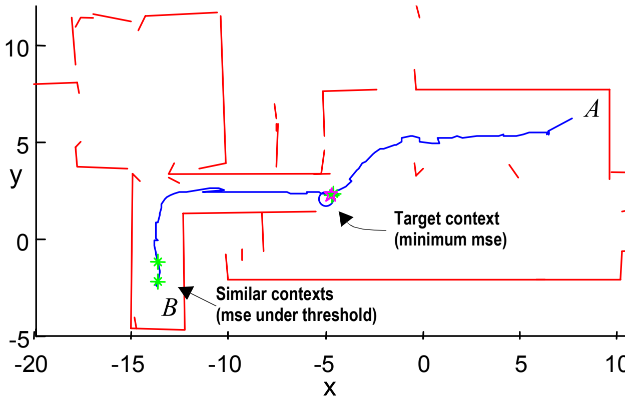


Figure 8: Robot path (from *A* to *B*) with context detection (distances are in meters).

The maximum mean square error of all three sectors is plotted in Fig. 9 for all the laser scans obtained during the execution of the path. Experimentally, a threshold of 0.06 for the mean square error has been selected for detecting the target context. Four scans have produced results under the desired threshold (represented as * in Fig. 8). The one with the least error corresponds to a localization very close to the target (coordinates (-4.7,-2.06) and orientation 1.63). Another one is the previous scan, which is situated very close to that position (coordinates (-4.61, 2.48)). However, the remaining two matches refer to positions that are different to the target, but similar in topology, as seen in Fig. 8. Obviously, context matching can be improved to a great extent if odometry is introduced to complement laser data. Accordingly, the last two matches can be discarded if a rough odometric estimation is considered.

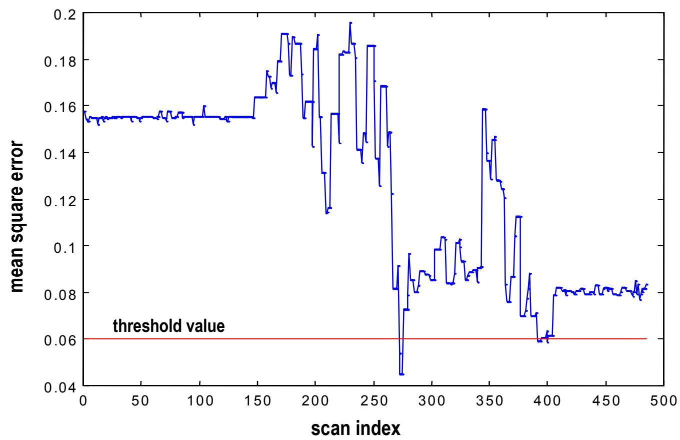


Figure 9: Mean squared error along robot's path. The maximum value of

The third experiment was made up of two executions of a task in the indoor enviroment shown in figure 10 . In the first execution 17 positions and associated scans were recorded to try to be recognized in the second execution. In the second execution all the 200 scans taken were recorded.

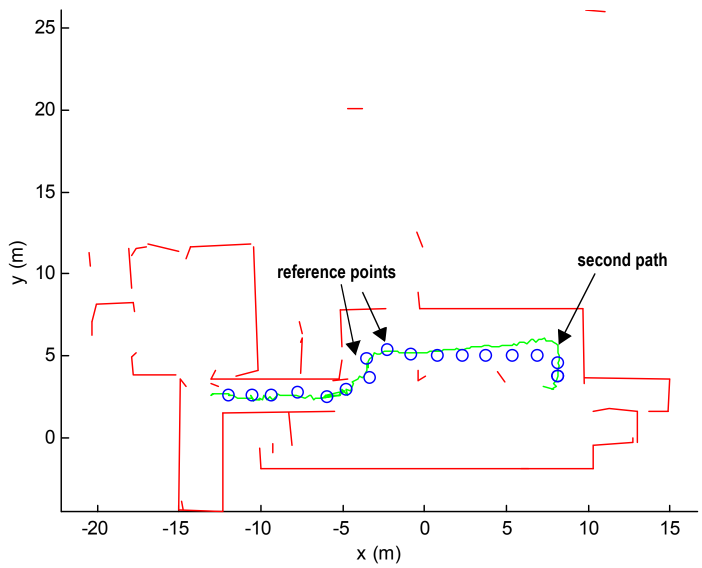


Figure 10: Reference points and second task execution.

