Enriching Wayfinding Instructions with Local Landmarks

Martin Raubal[1] and Stephan Winter[2]

[1] Institute for Geoinformatics, University of Münster, Robert-Koch-Str. 26-28, 48149 Münster, Germany
raubal@ifgi.uni-muenster.de
[2] Institute for Geoinformation, Vienna University of Technology, Gusshausstr. 27-29, 1040 Vienna, Austria
winter@geoinfo.tuwien.ac.at

Abstract. Navigation services communicate optimal routes to users by providing sequences of instructions for these routes. Each single instruction guides the wayfinder from one decision point to the next. The instructions are based on geometric data from the street network, which is typically the only dataset available. This paper addresses the question of enriching such wayfinding instructions with local landmarks. We propose measures to formally specify the landmark saliency of a feature. Values for these measures are subject to hypothesis tests in order to define and extract landmarks from datasets. The extracted landmarks are then integrated in the wayfinding instructions. A concrete example from the city of Vienna demonstrates the applicability and usefulness of the method.

1 Introduction

Assume that you are spending a few days as a tourist in Vienna. You have just enjoyed a cup of coffee in one of the traditional coffee houses, the Café *Diglas*, and you start thinking about dinner. Your tourist guide recommends one of the current in-restaurants, *Novelli*. Unfortunately, what you get is only the address, not the best or any route from the Café *Diglas* to *Novelli*. This is a typical scenario for a navigation service, a special case of a location-based service. Calling the service should provide a route guide, delivered in real time and tailored for the user's needs, in our case a pedestrian.

Navigation services calculate an optimal route and provide a sequence of instructions for this route. Each single instruction guides the user from one decision point to the next. Typically, the instructions use geometric data from the street network, which is the only dataset available. This paper addresses the question of enriching such wayfinding instructions with landmarks. Research in spatial cognition has shown that people use landmarks during spatial reasoning and communication of routes, therefore this question is not only of theoretical but also of high practical importance. The main challenges are the automatic definition and extraction of appropriate salient features, i.e., *landmarks*, from the available datasets. Data providers offer so-called *Points Of Interest* (POI) geo-coded in spatial datasets. These POI are hard-coded and predefined. A navigation service can use them or not; no method is provided to measure the attractiveness or relevance of a POI for being a landmark for a particular user involved in a navigation task.

The hypothesis of this paper is that a formal model of *landmark saliency* based on perceptual and cognitive concepts (i.e., vision and commonsense knowledge) allows for an automatic generation of route instructions, which include landmarks and are close to human communication. The goal is to improve existing navigation services by concepts closer to the human user, adaptive for individual users, with flexibility for different tasks.

Section 2 gives an overview of human wayfinding and highlights the importance of landmarks for navigation. It further describes the components of wayfinding instructions and how they are used in a navigation service. In section 3 we present the properties of features used to measure their attractiveness as landmarks and describe data sources from which property values can be derived. Section 4 explains hypothesis testing as the method for defining and extracting landmarks from datasets and combines the individual properties to form a global formal measure of landmark saliency for a feature. A case study in section 5 is used to demonstrate the proposed method. The final section gives conclusions and directions for future work.

2 Wayfinding, Navigation, and Landmarks

2.1 Human Wayfinding

Human wayfinding research investigates the processes that take place when people orient themselves and navigate through space. Theories try to explain how people find their ways in the physical world, what people need to find their ways, how they communicate directions, and how people's verbal and visual abilities influence wayfinding. Allen [1] and Golledge [9] describe wayfinding behavior as purposeful, directed, and motivated movement from an origin to a specific distant destination, which cannot be directly perceived by the traveler. Such behavior involves interactions between the traveler and the environment. Human wayfinding takes place in large-scale spaces ([6], [14]). Such spaces cannot be perceived from a single viewpoint therefore people have to navigate through large-scale spaces to experience them. Examples for large-scale spaces are landscapes, cities, and buildings.

People use various spatial, cognitive, and behavioral abilities to find their ways. These abilities are a necessary prerequisite to use environmental information or representations of spatial knowledge about the environment. The spatial abilities are task-dependent and seem to involve mainly four interactive resources: perceptual capabilities, information-processing capabilities, previously acquired knowledge, and motor capabilities [1]. As for the spatial abilities, the cognitive abilities also depend on the task at hand. Finding one's way in a city uses a different set of cognitive abilities than navigating in a building.

