Qualitative Navigation by Sensor Centric Landmark Tracking *

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Abstract: Sensor based navigation is a fundamental competence for any mobile robot. The essential problem with conventional statistical approaches to the navigation problem is the requirement for maintaining an exact global description of environment geometry. In practise the behaviour of real physical sensors and the observations they make of the environment make such central geometric representation of the environment extremely fragile.

To overcome such problems, this paper proposes the use of qualitative models of physical sensor observations. These aim to describe the world in terms of local sensor-centric representations of the *observed* environment. Each representation exploits those landmarks most natural to the physical sensor involved. No global description of the environment is maintained and no explicit geometric representation of the world is assumed. This leads naturally to a navigation process defined in terms of relationships between different sensor observables; an intrinsically more robust mechanism than found in conventional navigation algorithms.

The representation and navigation methodology proposed is illustrated using sonar data from a real vehicle.

1 Introduction

Often metrical information (from either sensory cues or models) is either incomplete, inaccurate or hard to interpret, and navigation using purely quantitative techniques is fragile [2, 6]. Quantitative models tend to produce either descriptions which are too accurate for the task at hand or, in the case when information is incomplete, no descriptions at all. For these approaches, robust navigation is possible only when the robot is able to construct accurate geometric models appropriate to the detail of its sensing information. A qualitative description of the processes can be sufficient to constrain the robot to perform to a certain specification (e.g. avoid collisions and move along a corridor) without over constraining and forcing the robot to follow exacting metrical descriptions. However, qualitative descriptions can be ambiguous. In such circumstances quantitative information can be used to constrain the models further.

The choice of landmark is dependent on the nature of the physical sensor employed. This is because different modalities detect different significant features in the environment. Furthermore, the significant features observed by a sensor are rarely those that one might expect from a visual analysis of the coarse geometry of an environment. It is important, therefore, to avoid the use of a central composite geometric representation of the environment. A more natural approach is a sensor centric representation of qualitative sensor data where each modality maintains its own qualitative representation of a subset of landmarks significant to its sensory processes.

Qualitative navigation, where the emphasis is on building, maintaining and planning with topological descriptions of the environment, have been studied [1, 5]. These approaches generally rely on the identification of distinctive objects (landmarks) in the environment which are either individual features or places. These are interconnected by procedural information describing travel routes between them. Navigation involves the determination of the robot's position in its environment and the construction of plans which take the robot to its goal destinations. Further, for a robot with no knowledge of the structure of its environment, it must construct and maintain a map.

The approach described here, that sensor behaviours are inferred from physical properties of the sensor processes, differs from previous approaches (for example [5]). We will show how a robot equipped with range sensors can infer the qualitative behaviours of its sensor cues, build qualitative maps for environments comprised of indistinct reflectors (i.e. features with no significant differentiating characteristics) and show how these maps can be used in navigation. We illustrate our approach to navigation in the sonar sensing domain. In Section 2 we introduce a qualitative model of the sonar. In Section 3 we present a qualitative model of how sonar cues are related to odometric

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(translational motion) and gyrometric (rotational motion). In Section 4 we show how these models can be used to derive the rules of navigation using QSim and, finally, in Section 5 we show how the robot can path plan using its map and derived knowledge of the behaviour of sensor cues. Throughout we will refer to a real robot application and illustrate the approach using real data.

2 The Sonar Model

For a typical in-air sonar there is no obvious direct correspondence between the environment and the recorded range measurements. Figure 1, for example, shows a sonar scan of a simple environment. However, from this scan it can be seen that the range measurements for reflections perpendicular to the walls at a, b, c and d in the figure, the edge at e and corners at f, g and h are in close correspondence to distance between the sensor at + and the reflectors. Further, range values are equal over a range of bearings each side of these points. This phenomenon has been noted by [3] and [6] and the latter has coined the phrase the region of constant depth (RCD). An RCD is a contiguous sequence of bearings with equal range values (RCD formations in the sonar map for a room in Figure 1 and a robot at '+', are shown in bold). They are formed because the sonar beam is wide and during a sweep scan a tiny part of the reflector is visible over a finite sequence of bearings. Since the sonar wavelength is large compared to reflector surface fluctuations walls behave like specular (i.e. mirror like) objects. Imagine walking through the room depicted in Figure 1. When walking towards location Y, for example, the RCD at a would move abreast of the observer. The edge at h would appear to move away from the observer.

