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Proximity in Context: an empirically grounded computational model of proximity for processing topological spatial expressions*

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Abstract

The paper presents a new model for context-dependent interpretation of linguistic expressions about spatial proximity between objects in a natural scene. The paper discusses novel psycholinguistic experimental data that tests and verifies the model. The model has been implemented, and enables a conversational robot to identify objects in a scene through topological spatial relations (e.g. “X near Y”). The model can help motivate the choice between topological and projective prepositions.

1 Introduction

Our long-term goal is to develop conversational robots with which we can have natural, fluent situated dialog. An inherent aspect of such situated dialog is reference to aspects of the physical environment in which the agents are situated. In this paper, we present a computational model which provides a context-dependent analysis of the environment in terms of *spatial proximity*. We show how we can use this model to ground spatial language that uses topological prepositions (“the ball near the box”) to identify objects in a scene.

Proximity is ubiquitous in situated dialog, but there are deeper “cognitive” reasons for why we need a context-dependent model of proximity to facilitate fluent dialog with a conversational robot. This has to do with the cognitive load that processing proximity expressions imposes. Consider the examples in (1). Psycholinguistic data indicates that a spatial proximity expression (1b) presents a heavier cognitive load than a referring expression identifying an object purely on physical features (1a) yet is easier to process than a projective expression (1c) (van der Sluis and Krahmer, 2004).

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- (1) a. the blue ball
- b. the ball near the box
- c. the ball to the right of the box

One explanation for this preference is that feature-based descriptions are easier to resolve perceptually, with a further distinction among features as given in Figure 1, cf. (Dale and Reiter, 1995). On the other hand, the interpretation and realization of spatial expressions requires effort and attention (Logan, 1994; Logan, 1995).

Similarly we can distinguish between the cognitive loads of processing different forms of spatial relations.

Focusing on static prepositions, topological prepositions

have a lower cognitive load than projective prepositions. Topological prepositions (e.g. “at”, “near”) describe proximity to an object. Projective prepositions (e.g. “above”) describe a region in a particular direction from the object. Projective prepositions impose a higher cognitive load because we need to consider different spatial frames of reference (Krahmer and Theune, 1999; Moratz and Tenbrink, 2006). Now, if we want a robot to interact with other agents in a way that obeys the Principle of Minimal Cooperative Effort (Clark and Wilkes-Gibbs, 1986), it should adopt the simplest means to (spatially) refer to an object. However, research on spatial language in human-robot interaction has primarily focused on the use of projective prepositions.

We currently lack a comprehensive model for topological prepositions. Without such a model,

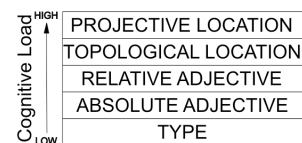


Figure 1: Cognitive load

a robot cannot interpret spatial proximity expressions nor motivate their contextually and pragmatically appropriate use. In this paper, we present a model that addresses this problem. The model uses energy functions, modulated by visual and discourse salience, to model how spatial templates associated with other landmarks may interfere to establish what are contextually appropriate ways to locate a target relative to these landmarks. The model enables grounding of spatial expressions using spatial proximity to refer to objects in the environment. We focus on expressions using topological prepositions such as “near” or “at”.

Terminology. We use the term **target** (T) to refer to the object that is being located by a spatial expression, and **landmark** (L) to refer to the object relative to which the target’s location is described: “[The man]_T near [the table]_L.” A **distraCTOR** is any object in the visual context that is neither landmark nor target.

Overview §2 presents contextual effects we can observe in grounding spatial expressions, including the effect of interference on whether two objects may be considered proximal. §3 discusses a model that accounts for all these effects, and §4 describes an experiment to test the model. §5 shows how we use the model in linguistic interpretation.

2 Data

Below we discuss previous psycholinguistic experiments, focusing on how contextual factors such as distance, size, and salience may affect proximity. We also present novel examples, showing that the location of other objects in a scene may interfere with the acceptability of a proximal description to locate a target relative to a landmark. These examples motivate the model in §3.

