Relocation of a Mobile Robot Using Sparse Sonar Data

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In this paper, the relocation of a mobile robot is considered such that it enables the robot to determine its position with respect to a global reference frame without any *a priori* position information. The robot acquires sonar range data from a two-dimensional model composed of planes, corners, edges, and cylinders. Considering individual range returns as data features, the robot searches the best position where the data features of a position matches the environmental model using a constraint-based search method. To increase the search efficiency, a hypothesize-and-verify technique is employed in which the position of the robot is calculated from all possible combinations of two range returns that satisfy the sonar sensing model. Accurate relocation is demonstrated with the results from sets of experiments using sparse sonar data in the presence of unmodeled objects.

Key Words : Relocation, Robot, Sparce Sonar Data

1. Introduction

Determining the position of a mobile robot with respect to a global reference frame is a central problem in mobile robot navigation (Cox and Wilfong, 1990). Localization is the continual provision of robot's position deduced from a previous position estimation (Leonard and Durrant-Whyte, 1991). One can find a large amount of work on this kind of continuous position estimation. For long term navigation, localization, i. e., continuous position estimation alone may not be enough for position estimation, because it is strongly based on an a priori estimation of position with a dead reckoning system (e. g., an encoder system mounted on the wheels). An unexpected large amount of wheel slip when the ground condition is wet, even in indoor environments, or irregularity of the ground surface when the robot runs over a threshold of a room can cause incorrect estimation of the position.

If a mobile robot gets lost it should relocate its position for error recovery. Relocation is a different scenario from localization in that it directly measures the position in a way that is independent of previous movements (Leonard and Durrant-Whyte, 1992). The problem of relocation using sonar was first considered by Drumheller (Drumheller, 1987). He developed a search procedure for determining the robot's position based on the interpretation tree method of Grimson and Lozano-Perez (Grimson, 1990 ; Grimson and Lozano-Perez, 1984). Drumheller's approach is strongly based on the use of line segments as features that are extracted from scanning sonar data.

Kuc and Siegel (Kuc and Siegel, 1987), however, has demonstrated that in a specular wavelength regime, sonar scans should be expected to consist of circular arcs, not straight line segments. Leonard (Leonard and Durrant-Whyte, 1992) presented a simple thresholding technique for extracting these circular arc features from Polaroid sonar data. These features are called Regions of Constant Depth (RCDs). RCDs are caused by specular planes and cylinders and also by corners and edges. Since most reflective surfaces in man-

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made environments contain specular reflectors, RCDs are a more natural and useful feature for sonar data interpretation than straight-line segments. Using range information from a single sensor only, the RCD features produced by edges and corners are indistinguishable from the RCDs produced by planes. Hence, the extension to apply Drumheller's method with RCDs is not straightforward. In addition, it would be highly beneficial to develop a technique which can be applied to sparse sonar data collected by a ring of sensors instead of relying on the use of densely sampled sonar data from a rotating sensor.

The present paper addresses a limited form of the relocation problem, in which the mobile robot has an accurate, a priori map. The environment is a room or area inside a building, which can be modeled in terms of four types of geometric primitives-corner, edges, cylinders, and walls. It is also assumed that an approximate model of the objects in the environment is available in terms of these types of features. In practice, a small hole or narrow crack between two objects that is not in the model can also produce range returns. The relocation method does not rely on an exhaustively detailed model, but instead can be applied when the locations of key environmental features are known. An important characteristic of the method is that it does not need densely sampled data (e. g., from scanning sonar) from which line segments or RCDs can be extracted; rather, it can use sonar range returns individually.

This work assumes a feature-based representation of the environment. Alternative formulations of relocation and continuous localization employing grid-based representations were first considered by Moravec and Elfes (Moravec, 1989 ; Elfes, 1987), and more recently by Lim (1994), Kang and Lim (1999), and Shultz and Adams (1998).

2. Sonar Sensing Model

Because of the wide beam pattern of the Polaroid sonar, the angle to the reflection object cannot be reliably estimated from an individual return. If the echoes reflected from an object can be simultaneously detected by a multiple transducer (Barshan and Kuc, 1990), then one can also measure the direction to a reflection object. However, in the present paper, we assume that each transducer operates independently, and hence angle cannot be measured directly.