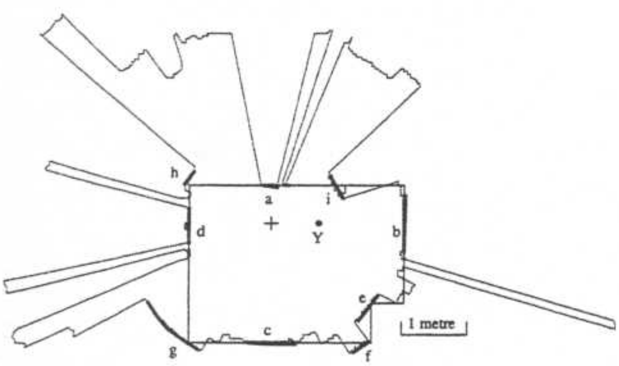


Figure 1: Range-bearing plot with overlaid environment

As a robot moves through the environment the RCDs move predictably. RCDs formed by reflections from walls move tangentially with the wall and abreast of the robot. Corner and edge RCDs rotate about the point of reflection. This is apparent in Figure 2 which shows the overlay of a set of RCDs taken from various positions in the environment. What is evident here is that the door-frame at i which is not an obviously significant feature in a global geometric map, is the most significant feature to a sonar. Conversely, the wall at c is significant in geometric terms, but is very weak to a sonar. Leonard [6] demonstrates how a robot can

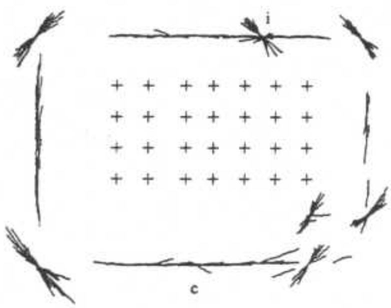


Figure 2: Accumulated RCDs from 24 scan positions

navigate by tracking RCDs as the robot moves. The essential point here is that the information obtained by a sonar does not correspond well with the underlying geometry of the environment. However, the information (i.e. RCDs) are predictable and have motion patterns which are well understood consequences of the underlying physics of the sensing process. In Section 3 we show how RCD range and bearing information to the same feature at different locations can be related to the robot's translational and rotational speed by two ordinary differential equations.

3 The Qualitative Model

Leonard [6] introduces a unified description of plane, edge and corner sonar reflectors. This is the generalised cylinder in which planes are cylinders with infinite radius and edges and corners are cylinders with zero radius. Equations 1 and 2 relate the radius of

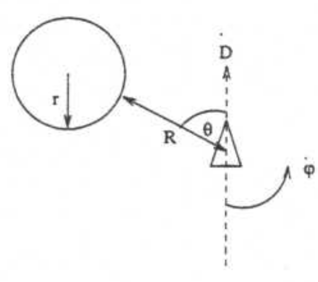


Figure 3: System geometry

a cylinder r and the perpendicular distance from its surface R to a robot moving with translational speed $\frac{dD}{dt}$ and rotational speed $\frac{d\phi}{dt}$ (see Figure 3).

