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Including Landmarks in Routing Instructions

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This paper addresses the problem of incorporating cognitively salient landmarks in computer-generated navigation instructions. Based on a review of the existing literature in the domain of navigation with landmarks, the paper develops algorithms for generating routing instructions that include references to landmarks. The most basic algorithm uses a new weighting model to annotate simple routes with references to landmarks. A key novel feature of this algorithm is that it depends only on commonly available data and generic capabilities of existing webmapping environments. A suite of extensions are also proposed for improving the cognitive ergonomics of the basic landmark instructions. A case study, implemented within a national online routing system, demonstrates practicality of the approach. The paper then concludes by reviewing a range of further issues for future work.

Keywords: Navigation; landmarks; cognitive engineering; webmapping.

1 Introduction

Landmarks are cognitively salient, prominent features in the environment. Landmarks play a central role in human spatial cognition. They are fundamental to the way humans learn an environment and construct mental representations of it. Landmark knowledge has been shown to be the first level of spatial knowledge a person develops through interaction with a new environment (Siegel and White, 1975), coming before the development of route knowledge or network knowledge. Because of their dominance in human mental representations of space, landmarks are widely used in human wayfinding and human communication about routes.

By contrast, today's spatial information systems and web mapping services for generating routing instructions rarely make reference to landmarks. The main reasons for this omission is the lack of available data about landmarks or even agreed characteristics defining a landmark. Existing research into identifying landmarks typically relies on information about the detailed visual or geometric characteristics of the environment, such as 3D city models, cadastral data sets, and/or imagery of building facades (cf. Raubal and Winter, 2002; Nothegger et al., 2004; Winter et al., 2005; Kolbe, 2002, 2004; Elias, 2003). While data about these characteristics is becoming more commonplace (at least in urban areas), all too often such highly detailed information about the spatial environment does not exist, is proprietary, is infrequently updated, or is otherwise unavailable except in restricted spatial locations. Further, procedures for identifying landmarks are not yet tested in practice, and hence not readily available.

This paper presents a model for incorporating landmarks into routing instructions that does not depend on specific *instance-level* data about the visual or geometric characteristics of *individual* buildings and streetscapes. Instead the model relies solely on *class-level* information about the *types* of landmarks present in the environment, in addition to the road network and route geometry. The motivation for this approach is primarily practical: these information sources are much more commonly available and easily accessible,

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for example in the form of a road network spatial database and a geocoded directory service, like Yellow Pages.

This paper addresses two key research questions that arise from this motivation. First, how can landmarks be identified from geographic feature types? Second, how should specific landmarks be selected from this set for a specific route, based on knowledge about landmark types? Accordingly, this paper presents a model that implements cognitive salience in two ways: first, by weighting types of spatial features for their expected experiential salience; and second, for their relevance in the context of a route.

Following the review of existing related work into landmarks, landmark identification, and landmark annotation of routes (Section 2), this paper presents a new model for generating navigation instructions that refer to landmarks based on semantic categories (Section 3). The core landmark navigation model and algorithm can easily be extended to allow a range of further refinements of routing instructions (Section 4). Section 5 outlines the implementation of the model within a nationwide web-based Australian navigation service, which enables us in Section 6 to study and discuss the behavior of the model through a range of examples taken from this web-based navigation service. Section 7 distinguishes our model from those found in other navigation services. Finally, the conclusions in Section 8 summarize the key lessons learned during the model, algorithm, and implementation development, and identify a number of avenues for future research in this area.

2 Background

This section reviews the existing literature by examining the nature of landmarks and the role of landmarks in human navigation, and then surveying the existing approaches to identifying landmarks for inclusion in routing instructions.

2.1 *Landmarks*

Landmarks are defined as prominent features in the environment that are unique or contrast with their neighborhood (Siegel and White, 1975); and as natural, built, or culturally shaped features that stand out from their environment (Golledge, 1999). As such, landmarks characterize a geographic location and structure geographic routes by forming points to move to or away from, or lines and areas to move along or across.

An informal but highly influential early attempt to characterize landmarks was undertaken by Lynch (1960). Lynch observed that people's descriptions of their home cities contain references to and relationships between five fundamental categories of feature: *paths* (channels along which people move), *edges* (linear features, like walls, that are not paths), *districts* (city districts with distinguishing characteristics), *nodes* (strategic locations with a particular focus or concentration, like a busy street intersection), and *landmarks*. Landmarks in Lynch's sense are external physical objects that act as reference points. Landmarks, according to Lynch, might include shops, hills, schools, or any other object that aids in orientation when wayfinding. It is now generally acknowledged that *all* of Lynch's elements can form landmarks in the more general senses of Siegel and White (1975) and Golledge (1999). For example, a busy street intersection might be a landmark for people regularly passing by.

Appleyard (1969) investigated one particular type of landmark: buildings. He asked human participants to list the buildings they could memorize best in their home town. Analysis of the buildings that participants identified revealed that the chosen buildings tended to exhibit significant qualities of *form* (e.g., size, inflow of people, and visual attributes of the facade); significant qualities of *visibility* (e.g., frequency of visibility, prominence of the viewpoint, and nearness of the building to its viewpoints); and significant qualities of *meaning* (e.g., intensity or uniqueness of use of the building). His results indicate that these characteristics are found in landmarks irrespective of geographic scale, the same qualities being important for both local comparisons (i.e., for a single neighborhood) and global comparisons (i.e., for an entire city).

More recently, Sorrows and Hirtle (1999) and Burnett et al. (2001) identified properties such as uniqueness, distinguished location, visibility, and semantic salience as important for landmarks. Sorrows and

Hirtle (1999) identified three basic types of landmarks:

- visual landmarks are distinguished by their visual peculiarities;
- semantic landmarks are distinguished by their use or meaning; and
- structural landmarks are distinguished by their location in the structure of the environment.

These categories are not mutually exclusive. For example, a landmark can be eye-catching (visual landmark) *and* culturally important (semantic landmark). A feature that is outstanding in more than one category is likely to have a stronger overall salience or "landmarkness." Sorrows and Hirtle (1999) also mention, but do not develop further, prototypicality of an individual as a further characteristic to assess its landmark quality. Prototypicality goes back to the work of Rosch et al. on radial categories (1976). In the center of the category is its prototype, and other individuals of that category can be described by their similarity (inverse distance) from the prototype. This fourth aspect, prototypicality, will play an important role in our model.