1.74	1.90	2.84	3.16	2.34	1.81	2.13
2.61	3.84	4.66	4.97	4.90	3.56	3.26
4.06	5.56	7.55	7.97	7.29	4.80	3.91
4.47	5.91	8.52	○	7.90	6.13	4.46
3.47	4.81	6.94	7.56	7.31	5.59	3.63
3.25	4.03	4.50	4.78	4.41	3.47	3.10
1.84	2.23	2.03	3.06	2.53	2.13	2.00

Figure 2: 7-by-7 cell grid with mean goodness ratings for the relation *the X is near O* as a function of the position occupied by X.

Spatial reasoning is a complex activity that in-

volves at least two levels of processing: a *geometric level* where metric, topological, and projective properties are handled, (Herskovits, 1986); and a *functional level* where the normal function of an entity affects the spatial relationships attributed to it in a context, cf. (Coventry and Garrod, 2004). We focus on geometric factors.

Although a lot of experimental work has been done on spatial reasoning and language (cf. (Coventry and Garrod, 2004)), only Logan and Sadler (1996) examined topological prepositions in a context where functional factors were excluded. They introduced the notion of a **spatial template**. The template is centred on the landmark and identifies for each point in its space the acceptability of the spatial relationship between the landmark and the target appearing at that point being described by the preposition. Logan & Sadler examined various spatial prepositions this way. In their experiments, a human subject was shown sentences of the form “the X is [relation] the O”, each with a picture of a spatial configuration of an **O** in the center of an invisible 7-by-7 cell grid, and an **X** in one of the 48 surrounding positions. The subject then had to rate how well the sentence described the picture, on a scale from 1(bad) to 9(good). Figure 2 gives the mean goodness rating for the relation “near to” as a function of the position occupied by X (Logan and Sadler, 1996). It is clear from Figure 2 that ratings diminish as the distance between X and O increases, but also that even at the extremes of the grid the ratings were still above 1 (min. rating).

Besides distance there are also other factors that determine the applicability of a proximal relation. For example, given prototypical size, the region denoted by “near the building” is larger than that of “near the apple” (Gapp, 1994). Moreover, an object’s salience influences the determination of the proximal region associated with it (Regier and Carlson, 2001; Roy, 2002).

Finally, the two scenes in Figure 3 show interference as a contextual factor. For the scene on the left we can use “the blue box is near the black box” to describe object (c). This seems inappropriate in the scene on the right. Placing an object (d) beside (b) appears to interfere with the appropriateness of using a proximal relation to locate (c) relative to (b), even though the absolute distance between (c) and (b) has not changed.

Thus, there is empirical evidence for several



Figure 3: Proximity and distance

contextual factors determining the applicability of a proximal description. We argued that the location of other distractor objects in context may also interfere with this applicability. The model in §3 captures all these factors, and is evaluated in §4.

3 Computational Model

Below we describe a model of relative proximity that uses (1) the distance between objects, (2) the size and salience of the landmark object, and (3) the location of other objects in the scene. Our model is based on first computing absolute proximity between each point and each landmark in a scene, and then combining or overlaying the resulting absolute proximity fields to compute the relative proximity of each point to each landmark.

3.1 Computing absolute proximity fields

We first compute for each landmark an *absolute proximity field* giving each point’s proximity to that landmark, independent of proximity to any other landmark. We compute fields on the projection of the scene onto the 2D-plane, a 2D-ARRAY of points. At each point P in ARRAY, the absolute proximity for landmark L is

$$prox_{abs} = (1 - dist_{normalised}(L, P, ARRAY)) * salience(L). \quad (1)$$

In this equation the absolute proximity for a point P and a landmark L is a function of both the distance between the point and the location of the landmark, and the salience of the landmark.

