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Selection of Salient Features for Route Directions

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People navigating in unfamiliar environments rely on wayfinding directions, either given by people familiar with the place, or given by maps or wayfinding services. The essential role of landmarks in human route communication is well-known. However, mapping the human ability to select landmarks ad hoc for route directions to a computational model was never tried before. Wayfinding services manage the problem by using pre-defined points of interest. These points are not automatically identified, and they are not related to any route. In contrast, here a computational model is presented that selects salient features along a route where needed, e.g., at decision points. We propose measures to formally specify the salience of a feature. The observed values of these measures are subject to stochastical tests in order to identify the most salient features from datasets. The proposed model is implemented and checked for computability with a use case from the city of Vienna. It is also cross-checked with a human subject survey for landmarks along a given route. The survey provides evidence that the proposed model selects features that are strongly correlated to human concepts of landmarks. Hence, integrating the selected salient features in wayfinding directions will produce directions with lower cognitive workload and higher success rates, compared to directions based only on geometry, or on geometry and static points of interest.

Keywords: Wayfinding, landmarks, salience, route directions.

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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 from the guide is only the address, not a route direction from your current place, the Café Diglas, to the Novelli. You realize that you have two options: ask a local resident, or call your mobile wayfinding service. The qualities of the two results would be quite different. While it is well-investigated that directions given by people rely on the use of landmarks, especially at decision points, automatically produced directions rely on geometry and place names. The basic assumption of this paper is that it is easier for people to follow route directions based on landmarks. Otherwise human communication of routes would have developed differently. There might be differences in the selected route also, which are not considered here.

Wayfinding services calculate a route, which is optimal with respect to some context-specific cost functions. They provide a sequence of directions for this route. Each single direction guides the user from one decision point to the next. Typically, the directions are based on the geometry of the street network, and on other attributes of network elements, such as place names. Sometimes the directions are enriched by *points of interest* (POI). In these cases POI serve as substitutes for landmarks in route directions. However, there are significant differences between POI and landmarks. POI are places where the traveler might consider spending some time, either because of their presumed attractiveness (museum, church) or because of some service offered there (hotel, bank, filling station). Landmarks on the other hand are defined primarily by their distinctiveness. There is also a difference in purpose: POI are presented with the intention to guide the traveler to these places, whereas landmarks are used for marking the way. Currently existing data on POI do not make transparent which features are selected as POI. Often this is determined by commercial interests. There is no method provided to measure the salience of a POI for a specific wayfinding communication, and data providers do not distinguish POI for different modes of traveling. Hence, POI are insufficient to substitute landmarks in route directions.

Automatically selecting reference features for route directions by cognitive criteria would increase the attractiveness of wayfinding services, compared to asking a local resident. Some problems, such as language issues, or identifying a reliable informant, would be excluded, and the quality of the route directions would be comparable to human communication. This paper addresses the automatic selection of such reference features. We develop a model to measure the *salience* of features. Individual measures of salience are related to perceptually or cognitively relevant feature attributes, such as form, color, or prominence. A feature is considered being salient with respect to a specific attribute if its measure deviates significantly from a local mean. Measuring several individual attributes, an overall measure of salience of a feature is calculated. At each decision point of a route, the most salient feature is selected as a local reference. Features considered so far are facades of buildings.

The hypothesis of this paper is that the proposed model of salience provides us with reference features at decision points that are close to human choices at these decision points. This hypothesis will be investigated in two directions. One goal is to design a model of salience that can be computed automatically, that is robust with respect to attribute variability (small changes in the attribute values should produce only small changes in the global measure of salience), that is robust with respect to external impact (attributes are chosen that do not change their appearance all the time), and that might be adaptable to different contexts. The other goal is to find a model that produces as much as possible coincidence in the results with human selections of reference objects. The paper presents such a model and compares the results of a use case with the results of a human subjects survey.

The next section gives an overview of human wayfinding and highlights the importance of landmarks for navigation. Then, we present the properties of features used to measure their attractiveness as landmarks and describe data sources from which property values can be derived. In the following section, we explain hypothesis testing as the method for defining and extracting landmarks from datasets, and combine the individual properties to form a global formal measure of landmark saliency for a feature. A case study in the next section is used to demonstrate the proposed method. In the discussion, we compare the automatically derived results with the results from the survey. The final section gives conclusions and directions for future work.