Based on this classification, Raubal and Winter (2002) and Elias (2006) have developed independent sets of characteristics of salient buildings in urban environments. These defining characteristics—buildings outstanding in visual, semantic, or structural properties—can also be applied to other categories of landmarks. However, very little literature on natural landmarks exists. A notable exception (Brosset et al., 2007) reports that landform, e.g., slope, if salient is the second largest category of landmarks in route directions in natural environments. To our knowledge, landform is not systematically investigated in urban environments. This may be caused by the larger number of local, fine-grained features to choose from in an urban environment (landform is of comparably coarse grain), or also by the fact that salient patterns of landform (e.g., steep slopes) are relatively rare in urban environments.

2.2 *Route directions and landmarks*

Landmarks, with their relation to cognitive spatial representations, will be found in any spatial discourse. For example, based on the procedures described by Sorrows and Hirtle (1999) and Raubal and Winter (2002), Grabler et al. (2008) develop a system to generate tourist maps enriched with landmarks. Route directions are another special form of spatial discourse (Daniel and Denis, 1998; Allen, 1997). The purpose of route directions is to enable a wayfinder to find a route from their current location to their destination. Virtually all existing studies investigate *turn-by-turn directions*: route directions of a procedural, sequential form (but see Tomko and Winter, 2009 which investigates *place descriptions*, an orthogonal form of route directions designed to describe the location of the destination to a person with some familiarity with the environment).

In human turn-by-turn route directions we almost never find numerical references to distances or turning angles. Instead people use landmarks. Daniel and Denis (1998) demonstrated that only about 15% of human route direction elements are *not* related to landmarks; the rest is either an action linked to a landmark ("cross the park"), a reference to a landmark ("in front of you is a bridge"), or a description of the landmark ("it's a stone bridge"). The references to landmarks in these directions have one of two purposes: first, anchoring a navigation action to a location (if the referred landmark is located at a *decision point*); or secondly, providing confirmation that the user is going the right way (if the referred landmark is located along a route segment).

The cognitive literature on preferences between landmarks and street names is mostly European and hence, could neglect cultural differences. North American grid street networks, with numbered streets and blocks, may favor references to street names by training. Asian street networks with mostly no street names may constrain landmarks completely. However, studying these preferences in a European environment, where both landmarks and street signs are present in irregular street networks, Tom and Denis (2004) showed that, compared to street names, landmarks lead to shorter learning times, better recall in route description tasks, and better response in wayfinding tasks.

The selection of landmarks for enriching the turn-by-turn instructions of a particular route has also been studied previously. For example, Richter (2008) studies the selection of landmarks from the perspective of the route providing the spatial and structural context of the selection process. Klippel et al. (2009)

exploit various relationships between landmarks and a route towards generating route instructions of varying granularity (see also Dale et al. (2005) in this respect). Their hierarchy of granularities starts at elementary turn-by-turn instructions. From here they form chunks, either by the structure of the route (e.g., "follow the signs"), or by landmarks available along the route (e.g., "follow the river").

The literature suggests that landmarks improve the quality of route directions in terms of their *cognitive ergonomics* (how easy the route instructions are for a human to understand, remember, and use). However, there is no universally accepted mechanism for including landmarks in route directions (Lovelace et al., 1999). The quality of route directions can depend on the number, type, or quality of references to landmarks; and the way references to landmarks are selected in the context of the route (Michon and Denis, 2001). Despite the difficulty in objectively identifying what constitutes "good" use of landmarks in route instruction, humans do exhibit strong commonalities in their assessment of landmarks. Using skeletal route directions derived from human route descriptions, Denis et al. (1999) showed that participants consistently identified incomplete as well as overly detailed directions, and ranked them low in quality. In this test, the results were the same regardless of whether the participants were local experts or novices. This means, an automatic generation of routing instructions requires two intelligent mechanisms: first, an identification of features that are cognitively salient in an environment ("good" landmarks), and second, a careful selection from the identified landmarks for the instructions of an individual route ("relevant" landmarks).

2.3 *Landmark identification*

So far, three main approaches to identify landmarks from spatial datasets are known in the literature.

Approach 1. The first approach (Raubal and Winter, 2002; Nothegger et al., 2004, later multiply extended) constructs a set of evaluation functions for the visual and semantic salience of building facades. These functions measure *differences* of individual properties, such as, for visual salience for example, the size or the form factor of the facade, from average properties in the local neighborhood. As a result, the salience of a facade, s_f, is computed from weighted components of visual salience, s_v, semantic salience, s_s:

$$s_f = w_v s_v + w_s s_s \tag{1}$$

with $w_v, w_s > 0$ and $\sum w = 1$. For the computation of salience the visual and semantic characteristics of buildings and their facades need to be accessible from some other data set. For example, facade imagery and image processing can be used to determine the visual characteristics, while access to Yellow Pages or point-of-interest collections is needed to assess the semantic characteristics.

In this way, the salience of (all) facades of buildings in a spatial dataset can be determined. A local maximum filter can identify the most salient facades in a neighborhood, identifying a candidate set of landmarks for the enrichment of route directions. Furthermore, changing the relative weights of visual and semantic differences enables the measures to be adapted to different contexts (Winter et al., 2005).

While visual and semantic salience describes the global properties of a facade, structural salience describes the properties of a facade by their location in the structure of the environment. The way Klippel and Winter (2005) have modeled structural salience it is even route dependent, i.e., not applicable to identify a route independent set of landmark candidates. For the computation of structural salience the street network is needed, as well as the location of the buildings relative to the street network. Klippel and Winter also bring up advance visibility, acknowledging that a facade that is hardly visible is not useful for navigation. Advance visibility requires a cadastral dataset representing street space as open space. The salience of a facade in the context of a route is then computed from weighted visual, semantic, and structural (s_t) salience and advance visibility, s_a by:

$$s_f = (w_v s_v + w_s s_s + w_t s_t) \cdot s_a \tag{2}$$

with $w_v, w_s, w_t > 0$ and $\sum w = 1$.

Approach 2. The second approach, by Kolbe (2002, 2004), computes the salience of building facades using information theoretic measures. This approach determines the peculiarity or degree of surprise in visual characteristics of facades. The entropy of the visual appearance of a facade is 0 if its probability is 1 (thus, if the appearance is the same as for all other facades in the neighborhood), and it becomes larger the smaller the probability of its occurrence in this neighborhood is. The facade with the largest entropy in a neighborhood is identified as a landmark. Although the underlying theoretical background is different, in effect the broad idea is very similar to Approach 1.