Allen [1] distinguishes between three categories of wayfinding tasks: travel with the goal of reaching a familiar destination, exploratory travel with the goal of returning to a familiar point of origin, and travel with the goal of reaching a novel destination. A task within the last category, which is also the focus in this paper, is most often performed through the use of symbolic information. Here, we concentrate on landmark-based piloting where success depends on the recognition of landmarks and the correct execution of the associated wayfinding instructions.

2.2 Landmarks and Navigation

Among the different meanings of *landmark* is that of an object or structure that marks a locality and is used as a point of reference [21]. The concept is bound to the *prominence* or *distinctiveness* of a feature in a large-scale environment or landscape ([10], [7]). Thus the landmark saliency of a feature does not depend on its individual attributes but on the distinction to attributes of close features. Being a landmark is a relative property.

Landmarks are used in mental representations of space [28] and in the communication of route directions ([31], [19], [17]). Route directions shall provide a 'set of procedures and descriptions that allow someone using them to build an advance model of the environment to be traversed' ([23], p. 293). Landmarks support the building of a mental representation of such an advance model. Studies show that landmarks are selected for route directions preferably at decision points ([12], [23]). Another study has shown that mapped routes enriched with landmarks at decision points lead to better guidance, or less wayfinding errors, than routes without landmarks. Furthermore, different methods of landmark presentations were equally effective [4].

Lovelace et al. [17] distinguish between landmarks at decision points (where a re-orientation is needed), at potential decision points (where a re-orientation would be possible, but should not be done to follow the current route), route marks (confirming to be on the right way), and distant landmarks. According to [18], distant landmarks are only used in navigation by a novice for overall guidance. We call landmarks at decision points and route marks the *local* landmarks with respect to a specific route.

Lynch [18] defines landmarks as external points of reference—points that are not part of a route like the nodes in a travel network. He characterizes the quality of a landmark by its singularity, where singularity is bound to a clear form, contrast to the background, and a prominent location. The principal factor is the figure-background contrast ([32], [22]). The contrast can be produced by any property, such as uniqueness in form or function in the local or global neighborhood. Sorrows and Hirtle [29] categorize landmarks into *visual* (visual contrast), *structural* (prominent location), and *cognitive* (use, meaning) ones, depending on their dominant individual quality. A landmark will be stronger the more qualities it possesses.

However, a formal measure for the landmark saliency of an object is still missing. Research is done in mainly two directions: the investigation of what objects are selected as landmarks in human route directions ([5], [23]) and the test of the success of pre-selected landmarks ([4], [8]). Little research is concerned with the identification of salient characteristics for the choice of landmarks for a route, as for instance in the context of car navigation by Burnett ([2], [3]). This issue is investigated more in the domain of robotics. Robots use automatic selection of landmarks for their self-orientation and positioning. Landmarks in this context are merely feature details, such as vertical lines, rather than features ([33], [16]). Such concepts do not seem appropriate for supporting human wayfinding.

Progress in telecommunication technology allows the enrichment of environments with beacons that can act as active landmarks by attracting nearby mobile devices [26]. Such landmarks are not perceived directly by humans but through their interaction with software. Hence, active landmarks—although they can play a role in navigation—cannot be used as a reference for human users. Also, virtual landmarks, like virtual information towers embedded in a model of the real world [24] cannot serve as reference points for human wayfinders, because they have no physical counterpart.

2.3 Wayfinding Instructions

The basic assumption of this paper is that route directions enriched by local landmarks are easier to understand than the ones, which are only direction- and distance based. We propose the following formal model for the test of this assumption.

- A route consists of a sequence of nodes and edges.
- At nodes, the traveler needs information whether she shall continue moving in the present direction, or turn. Hence, nodes are called decision points in this model. One can distinguish between nodes where a re-orientation has to take place and other nodes where re-orientation is not necessary.
- Orientation and re-orientation shall be referenced to:
  - Landmarks as anchors. This means we need at least one landmark at each decision point. If there are more, context-dependent selection criteria need to be applied to find the best one (direction of view, means of traveling, time of day).
  - Egocentric cardinal orientations (front, back, left, right), assuming the orientation of the present direction.
- Along edges no orientation action needs to take place. The traveler shall move from the start node to the end node, i.e., from decision point to decision point.
- Optionally, landmarks along edges (route marks) can be used to confirm to the traveler that she is on the right track.