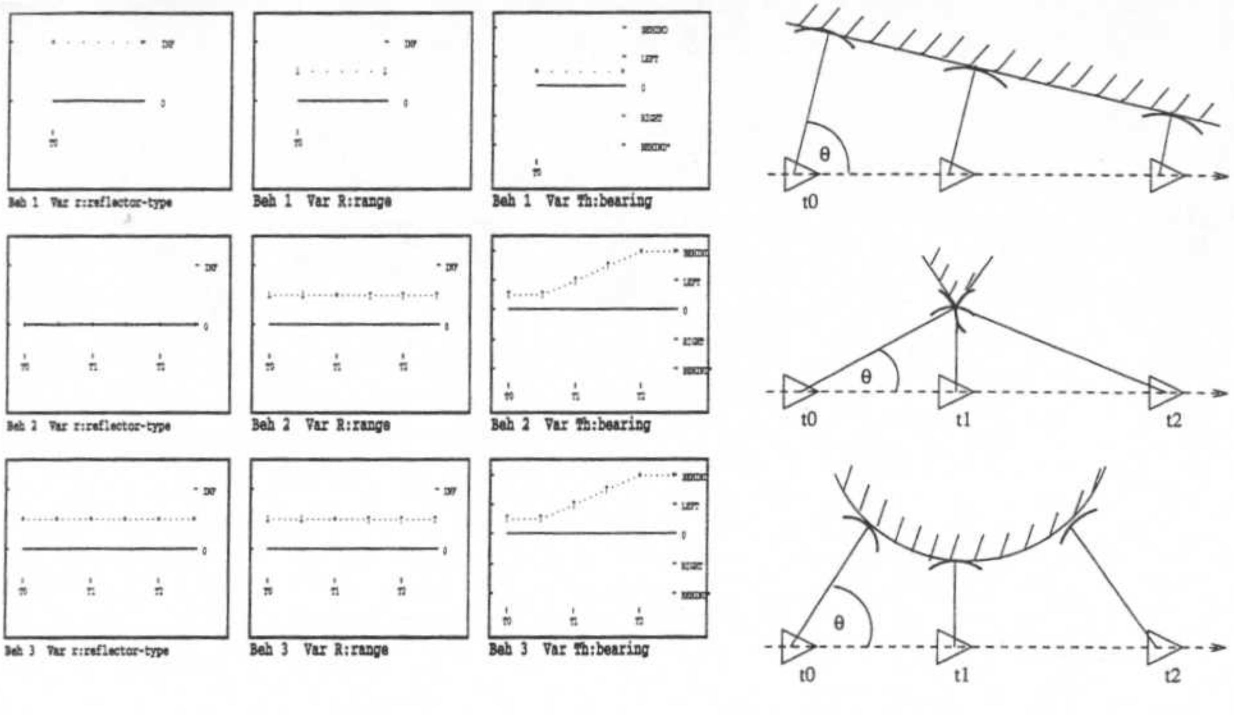


Figure 4: QSim generated behaviours

$$\frac{dD}{dt} sin\theta = (R + r)\frac{d(\theta + \phi)}{dt} \tag{1}$$

$$\frac{dD}{dt} cos\theta = -\frac{d(R + r)}{dt} \tag{2}$$

These equations form the basis for qualitative navigation. From these we can use qualitative simulation to construct a set of qualitative rules which can be used to constrain the qualitative interpretation of sensor measurements.

QSim [4] is used to generate the qualitative behaviours from qualitative descriptions of the continuously differentiable equations governing the system. We shall use the notation $< Qv\ Qd >$ to denote a qualitative variable with value Qv and derivative Qd. To implement the interpretation of qualitative sensor cues, QSim was extended to deal with persistently infinite variables. QSim treats infinities as point values and, therefore, a variable cannot remain at infinity and be decreasing simultaneously. It is not possible to represent plane reflectors in such a system since $(R+r)$ in Equations 1 and 2 is infinite but not necessarily constant. In general, we want to allow behaviours for $A(t)$ when $A(t) = lim_{x\to\infty} X + B(t)$ and $A(t)$ remains infinite but $\dot{B}(t) < 0$ or $\dot{B}(t) > 0$. This is achieved by allowing the infinity landmarks to be both successors and predecessors of themselves in QSim quantity spaces.

Each variable in Equations 1 and 2 is assigned *sensor centric landmarks*. The angle type landmarks characterise orientation: *left*, *forward*, *right* and *behind*. The quantity spaces are shown in table 1. The zero angle landmark means *forward* in QSim notation. The reflector type landmarks 0 and inf denote edges (and corners) and planes respectively.