Both Approaches 1 and 2 are particularly suited to use with 3D city models and the large-scale capture of video sequences along street segments. These 3D city models also provide potential for novel visual communication of routes and landmarks (e.g., in the form of augmented reality).

Approach 3. The third approach, by Elias (2003), aims to identify *interesting buildings*; in this case, facades play only one contributing factor. Compared to the previous methods, this approach does identify salient buildings, but does not provide a measure for relative or absolute ranking in a neighborhood. Instead, it aims to identify landmarks by detecting outliers (i.e., the most interesting of a set of buildings) using a classic machine learning algorithm called ID3 (Quinlan, 1986). For the characteristics of individual buildings Elias draws also on their category, i.e., in a neighborhood, a building of a unique category is "interesting." This approach is in some senses opposite to our model; our approach assumes characteristics of the individual instances based on knowledge of the characteristics of that instance's category. What Elias *measures*—the salience of individuals—we will *estimate*.

More recently, Winter et al. (2008) generalized the identification of salient buildings. They suggested a method to rank (building) landmarks hierarchically, with the purpose of distinguishing between local and global landmarks. In the same vein, Tomko et al. (2008) suggested a hierarchical ranking of *streets*. The salience of streets was determined by their centrality (a structural property), arguing that centrality correlates with prominence.

2.4 *Summary*

The literature clearly indicates that landmarks are fundamental to how humans structure geographic environments, and to how humans communicate, remember, and use route directions. Almost all human route directions include references to landmarks. Landmarks are distinguished in some way by the characteristics with respect to their visual or semantic properties. Despite considerable individual differences, there exists clear evidence of strong commonality in what individuals regard as a "good" landmark with respect to these properties. There are three main existing approaches in the literature for global landmark identification, each of which use different mechanisms for identifying features that are somehow distinguished from their immediate environment. However, all three mechanisms rely on data about the specific landmark instances, such as imagery of building facades or detailed cadastral data on building shapes.

3 Core landmark navigation model (LNM)

The previous section argued that current approaches to the generation of route instructions that refer to landmarks rely on detailed *instance-level* information about the detailed visual or geometric information about buildings. However, in many instances such detailed information may be unavailable, proprietary, infrequently updated, or simply will not exist. Such considerations are arguably one of the reasons why so few commercial mapping engines even attempt to provide navigation instructions with landmarks (see Section 5).

In order to address this gap, this section presents the top-level design of a landmark navigation model (LNM) capable of generating landmark sets using category-level information about *types* of landmarks, rather than instance-level information about *individual* landmarks. The key motivation for this design is primarily practical. Category-level information about features in geographic environments is typically much more widely available, and more frequently updated. Most countries possess geocoded business directories, such as digital Yellow Pages, national address files, or typed toponym gazetteers. Other datasets can also be used, for example typed points of interest datasets, as maintained by map publishing houses, location-based service providers, or even collected through crowd-sourcing. Hence, we believe that our method can be rapidly applied anywhere today, at least in a commercial environment.

Our core LNM has two key components:

(i) A landmark weighting system, which is used to assign general weights to categories of points of interest (landmark identification, Section 3.1); and
(ii) An algorithm for annotating route instructions with landmarks based on the weighting system (landmark selection, Section 3.2).

3.1 *Landmark weighting*

Unlike the reviewed literature, this paper does not assume access to information about *individual* landmarks (e.g., visual imagery, or building outlines). Consequently, our approach is to develop a weighting system that assigns weights based on the expected (e.g., "average") properties of the *categories* of points of interest (POIs), such as might be found in a directory service like Yellow Pages (e.g., "Hotels," "Restaurants," "Parks," "Museums," etc.). In scoring the suitability of categories of POIs as landmarks, we therefore have two independent factors to consider:

(i) How suitable a typical instance of a POI category is as a landmark; and
(ii) How likely it is that a particular instance of a POI category is typical.

For example, a typical church would be highly suitable as a landmark, in the sense that it will be physically large, architecturally and semantically distinct from its surroundings, and recognizable to a wide range of people. However, churches come in all shapes and sizes: while a typical church may be highly suitable, some may be highly atypical and so possibly unsuitable. For example, chapels in hospitals or quaker meeting houses are generally not very visible.

Our objective is to use these two factors to weight POI categories according to how suitable they are as landmarks. Inevitably, achieving such an objective requires a heuristic: there might be many ways such suitability could be weighted. In Section 5 we explain and justify a specific heuristic used within the context of a nationwide Web-based routing system. However, at this point we simply note that a heuristic process is used in order to generate for a set C of POI categories a normalized weighting function:

$$\mathit{weight} : C \to [0, 1] \tag{3}$$

Thus, following the heuristic weighting process, for each POI category $c \in C$, $\mathit{weight}(c)$ gives the normalized suitability of that category, with $\mathit{weight}(c) = 1$ most highly suitable and $\mathit{weight}(c) = 0$ totally unsuitable. A category is highly suitable if it consists of uniformly salient individuals.

3.2 *Annotation algorithm*

In addition to a set of categories C and a category weighting function $\mathit{weight} : C \to [0, 1]$ (Equation 3) our algorithm assumes two further data sources:

(i) The road network for the area of interest, structured as a graph $G = (V, E)$. The graph is assumed to be embedded in planar geographic space (i.e., the locations of nodes in geographic space are known) and have associated edge weights (i.e., travel distances or times along edges) and edge labels (representing the name of each road).
(ii) A geocoded POI directory for the area of interest, comprising a set P of POIs, the geographic location of each POI $p \in P$, and information about the category of each POI, represented as the function $\mathit{category} : P \to C$. The POI directory may also contain some instance-level information about individual POIs (such as the name of the POI), but is assumed not to contain detailed imagery, 3D, or cadastral data about each POI.

We note that any current web-mapping or routing service would typically already rely on this basic information. Using these structures, Figure 1 presents a basic landmark annotation algorithm, for generating simple turn-by-turn routing instructions with references to landmarks from an origin $o \in V$ to a destination $d \in V$. Since prominent features that are located at a decision point on a route are more relevant than prominent features along its segments (Klippel and Winter, 2005; Michon and Denis, 2001; Tom and Denis, 2003), the basic algorithm chooses only landmarks at decision points. Should no landmark be available at a decision point, the algorithm reverts to a standard turn-by-turn instruction, like "⟨Perform action⟩ onto ⟨Street Name⟩ after ⟨Distance⟩".