To represent distance we use a normalised distance function $dist_{normalised}(L, P, ARRAY)$, which returns a value between 0 and 1.¹ The smaller the distance between L and P , the higher the absolute proximity value returned, i.e. the more acceptable it is to say that P is close to L . In this way, this component of the absolute proximity field captures the gradual gradation in applicability evident in Logan and Sadler (1996).

¹We normalise by computing the distance between the two points, and then dividing this distance it by the maximum distance between point L and any point in the scene.

We model the influence of visual and discourse salience on absolute proximity as a function $salience(L)$, returning a value between 0 and 1 that represents the relative salience of the landmark L in the scene (2). The relative salience of an object is the average of its visual salience (S_{vis}) and discourse salience (S_{disc}),

$$salience(L) = (S_{vis}(L) + S_{disc}(L))/2 \quad (2)$$

Visual salience S_{vis} is computed using the algorithm of Kelleher and van Genabith (2004). Computing a relative salience for each object in a scene is based on its perceivable size and its centrality relative to the viewer’s focus of attention. The algorithm returns scores in the range of 0 to 1. As the algorithm captures object size we can model the effect of landmark size on proximity through the salience component of absolute proximity. The discourse salience (S_{disc}) of an object is computed based on recency of mention (Hajicová, 1993) except we represent the maximum overall salience in the scene as 1, and use 0 to indicate that the landmark is not salient in the current context.

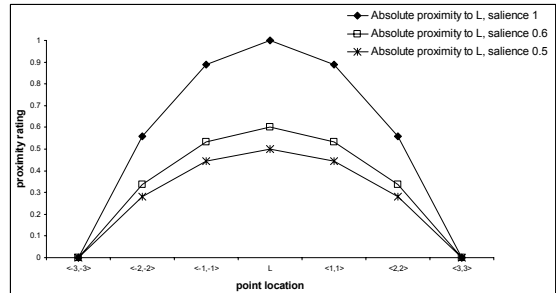


Figure 4: Absolute proximity ratings for landmark L centered in a 2D plane, points ranging from plane’s upper-left corner ($\langle -3, -3 \rangle$) to lower right corner ($\langle 3, 3 \rangle$).

Figure 4 shows computed absolute proximity with salience values of 1, 0.6, and 0.5, for points from the upper-left to the lower-right of a 2D plane, with the landmark at the center of that plane. The graph shows how salience influences absolute proximity in our model: for a landmark with high salience, points far from the landmark can still have high absolute proximity to it.

3.2 Computing relative proximity fields

Once we have constructed absolute proximity fields for the landmarks in a scene, our next step is to overlay these fields to produce a measure of

relative proximity to each landmark at each point. For this we first select a landmark, and then iterate over each point in the scene comparing the absolute proximity of the selected landmark at that point with the absolute proximity of all other landmarks at that point. The relative proximity of a selected landmark at a point is equal to the absolute proximity field for that landmark at that point, minus the highest absolute proximity field for any other landmark at that point (see Equation 3).

$$prox_{rel}(P, L) = prox_{abs}(P, L) - \underset{\forall L_X \neq L}{MAX} prox_{abs}(P, L_X) \quad (3)$$

The idea here is that the other landmark with the highest absolute proximity is acting in competition with the selected landmark. If that other landmark’s absolute proximity is higher than the absolute proximity of the selected landmark, the selected landmark’s *relative* proximity for the point will be negative. If the competing landmark’s absolute proximity is slightly lower than the absolute proximity of the selected landmark, the selected landmark’s *relative* proximity for the point will be positive, but low. Only when the competing landmark’s absolute proximity is significantly lower than the absolute proximity of the selected landmark will the selected landmark have a high relative proximity for the point in question.