The 17 scans of the first experiment were compared with the scans of the second execution by using different number of sectors and histogram resolution. For every case, the number of right detections and the number of mismatches were recordered. It was considered a right detection when a position recognized in the second task is closer than 0.25 m to the reference position selected from the first task. On the other hand, a mismatch occurs when the target scan is matched from a localization that is not within its 0.25 m range.

In the Figure 11 is shown the the percentage context failure in front of sectors and histogram resolution. The best result obtained is a 3% failures with 3 sectors and a resolution of 0.5 m.

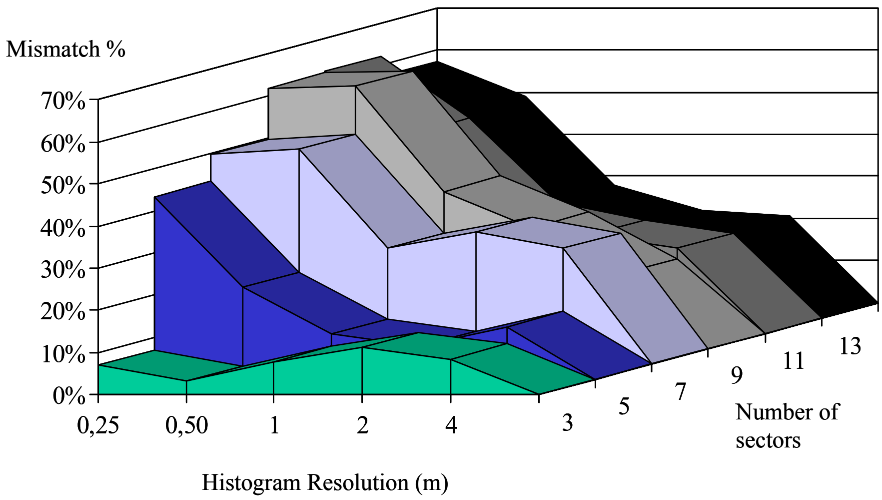


Figure 11: % Mismatches of context recognition by using fuzzy histograms.

This experiment was repeated to compare this method with another methods, such as cross correlation, angle histogram and distance histograms. To compare every case, the threshold values was selected to obtain a 90 % of right detection for every case. The results obtained are in the table 1.

Table 1: Comparative of differents methods

	Cross Correlation	Angle Histograms	Distance Histograms	Fuzzy Distance Histograms
% Mismatches for 90 % of right matches	11%	15%	6%	3%

5 CONCLUSIONS AND FUTURE WORK

The work presented in the paper approaches the problem of context recognition with scanner laser rangefinders. These sensors offer data which is too accurate to be matched in a crisp manner. The robot's motion, the scanning frequency, and odometry errors concerning position and orientation make it impossible to have two equal sets of ranges even if both are taken from almost the same position. Approximate matching has been used instead.

Furthermore, considering range distributions in local polar coordinates rather than a geometric interpretation of the data simplifies the pattern matching problem. This is suitable for cases in which an immediate response may be necessary. In this sense, similar range distributions in a number of sectors around de robot are sufficient to identify one of several expected contexts, while real-time constraints are achieved during task execution.

Fuzzy inference provides a straightforward method for matching the actual and the target distributions. However, it is still necessary to define a threshold value in order to definitely determine whether target and actual distributions are considered to be equal or not. A set of rules could be considered to ponder that threshold with additional information about the context provided by different sensors and odometry. Certainly, sensor and task status data is necessary to complement the context matching procedure, since it is possible to encounter similar contexts along the different stages of a task, as demonstrated by the experimental results presented in the paper.

Furthermore, another promising lines for future actions based on the present work can be envisaged. In the first place, other kinds of distribution instead of ranges could be studied. Particularly, a distribution of relative angles between consecutive scan points could incorporate information of actual orientation besides context recognition - similar to the angle histogram concept [5]. Secondly, this approach can be of interest for decision making in exception handling, such as when an obstacle is encountered. A perception based approach could be useful to identify some of a typical set of obstacle configurations in order to start the most appropriate avoidance strategy.

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