(i) Generate a route from origin $o \in V$ to destination $d \in V$ from the graph $G = (V, E)$ using a standard shortest path algorithm (e.g., Dijkstra's (1959) or the A* algorithm (Hart et al., 1968, 1972)).
(ii) Find the set of POIs $P' \subseteq P$ that lie on the route decision points.
(iii) Associate with each POI instance $p \in P'$ the landmark weight, $weight(c)$, for that POI's associated category $c \in C$ such that $category(p) = c$.
(iv) At each decision point with at least one landmark, select the landmark that is incident with that decision point and has the highest weight. If two or more landmarks have the same weight, arbitrarily select one landmark to use.
(v) For each decision point with a selected landmark, generate the routing instruction of the form "⟨Perform action⟩ onto ⟨Street Name⟩ at ⟨Selected landmark⟩", else generate a traditional routing instruction.

Figure 1. Core LNM algorithm

The action performed in the final step of the algorithm in Figure 1 can be drawn from any standard set of actions (such as "turn right," "bear left" etc.). As discussed in Section 2 a decision point is any location on the route where a user must perform the action of choosing between different directions. Although the *category* of POI is used to weight and select landmarks, the specific instruction can make use of any *instance* level information about the specific POI, such as the name of the POI. For example, "Turn left at Crown Casino" can be used in place of "Turn left at the casino" where data about the specific casino name is available.

4 Extending the core LNM

The core LNM generates "vanilla" turn-by-turn routing instructions with simple references to landmarks that encapsulate the basic information about POI suitability. However, it is possible to design a range of further refinements of these vanilla routing instructions, while still relying only on widely available data sources, the road network and a geocoded directory service. These additional extensions fall into three categories:

- Adjusting POI category weights by generating refined landmark weighting functions (Section 4.1);
- Adjusting POI instance weights based on the spatial or route structure (Section 4.2); and
- Altering routing instructions and providing a wider variety of instruction forms (Section 4.3).

4.1 *Adjusting POI category weights*

One of the simplest extensions to the LNM is to repeat the landmark suitability weighting process, described in the previous section, for different user contexts. For example, the question of what is a good landmark can depend on the mode of traveling. Features in a car driver's focus of attention, such as traffic lights, crosswalks or bridges, are more suited to being a landmark in route directions for drivers (Streeter et al., 1985; Burnett et al., 2001). Conversely, a pedestrian's concentration is generally directed toward other urban features, due to their lower traveling speed and also their separate traveling space, such that buildings may be more appropriate landmarks (Ross et al., 2004; May et al., 2003).

Thus, one refinement of the core LNM algorithm is to adjust landmark weights described in Section 3.1 for different user groups, for example generating one set for car drivers, and another one for pedestrians.

Instead of a single weighting function, this process will then generate a family of weighting functions, $weight_i$ for a variety of different user contexts i. As already mentioned, a specific example of a weighting heuristic is explored in Section 5.

4.2 *Adjusting POI instance weights*

It is possible to refine weights for specific instances of POIs based on their spatial characteristics or role within the route. Two specific refinements are identified here.

4.2.1 ***Side of road.*** Prominent features that are easily visible from the direction of travel for a route are more salient to a wayfinder following that route. Conversely, prominent features that happen *not* to be visible on a particular route should not be ranked as highly as candidate landmarks (Winter, 2003). Advance visibility is route dependent and relatively expensive to calculate.

Of significantly less complexity is considering the wayfinder's visual attention. Maaß (1996) argues that the side of the street matters: wayfinders focus more on the side of the street that the next turn will be made toward. Hence, features on that side should be ranked more highly by a selection algorithm. Incorporating this principle into the landmark weighting process simply requires a heuristic for incrementing or decrementing the weight for a POI based on its side of the road in relation to the action. A specific example of such a heuristic is explored in Section 5.

4.2.2 ***Multiple landmarks on same route leg.*** It is possible that several landmarks of the same category occur on a particular route leg. In such cases, the individual landmark salience should be adjusted: only the first instance of a particular category of landmarks on a route leg keeps its salience; the following ones are set to zero. This in turn should avoid potentially ambiguous instructions such as "Turn left at the police station" when in fact the user must pass one or more previous police stations before reaching the one to turn at. Alternatively, an algorithm can introduce numerical chunking (Klippel et al., 2009) to produce routing instructions such as "Turn left at the second police station." However, this strategy should be applied only for small counts and has potentially a higher cognitive workload since counting happens over the longer time period of traveling along the leg.

4.3 *Altering routing instructions*

The third class of extension adapts the form of the routing instructions generated.

4.3.1 ***Absence of landmarks.*** In some situations landmarks may not be available where needed, e.g., at a decision point. However, since any feature in the dataset has at least some salience, it may also be desirable to also apply some minimum suitability threshold $s \in [0, 1)$ such that no landmark is ever selected with a suitability weighting below s.

In other situations landmarks may not be necessary, such as where turns are expected to be adequately signposted or otherwise structurally unambiguous. For example, checking if the upcoming route segment is a major road or freeway, from its name or associated information, would allow no landmark to be selected for that decision point (on the assumption that adequate signposting already exists to alleviate the need for references to a landmark).

In our extended LNM algorithm such cases are automatically detected, leading the algorithm to revert to standard navigation instructions referring to street names and distances.

4.3.2 ***Landmarks off decision points.*** Landmarks on the route, but off decision points (termed "in-leg POIs") can play several roles. First, additional routing instructions on longer route legs can be used to provide confirmation to users that they are on the correct route. The core LNM algorithm only selects landmarks at decision points. However, having retrieved all the landmarks incident with the entire route (not only at the decision points), in-leg POIs can be selected for confirmation based on at least two possible criteria:

(i) the in-leg POIs have an especially high landmark suitability; and/or
(ii) the in-leg POIs are located on especially long legs in the route.

Deciding what constitutes "especially" high landmark suitability or long route legs will again require heuristics. One simple heuristic would set some threshold travel time t for a route leg (such as 5 minutes) beyond which a user can expect a confirmation landmark. A refinement of this heuristic could select in-leg landmarks only along long legs of local streets, excluding in-leg landmarks along highways.

Secondly, where an upcoming decision point has no suitable landmark, in-leg landmarks can be used to alter the standard routing instruction to the form "⟨Perform action⟩ onto ⟨Street Name⟩ after ⟨selected in-leg landmark⟩".