A physics-based sonar sensor model can be used to derive the geometric constraints provided by measurements for different types of objects. We assume that environmental features can be classified according to four types: planes, cylinders, corners, and edges. The world is approximated as being two-dimensional, so that planes are represented by lines, cylinders by circles, and corners or edges by points. We use the word target to refer to environmental features. In addition, we assume the surfaces of the environment are smooth in relation to the wavelength of the sonar. In a specular wavelength regime, rough surface diffraction (Bozma and Kuc, 1991a) can be ignored. If rough surfaces are encountered, extra returns will be produced at high angles of incidence from line targets; these will need to be rejected as outliers as a by-product of the constraint-based search.

Bozma and Kuc (Bozma and Kuc, 1991b) have found that with short, impulsive excitations, the beam pattern of the Polaroid transducer has a Gaussian shape and side-lobe effects are minimized. However, with the standard Polaroid driver circuit, which uses a longer transmitted pulse, side-lobe levels can be significant. While under normal circumstances a range return is produced by the main central lobe, returns can also be generated from the side lobes of the radiation pattern.

For specular surfaces, only the perpendicular portion of the surface reflects the beam directly back to the transducer (Kuc and Siegel, 1987). Let θ_s be the sensor orientation and θ_t be the angle between the x axis of the global reference frame and the line drawn from the sensor location to a target. For a line target, then, θ_t will be the angle with respect to the x axis of a perpendicular drawn from the line to the sensor location as shown in Fig. 1. The range of the values of sensor bearing, θ_s, that can produce a range return is

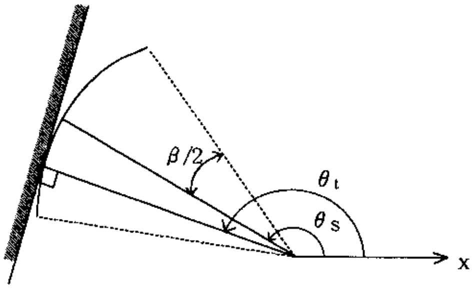


Fig. 1 Target direction and the range of visible angle for a line target, θ_s is the orientation of the sensor, and θ_t is the target direction

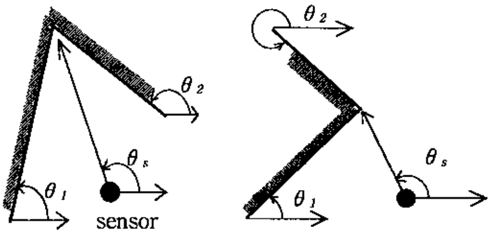


Fig. 2 Range of target directions for a point target

$$\theta_t - \frac{\beta}{2} \leq \theta_s \leq \theta_t + \frac{\beta}{2} \tag{1}$$

where β is defined as the effective beam width of the sensor and represents the maximum range of angles over which a return is produced by a target. We define Eq. (1) as the *visible angle constraint*, and θ_t as the *target direction constraint* for a line target.

For a point target such as a corner or edge, the range of values of θ_s, i.e., the visible angle constraint, is identical to Eq. (1). The target direction constraint is, however, much different from that of a line target. As shown in Fig. 2, all values of θ_t within θ_1 and θ_2 that form the corner or edge can produce a range return. Hence, the constraint for the target direction is

$$\theta_1 \leq \theta_t \leq \theta_2 \tag{2}$$

A cylinder is represented by a circle and is defined by the x and y coordinates of the center and the radius of the circle. As shown in Fig. 3, θ_t for a cylinder is defined as the angle between the x-axis of the global reference frame and the line drawn from the sensor location to the center

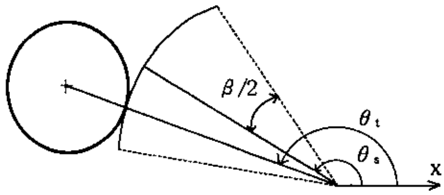


Fig. 3 Target direction and the range of visible angle for a cylinder

of the cylinder. The visible angle constraint is also identical to Eq. (1), but unlike a line or point target, no constraints for target direction are necessary because the cylinder can produce a range return in any direction as long as the visible angle constraint is satisfied. One could readily amend the model to include partial cylindrical surfaces that do not extend a full 360 degrees.

Consequently, visible angle constraints for all geometric primitives are identical to Eq. (1), but the target direction constraints, i.e., the range of θ_t, are different (normal direction to the target for a plane, Eq. (2) for point targets, and no constraint for cylinder target). In our sensing model, we assume that an unoccluded target produces a range return only if the target direction constraint and the visibility angle constraint are satisfied.

3. Relocation

Relocation is basically a searching problem that finds the best correspondence between sensor data and the model features. Thus the reduction of the search cost as well as the accuracy of the result is very important. If we have m data features (sonar returns) and n model features, the search cost will grow at the rate of $(n+1)^m$ when we use the basic interpretation tree algorithm of Grimson and Lozano-Perez (Grimson and Lozano-Perez, 1984).

