Qualitative Reasoning with Visibility Information for Environmental Learning

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1. Introduction

We investigate environmental learning and navigation capabilities based on qualitative observations and formal spatial reasoning. Our approach is based on previous work in the area of qualitative navigation (Davis 1983, Schlieder 1993, Wagner et al. 2004) in which a classification of perceptions into qualitative categories is used to derive a decomposition of space leading to a graph-based representation of the environment called topological map. As described in Kuipers (2000), the use of topological map is motivated by a cognitively inspired approach to robot navigation that requires to execute a sequence of local behaviors in order to reach a target position. In Fogliaroni et al. (2009) we described a novel qualitative approach able to explore, navigate and build a topological map of an unknown environment based on a model of visibility between extended objects. We now extend the visibility model into a qualitative spatial calculus to apply qualitative spatial reasoning techniques (Cohn and Hazarika 2001). This allows us to employ formal spatial reasoning to improve map learning and navigation.

2. Visibility-based Navigation

The visibility model underlying our work is an extension of the visibility model presented in Tarquini et al. (2007). It defines five qualitative ternary relations describing the relationship between an observed object A and an observer object C with object B seen as an obstacle. The definitions are based on the acceptance zones defined by the frame of reference (FoR) depicted in Figure 1. The FoR is inspired by work of Billen and Clementini (2004) in that it relies on the internal and external tangents between objects B and C. The distinguished relations are:

$$Visible : V(A,B,C) \iff A \subseteq LZ(B,C) \quad (1)$$
$$PartiallyVisible^{Left} : L(A,B,C) \iff A \subseteq TZ^{Left}(B,C) \quad (2)$$
$$PartiallyVisible^{Right} : R(A,B,C) \iff A \subseteq TZ^{Right}(B,C) \quad (3)$$
$$PartiallyVisible^{Joint} : R(A,B,C) \iff A \subseteq TZ^{Joint}(B,C) \quad (4)$$
$$Occluded : O(A,B,C) \iff A \subseteq SZ(B,C) \quad (5)$$

In addition to these five elementary relations, the overall set of base relations also contains relations in which A intersects several acceptance zones. These relations can be expressed as matrices as in Goyal and Egenhofer (2001). We will here write these complex relations as conjunctions of the elementary ones, e.g., L ∧ J.

The FoRs induced by all pairs of objects split the plane into zones as shown in Figure 2. The topological map is directly derived from this decomposition as depicted in Figure 3. The zones can be distinguished and recognized by the visibility relations holding between the perceived objects. We, hence, label each zone or node in the topological map with a string representation called VCO (Visual Cyclic Ordering) of the visibility relations holding for that zone (explained further in Section 4.1).

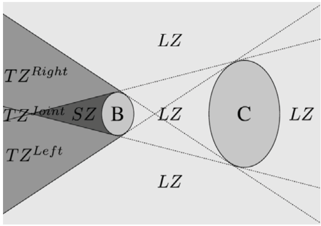

Figure 1. Acceptance areas underlying the visibility model.

Knowing the topological map of an environment, an autonomous agent is able to navigate in a qualitative manner based on the VCOs. In addition, it is possible to learn the topological map by exploring the environment and processing changes in the perceived VCOs. However, a limiting factor so far has been that the agent does not know when its topological map is complete.

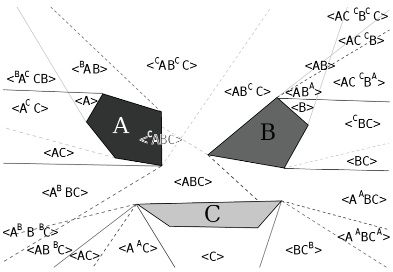

Figure 2. Space subdivision.

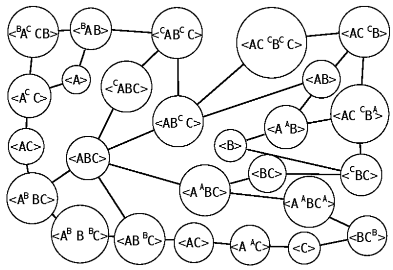

Figure 3. Topological map.