In (3) the proximity of a given point to a selected landmark rises as that point’s distance from the landmark decreases (the closer the point is to the landmark, the higher its proximity score for the landmark will be), but *falls* as that point’s distance from some other landmark decreases (the closer the point is to some other landmark, the lower its proximity score *for the selected landmark* will be). Figure 5 shows the relative proximity fields of two landmarks, L1 and L2, computed using (3), in a 1-dimensional (linear) space. The two landmarks have different degrees of salience: a salience of 0.5 for L1 and of 0.6 for L2 (represented by the different sizes of the landmarks). In this figure, any point where the relative proximity for one particular landmark is above the zero line represents a point which is proximal to that landmark, rather than to the other landmark. The extent to which that point is above zero represents its degree of proximity to that landmark. The overall proximal area for a given landmark is the overall area for which its relative proximity field is above zero. The left and right borders of the figure represent

the boundaries (walls) of the area.

Figure 5 illustrates three main points. First, the overall size of a landmark’s proximal area is a function of the landmark’s position relative to the other landmark and to the boundaries. For example, landmark L2 has a large open space between it and the right boundary: Most of this space falls into the proximal area for that landmark. Landmark L1 falls into quite a narrow space between the left boundary and L2. L1 thus has a much smaller proximal area in the figure than L2. Second, the relative proximity field for some landmark is a function of that landmark’s salience. This can be seen in Figure 5 by considering the space between the two landmarks. In that space the width of the proximal area for L2 is greater than that of L1, because L2 is more salient.

The third point concerns areas of ambiguous proximity in Figure 5: areas in which neither of the landmarks have a significantly higher relative proximity than the other. There are two such areas in the Figure. The first is between the two landmarks, in the region where one relative proximity field line crosses the other. These points are ambiguous in terms of relative proximity because these points are equidistant from those two landmarks. The second ambiguous area is at the extreme right of the space shown in Figure 5. This area is ambiguous because this area is distant from both landmarks: points in this area would not be judged proximal to either landmark. The question of ambiguity in relative proximity judgments is considered in more detail in §5.

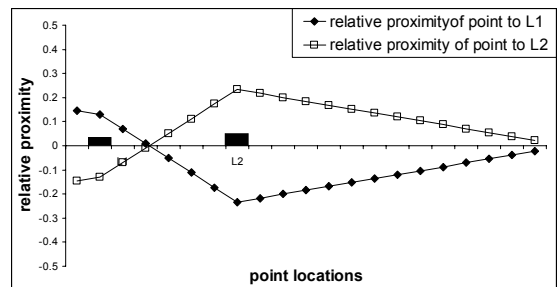


Figure 5: Graph of relative proximity fields for two landmarks L1 and L2. Relative proximity fields were computed with salience scores of 0.5 for L1 and 0.6 for L2.

4 Experiment

Below we describe an experiment which tests our approach (§3) to relative proximity by examining

the changes in people’s judgements of the appropriateness of the expression *near* being used to describe the relationship between a target and landmark object in an image where a second, distractor landmark is present. All objects in these images were coloured shapes, a circle, triangle or square.

4.1 Material and Procedure

All images used in this experiment contained a central landmark object and a target object, usually with a third distractor object. The landmark was always placed in the middle of a 7-by-7 grid. Images were divided into 8 groups of 6 images each. Each image in a group contained the target object placed in one of 6 different cells on the grid, numbered from 1 to 6. Figure 6 shows how we number these target positions according to their nearness to the landmark.

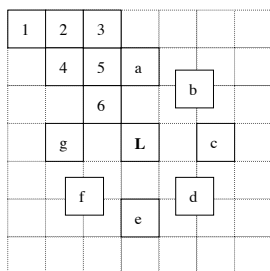


Figure 6: Relative locations of landmark (L) target positions (1..6) and distractor landmark positions (a..g) in images used in the experiment.

Groups are organised according to the presence and position of a distractor object. In group *a* the distractor is directly above the landmark, in group *b* the distractor is rotated 45 degrees clockwise from the vertical, in group *c* it is directly to the right of the landmark, in *d* it is rotated 135 degrees clockwise from the vertical, and so on. The distractor object is always the same distance from the central landmark. In addition to the distractor groups *a,b,c,d,e,f* and *g*, there is an eighth group, group *x*, in which no distractor object occurs.