In Drumheller's work, line segments extracted from sonar scans were effectively used as constraints for relocation. A line segment can reduce dramatically both the search cost and the angle uncertainty of the robots configuration. As stated earlier, however, it is impossible to extract line segments from sparse data at one position in a specular environment.

The relocation method presented here is strongly based on the sonar sensing model presented in Sec. 2 in a hypothesize-and-verify search procedure (Grimson, 1990). The algorithm does not require that line segments or RCDs be extracted from densely sampled sonar data. Instead, individual sonar returns are considered as a data feature.

3.1 Search of trial positions (Hypothesize procedure)

The first step of the relocation is to search all possible trial positions using the range returns at the current position. Let R_i be i-th range return originated from the i-th sensor, and F_p be the p-th model feature in the environment. For any two returns R_i and R_j, we consider all possible ways of pairing the returns with targets F_p and F_q, i.e., sets of pairing R_i:F_p and R_j:F_q. If we have m range returns and n targets, the maximum number of pairing will be $\frac{m(m-1)(n(n-1)}{4}$. The actual number of pairings, however, will be lower than the maximum number, because any pairings which employ parallel line targets that would produce zero or infinitely many trial positions are discarded.

Each pairing generates zero, one, or two possible positions of the robot. Suppose F_p and F_q are lines (plane features). This pairing can generate zero or one possible position of the robot, as illustrated in Fig. 4. In the figure, L_i or L_j is the line that represents the possible location of the robot considering only R_i or R_j respectively. The possible location of the robot, therefore, would be the intersecting point P of the two lines when we consider the two ranges together. This point P is considered to be a trial position that might be the robot's current position.

If the target F_q is a corner or edge, the possible location of the robot would be a circle whose center is the point that defines the point target, and radius is R_j as shown in Fig. 5. A point target can produce 0, 1 or 2 trial positions when pairing another target. Similarly to a point target, a cylinder generates a circle for possible location of the robot; the radius of the circle is the sum of the R_j and the radius of the cylinder. It can also give 0, 1 or 2 trial positions when paired with another target.

The trial position generated in this way does not always satisfy the physical constraint of the sonar sensing model. Therefore, such a false trial position is removed by using the target direction and visibility angle constraints and occlusion test defined in Sec. 2. Also, the trial angle for each trial position that satisfies the constraints is estimated. Suppose we have the pairings R_i:F_p and R_j:F_q, and F_p is a line and F_q an edge as shown Fig. 6. The orientation of the robot, θ_{oi}, is calculated by making the direction R_i coincide with the target direction of the line target F_p. Likewise, θ_{oj} is calculated by making the direction R_j coincide with the target direction of the line target F_q. These angles are used to perform target direction, visibility angle and occlusion tests for the two ranges. If the tests are successful, the

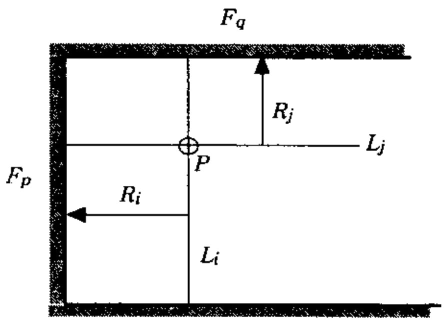


Fig. 4 A possible trial position P hypothesized from the match of return R_i with a line target F_p and return R_j with a line target F_q

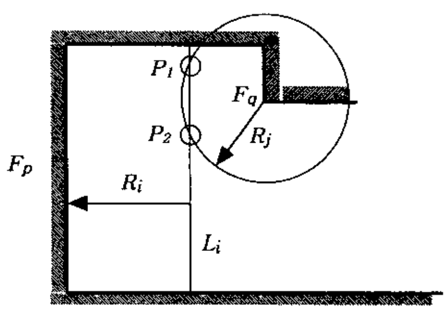
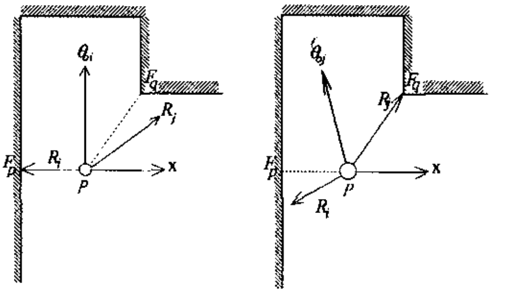


Fig. 5 Possible trial positions P_1 and P_2 hypothesized from the match of return R_i with a line target F_p and return R_j with a point target F_q



(a) (b)

Fig. 6 Possible orientations of the robot for a trial position P. (a) θ_{oi} is the orientation of the robot calculated by making the direction R_i coincide with the target direction of the line target F_p. (b) θ_{oj} is calculated from R_j and F_q in the same manner.

average angle of the two θ_{oi} and θ_{oj} is chosen as the trial angle for the trial position.