3. Reasoning about Visibility

To develop the visibility model into a qualitative spatial calculus and use it for spatial reasoning, we need to define two kinds of algebraic operations for the visibility relations: unary operations for changing the order of objects in a relation tuple and operations for composing information from two relations. To generate all permutations of ternary relation tuples, a permutation and a rotation operation are needed:

$$r(A,B,C) \rightarrow p(A,C,B) \qquad \textit{(permutation)} \quad (6)$$
$$r(A,B,C) \rightarrow q(C,A,B) \qquad \textit{(rotation)} \quad (7)$$

The permutation and rotation operations are specified in Table 1. We here restrict us to elementary relations, leaving out complex relations in which an object overlaps several acceptance areas. One observation is that the operations yield rather unspecific results and, hence, have rather weak algebraic properties leading to information loss. A consequence of this is that for the composition operations we need to specify and use all six possible composition operations as we cannot generate the other cases by employing the permutation operations. We here only give one of these composition tables (see Table 2), which we will need later on:

$$r_1(A,B,C) \circ r_2(A,D,B) \rightarrow r_3(D,B,C) \qquad \textit{(composition)} \quad (8)$$

Algebraic closure (i.e., applying the composition operations until a fixpoint has been reached) can be used to deduce new information about the involved objects as we will demonstrate in the following.

Table 1. Permutation and rotation operations.

r(A,B,C)	p(A,C,B) (permutation)	q(C,A,B) (rotation)
V	V,L,J,R,O	V,L,J,R,O
L	V	V
J	V	V
R	V	V
O	V	V

Table 2. Table for one of the six possible composition operation.

$r_1 \backslash r_2$	V	L	J	R	O
V	V,L,J,R,O	V,L,O	V,L,R,O	V,R,O	V
L	V,L,J,R,O	L,O	L,O	L	L
J	V,L,J,R	R,J	L,J,R,O	L,J	J
R	V,L,J,R,O	R	R,O	R,O	R
O	V,L,J,R,O	O	O	O	O

4. Reasoning for Map Learning

We now show how compositional reasoning based on the operations defined in the previous section can be exploited for map learning. The general approach is to use constraint propagation based on the composition operations to narrow down the relations between all objects and zones as much as possible to derive information about the configuration of objects. As we will show in a simple example, this information allows for drawing conclusions about the existence of zones without visiting them and to recognize when the exploration is complete, a significant improvement over the original approach. For this, we first need to be able to map perceptions given in the form of VCOs to visibility relations and vice versa.

4.1 From VCOs to Visibility Relations and back

Every zone of the topological map represents the intersection of several acceptance areas for different pairs of reference objects. As explained in Fogliaroni et al. (2009), a VCO label can be derived for each zone directly from the acceptance areas constituting the zone or, alternatively, from the panoramic view of surrounding objects for every point in the zone. The VCO lists object identifiers in a base-exponent fashion. All non-occluded objects are listed in a clockwise cyclic order as bases. Partially visible objects are also listed as exponents beside the object that occludes them. Some VCO examples are <A B C> (A,B,C are completely visible), <A ^{A}B C> (B partially occludes A from the right, B and C are completely visible) and <A ^{A}B^{A} A C> (B occludes the central part of A, B and C are visible). From a specific label VCO_R, we can generally infer visibility relations occurring between zone R and some objects in the plane. We here only give one example of this mapping instead of a full table: If

VCO_R=<A ${}^{A}B^{A}$ A C>, one can infer the relations V(R,A,B), V(R,A,C), J(R,B,A), V(R,B,C), V(R,C,A), V(R,C,B).

A new result is that one can also use knowledge about the visibility relations between objects to rule out possible VCOs and, hence, nodes in the topological map. Table 3 contains the mapping from visibility relations to patterns that cannot occur in the VCOs if this relation holds.

Table 3. Impossible VCO substrings given a visibility relation.

V(A,B,C)	L(A,B,C)	J(A,B,C)	R(A,B,C)	O(A,B,C)
-	...C ^{C}A... ...A ^{A}C... ...C ${}^{C}A^{C}$ C... ...A ${}^{A}C^{A}$ A...	-	... A^{C} C... ... C^{A} A... ...C ${}^{C}A^{C}$ C... ...A ${}^{A}C^{A}$ A...	...C ^{C}A... ...A ^{A}C... ... A^{C} C... ... C^{A} A... ...C ${}^{C}A^{C}$ C... ...A ${}^{A}C^{A}$ A...

If we assume that the set $\mathcal{O} = \{O_1, O_2, \cdots, O_n\}$ is the set of known objects, $\mathcal{V} = \{VCO_1, VCO_2, \cdots, VCO_p\}$ is the set of all possible VCOs given $\mathcal{O}$, and $\mathcal{V}_{\mathcal{K}} = \{VCO_1, VCO_2, \cdots, VCO_q\}$ is the set of all VCOs that actually occur given a concrete spatial configuration $\mathcal{K}$ for $\mathcal{O}$. The more relations we can derive that describe the actual configuration $\mathcal{K}$, the more VCOs we can rule out from $\mathcal{V}$ and by this get closer to $\mathcal{V}_{\mathcal{K}}$. Moreover, when all the remaining regions have been visited, we know that the exploration is complete.