Range R	{ 0, inf }
Reflector bearing θ	{ behind*, right, 0, left, behind }
Travel bearing ϕ	{ behind*, right, 0, left, behind }
Reflector type r	{ 0, inf }
Travel distance D	{ 0, inf }

Table 1: Sensory modality quantity spaces.

Figure 4 shows the qualitative behaviours obtained from Equations 1 and 2 for a robot moving with zero angular velocity (i.e. $\phi =< 0\ std >$) towards a plane and past a cylinder and an edge. The top three graphs in Figure 4 (*beh1*) show the qualitative behaviour for the case of the plane RCD. In the top left graph *beh1-var-r:reflector-type*, the generalised cylinder radius is infinite and steady corresponding to a plane reflector. Graph *beh1-var-R:range* shows that the range value decreases and graph *beh1-var-Th:bearing* shows us that the bearing θ to the plane remains constant. For plane reflectors the RCD moves tangentially to the reflector and abreast of the robot and this is the reason why θ, in this case, is constant.

The second row of graphs (*beh2*) describe the behaviour of an edge (or corner) RCD. In the middle left graph *beh1-var-r:reflector-type*, the generalised cylinder radius is zero and steady corresponding to an edge reflector. In *beh2-var-R:range* we see that the range gradually decreases until some time point $t1$ and then increases indefinitely. This corresponds to a robot moving towards a point like object fixed in space, passing close to it and then moving away from it. In graph *beh2-var-th:bearing* we can see that this RCD moves gradually further to the left and then recedes behind. The third row of graphs shows the RCD behaviour *beh3* for an arbitrary cylinder of finite radius.

In general, purely qualitative information is insufficient to differentiate reflector types for small odometric displacements. It is impossible to determine, for example, whether a change in bearing is due to the motion of an edge or noisy data from a plane reflection. However, numerical information can be used to distinguish these cases. Using Q2 [4] we can estimate numerical bounds for future bearing readings from current values for each type of reflector and thus disambiguate the types of observed reflectors. This is crucial for navigation by feature tracking.

4 Sensor Centric Navigation

In the previous section we demonstrated that a robot can predict the behaviour of its sensor cues from a qualitative model of the sensor. In this section we emphasise that this mechanism can be used in path planning. From the current state the robot can infer a sensor centric behavioural description of its motion towards a goal state. We illustrate this by showing how a robot can plan qualitatively to pass between two objects by predicting its sensor cue behaviours under the constraint that collisions should be avoided (i.e. R=0 is a QSim unreachable condition).

Figure 5 shows a plane (P) lying initially *frontal-left* and a narrow cylinder (C with $r = 0$) lying to the *frontal-right* of the robot. The goal is to pass between both objects without colliding with either. The goal state is that the plane is *left-rear* and the cylinder is *right-rear*. We build a combined two object qualitative differential equation from Equations 1 and 2 in which both range-bearing pairs are related by shared translational and rotational speed variables. We constrain the envisionment further by insisting that the speed and angular velocities remain constant, that the robot turns to the right and that it passes between the cylinder and the plane (i.e. by insisting that θ_1 remains negative).

Figure 6 shows one of the many behaviours generated by QSim. The robot would expect to observe decreasing range cue values to both the cylinder and the plane initially (i.e. in graphs *R1:range* and *R2:range* $R_1 = R_2 =< (0\ inf)\ dec >$) in the time interval ($t0\ t1$)). The bearing of both features would gradually increase until the robot finds itself at its closest approach to both features simultaneously (i.e. where the range values are steady at $t1$). At this stage the plane would be parallel to the direction of motion since

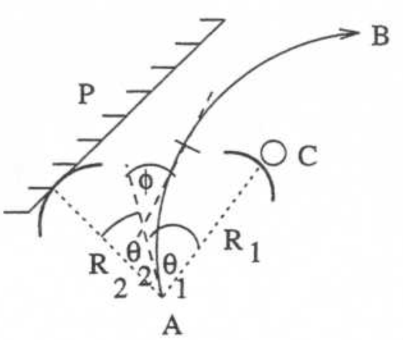


Figure 5: System geometry

$\theta_2 = left$. The robot would then observe R_1 and R_2 begin to increase and $\theta_2 =< (behind\ left)\ inc >$ indicating that it has turned away from the plane and is moving away from both objects. In summary, this is a specification of a path which allows the robot to safely navigate between the plane and the cylinder by keeping the cylinder to its right and the plane to its left.