3.2 Position estimation (Verify procedure)

The other ranges except R_i and R_j are matched against the targets based on each trial position and angle. For each sensor k, a possible range $\hat{R_k}$ is generated directly using the sonar sensing model. If the occlusion test is satisfied, $\hat{R_k}$ is then compared with the actual range $\hat{R_k}$ of sensor k. An error range R_e is used to determine the correspondence between generated and actual ranges, i. e.,

$$\hat{R_k} - R_k \leq R_e \tag{3}$$

If Eq. (3) holds true, we get a successful match. The value of R_e is chosen based on the range accuracy of the sensor and the uncertainty of the trial position.

By performing the matching process for each trial position, we count the number of ranges that match against the targets for each trial position. Among the trial positions, the one that gives the maximum number of matches is selected as the robots current position and orientation. If more than one position has the maximum number of matches, and if they all fall within a specified error range (x_e, y_e, θ_e), then we simply average these positions.

Occasionally, all the best match positions do not fall in the error ranges. In this case, they are clustered into groups according to the position and angle considering the error ranges, and the number of positions in each group are counted. If there is again more than one group of which the number of positions is maximum, then relocation is considered to have been unsuccessful, and the algorithm reports failure. If not, we choose the group which has the maximum number, and average the positions and angles of the trial positions in the group to find the robots position and orientation.

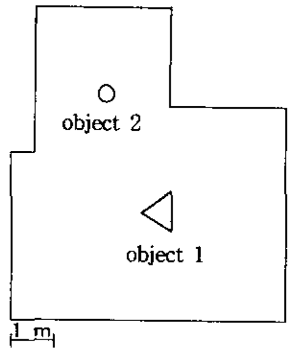


Fig. 7 Outline of the room. Small cracks between objects were not modeled

4. Experimental Results

The algorithm described above has been implemented on a Nomad Scout robot equipped with a ring of 16 sonar sensors spaced at 22.5-degree angular intervals. Due to a restriction in the robot communications software, the range resolution of the sonar data is 0.025 m. This may limit the accuracy of the results but does not detract from the viability of the method. Sonar range values were obtained from the room of which the outline is shown in Fig. 7. The objects in the room are paper boxes, desks, a cylinder and triangular shaped object made of metal. Narrow cracks between some of the objects are not modeled. The robot's actual position was estimated by using the initialization technique for model-based localization method described by Leonard (Leonard and Durrant-Whyte, 1992); it is accurate to within 0.02 meters and about 2 degrees. The program parameters used in this paper were $\beta=50$ degrees, $x_e=0.1$ m, $y_e=0.1$ m,

Table 1 Results of relocation at 83 test positions (x,y : m θ : deg.)

error range	x, y<	0.02	0.06	0.1	0.1	failure	known failure
	θ<	2	6	10	15		
positions		24	67	78	83	0	0
%		29	81	94	100	0	0

Table 2 Results of relocation with some unexpected object (x,y : m θ : deg.)

error range	x, y<	0.02	0.06	0.1	0.1	failure	known failure
	θ<	2	6	10	15		
positions		27	67	78	82	1	0
%		32	81	94	98.8	1.2	0

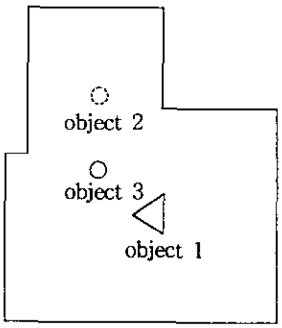


Fig. 8 Environmental model for testing the effects of the appearance of an unmodeled object and a non-existence object. Object 2 was present but was not modeled, and object 3 was modeled but did not exist

$\theta_e = 10$ degrees, and $R_e = 0.1$ m.

We have tested the algorithm for 83 different positions in the room, and the results of the relocation are shown in Table 1. The estimated positions (x, y) are fairly accurate in spite of the low resolution (0.025m) of the sensor measurements. The angle errors are, however, comparatively large. This is because both the effective beam width of the sensor and the angular interval of the sampled data are large.