Thirdly, where an upcoming decision point has a suited landmark, but in-leg POIs of the same category exist as well, in-leg landmarks can be used to alter the standard routing instruction to numerical chunking (Klippel et al., 2009). While numerical chunking can be observed in human directions as well, it is a delicate method. Numbers should not be larger than 2 or 3 to keep the cognitive effort low (see especially Dehaene, 1997). Also the fact that they are based on repetitive POIs reduces some of their salience of such landmarks (see Section 4.2.2).

4.3.3 *Spatially extended objects.* Finally, the POIs thus far have all been assumed to be exactly that: points. However, at the level of granularity of human navigation, some spatial objects may be better represented with spatial extents, termed areas of interest (AOIs). In cases where geometric information about the extensions of AOIs is available, these can potentially be used as landmarks for in-leg instructions. The spatial extents of AOIs make them unsuitable as landmarks at decision *points*.

Spatially extended landmarks can be included in routing instructions using three steps: 1) identify the AOIs that intersect or abut some part of the route; 2) increase the landmark suitability weighting of these AOIs accordingly; and 3) generate a new instruction of the form "Continue along/through ⟨selected landmark⟩" for any AOI selected as in-leg landmark. Deciding on whether to use "along" or "through" would depend on the spatial relationship between the route leg and the extended region (i.e., "along" is used where the route abuts the AOI; "through" is used where the route overlaps the AOI).

4.4 *Extended algorithm*

The algorithm in Figure 2 extends the core LNM algorithm given in Section 3.2 with pseudocode for the refinement described above.

5 Case study: Whereis navigation

A version of the extended LMN was implemented as a customized component in a national Australian routing service, Whereis[1]. The Whereis service is based on a map server that uses map data that was developed by Sensis Pty Ltd in conjunction with Universal Publishers Pty Ltd, and includes some data from Geoscience Australia (Commonwealth of Australia) and the Department of Treasury and Finance, Geographic Data Victoria. For our case study, the Australian Yellow Pages (Sensis Pty Ltd) and data from Universal Publishers Pty Ltd were used as a source of POIs. The Universal Publishers data contained a total of 60 different categories of POIs, ranging from the familiar (e.g., hotels, schools, railway and service stations), through the peculiarly Australian (e.g., barbecues), to the less frequently encountered (e.g., skating rinks, weighbridges, and bowling clubs). In addition, six categories (galleries and museums, theaters,

[1] `http://whereis.com.au`

(i) Generate a route from origin $o \in V$ to destination $d \in V$ from the graph $G = (V, E)$ using a standard shortest path algorithm.
(ii) Find the set of POIs $P' \subseteq P$ that lie anywhere along the route (on decision points or along route legs).
(iii) Associate with each POI instance $p \in P'$ the landmark weight, $weight_i(c)$, for the specific user context i (Section 4.1) and that POI's associated category $c \in C$ such that $category(p) = c$.
(iv) For any POI $p \in P'$ at a decision point, increase the suitability weighting if the POI is on same side of the road as the upcoming instruction (Section 4.2.1).
(v) Set to zero the weight of every POI which is not the first instance of its category on each route leg (Section 4.2.2).
(vi) For each decision point, select the POI that is incident with that decision point and has the highest weight. If two or more landmarks have the same weight, arbitrarily select one landmark to use.
(vii) For each route leg that is longer than some travel time threshold t, select the in-leg landmark with the highest landmark suitability weight (Section 4.3.2).
  a) If the decision point has no selected landmark generate a new routing instruction of the form "⟨Perform action⟩ onto ⟨Street Name⟩ after ⟨Selected in-leg landmark⟩" (Section 4.3.1).
  b) Otherwise generate a new routing instruction of the form "Continue ⟨Action⟩ the ⟨Selected landmark⟩" where
    i. If the selected landmark is point-based, then associated ⟨Action⟩ is "past".
    ii. Otherwise, if the selected landmark has spatial extents, determine whether the selected landmark abuts or overlaps the route, and set the upcoming ⟨Action⟩ to be "along" (abuts) or "through" (overlaps) (Section 4.3.3).
(viii) For each decision point with a selected landmark, generate the routing instruction of the form "⟨Perform action⟩ onto ⟨Street Name⟩ at ⟨Selected landmark⟩".
(ix) For each decision point without a selected landmark and not already preceded by an in-leg routing instruction, generate a standard routing instruction of the form "⟨Perform action⟩ onto ⟨Street Name⟩ after ⟨Distance⟩" (Section 4.3.1).

Figure 2. Extended LNM algorithm

pubs, take away food, casinos, and other gambling establishments) were selected from the Australian Yellow Pages. Only a small subset of the Yellow Pages categories was selected because of the very large number of categories (in total more than 2500) most of which have low salience for navigators (exemplified by categories like "Armoured car services" through "Zinc supplies and products"). Despite excluding most Yellow Pages categories, together these two data sources still contributed approximately 170,000 POIs nationwide.

The following subsections detail some of the implementation-specific design parameters, including the heuristics used to weight landmark suitability in this particular environment.

5.1 *Landmark weighting*

Section 3.1 outlined the structure of the landmark weighting system, for generating suitability weights for categories rather than specific instances of landmarks. This section explains the heuristics used within that structure to weight landmark suitability in our case study. As discussed in section 3.1 developing the landmark weighting heuristic has two phases: first, identifying the factors that contribute to landmark suitability; and secondly, designing a scoring system to convert the suitability factors into a normalized score.

5.1.1 ***Suitability factors.*** As Section 2 has already identified, a landmark becomes suitable the more it differs to its surroundings with respect to its visual, semantic, and structural characteristics (see also Raubal and Winter, 2002). However, in the context of the case study it was helpful to develop a more detailed list of sub-characteristics, tailored to determining the landmark suitability of POI categories (rather than instances). Table 1 outlines nine specific suitability factors related to the three top-level

Table 1. Detailed factors for scoring landmark suitability for POI categories.

Character	Factor	Explanation
Visual	Physical size	Larger POIs are more easily seen, and so better candidate landmarks than smaller POIs.
	Prominence	POIs that are visually prominent (e.g., bear visible signs, markings, architecturally imposing) are better candidate landmarks than those with few or no distinguishing markings.
	Difference from surroundings	POIs that are typically different from their surroundings are preferable landmark candidates.
	Nighttime vs daytime salience	POIs that are highly visible both in day and night are better candidate landmarks in the context of the case study, since Whereis routing instructions may be printed out and later used during day or night.
	Proximity to road	POIs that are closer to the road are more likely to be seen by navigators, and so are better candidate landmarks.
Semantic	Ubiquity and familiarity	POIs that are ubiquitous and familiar (e.g., that occur across the country or are widely advertised) represent better candidate landmarks.
	Length of description	POIs that require short or very familiar descriptions (e.g., police station or hospital) are more suitable landmarks than POIs that require longer or more complex descriptions (e.g., state government offices)
Structural	Spatial extents	Point-based POIs are likely to be more suitable landmarks, as they are less ambiguous than landmarks with spatial extents (although see Section 4.3.3)
	Permanence	POIs that are expected to change or move less frequently make better candidate landmarks (e.g., toilets and service stations change or move more often than schools or hospitals).

characteristics of landmarks.