With these elements a general form of directions is the following ('[]' denoting required elements, '{}' optional elements, 'UPPER CASE' language elements, and 'lowercase' variables):

$$\texttt{[AT landmark}_i\texttt{] +}$$
$$\texttt{[TURN LEFT | RIGHT | MOVE STRAIGHT] +}$$
$$\texttt{\{ONTO street name\} +}$$
$$\texttt{\{(PASSING | CROSSING) landmark}_j\texttt{\}}_{0\ldots n}\texttt{ +}$$
$$\texttt{[UNTIL landmark}_k\texttt{].}$$

with $i \neq j \neq k$. There shall be no reference to distance information or cardinal directions. Such survey information might nevertheless be useful for wayfinders and can easily be integrated if needed. All that is left now is the automatic extraction of suitable landmarks for use in these route directions.

3 Measures for the Attractiveness of Landmarks

The main contribution of this paper is a formal model of *landmark saliency*, which includes measures for the attractiveness of landmarks. In order to determine whether a feature qualifies as an attractive landmark we specify properties, which determine the strength of a landmark. In this section we identify such measures by taking into account the three types of landmarks as proposed by Sorrows and Hirtle [29]. Following their framework we presume that the *visual*, *semantic*, and *structural* attraction of features in geographic space determine their use as landmarks in human spatial reasoning and communication. The final part of the section describes the necessary data sources from which to derive values for the measures.

3.1 Visual Attraction

Landmarks qualify as visually attractive if they have certain visual characteristics such as a sharp contrast with their surroundings or a prominent spatial location. Our formal model of landmark saliency includes four measures regarding visual attraction: *Façade area*, *shape*, *color*, and *visibility*. Table 1 shows the individual properties for visual attraction of an object, gives an example for each kind, and describes how these properties are measured. We propose to apply a statistical measure, i.e., a hypothesis test (see 4.1), to find out whether the values of these properties are significantly different to objects in the local area, e.g., along the same street segment.

Façade Area. The façade area of an object is an important property for determining its contrast to surrounding objects. People tend to easily notice objects whose façade areas significantly exceed or fall below the façade areas of surrounding objects. In the trivial case of a regularly shaped building (of rectangular form) the façade area is calculated by multiplying its width and height.

Shape. Visual attraction of an object is also determined by its shape. Unorthodox shapes amidst conventional rectangle-like shapes strike one's eyes. We formally specify the shape measure of an object by considering its shape factor and also the deviation of its shape from that of a rectangle. The *shape factor* represents the proportion of height and width. For example, skyscrapers have a high shape factor, whereas long and low buildings have a low shape factor. The value of *deviation* is the difference between the area of the minimum-bounding rectangle of the object's façade and its façade area. Notice that the value of deviation is not unique: Although two objects are of different shape they can have the same value of deviation.

Color. An object can stand out from surrounding objects based on its color. For example, imagine a red fire department building in the midst of a set of gray buildings. We appoint a color value to each object by assigning decimal values from the RGB color chart and then determine whether this color is different from the colors of surrounding objects.

In principle, color is a property difficult to measure and compare. Perceived light is a complex function of illumination, reflectance/absorption on surfaces, and receptive abilities of the visual sense. As Mallot [20] states, it makes no sense to define a metric in a color space, having no single basic color space. However, in the given context one can reasonably argue for a white and not too specific illumination (daylight). If the images are taken in diffuse daylight, color should be roughly comparable. In a first approach, the color of a building can be measured globally (mean or median), by a single [R,G,B] triple. A refined approach needs high-level knowledge for image interpretation to select segments of the background color of a building for measurement.

Given a triple for all buildings in the neighborhood, a mean color can be estimated, and distances (L_2 norm) from the mean can be calculated for the hypothesis test.