2 Previous Work

Research on human wayfinding has shown the importance of landmarks for human route communications. This section summarizes results from wayfinding research, identifies roles of landmarks, and tries to define salience as a formal concept of measurable landmarkness.

2.1 Human Wayfinding

Current research in human wayfinding 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 (1999) and Golledge (1999) describe wayfinding behavior as purposeful, directed, and motivated movement from an origin to a specific distant destination that cannot be directly perceived by the traveler. Such behavior involves interactions between the traveler and the environment, like moving. Hence, wayfinding takes place in large-scale spaces (Downs & Stea, 1977; Kuipers, 1978; Montello, 1993). 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 and cognitive 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 (Allen, 1999). 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 wayfinding in a building.

Allen (1999) 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 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 in Wayfinding

In dictionaries, the term *landmark* is defined as an object or structure that marks a locality and is used as a point of reference (Merriam-Webster, 2001; Fellbaum, 1998). The concept is bound to the prominence or distinctiveness of a feature in a large-scale environment or landscape (Golledge, 1993). Thus, the salience 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 (Hirtle & Heidorn, 1993; Siegel & White, 1975; Tversky, 1993), and in the communication of route directions (Daniel & Denis, 1998; Denis, Pazzaglia, Cornoldi, & Bertolo, 1999; Freundschuh, Mark, Gopal, Gould, & Couclelis, 1990; Lovelace, Hegarty, & Montello, 1999; Maaß & Schmauks, 1998; Werner, Krieg-Brückner, Mallot, Schweizer, & Freksa, 1997). 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*' (Michon & Denis, 2001, 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 (Habel, 1988; Michon & Denis, 2001). 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 (Deakin, 1996).

Lovelace, et al. (1999) 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 Lynch (1960), distant landmarks are used in wayfinding only for overall orientation. We call landmarks along a specific route *local landmarks*, in contrast to distant landmarks.

Lynch (1960) defines landmarks as external points of reference: points that are not part of a route or of the travel network itself. 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 (Wertheimer, 1925; Metzger, 1936), the contrast between a feature (the figure) and other features in the environment (background). Contrast is observed with respect to the local neighborhood.

The contrast can be produced by any attribute, such as uniqueness in form or function in the local or global neighborhood. Sorrows and Hirtle (1999), for instance, categorize into visual properties (visual contrast), structural properties (prominence of location), and cognitive properties (use or meaning). The prominence of a landmark will be stronger the more qualities it possesses. Our model will be based on this classification.

However, a formal measure for the salience of a feature is still missing. Research is done in mainly two directions: the investigation of what objects are selected as landmarks in human route directions (Denis, et al., 1999; Michon & Denis, 2001) and the test of the success of preselected landmarks (Deakin, 1996; Fontaine & Denis, 1999). 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, Smith, and May (2001; Burnett, 1998). 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 complex features (Livatino & Madsen, 2000; Yeh, 1995). Such concepts do not seem appropriate for supporting human wayfinding.

Salience is investigated in research on visual attention. For example, *salience maps* encode the salience of every location in a visual scene: locations that get more attention than others are called salient (Wolfe, 2000). Properties that contribute to the salience may be found at different scales and modalities. Wolfe (2000) counts the visual parameters color, orientation, curvature, size, frequency, scale, motion, shape, and depth cue, among others. Thus, the problem of measuring salience is to combine the measures of different properties to a unique salience map (Itti & Koch, 1999; Treisman & Gelade, 1980). Visual search is the guided visual attention to an item in presence of many distractors (Wolfe, 2000). It is argued that in visual search it is easier to find a deviation among canonical stimulus than it is to find a canonical stimulus among deviations (Treisman, 1985). This observation supports our approach to measure salience by deviations from means.