5.1.2 ***Scoring system.*** Having identified the detailed factors that affect landmark suitability, a heuristic scoring system was developed for landmark suitability. The scoring system is two-dimensional to account for the two components of category suitability identified in Section 3.1: how suitable a typical instance of a category is, and how frequent typical instances are in a category. The scoring system uses a five point rating for the suitability of typical landmarks of a category (from "Ideal" through "Highly suitable," "Suitable," "Somewhat suitable" to "Never suitable") as well as a five point rating for the frequency of typical landmarks in a category (from "All typical," through "Most," "Many," "Some" to "Few").

This system was applied by a group of experts who had to agree on a ranking for each category. For example, a typical *petrol station* might be ranked as "Highly suitable" or "Ideal" as a candidate landmark in terms of physical size (large), prominence (highly visible with recognizable markings), proximity to the road, difference from surroundings, nighttime and daytime salience (visible both day and night), ubiquity and familiarity (in the sense that they occur across the country and are known across all sectors of society), have limited spatial extents (essentially point locations), and have relatively short, simple descriptions. Most or all petrol stations might be viewed as possessing these characteristics. However, petrol stations might only be ranked "Somewhat suitable" in terms of permanence, as a reasonable number might be expected to open or close over a 12 month period.

Further validation of the ranking is possible only in two ways. One way would be going back to the individual instances of each category, calculating their average salience (suitability of the category) and their standard deviation (typicality of the instances of this category). This pathway is not manageable in practical terms with the potentially large numbers of individuals; in the example in Section 6 there can be tens of thousands of individuals in a category. Alternatively, the ranking can be used and tested by user satisfaction. The weights can be adapted any time if experience or feedback recommends a fine tuning. While we expect that our approach of constructing a scoring system works everywhere, the actual scores are expected to vary from country to country—as the directories and their lists of categories will do.

Further examples for a generally suited category (*takeaway food*) and for a less suited category (*consulates*

Table 2. Expert's rating of two categories, *takeaway food* and *consulates and embassies*.

	Takeaway food		Consulates and Embassies	
	Suitability	Typicality	Suitability	Typicality
Physical size	suitable	most	highly	many
Proximity to road	highly	most	somewhat	most
Visibility	ideal	all	highly	some
Difference from surroundings	suitable	all	highly	some
Ubiquity	ideal	all	suitable	some
Nighttime vs. daytime salience	ideal	most	somewhat	most
Permanence	somewhat	all	highly	many
Length of description	suitable	all	somewhat	all
Spatial extents	ideal	all	highly	many

and embassies) are given in Table 2. In this table, experts have ranked category *takeaway food* higher both in terms of the suitability of the category as well as of the typicality of instances of the category.

Having decided on a suitability for a typical instance of a category, and the frequency of typical instances in the category, these expert ratings (Table 2) are then combined to the overall scores defined in Table 3. This scoring system is pessimistic in the sense that to ensure the resulting scores are as robust as possible, the lowest possible score is taken overall. For example, even though a typical instance of a category might be highly suitable as a landmark, if the category is expected to have many atypical instances, then the overall landmark score will be low. The heuristic also uses exponentially increasing scores to ensure highly suitable landmarks are strongly preferred. However, the absolute numerical values of scores are not significant, as the overall scores will later be normalized.

Table 3. Landmark scoring system based on POI categories.

	Frequency of typical landmarks in category				
Typical landmark	All	Most	Many	Some	Few
Ideal	8	4	2	1	0
Highly suitable	4	4	2	1	0
Suitable	2	2	2	1	0
Somewhat suitable	1	1	1	1	0
Never suitable	0	0	0	0	0

5.2 *Overall suitability score*

After ranking each POI category against each of the nine suitability factors with respect to both category suitability dimensions, an overall suitability score for the POI category was derived. This score can be computed as a simple linear sum of scores for all suitability factors. The linear sum was a reasonable heuristic in our case study, but naturally it would be straightforward to adapt this approach to specific applications requirements (e.g., take the minimum score in all factors, or weight the factors according to importance). For the example given in Table 2 the results for the overall suitability score are shown in Table 4.

Finally, the weighting for a particular POI category c, $weight(c)$ (see Equation 3), is normalized in the range [0,1] (with 1 being most suitable and 0 being least suitable) as follows:

$$weight(c) = \frac{\sum_{f \in F} score_f(c) - \min\left(\left\{\sum_{f \in F} score_f(c') | c' \in C\right\}\right)}{\max(\{\sum_{f \in F} score_f(c') | c' \in C\})} \tag{4}$$

where $score_f(c)$ is the suitability score from Table 3 for a category $c \in C$ with respect to the suitability

Table 4. Scoring of two categories, *takeaway food* and *consulates and embassies.*

	Takeaway food	Consulates and Embassies
Overall suitability score	39	12
Weight normalized with respect to all 66 categories assessed	0.88	0.20

factor f, and F is the set of all nine suitability factors. Again, the results for the example are shown in Table 4.

5.3 *Extensions implemented*

With reference to Section 4, all of the extensions discussed were implemented and successfully tested within a prototype routing system. However, commercial and technical considerations meant that a subset of these extensions was implemented in the final, nationally available, online system. Of the six extensions discussed in Section 4, the two extensions that were *not* implemented in the final online system were: developing different weightings for different classes of user (e.g., pedestrians versus drivers, see Section 4.2); and reducing weights for landmarks that appear multiple times on the same leg (Section 4.2.2). All of the other extensions (described in Sections 4.2.1, 4.3.1, 4.3.2, 4.3.3) were implemented in the final system, and used to generate the example route instructions discussed in the following section.

6 Examples

The implementation in the Whereis national web-based navigation service will be illustrated by the following examples.