Visibility. The final property to be measured is the prominence of spatial location. We propose to measure this property by calculating two-dimensional visibility. Visibility is considered for the space used in the actual mobility mode—for pedestrians this is the public street space plus some private areas. It is assumed that visibility is limited by recognizability, for which reason a pre-defined buffer zone limits the considered space (and reduces computational complexity). The value of visibility is then derived from the area of the space covered by the visibility cone of the front side of a built object (Figure 1), which can then be ordered for the whole set of objects within a street segment.

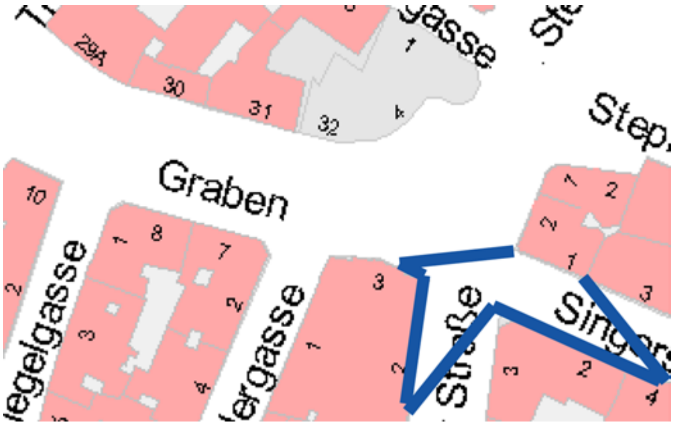

Fig. 1. Example for visibility area for 'Singerstrasse 1' within buffer zone (100m).

Other Visual Properties. Other properties of an object, such as its texture and condition, may also influence the contrast to surrounding objects. The reasons for not including them in our formal model are their subjectivity and lack of formality. The texture of an object is often hard to identify, both from databases and in the real world. The condition of an object refers to its age and cleanliness. Age is easy to determine from a database, but often very hard to guess in the real world. For example, a building may be very old but due to a recent renovation looks new. Cleanliness is a subjective measure and therefore hard to specify within formal terms.

Although these properties can be measured objectively according to the specified rules and criteria, their actual perception by wayfinders is influenced by temporal constraints. For example, it can be hard to detect the color of a building at night (on the other hand brightly illuminated buildings are very prominent at night) and the visibility of a landmark decreases dramatically on a foggy day.

Table 1. Properties for visual attraction and how they are measured.

Properties for visual attraction	Example	Measurement
Façade area	α = 25m * 15m = 375sqm	$\alpha = \int x \mid x \in facade$
Shape		
• Shape factor	β_1 = 15m / 25m = 0.6	β_1 = height / width
• Shape deviation from rectangle	β_2 = 375sqm – 295sqm = 21%	β_2 = (area of minimum bounding rectangle – α) / area of minimum bounding rectangle
Color	γ = [255, 0, 0] = red	γ = [R, G, B]
Visibility	δ = 2400 sqm	$\delta = \sum x \mid y\ visible$

3.2 Semantic Attraction

Our notion of semantic attraction is similar to that of cognitive attraction [29], which focuses on the meaning of a feature. Semantic measures for the formal model of landmark saliency comprise *cultural* and *historical importance* of an object, and *explicit marks*. The properties for semantic attraction, typical examples, and how these properties are measured can be seen in Table 2.

Cultural and Historical Importance. Semantic attraction can result from the cultural and historical importance of an object. For example, the 'Looshaus' in the first district of Vienna is famous for its architectural style (Art Nouveau). This property can be deduced from a database including cultural and historical objects. For the City of Vienna such information is available from the so-called 'Kulturgüterkataster'—a database of cultural, archeological, and architectural treasures[1]. This database also includes pictures of the objects. Here, we assign a Boolean value to each object: 'True' if it is of cultural or historical importance and 'False' otherwise. One could refine this assignment by using a classification system similar to the ones of travel guides for important sites. There, the cultural and historical importance of objects is often measured on a predefined scale, e.g., from 1 to 5.

Explicit Marks. Marks such as signs on the front of a building explicitly specify its semantics to the wayfinder. For example, a street sign gives information on what street the building is located. If a building is marked as 'coffee house X' or 'museum Y' then we can also know something about it, which cannot be inferred from its other visual properties. From the point of view of the provider offering a service with wayfinding instructions, the commercial semantics of buildings (which is most often highlighted by explicit marks such as the sign of a supermarket), can be easily extracted from the yellow pages of the area. An object with an explicit mark is

[1] http://service.magwien.gv.at/kulturkat/

assigned the Boolean value ‘True’ whereas objects without explicit marks have the value ‘False.’