Progress in telecommunication technology allows the enrichment of environments with beacons that can act as *active landmarks* by attracting nearby mobile devices (Pradhan, Brignone, Cui, McReynolds, & Smith, 2001). 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 (Nicklas, Großmann, Schwarz, Volz, & Mitschang, 2001), cannot serve as reference points for human wayfinders, because such landmarks have no physical counterpart.

2.3 Wayfinding Directions

The basic assumption of this paper is that route directions enriched with local landmarks are easier to understand, or more useful, than directions based solely on geometry and place names. The proposed model shall select features that can play the role of landmarks in route directions. Hence, improving route communication is the motivation of this paper, although the communication itself is not in its focus.

Consider route planners on the Web.[1] Each of them provides route directions in formal instructions; the typical operations are *startAt*, *move*, and *turnTo*. Typical objects are *placeName*, *distance*, and *direction*. Frank (2003) discusses several possible forms of instructions, showing that the practical information content of route directions should be measured by the induced actions, not by description lengths. The induced actions depend on the context of traveling, the individual agent's information needs, and its decisions under uncertainty. Hence, the quality of route directions can be measured only by human subject tests, or by simulation with agent-based systems (Frank, 2003); it cannot be measured by objective criteria, such as the presence of landmarks. However, others have shown in human subject tests already that route directions using landmarks are generally more successful.

2.4 Related Work

In a recent paper, Raubal and Winter (2002) proposed salience measures based on visual, semantic, and structural properties of built-up and network features. The current paper concentrates on built-up features, namely facades, and their visual and semantic properties. It extends the work by Raubal and Winter (2002) by proving the concept with real world data, and by cross-checking with human judgment. In another paper, the structural salience of features is investigated further (Winter, 2003a). The usability of salient features in wayfinding directions can be further improved by considering their visibility along the specific route (Winter, 2003b).

In a similar approach, Elias (2003) extracts landmarks from databases. She investigates data mining methods (supervised and unsupervised learning) for the identification of buildings with salient (two-dimensional) geometry in a cadastral dataset. Her criterion gives only indirect clues for salient visual and

[1]For example, http://www.mapquest.com, http://www.maporama.com, http://www.reiseplanung.de, http://www.falk.de, http://www.map24.de, http://www.viamichelin.com, http://mappoint.msn.com

semantic properties, although we share the basic assumption of salience being proportional to the deviation from the mean. Further, her identified salient features are local to a route, but not necessarily local to decision points.

3 Modeling Feature Salience

We consider a prototypical class of features in urban environments (facades), and discuss the formal model to characterize their salience proposed by Raubal and Winter (2002). Salience shall be measured by observing individual visual and semantic attributes from different data sources; structural attributes are not taken into consideration here. Finally, the individual measures are combined to a global measure of salience.

3.1 Visual Attraction

Features qualify as visually attractive if they have certain visual characteristics in sharp contrast to their neighbors. Proposed characteristics of visual attraction are the facade *area*, *shape* (shape factor and shape deviation), *color* and *visibility*. Measures for area and shape can to some extent be computed either from orthoimages or a map, if the map contains height information. Facade color can only be observed in images, and visibility only in a map.

3.1.1 Facade Area

People tend to easily notice features whose size significantly exceeds or falls below the sizes of surrounding features. Therefore, the facade area is a primary measure for salience. For a rectangular facade, the facade area is calculated by width times height. In other cases, it can be accurately computed from orthoimages, by counting the pixels that make up the facade, and multiplying the number with the scale factor of the image.

In most cases it will, however, be hard to classify the facade pixels automatically. Additional information from maps that show the ground plan and, hence, the boundaries of buildings, can improve the classification results. Although images of facades are commercially available, in narrow streets it is difficult to produce and automatically process orthoimages. If some information about the height of the buildings is available from other sources, the facade area (and shape factor) can be calculated entirely without resorting to images. For some cities, there are even three dimensional city models available. Commercial providers guarantee a sufficient height accuracy.[2]

This paper distinguishes between rectangular and non-rectangular facades. For rectangular facades the width and height information from a map was used. The area of non-rectangularly shaped facades was calculated from orthoimages. In these cases the facade area was traced manually, and the pixels of the selection were counted.

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[2]See, for example, http://www.geoville.com/3d_city.