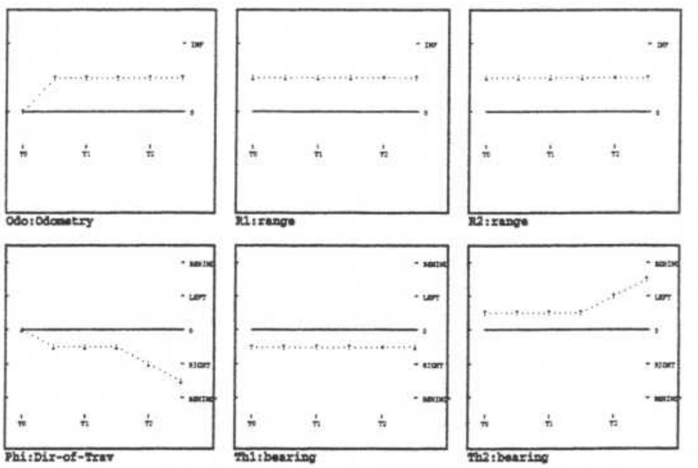


Figure 6: QSim generated behaviours

In the next section we develop a global spatial representation and we will show how the mechanism described in this section can be utilised in conjunction with the spatial map for path planning.

5 Map Building and Navigation

The approach presented in this paper gives an insight into how sensor centric qualitative maps can be derived by a mobile robot equipped with qualitative information of how its sensory cues are inter-related. Map building is necessary for determining position relative to some goal location (this is the referencing problem). Qualitative map building and navigation have been studied. Kuiper's [5] approach maintains a network description of distinct places in the environment. Distinctiveness measures are metrical and are not invariant within the boundaries of the distinct place. An example of a distinctiveness measure is the range and bearing information measured from a point from which there is an equal distance to near objects. Inter-region travel paths are encoded as procedural information between nodes (e.g. move along object on left). Dai and Lawton [1] describe an algorithm for region acquisition and robot navigation using visual sensors. Their approach requires either the presence of distinctive landmarks in the environment or a compass. For the case of compass-less navigation distinctive regions are separated by *landmark boundary pairs* (LBP). For example, in Figure 7, the LBP 'a to b' distinguishes two regions X and Y on either side. When a is observed to be to the left of b (written a-b) the robot is in region X. Distinctive LBP regions are identified by the conjunction of all LBPs between locally observed features and the LBP signature is invariant within the LBP region. The robot navigates by following LBPs.

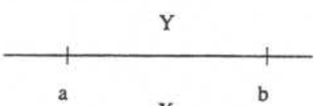
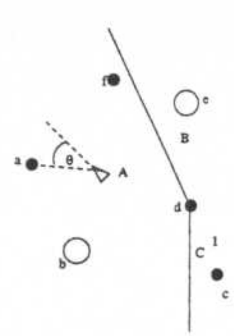


Figure 7: LBP regions

RCDs have no clear individual distinguishing characteristics and so a distinctive landmark approach is not feasible in the ultrasonic sensing domain. However, the positional relationship between RCDs does allow a distinctive place formalism. We define a *generalised cylinder centre (GCC) region* (see Section 3) as that spatial area in which the orientational ordering of a set of landmarks is invariant. The distance ratios between orientationally neighbouring RCDs are invariant within the GCC region and this can be used to define a referential signature for the region. The distances between neighbouring GCCs can be determined from range sensor information using the cosine rule.