Other Semantic Properties. Other measures for semantic attraction, which are not included in our formal model, are *prototypicality* and *implicit semantics*. A prototypical object is easy to recognize. For example, St. Stephen’s dome in Vienna is regarded as a prototypical example for a church, whereas a modern church without a steeple is not considered prototypical. Although categories and prototype effects have been widely studied among psychologists and linguists ([27], [15]), extensive human subjects testing concerning the prototypicality of objects along a given route would be necessary to derive useful results, which could then be implemented in a database.

In the real world, people derive the meaning of an object from either implicit or explicit semantics. For example, by looking through the windows of a building one might detect people sitting at tables drinking coffee, talking to other people, or reading newspapers. The conclusion would be that this is a coffee house, although the building is not explicitly marked as such, therefore *implicit semantics*. Another example is the conclusion that ‘this building must be the museum we are looking for, because there is a crowd of people lining up in front of the entrance.’ Implicit semantics is difficult to specify because it is both user- and context dependent, and also temporally constrained, e.g., opening hours of a coffee house.

Table 2. Properties for semantic attraction and how they are measured.

Properties for semantic attraction	Example	Measurement
Cultural and historical importance	$\varepsilon = T$	$\varepsilon \in \{T, F\}$
	$\varepsilon = 1$ (building very famous for its architecture)	$\varepsilon \in \{1,2,3,4,5\}$ Scale of importance: 1 (high) – 5 (low)
Explicit mark	$\zeta = T$ Sign on front of a building	$\zeta \in \{T, F\}$ Boolean

3.3 Structural Attraction

A landmark is structurally attractive if it plays a major role or has a prominent location in the structure of the spatial environment. Examples are intersections and downtown plazas [29]. The structure considered here is the travel network of a traveler with a single means of transport (fixed context). Corresponding to Lynch’s [18] elements that structure a city, *nodes*, *boundaries* (edges), and *regions* (districts) are structural elements that are perceivable and might become prominent due to their individual structuring properties. In this paper we focus on local landmarks for wayfinding, therefore only nodes and boundaries need to be considered. The individual properties for structural attraction, examples for these properties, and how they are measured can be seen in Table 3.

Nodes. Nodes in a travel network are its intersections. For car drivers nodes may be street intersections, for pedestrians nodes may be places, and for business travelers nodes may be airports. The central structural characteristic of a node is its grade of connectivity, or, in terms of graph theory, its degree (Figure 2). The degree may be additionally weighted by the quality of the incoming and outgoing edges. For example, the street network hierarchy [30] allows for making a distinction between two intersecting highways and two intersecting lanes in a street network. Weights could be defined on a scale from 5 (highways) to 1 (footpaths), with state streets, overland streets, and town streets in between.

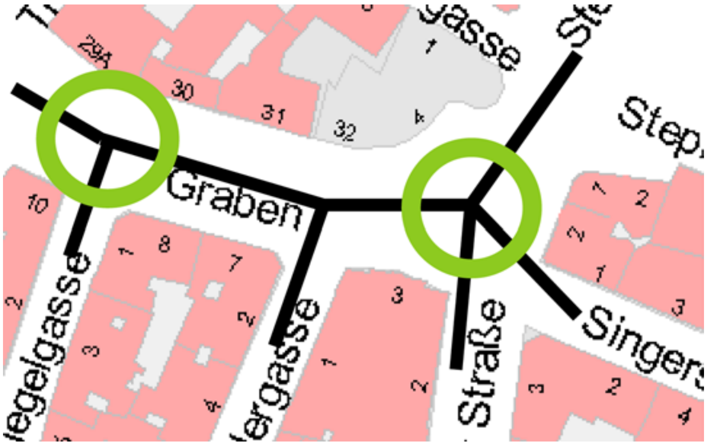

Fig. 2. A T-junction (degree = 3) is quite common in street networks and therefore less remarkable than a central place (degree = 4).