6.1 *Detailed example along Spring Street*

Spring Street is a major road at the east end of the central business district of Melbourne, characterized by the Victorian State Parliament building, other government buildings, old hotels, and theaters—a rich structure of cognitive salient (i.e., highly individual) buildings. This is reflected by the high density of POIs in proximity to Spring Street contained in the database for the LNM, shown in Figure 3. The 38 POIs in Whereis' directory close to Spring Street consist of 9 hotels, 5 car parks, 4 parks, 3 express post boxes (striking yellow boxes in Australia), 3 places of worship, 3 WiFi hotspots, 2 theaters, 2 public telephones, 2 fixed traffic cameras, 1 traffic light, 1 tertiary education institution, 1 post office, 1 nursing home, and 1 other place of interest. Notably the directory contains feature categories we would expect to be considered for landmarks, but also other ones, even non-visual ones like the WiFi hotspots. All categories in the directory were scored according to Table 4.

With this richness of POIs available, the challenge facing our landmark navigation model is to select the most suitable landmarks for routes traversing Spring Street. The selection process described in previous sections considers multiple factors, such as the structure of the route (landmarks are primarily needed at decision points along a route), the mode of traveling (car drivers have a different view on their urban environment than pedestrians), and the cognitive salience of the landmark. An example of the route instructions generated by our LNM as implemented in the Whereis navigation services is shown in Figure 4. For the route from the corner of Russell St and Bourke Street to the Melbourne Museum at Nicholson Street, the service has selected only two landmark references. These two landmarks are the Imperial Hotel (Number 2 in Figure 3) and the Princess Theater (Number 6 in Figure 3). The first landmark, Imperial Hotel, is linked to a *turn* action, i.e., characterizes a decision point of the route. It is also chosen from a category of high suitability to support a car driver's navigation. The other landmark, Princess Theater, is a confirmative landmark, linked to a *continue along* action. Our implementation tries to provide confirmative references to landmarks if a leg of a route is longer than a predefined length, as described in Section 4.3.2. This landmark can also be chosen because of the local complexity: Spring Street makes a veer right turn

Figure 3. POIs along Spring St, Melbourne (`http://whereis.com` © Telstra Corp. Ltd., 2009).

at the Princess Theater. All other landmarks along Spring Street (and also along the parts of the route beyond Spring Street) are rejected as irrelevant or not suited.

This automatic selection is easy to justify from a cognitive perspective. The single turn of the route is characterized by a salient landmark, and another difficult situation is supported by a confirming landmark. The chosen landmark, the Princess Theater is one of Melbourne's most prominent places, and hence an excellent choice.

However, the example also demonstrates some gaps in our model. First, only features in the directory will appear as landmarks. For example, at the turning point is another "landmark," the Victorian Parliament. The Parliament is visually and semantically more salient than the hotel (it is unique in Melbourne), but it is lacking in the directory, and hence, does not compete with the hotel in our algorithm. Also, the street intersection at this location is special and can be counted as landmark (Klippel et al., 2005a), but these types of landmarks are also not contained in the directory. Further, selected landmarks are currently only referred to in the verbal route directions, but not in the map. In a future revision both expressions will be consistently linked.

6.2 *Observations from a larger number of route descriptions*

To validate the detailed findings of the single exemplar route description in Section 6.1, an additional 23 route descriptions containing landmarks were generated (Figure 5). This larger set of route descriptions was analyzed using expert opinion about the appropriateness of the behavior of the selection model. Unfortunately, more quantitative assessments of the routes generated by the algorithm (for example human subject testing) are not currently feasible for two main reasons:

- Only a small portion of geographic features in the environment are currently included in Whereis service (66 categories, or 170,000 POIs nationwide, as mentioned above). Thus, the selection process is a selection among these included features, but not among the features available in the environment. We therefore do not claim that the landmarks chosen by online service would necessarily have been the same as

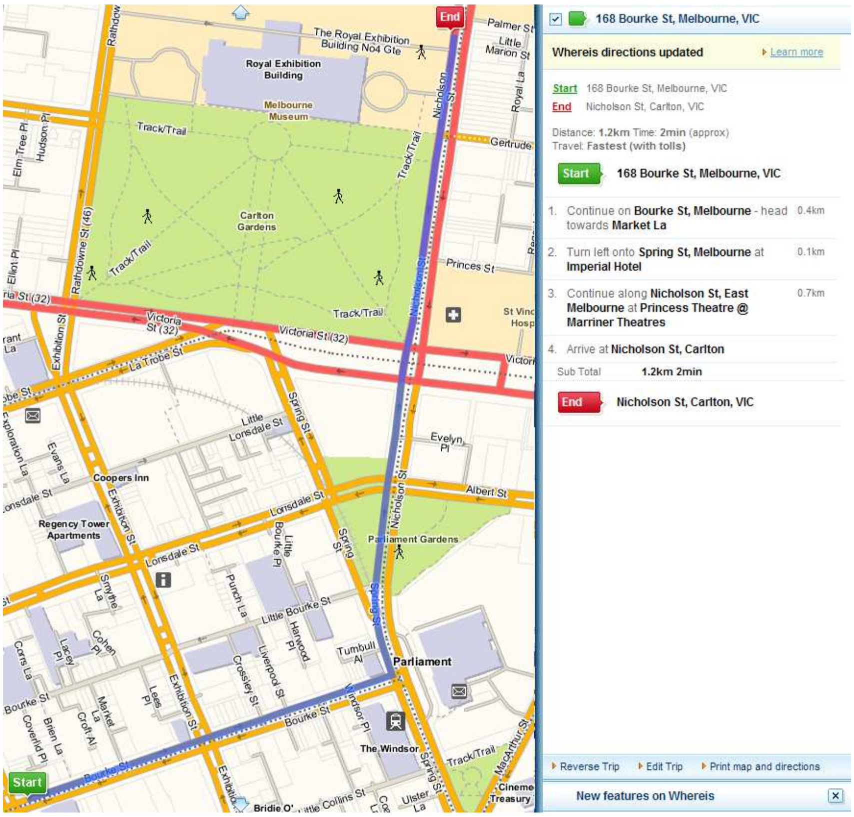

Figure 4. Route instructions including two carefully selected references to landmarks (`http://whereis.com` © Telstra Corp. Ltd., 2009).

those chosen by humans. Consequently, comparisons of the algorithm-generated route descriptions with human-generated route descriptions would be misleading.

- The algorithm is designed to choose landmarks that can easily be identified by people, and hence are suited for a wayfinder to follow the described route. Experimentally evaluating the quality of automated route instruction might be achieved by asking human subjects to follow the route descriptions and observing routing errors. This approach, however, raises the problem of statistical significant sample sizes for the 170,000 POIs nationwide in the Whereis directory.