$$\Delta_{i,j}^2 = (R_i+r_i)^2+(R_j+r_j)^2-2(R_i+r_i)(R_j+r_j)cos\theta_{i,j}$$

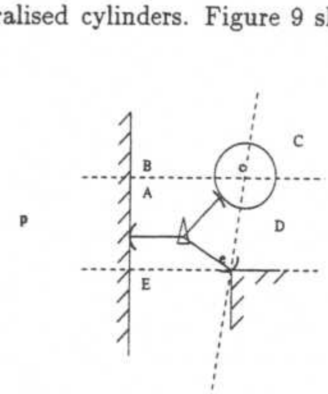
where r_i, r_j are the hypothesised reflector generalised cylinder radii and R_i, R_j and $\theta_{i,j}$ are the range and bearing information. In the example in Figure 8 a, b, c, d, e, f are edges or cylinders [1]. In region A, for example, the reflectors are ordered in decreasing bearing θ: $a \succ b \succ c \succ d \succ e \succ f$. The relative distances between adjacent features is $\Delta_{b,c} \succ \Delta_{f,a} \succ \Delta_{a,b} \succ \Delta_{d,e} \succ \Delta_{e,f} \succ \Delta_{c,d}$.



Region	Bearing order	GCC Signature
A	a b c d e f	4 6 1 3 2 5
B	a b d c e f	3 5 1 6 2 4
C	a b c e d f	3 5 6 1 2 4

Figure 8: Qualitative region signatures

The referencing problem is solved by matching equivalent GCC signatures. Two GCC regions are equivalent if one is a cyclic permutation of the other. Hence, a robot can determine its GCC region irrespective of its orientation or position within the region. Further, signature matching between GCC regions automatically gives the pairwise matching of reflectors between scans. This paves the way for the extension of the LBP approach to the sonar range domain. We define the LBP with respect to the centres of the reflector generalised cylinders. Figure 9 shows a cylinder, edge and a plane reflector with LBPs through



Region	LBP signatures
A	p-c, c-e, e-p
B	c-p, c-e, e-p
C	c-p, e-c, e-p
D	p-c, e-c, e-p
E	p-c, c-e, p-e

Figure 9: LBP regions. Hashed lines are LBPs.

[1] Since for planes the generalised cylinder radius $d = \infty$ and since environments comprise alternating planes and corners generally, planes reduce the uniqueness of GCC signature. Planes are therefore not included in the signature.

the centres of the generalised cylinders. These LBPs divide the space into LBP regions A, B, C, D and E.

The spatial map is a network of range sensor cue nodes containing information gathered at locations within the environment. The inter-node links represent motional (translational and rotational) cues between locations. Each node describes an LBP region and the sub-network of neighbouring nodes with similar GCC signatures describe the GCC region. Each