Boundaries. The perception of the structural properties of *boundaries* is linked to the energy that has to be spent to cross them. We hypothesize that a boundary is the more prominent the larger its resistance is. For example, the 'Westbahn' (westbound train line) in Vienna separates two districts, and can be crossed only over two bridges or through a tunnel of 2 km length. A similar perceivable boundary is the 'Donaukanal' (channel of the Danube) that separates the dense street networks of the first and second districts by only a few links. Such barriers form significant shapes in city maps: the travel networks show enclosed cells of large boundary edges with a small distance between opposite edges, i.e., with a large form factor (Figures 3, 4). A measure such as the product of cell size and form factor characterizes the structural landmark saliency of the objects in these cells.

Other Structural Properties. The last of Lynch's structural elements, i.e., regions, corresponds to quarters, districts, and other areal subdivisions in the city. Such elements may be useful landmarks in larger scale applications.

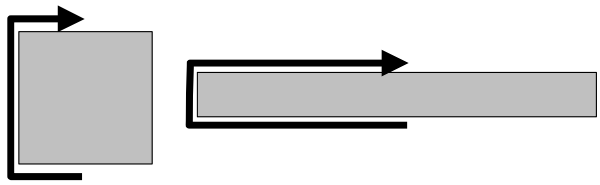

Fig. 3. Both cells have the same size but the right cell has a bigger form factor and creates the larger barrier.

Fig. 4. The way from Spiegelgasse 9 to Dorotheergasse 7 (Jewish Museum) is long compared to the distance. The shape of the block of buildings creates a barrier.

Table 3. Properties for structural attraction and how they are measured.

Properties for structural attraction	Example	Measurement
Nodes	$\eta = (4*2+4*2)$ Second node in Figure 2 for pedestrians; all streets are town streets (w=2)	$\eta = (i+o)$ Weighted incoming (i) and outgoing (o) edges to and from a node
Boundaries	$\theta = 2500$ Channel dividing a district	θ = cell size * form factor Form factor: long side / short side

3.4 Used Data

For the automatic selection of context-dependent landmarks for navigation a number of data sources need to be available. According to the nature of landmarks, visual data as well as semantic and structural data are required. Hence, city maps and street graphs are complemented with images and content databases.

The following data sources are implied:

- Digital city maps, such as the multipurpose map of Vienna. City maps provide boundaries and classifications of the built areas. This information is useful for model-driven image segmentation and rectification ([11], [25]).
- Navigation graphs for the actual means of travel. Navigation graphs are needed for route selection algorithms as well as for the route-specific classification into possible and real decision points.
- Rectified, geo-referenced images of façades of each single building located at elements of the navigation graph. TeleInfo[2] provides a complete coverage of geo-referenced images for the street network in Germany and Austria. Figure 5 shows a (distorted) 360°-view of an intersection demonstrating the richness and complexity of this type of data.

Fig. 5. A 360°-view of the intersection Stephansplatz / Singerstrasse / Kärntner Strasse / Graben in Vienna.

- Accessible databases such as yellow pages, or databases of cultural heritage, provide the required semantic content.

4 Assessment of Landmark Saliency

This section introduces the method used to assess the landmark saliency of a feature, i.e., hypothesis testing. Applying this method to the properties presented in section 3 allows for defining a total measure of landmark saliency for each feature in a dataset.

[2] http://www.teleinfo.de

4.1 Finding Landmarks

As the landmark saliency of a feature is bound to its prominence or distinctiveness, it is straightforward to evaluate the distinction between the feature attributes and attributes of other features. A global landmark needs to be distinctive from all other features, but our limitation to *local* landmarks allows a reduction to features that are nearby. The computationally simplest approach to find the most distinctive feature at a given location is a maximum (minimum) operator for each attribute, and also for the total value of attraction. This procedure guarantees finding a local landmark in any case, even if the difference from a local mean is small. However, the result cannot be assessed in terms of significance.