3.1.2 Facade Shape

Unorthodox shapes amidst conventional shapes strike one's eyes. We observe the *shape deviation*, the difference between the facade's area and the area of its minimum bounding rectangle, and the *shape factor*, the proportion of height to width of this rectangle. Note that both measures do not compare shapes directly.

The shape deviation can be computed from orthoimages. Without orthoimages, a detailed three-dimensional model would be required. Data from aerial laser scanning can also be used. Rudimentary height information, such as the single height point at roof level in our map, is not sufficient to compute shape deviation.

For this paper, a pragmatic approach was used for computation. Most facades in a dense urban environment are rectangular, and the shape deviation is therefore zero. If there was no clear indication to the contrary, the shape deviation was assumed to be zero. If there was such indication, the shape deviation was calculated from orthoimages by manually tracing the outline. This way in most cases the rectification could be avoided.

3.1.3 Facade Color

Color has a strong correlation to the discrimination of features (Ennesser & Medioni, 1995) as well as to visual attention (Wolfe, 2000). A facade with a color different from the colors of the surrounding facades will receive some attention. Hence color should be a primary measure of distinction among the features' properties. But urban space is an open system with continuously changing illumination.

A measure based on the average color of the entire facade is problematic, because the average color of a scene is usually gray, according to the so called gray world assumption (Wandell, 1995). Furthermore, the distribution of color values in the area of a facade is multi-modal, which makes it hard to find a single representative color value. Using global averages will therefore detect mainly differences in the recorded radiation intensity, because this affects every pixel. This is, however, to a large extent external to the phenomenon the measure is supposed to describe, as recorded radiation intensity is influenced by factors such as cloud cover, time of day, and exposure settings.

The metric of the RGB color space is usually different from the perceived metric (Mallot & Allen, 2000). This means that two triples that appear to be similar in the seemingly Cartesian space of RGB coordinates, are perceived as quite different, and vice versa. A solution to this problem is to use a color model that is closer to perception, for example the HSB (hue, saturation, brightness) model.

If using a perception based model like HSB it is possible to assign different weights to the significance of the individual color components, and thus fine tune the measure. The greatest weight could be assigned to the hue, because this is the component that describes the actual color. Brightness could receive a rather low weight, because brightness is influenced more than any other component by transient lighting conditions. Assigning a weight to the significance of the saturation component is more difficult, because a low value means that the color is actually gray and the saturation is the component determining the perception.

For this paper, the color was measured by manually tracing the outline of the facade and taking the median of the intensity values of the red, green and blue color channel. These RGB triples were converted into HSB triples, and both were recorded. The reason why an average color was used despite the drawbacks discussed above was that computing the median is well understood and its computation is not dependent on any parameters. Furthermore, this way empirical evidence about the usefulness of this measure can be collected.

3.1.4 Facade Visibility

A measure describing the prominence of location could be the size of the area from which a facade is visible. A location is prominent if it is visible from afar. Visibility is calculated here in the map plane, i.e., as visibility of the ground line of a facade.

Line-of-sight algorithms calculate visibility of points, but our interest is the visibility of a line in a map. Furthermore, it might be sufficient to declare a facade visible from a location if only parts of its ground line are in the actual visual field. As far as recognizability is concerned, visibility is limited by a maximal distance. Such considerations make an algorithmic approach complex. Batty (2001) proposes some solutions for interior spaces.

The approach taken here was to approximate the visibility measure. A raster line-of-sight algorithm was applied to two points close to the corners of the facade, and the results were merged. The two points are not the actual corners of the facade, but are offset both along the facade and perpendicular to the facade. The offset perpendicular to the facade is necessary to ensure that the point from which the line-of-sight calculation is computed is on the ground and not on the building. It must therefore at least be $gridsize * \sqrt{2}$. The offset along the facade is determined by how much should be visible before it is declared recognizable. Here the offsets used were 1 m in perpendicular direction and 2 m along the facade, with a grid resolution of 0.5 m. Areas from which the facade is considered invisible—because they are further away than the maximum distance, they are at the back of the facade, or the angle from which the facade is seen is too small—are excluded from the calculation.