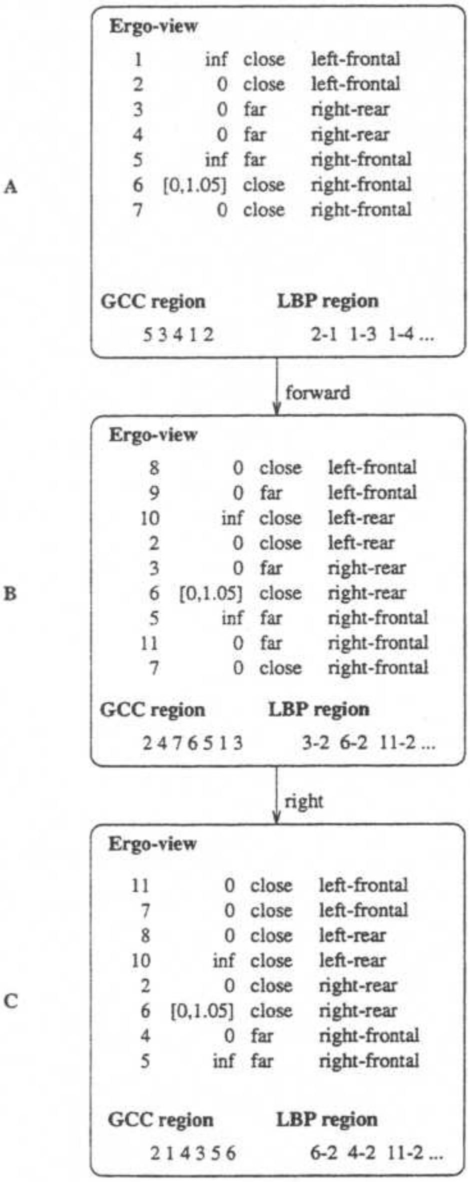


Figure 10: Spatial map

node comprises the LBP region and GCC region signatures and an *ergo-view* which is a qualitative description of the range and bearing to local reflectors for a specific robot position and orientation. Qualitative values are assigned to ranges according to the average range to local reflectors. Ranges greater than the average in the ergo-view correspond to 'far' objects and those less than the average are 'close' objects. This description is invariant about a finite region around the robots actual position. The ergo-view is a list of quadruples. Each quadruple contains a global map index value for the reflector, the type of reflector (or in the case of a cylinder, a range of numeric values binding its radius estimated from range and bearing information using Q2) and an ergo-view. The example spatial map in Figure 10 shows the qualitative map constructed as the robot moves through locations A, B and C in the environment depicted in figure 11. Figure 12 shows the range sensory data at each of these locations.

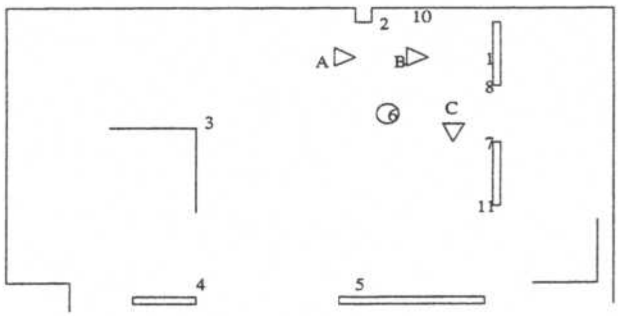


Figure 11: Example environment

In Section 4 we demonstrated how a robot can use qualitative simulation to predict how its sensory cues behave while moving between locations. This, in conjunction with the spatial map, can be used by the robot to plan paths to goal states. The spatial map describes how to move from one LBP region to the next and also specifies how the range sensor cues should behave in the process. For example, when moving between locations B and C in Figure 11 the robot should move according to the following criteria:

Keep turning to the right allowing the edge reflector (8) to move to the left-rear quadrant but keeping the cylinder reflector (6) close and to the right-rear ...

However, the robot is generally never in the configuration specified in the ergo-view. As demonstrated in Section 4, QSim can be used to derive the actions required by the robot to take it from its current sensory cue specification to that of the ergo-view. Thus, it is possible that an adequate qualitative path can be composed from a novel set of sensory descriptors which take the robot into a familiar LBP node followed by a sequence of nodes which take the robot to its goal destination. This is ongoing research.

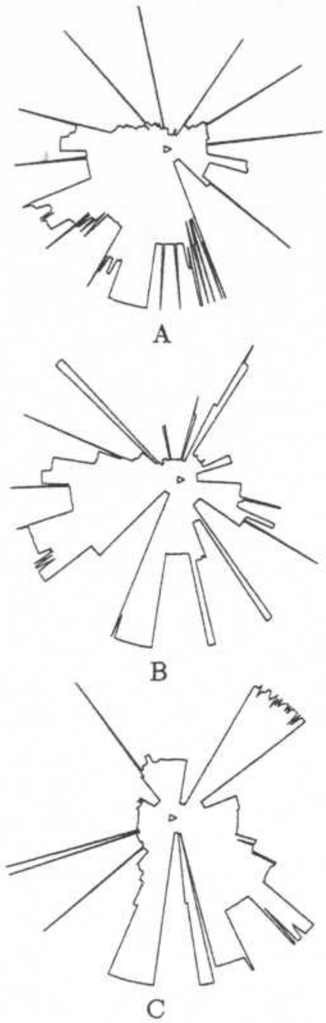


Figure 12: Example cartesian range-bearing plots.

6 Conclusion

We have shown that a robot can construct qualitative models of its sensing cues from physical descriptions of its sensing processes. We have shown how these sensor centric models can be used in the map building and navigation tasks.

Acknowledgements

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