Since the online service still relies on a relatively small set of candidate landmarks, the absence of a landmark in the description of the action at a decision point is in most cases not the consequence of the scoring in our selection algorithm. The relatively dense POI population of Spring Street (Figure 5; or highlighted in Figure 3) is an exception, and was chosen for this reason in Section 6.1 to study the selectivity of the algorithm.

For the same reason, the additional routes analyzed were all chosen from the central business district of Melbourne. The routes varied in the directions of travel along segments, and in the intersections with "interesting" POIs. The following observations were made:

- The other landmarks referred to in this set of routes were *Melbourne Museum*, *Grossi Florentino* (a restaurant), *Waterfront City* (an areal landmark at Docklands), *car park* (multiple, unnamed), *Flagstaff Train Station*, and *Assessment Prison*.
- Landmark selection is, as expected, direction dependent. Different landmarks do indeed occur in the reverse route directions.
- Landmark selection is route dependent. Landmarks mentioned at a decision point for one routes context are frequently absent on routes where an intersection is not a decision point (i.e., where the route continues straight over the intersection).

Figure 5. Landmark candidates in Melbourne CBD, and some of the tested routes highlighted.

The selection of Flagstaff Train Station is worth some attention. Train stations are a category in the Whereis directory. However, other prominent train stations like Flinders Street Station or Southern Cross Station did not appear in route directions. We believe that this happens because Flagstaff Train Station is an underground train station with an entrance (point georeference) at a street intersection. The other prominent train stations are extended complex buildings, but represented in the database as point geocodes. If their (point) georeference is not close enough to a street intersection, then they are not found as landmark candidates. This issue could be addressed by augmenting the data sets with large stations as spatially extended (polygonal) areas of interest (see Section 4.3.3), just as already had occurred with some other classes of POIs in our case study (such as parks).

The multiple selections of car parks reveal their relatively high scoring due to the size, ease of recognition, and general high visibility of these features (for example, adorned with numerous blue road signs in Australia). Because car parks in the central business district are multi-storey, they are typically stored as points of interest. Unlike train stations, representing car parks as points of interest is advantageous, since the point georeference is typically located near highly visible entrances, and close to intersections.

In summary, the landmarks chosen are acceptable to a local expert as suitable for the communication of those routes. However, quantitative analysis of the outputs of the online system using human subject test remain a task for future work.

7 Related navigation services

Finally, we briefly highlight the current state-of-the-art in other related navigation services. There are very few existing systems that refer to landmarks. But those services we cannot rigorously assess, since they do not disclose their landmark identification and selection mechanisms. Hence, we are dependent on drawing conclusions about their landmark inclusion process from observations of the routes they generate.

Figure 6 shows a short sequence of instructions provided by a current navigation service. The references to points of interest (Travelodge, British Library) may be salient, but their lack of relevance and integration with the route instructions suggests that this service does not select landmarks at all, merely includes POIs. The choice and presentation of references to POIs also suggests commercial rather than cognitive considerations play a large part in the selection of POIs.

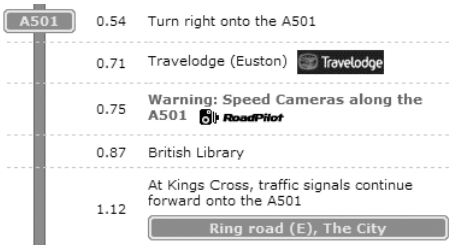

Figure 6. Points of interest (*Travelodge*, *British Library*) of intransparent, and in this case questionable relevance (taken from AA 2009).

Figure 7 shows a short sequence of instructions provided by another current navigation service. The three points of interests in this sequence are all branches of the same bank. If these branches are so frequent in that area, one can barely argue that a single branch stands out in that environment, or that wayfinding by them is safe from the risk of mix-ups: only the route itself can disambiguate between the individuals of the same name, and that is already forming a cognitively complex operation. This choice of references again suggests commercial rather than cognitive considerations in the selection process.

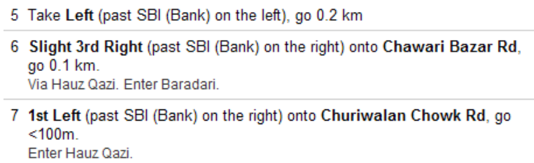

Figure 7. Points of interest (*SBI (Bank)*) of questionable salience (taken from Yahoo India 2009).

In summary, the few other existing navigation services that claim to include landmarks in their route instructions do not appear to use the basic cognitive principles in the literature, which have provided the basis for our implementation.

8 Conclusions

This paper presents a conceptual model and related algorithms for generating routing instructions with landmarks. A key feature of this model is that it relies on commonly available data about categories of landmarks, rather than detailed instance level data about the visual characteristics and facades of buildings. Thus, the process of annotating routing instructions with landmarks has two phases: an offline process of landmark identification from available categories; and an online landmark selection process based on route-specific factors. The algorithms generated have been implemented within a national online routing system, and the results indicate that the cognitive principles used in algorithm design are embodied by the landmarks chosen in routing instructions generated.

A very wide range of future work is suggested by this work, including:

- *Route selection*: The LNM model selects landmarks with which to annotate a given route (such as the shortest path). However, potentially it would also be possible to generate algorithms that select routes themselves based on their landmark properties, and ease of description (cf. work on "simplest paths" Duckham and Kulik (2003); Richter and Duckham (2008)).

- *Corrections*: Many human navigation instructions include not simply confirmations (such as "continue past the Princess Theater") but also include correction instructions, like "If you reach the river, you've gone too far." Potentially, the LNM might be extended to provide such instructions, but would need to be adapted to search for selected off route landmarks.
- *Chunking*: Chunking is the process of combining actions for multiple decision points into a single routing instruction (e.g., "Turn left at the third intersection"). It has been argued that chunking is an important factors in route instructions (e.g., Klippel (2003); Klippel et al. (2005b)) and potentially might relatively easily be included in further extensions to the LNM in this paper.
- *3D imagery*: While one of the objectives of this research was to avoid the *requirement* for detailed 3D facade imagery, where such data exists, existing measures of visual salience could potentially be integrated with the LNM to provide landmark selection that was more sensitive to the specific visual characteristics of a POI.
- *Human subject testing*: At several points we have highlighted the need for heuristics in selecting landmarks (for example in deciding the length of time before an in-leg confirmation by landmarks should be given). Future work might empirically examine these heuristics with human usability studies, helping to parameterize the model (e.g., changing relative weighting, generation of overall weights, module weights).

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