In some cases, the procedure is too limited. Results are unsatisfying if there exists an open space that cannot be seen from any of the two endpoints of the facade. Consider for example T-junctions, where neither of the two facade endpoints is visible from the incoming street. One endpoint is too far to the right, the other too far to the left. The facade, however, is visible at least in part from this street. To include such cases in the general approach, an additional point in the middle of the facade is analyzed in a line-of-sight algorithm, and its results are merged with the previous figure.

3.2 Semantic Attraction

Semantic attraction focuses on the meaning of a feature. Semantic measures of salience comprise *cultural or historical attraction*, and *identifiability* by explicit marks. Such measures have to be ordinal. In the simplest case, they are Boolean. Usually, the characterization applies to buildings, not to single facades.

For cultural or historical attraction, the criteria for assigning measures are difficult to define, independent of the number of levels used in the representation. If information on cultural and historical attraction is available, it is usually intended for a different purpose, namely the evaluation whether monumental protection should be awarded to certain objects. Whether a building was designed by a famous architect is highly relevant for monumental protection, but this fact is usually not recognizable for people with no background in architecture. Medieval arcades around the court yard are culturally quite interesting, however, courtyards cannot be seen from the outside. Historical importance has no visual evidence if there is no commemorative plaque. Plaques, however, tend to be quite inconspicuous.

The other measure for semantic attraction is whether the facade is explicitly marked. This is also a Boolean value in the simplest case and could be extended to a small number of values. A viable way to assign these values is to look into the yellow pages, if there is a retail store, restaurant, supermarket, movie theater or any other class of usually well marked commercial venture located at that address. Another option would be trying to detect text in images of the facade. Since the signs are usually either parallel or orthogonal to the facade, at least two images would be required since text orthogonal to the facade cannot be read in an orthoimage.

3.3 Overall Salience

To assess the overall salience of a feature, the individual measures need to be combined. To calculate the overall salience measure, a significance score based on resistant statistical measures is calculated. This score is proposed as:

$$score = \frac{|x\text{-}med(x)|}{\mathrm{MAD(x)}}$$

In this equation, x is the individual measure, $med(x)$ denotes the median, and MAD(x) the median absolute deviation from the median:

$$MAD(\mathrm{x}) = \frac{med(|x\text{-}med(x)|)}{0.6745}$$

The constant factor in the denominator, approximately the 75% quantile of the standard normal distribution, makes MAD(x) asymptotically equal to the standard deviation for normally distributed variables, and is thus not strictly necessary for the purpose of comparing scores. It was kept, however, because this way the scores of normally distributed measures approximately have a standard normal distribution. Other choices for the standardizing measure are the interquartile range or the mean absolute deviation from the median (Iglewicz, 1983). The median absolute deviation from the median is preferred because it is most resistant to outliers in the data.

All salience measures except color can be expected to be skewed to the right. The effect is that values on the lower tail of the distribution get lower scores than their corresponding values on the upper tail. To eliminate this effect the data should be transformed such that its distribution is symmetric before the scores are computed. An approach to achieving symmetry in a batch of data in a robust way is described by Emerson and Stoto (1983).

If low values, e.g., low visibility, are not to receive high scores, the computation of the absolute value has to be dropped from the computation of the scores and negative values be set to zero. In this paper this was done for both measures of semantic attraction and for facade visibility.

To find the most salient feature of a given intersection, the facades that should be taken into account need to be determined. In other words the local neighborhood needs to be defined. In this case only facades immediately adjacent to the intersection were used. Only when it is known which facades are to be considered, can the scores then be computed according to the formula above.

Once the individual scores are known, the total salience score can be computed for each intersection. The total score is the weighted mean of the subtotal scores for visual and semantic attraction. In this case equal weights were assigned, so it is simply the arithmetic mean of the two subtotal scores. These in turn are the weighted means of their individual scores. Again equal weights were assigned.

4 Computation of Feature Salience

The presented measures and algorithms are applied to a use case scenario in Vienna's first district. The pedestrian route from *Café Diglas* to *Restaurant Novelli* consists of eight segments or nine decision points. For each decision point, the most salient facade is determined.