For those measures that are continuous and a normal distribution can be assumed, the assessment can be reached by hypothesis testing of the significance of deviations from local mean characteristics [13]. Assuming a *typical* local appearance of objects we may suppose a normal distribution for some of the characteristics. Further assuming that there are outliers (namely the landmarks) the estimated mean of the distribution shall be determined by the median of all local observations. Also, the standard deviation can be calculated. Both parameters—mean and standard deviation—depend on the definition of a local neighborhood. This definition should be linked to the perceptual capabilities of the human users in a specific mode of traveling, e.g., for pedestrians the neighborhood should be chosen smaller than for car drivers. The parameters of a distribution are calculated once and then updated only when changes in the local environment occur, which happens rarely. This means that the local neighborhood can be bound to each feature, similar to a local filter operation. One could choose a rectangle of a specific side length depending on the mode of travel.

Given the local parameters of the distribution for each characteristic, the feature attributes can be tested for their difference from the mean. The hypothesis is that the feature attributes deviate significantly from the local mean. If the hypothesis is rejected, the feature attribute is not significantly different from its surroundings. If the hypothesis is accepted, the feature has some kind of landmark saliency, related to the tested attribute. *Type I errors* (rejecting a correct hypothesis) lead to distinctive features that are not detected. *Type II errors* (accepting a wrong hypothesis) lead to the use of features as landmarks that are not distinctive. Type II errors are more expensive because they lead to instructions, which are not useful. This means the power of the test—the probability β of avoiding a Type II error—will be set high in the test procedure.

4.2 Combination of Property Values for Measuring Landmark Saliency

The individual measures of properties shall now be combined to a global measure of landmark saliency for each feature in a dataset. In a first computational step the vector of property values is determined for each feature (Table 4). Then, for each feature and each property the local mean and standard deviation are determined (see 4.1). Each triple of value, local mean, and standard deviation, is subject to a hypothesis test that determines whether a property value is significant (s=1) or not (s=0). The vector of *significance* values can be grouped for visual, semantic, and structural significance. With predefined weights for each group a total measure for the landmark saliency of a feature can be calculated. The predefined weights allow for an adaptation to the context (mode of travel) or individual user preferences.

Table 4. Deriving the total value of landmark saliency for a feature.

Measure	Property	Value	Significance (Property)	Significance (Measure)	Weight	Weighted Significance	Total
Visual attraction	α	…	s_α	$s_{vis} = (s_\alpha + s_{\beta1} + s_{\beta2} + s_\gamma + s_\delta) / 5$	w_{vis}	$s_{vis} * w_{vis}$	$s_{vis} * w_{vis} + s_{sem} * w_{sem} + s_{str} * w_{str}$
	β_1	…	$s_{\beta1}$				
	β_2	…	$s_{\beta2}$				
	γ	…	s_γ				
	δ	…	s_δ				
Semantic attraction	ε	…	s_ε	$s_{sem} = (s_\varepsilon + s_\zeta) / 2$	w_{sem}	$s_{sem} * w_{sem}$	
	ζ	…	s_ζ				
Structural attraction	η	…	s_η	$s_{str} = (s_\eta + s_\theta) / 2$	w_{str}	$s_{str} * w_{str}$	
	θ	…	s_θ				

5 Wayfinding Instructions with Local Landmarks – An Example

This section demonstrates the applicability and usefulness of the presented approach by showing an example from the introductory case study (section 1).

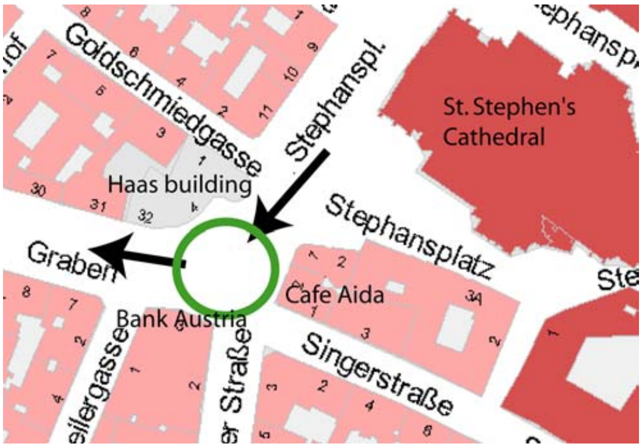

Fig. 6. The instruction at the decision point shall use the most salient feature at the decision point.