In the experiment, each image was displayed with a sentence of the form *The __ is near the __*, with a description of the target and landmark respectively. The sentence was presented under the image. 12 participants took part in this experiment. Participants were asked to rate the acceptability of the sentence as a description of the image using a 10-point scale, with zero denoting not acceptable at all; four or five denoting moderately

acceptable; and nine perfectly acceptable.

4.2 Results and Discussion

We assess participants’ responses by comparing their average proximity judgments with those predicted by the absolute proximity equation (Equation 1), and by the relative proximity equation (Equation 3). For both equations we assume that all objects have a salience score of 1. With salience equal to 1, the absolute proximity equation relates proximity between target and landmark objects to the distance between those two objects, so that the closer the target is to the landmark the higher its proximity will be. With salience equal to 1, the relative proximity equation relates proximity to both distance between target and landmark and distance between target and distractor, so that the proximity of a given target object to a landmark rises as that target’s distance from the landmark decreases but *falls* as the target’s distance from some other distractor object decreases.

Figure 7 shows graphs comparing participants’ proximity ratings with the proximity scores computed by Equation 1 (the absolute proximity equation), and by Equation 3 (the relative proximity equation), for the images in group *x* and in the other 7 groups. In the first graph there is no difference between the proximity scores computed by the two equations, since, when there is no distractor object present the relative proximity equation reduces to the absolute proximity equation. The correlation between both computed proximity scores and participants’ average proximity scores for this group is quite high ($r = 0.95$). For the remaining 7 groups the proximity value computed from Equation 1 gives a fair match to people’s proximity judgements for target objects (the average correlation across these seven groups in Figure 7 is around $r = 0.93$). However, relative proximity score as computed in Equation 3 significantly improves the correlation in each graph, giving an average correlation across the seven groups of around $r = 0.99$ (all correlations in Figure 7 are significant $p < 0.01$).

Given that the correlations for both Equation 1 and Equation 3 are high we examined whether the results returned by Equation 3 were reliably closer to human judgements than those from Equation 1. For the 42 images where a distractor object was present we recorded which equation gave a result that was closer to participants’ normalised aver-