Several data sources are consulted. The multi-purpose map of Vienna (*Mehrzweckkarte Wien*) is a city map at cadastral level of detail. The map contains ground plan outlines of each building as well as a single height value at the bottom and the top of each building. Images / Orthoimages of each building facade were available. Cultural and historic attraction is determined from an online database of cultural heritage, the *Kulturgüterkataster Wien*[3], and a travel guide (Weiss, 2002). Finally, the *Yellow Pages* are accessed.

[3]http://service.wien.gv.at/kulturkat/

4.1 Individual Salience Measures

4.1.1 Facade Area and Shape

The computation of facade area and shape factor for rectangular facades using plan view and additional height information is straight-forward. When the facade was not rectangular, orthoimages were used. For reasons of simplicity and feasibility, a plane rectification algorithm was chosen. If the facade has protrusive parts these will be exaggerated, compared to a true orthoimage of the facade. This means that the measure of shape deviation will also be exaggerated, and to a lesser degree the measure for facade area. Facade shape is also influenced. The magnitude of this exaggeration is, apart from the properties of the facade itself, dependent on the distance of the facade to the projection center and the focal length of the lens used. These influences are entirely external.

4.1.2 Facade Color

The tracing of the outlines of the facade was done manually with the software *Adobe Photoshop*. This same software was also used to calculate the median, and the conversion from the RGB to the HSB color model. Automatic procedures for feature extraction exist and can be applied instead of the manual editing.

4.1.3 Facade Visibility

To compute the visibility of facades the objects obstructing the vision are needed in a raster representation. For this the multi-purpose map of Vienna was rasterized with a grid size of 0.5 m. Since the map only contained building outlines, they were combined into areas before the rasterization. The software used for rasterization was *Feature Manipulation Engine* from *Safe Software*. All raster cells belonging to obstructions were assigned a high value, cell values for cells belonging to open space were set to zero.

Furthermore, the endpoints of the facades are needed. These were digitized manually. When additional points were needed, they were also digitized. This is necessary if there are larger areas that are not visible from either endpoint, or if the facade is not flat.

The implementation consisted of a script tying together existing functions of the open source Geographic Information System *GRASS*. Upon entering the coordinates of two or more points a script performed the following tasks: First a mask is computed, which is used to indicate the space outside the viewing area. This area needs to be excluded from the computation. Next the visibility from each of the input points is computed using the *GRASS* supplied function *r.los* (line of sight). In a final step the visibility maps from the individual input points are overlaid, and the total area is calculated.

4.1.4 Semantic Attraction

For cultural or historic attraction, an ordinal scale with four levels was used for both measures. The levels are:

0: Nothing interesting
1: Building has historic facade
2: Building is culturally notable (use, age, known architect, etc.)
3: Building is highlighted in a travel guide

Level zero was assigned if there was nothing remarkable about this building. Buildings without a historic facade are rare in Vienna's first district. Level two was assigned if there was something notable about the building other than being historic. This could be because of its use (churches, museums, etc), because of its age, or something else, for example, because it was designed by a famous architect. Level three, finally, was assigned to buildings that are especially highlighted in the travel guide.

For identifiability, an online Web version of the Yellow Pages[4] was used, although it does not allow a search by address. Therefore evidence from the images was taken for searches by categories. If an entry for the given address was found the building was assigned to the respective category. Identifiability was also measured on a four level scale:

0: No marks
1: Building is used commercially
2: Building is used commercially, by a category of usually well marked ventures (restaurants etc.)
3: Building is used by well known international (retail/food/hotel) chain

Level zero was assigned to buildings without any prominent marks. Levels one through three were assigned to commercially used buildings, depending on the class of business. Level two was assigned if the building was used by one of these business categories: restaurants, retail chains, banks. Level three was assigned to the same categories of business, but only if they were internationally well known, for example *McDonald's*.

4.2 Overall Salience

The overall salience of each facade at a decision point can be compared, and the most salient one can be selected. In the following the computation of the overall salience for each individual intersection is discussed. The intersections are numbered from 1 to 9. Figure 1 shows a map with a plot of the route from *Café Diglas* to the *Restaurant Novelli*, the intersection numbers, and the identified most salient facades.