To test the effect of the appearance of unknown objects, we did not model some of the objects (object 1 and 2 in Fig. 7) in the environment. Table 2 displays the performance of the relocation method. One can see that the results are not much different from those of Table 1. In addition,

Table 3 Results of relocation with an unexpected object and a phantom object (x,y : m θ : deg.)

error range	x, y<	0.02	0.06	0.1	0.1	failure	known failure
	θ<	2	6	10	15		
positions		28	63	70	73	3	7
%		33	76	84	88	3.6	8.4

Table 4 Summary of relocation results

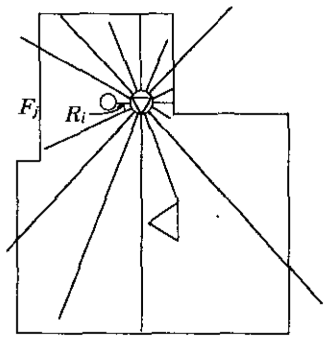
parameters		table 1	table 2	table 3
mean	x(m)	0.012	0.013	0.013
	y(m)	0.016	0.016	0.0149
	θ(deg.)	2.77	2.865	2.38
standard deviation	x(m)	0.009	0.012	0.011
	y(m)	0.014	0.014	0.015
	θ(deg.)	3.72	3.82	3.43

* Mean and standard deviation are estimated except failures and known failures

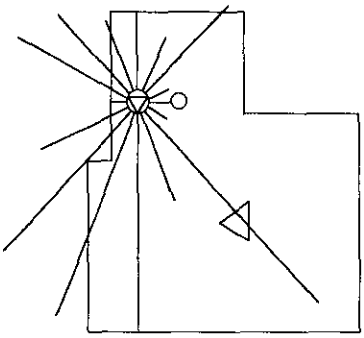
the sonar data sets were reprocessed with one non-existent feature placed in the model at an erroneous location and with one actual feature not contained in the model as shown in Fig. 8. Table 3 illustrates that the algorithm continues to work fairly well in this situation. A Summary of the relocation results are shown in Table 4.

At 7 positions for Fig. 8, the algorithm reported known failure; two groups, i.e., two estimated positions, persisted till the end of the relocation step. Figure 9 shows an example of a known failure. 21,655 trial positions were hypothesized, and 343 positions among these passed the target direction, visible angle, and occlusion tests. Of these 343 positions, the figure shows two of the positions that matched the highest number of returns (9 out of 16).

One might think that an additional physical constraint such as the sonar barrier test employed by Drumheller (1987) can eliminate false estimates. We believe, however, that the sonar barrier test is not a good constraint because it can work only when the angle uncertainty is very low and the modeled target is not removed. For example, suppose the cylinder in Fig. 9 was modeled but



(a) Estimated position 1 (good)



(b) Estimated position 2 (false)

Fig. 9 Configurations of the robot and range returns at the position where the relocation method failed

removed out of the room later; the sensor that produced R_i will detect the wall F_j. As a result, the estimated position will be eliminated even though R_{13} is correct, because it will not pass the sonar barrier test.

Consequently, we can conclude that the algorithm is robust in the presence of unexpected or non-existence features if they do not change the major configuration of the environment. The program was run on an IBM compatible Pentium PC (330 MHz). The average run time was about 0.7 seconds for each position calculation.

5. Conclusions

A method for mobile robot relocation using sonar has been implemented and tested with real data obtained in an indoor environment. Since most object surfaces in an indoor environment are specular, it is difficult to extract line segments reliably in typical indoor environments using data obtained from only one position. While an approach based on circular arc features (regions of constant depth) would agree more with a physics-based sensor model (Kuc and Siegel, 1987), it is still unattractive for a robot to stop and wait to acquire densely sampled scans with a single rotating sonar. The algorithm presented in this paper does not attempt to extract features from sonar scans. Instead, it uses the range returns themselves to define simple geometric constraints that can be used to guide a constraint-based search.

The two key ideas of the approach are the physics-based sensor model to define the geometric constraints, and the use of a hypothesize-and-verify technique to control the search complexity. Trial positions and orientations of the robot are calculated by considering all possible pairs of range values and model primitives that satisfy the geometric constraints. This results in a considerable reduction of search cost. Among all possible trial positions, the algorithm determines the position that produces the best correspondence between the environment and the measurements. The algorithm has been successfully implemented with real data, and turned out to be very efficient even in the presence of some unknown or unmodeled objects.

An important objective for future research is to integrate the above relocation method with concurrent mapping and localization. This can provide a means of error recovery for a mobile robot building a map of an unknown environment while simultaneously using that map to navigate.

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