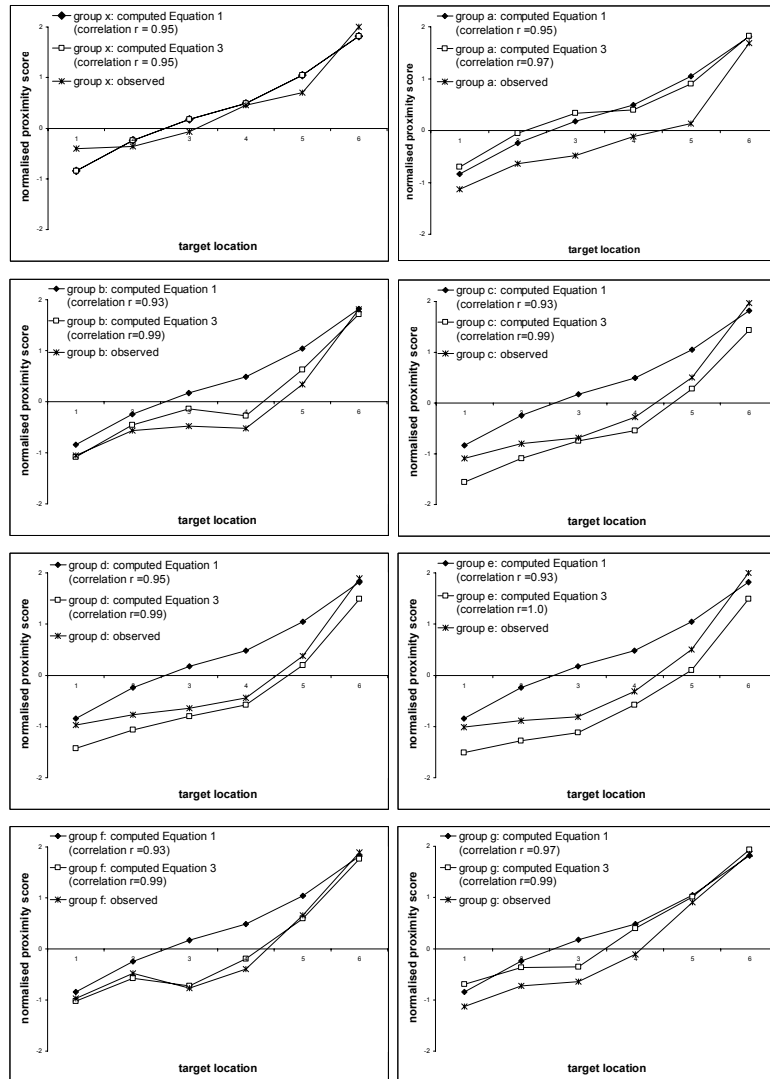


Figure 7: comparison between normalised proximity scores observed and computed for each group.

age for that image. In 28 cases Equation 3 was closer, while in 14 Equation 1 was closer (a 2:1 advantage for Equation 3, significant in a sign test: $n_+ = 28, n_- = 14, Z = 2.2, p < 0.05$). We conclude that proximity judgements for objects in our experiment are best represented by relative proximity as computed in Equation 3. These results support our ‘relative’ model of proximity.²

It is interesting to note that Equation 3 overestimates proximity in the cases (*a*, *b* and *g*)

²Note that, in order to display the relationship between proximity values given by participants, computed in Equation 1, and computed in Equation 3, the values displayed in Figure 7 are normalised so that proximity values have a mean of 0 and a standard deviation of 1. This normalisation simply means that all values fall in the same region of the scale, and can be easily compared visually.

where the distractor object is closest to the targets and slightly underestimates proximity in all other cases. We will investigate this in future work.

5 Expressing spatial proximity

We use the model of §3 to interpret spatial references to objects. A fundamental requirement for processing situated dialogue is that linguistic meaning provides enough information to establish the *visual grounding* of spatial expressions: How can the robot relate the meaning of a spatial expression to a scene it visually perceives, so it can locate the objects which the expression applies to?

Approaches agree here on the need for ontologically rich representations, but differ in how these are to be visually grounded. Oates et al. (2000)

and Roy (2002) use machine learning to obtain a statistical mapping between visual and linguistic features. Gorniak and Roy (2004) use manually constructed mappings between linguistic constructions, and probabilistic functions which evaluate whether an object can act as referent, whereas DeVault and Stone (2004) use symbolic constraint resolution. Our approach to visual grounding of language is similar to the latter two approaches.

We use a Combinatory Categorical Grammar (CCG) (Baldrige and Kruijff, 2003) to describe the relation between the syntactic structure of an utterance and its meaning. We model meaning as an ontologically richly sorted, relational structure, using a description logic-like framework (Baldrige and Kruijff, 2002). We use OpenCCG for parsing and realization.³

- (2) the box near the ball
- @_{b:phys-obj} (**box**)
 - & <Delimitation>**unique**
 - & <Number>**singular**
 - & <Quantification>**specific_singular**)
 - & @_{b:phys-obj} <Location>(r : region & **near**
 - & <Proximity>**proximal**
 - & <Positioning>**static**)
 - & @_{r:region} <FromWhere>(b1 : phys - obj
 - & **ball**
 - & <Delimitation>**unique**
 - & <Number>**singular**
 - & <Quantification>**specific_singular**)

Example (2) shows the meaning representation for “the box near the ball”. It consists of several, related *elementary predicates* (EPs). One type of EP represents a discourse referent as a proposition with a handle: @_{b:phys-obj} (**box**) means that the referent *b* is a physical object, namely a **box**. Another type of EP states dependencies between referents as modal relations, e.g. @_{b:phys-obj} <Location>(r : region & **near**) means that discourse referent *b* (the box) is located in a region *r* that is near to a landmark. We represent regions explicitly to enable later reference to the region using deictic reference (e.g. “there”). Within each EP we can have semantic features, e.g. the region *r* characterizes a static location of *b* and expresses *proximity* to a landmark. Example (2) gives a ball in the context as the landmark.