5.1 Description of the Situation

When taking the shortest path from the Café *Diglas* to the restaurant *Novelli*—both located in Vienna's first district—the wayfinder reaches at some point the intersection of 'Graben', 'Kärntner Strasse', and 'Stephansplatz' (Figure 6 gives a panoramic view). This decision point is used to demonstrate the selection of a landmark based on the method developed in the paper. The instruction at the decision point has to direct one to turn right, and the available data is evaluated for the automatic selection of a local landmark.

5.2 Measures and Weights for the Extraction of a Local Landmark

The measures for the attractiveness are calculated for all features at the decision point. Table 5 shows the individual property values and the total value of landmark saliency for the 'Haas' building. The total value of landmark saliency is 1.8, which is the maximum value for all features. The next total value is 1.2 for the 'Bank Austria' building. It is therefore recommended to use the 'Haas' building as a local landmark in an instruction at this decision point.

Table 5. Deriving the total value of landmark saliency for the 'Haas' building.

Measure	Property	Value	Significance (Property)	Significance (Measure)	Weight	Weighted Significance	Total
Visual attraction	α	17400	1	$s_{vis} = 0.8$	$w_{vis} = 1$	0.8	1.8
	β_1	0.62	1				
	β_2	0	0				
	γ	21 24 38	1				
	δ	10600	1				
Semantic attraction	ε	T	1	$s_{sem} = 2 / 2$	$w_{sem} = 1$	1	
	ζ	T	1				
Structural attraction	η	-	0	$s_{str} = 0 / 2$	$w_{str} = 1$	0	
	θ	-	0				

In the given example, the weights are set to $w_{vis} = 1$, $w_{sem} = 1$, and $w_{str} = 1$. Different sets of weights could be selected for different user groups. For example, the set of weights $w_{vis} = 3$, $w_{sem} = 1$, and $w_{str} = 1$ would reflect the visual capabilities of certain users and might lead to a different resulting landmark (it would nevertheless not change the outcome in this case).

5.3 The Wayfinding Directions

Having identified a local landmark at the decision point, an instruction can be created following any grammar, for instance the grammar defined in section 2.3. The way a landmark is communicated is not of central concern in this paper; however, at the time of creating the instruction all significant properties of the landmark are known and can be used.

In our case, the identified landmark is the 'Haas' building, which is known for its controversial architecture (Figure 7). The instruction using the feature *'Haas' building* as a destination landmark is then:

```
AT previous landmark
TURN LEFT ONTO "Stephansplatz"
UNTIL "Haas building, a dark building of architectural
significance containing a (signed) Zara shop at the
right"
```

Fig. 7. The most salient feature at the considered decision point: the 'Haas' building by architect Hans Hollein.

The example can be extended by showing the (optional) use of a route mark in the instruction. With the landmark 'St. Stephen's cathedral' along the considered route segment, the instruction has the following form:

```
AT previous landmark
TURN LEFT ONTO "Stephansplatz"
PASSING "Stephansdom, a visually salient world cultural
heritage building"
UNTIL "Haas building, a dark building of architectural
significance containing a (signed) Zara shop at the
right"
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Note the chosen freedom to generalize different visually significant properties (façade area, shape factor) into 'visually salient.'

6 Conclusions and Future Work

In this paper we presented a method to automatically extract local landmarks from datasets to be integrated in wayfinding instructions. Different individual properties for the attractiveness of a landmark were first defined and then put together to form a global measure of landmark saliency for each feature in a dataset. Hypothesis testing was used to select the most significant landmark at each decision point for inclusion in the wayfinding instruction. We applied the formal framework to an actual wayfinding scenario to show the applicability and usefulness of our approach.

The work leads to many different directions for future research:

1. Activity- and profile-based selection of landmarks: Human subjects testing will show how the weights of the attraction measures have to be adapted for different modes of travel (e.g., pedestrian, bicycle, car) and user groups (e.g., tourist, business traveler, handicapped).
2. One needs to find out how accurate the data have to be to get useful results.
3. The method needs to be implemented and applied to larger datasets in order to analyze performance and computational cost.
4. In the case study we have calculated measures of landmark saliency for individual features only. How can aggregate landmarks (formed by connected objects such as a block of buildings) be extracted automatically?
5. Different times (e.g., day- or nighttime) may require different landmarks therefore the integration of temporal constraints into route instructions is necessary.

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