4.2 Example

Figure 4 depicts a scenario in which a robot is exploring an unknown environment containing (among others) the three obstacles B, C and D.

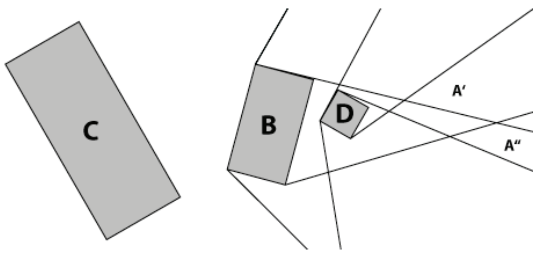

Figure 4. Example configuration.

During the exploration, the robot passes through zones A' and A". In A' the VCO is <B ${}^{B}D^{B}$ B^{C} C> while in A" it is <C ^{C}B ${}^{B}D^{B}$ B>. As described in Section 4.1, it is possible to infer the following relations:

$$L(A', B, C) \quad (9)$$
$$J(A', D, B) \quad (10)$$
$$R(A'', B, C) \quad (11)$$
$$J(A'', D, B) \quad (12)$$

We now compose these relations to derive information about the configuration of B, C, D. For the composition, we use a version of the composition table in Table 2 in which the entries also contain possible complex relations. Composing (9) with (10) and (11) with (12) yields the following results about the relation for (D,B,C):

$$\{L\} \circ \{J\} \Rightarrow \{L, O, L \wedge O\} \tag{13}$$
$$\{R\} \circ \{J\} \Rightarrow \{R, O, R \wedge O\} \tag{14}$$

Combining this information by taking the intersection results in a single relation, namely *O(D,B,C)*. Knowing now that B occludes C from D (and vice versa) allows us to use Table 3 to deduce that no zones with substrings from {$C\ {}^{C}A$, $A\ {}^{A}C$, $A^{C}\ C$, $C^{A}\ A$, $C\ {}^{C}A^{C}\ C$, $A\ {}^{A}C^{A}\ A$} in their VCOs are possible.

Exploiting this kind of compositional reasoning to the full extent will at some point allow the conclusion that the entire topological map has been learned and yield complete qualitative information about the arrangement of objects.

5. Conclusions

We defined algebraic operations for a set of visibility relations between extended objects. We then described how qualitative spatial reasoning based on these operations improves environmental learning capabilities of an autonomous agent in the context of a qualitative mapping and navigation approach. We expect that a similar improvement is possible wrt. the agent's navigational abilities which will be a topic for future research. The next step will be to derive and verify tables for the complete set of composition operations and implement a full spatial reasoning system utilizing all operations for constraint propagation.

Acknowledgements

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References

Billen R and Clementini E, 2004, A model for ternary projective relations between regions. In: Bertino E (eds), *EDBT2004 - 9th International Conference on Extending DataBase Technology*, 310–328.

Cohn AG and Hazarika SM, 2001, Qualitative Spatial Representation and Reasoning: An Overview. *Fundamenta Informaticae*, 46(1-2):1–29.

Davis E, 1983, The MERCATOR representation of spatial knowledge. In: Bundy A (eds), *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*, 1:295–301.

Fogliaroni P, Wallgrün JO, Clementini E, Tarquini F and Wolter D, 2009, A qualitative approach to localization and navigation based on visibility information. In: Hornsby KS, Claramunt C, Denis M and Ligozat G (eds), *Proceedings of the 9th International Conference on Spatial Information Theory, 312–329.*

Goyal RK and Egenhofer MJ, 2001, Similarity of Cardinal Directions. In: *Advances in Spatial and Temporal Databases*, 36–58.

Kuipers BJ, 2000, The spatial semantic hierarchy. *Artificial Intelligence*, 119:191–233.

Schlieder C, 1993, Representing visible locations for qualitative navigation. In: Carreté NP and Singh MG (eds), *Qualitative Reasoning and Decision Technologies*, 523–532.

Tarquini F, De Felice G, Fogliaroni P and Clementini E, 2007, A Qualitative Model for Visibility Relations. In: Hertzberg J, Beetz M and Englert R (eds), *Proceedings of the 30th annual German Conference on Advances in Artificial Intelligence,* 510–513.

Wagner T, Visser U and Herzog O, 2004, Egocentric qualitative spatial knowledge representation for physical robots. *Robotics and Autonomous Systems, 49*:25–42.