We use the sorting information in the utterance’s meaning (e.g. phys-obj, region) for further

interpretation using ontology-based spatial reasoning. This yields several inferences that need to hold for the scene, like DeVault and Stone (2004). Where we differ is in how we check whether these inferences hold. Like Gorniak and Roy (2004), we map these conditions onto the energy landscape computed by the proximity field functions. This enables us to take into account inhibition effects arising in the actual situated context, unlike Gorniak & Roy or DeVault & Stone.

We convert relative proximity fields into proximal regions anchored to landmarks to contextually interpret linguistic meaning. We must decide whether a landmark’s relative proximity score at a given point indicates that it is “near” or “close to” or “at” or “beside” the landmark. For this we iterate over each point in the scene, and compare the relative proximity scores of the different landmarks at each point. If the primary landmark’s (i.e., the landmark with the highest relative proximity at the point) relative proximity exceeds the next highest relative proximity score by more than a predefined confidence interval the point is in the vague region anchored around the primary landmark. Otherwise, we take it as ambiguous and not in the proximal region that is being interpreted. The motivation for the confidence interval is to capture situations where the difference in relative proximity scores between the primary landmark and one or more landmarks at a given point is relatively small. Figure 8 illustrates the parsing of a scene into the regions “near” two landmarks. The relative proximity fields of the two landmarks are identical to those in Figure 5, using a confidence interval of 0.1. Ambiguous points are where the proximity ambiguity series is plotted at 0.5. The regions “near” each landmark are those areas of the graph where each landmark’s relative proximity series is the highest plot on the graph.

Figure 8 illustrates an important aspect of our model: the comparison of relative proximity fields naturally defines the extent of vague proximal regions. For example, see the region right of L2 in Figure 8. The extent of L2’s proximal region in this direction is bounded by the interference effect of L1’s relative proximity field. Because the landmarks’ relative proximity scores converge, the area on the far right of the image is ambiguous with respect to which landmark it is proximal to. In effect, the model captures the fact that the area is relatively distant from both landmarks. Follow-

³<http://www.sf.net/openccg/>

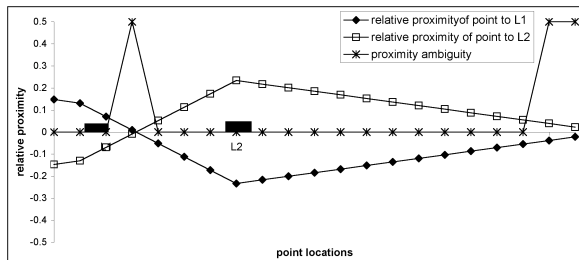


Figure 8: Graph of ambiguous regions overlaid on relative proximity fields for landmarks L1 and L2, with confidence interval=0.1 and different salience scores for L1 (0.5) and L2 (0.6). Locations of landmarks are marked on the X-axis.

ing the cognitive load model (§1), objects located in this region should be described with a projective relation such as “to the right of L2” rather than a proximal relation like “near L2”, see Kelleher and Kruijff (2006).

6 Conclusions

We addressed the issue of how we can provide a context-dependent interpretation of spatial expressions that identify objects based on proximity in a visual scene. We discussed available psycholinguistic data to substantiate the usefulness of having such a model for interpreting and generating fluent situated dialogue between a human and a robot, and that we need a context-dependent representation of what is (situationally) appropriate to consider proximal to a landmark. Context-dependence thereby involves salience of landmarks as well as inhibition effects between landmarks. We presented a model in which we can address these issues, and we exemplified how logical forms representing the meaning of spatial proximity expressions can be grounded in this model. We tested and verified the model using a psycholinguistic experiment. Future work will examine whether the model can be used to describe the semantics of nouns (such as *corner*) that express vague spatial extent, and how the model relates to the functional aspects of spatial reasoning.

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