At the first intersection the facade belonging to the Café Diglas is selected, but only by a small margin. One factor influencing this decision is the high value of visibility of this facade. For this intersection, however, this is misleading, because the visibility is from a future part of the route which was not experienced by the traveler yet.

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[4]http://www.superpages.at

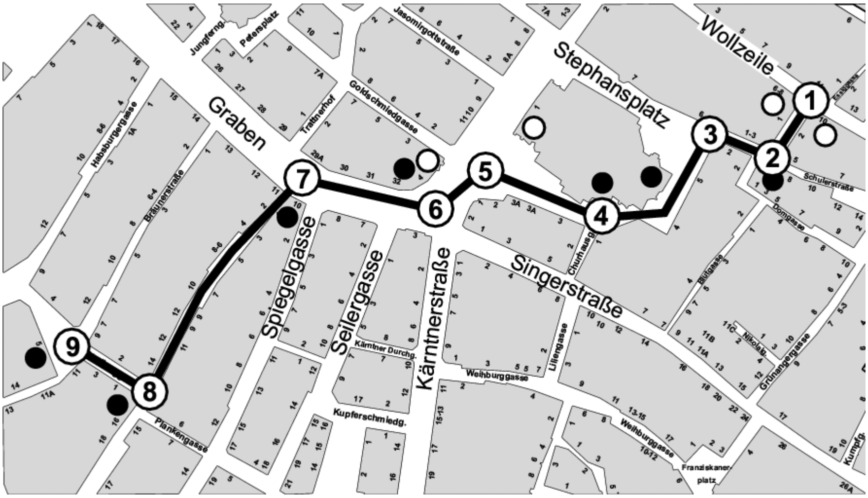

Figure 1. Map of the route investigated. The numbers along the route are the intersection numbers. The dots within the building blocks show the selection; black dot: coinciding selection by model and survey; white dot: different selection.

Two facades of intersection 1, including the facade with the highest score there, are also part of intersection 2. At this intersection the high visibility of the facade of the Café Diglas is justified. In fact, a large sign is located at this prominent corner. The facade that receives the highest score, however, is a restaurant that is chosen because of its distinctive shape factor: it is tall, but very narrow.

At intersection 4 (*Stephansplatz*) the St. Stephen's Cathedral (*Stephansdom*) is the only outstanding building. It receives the highest overall score by a large margin. It has also the highest score on all individual scores except identifiability. This might be surprising, as *Stephansdom* is arguably among the most easily identifiable buildings in Vienna, but the measure of identifiability used here is bound to the presence of prominently placed signs, and the cathedral is not signed.

Intersection 5 is still on *Stephansplatz* with two prominent features, *Stephansdom* and *Haas Haus*. The *Stephansdom* gets a higher score than *Haas Haus* mainly because of its size and the shape deviation. In this example the shape deviation plays a crucial role in the selection process. The shape factor of the cathedral (166 m / 110 m = 1.51) is close to the local average. It is only the shape deviation that makes the shape measure distinctive. The reason why the *Haas Haus* has a higher visibility score is that only the two facades of the cathedral facing this intersection were considered. If the whole cathedral were considered, the result would be the other way round.

Table 1
Individual and Total Scores for Intersection 7 (Graben/Dorotheergasse)

No.	Address	α	β_1	β_2	γ_{rgb}	γ_{hsb}	δ	$\in$	ζ	S_{vis}	S_{sem}	S_{tot}
1	Graben 29A	0.87	0.69	0	1.58	2.02	0	0	0.67	0.72	0.34	0.53
2	Graben 30	0.09	0.12	0	0	0.30	0	0	0	0.10	0	0.05
3,4	Graben 8	0.43	0.67	0	0.97	0	0.70	0.90	0	0.36	0.45	0.41
5	Graben 10	1.18	1.07	0	0.71	2.29	0	2.47	0.67	0.91	1.57	1.24
6	Graben 11	1.43	0.52	0	0.49	0.62	0.87	0	0.67	0.69	0.34	0.51
7	Graben 12	0.67	1.02	0	0.57	0.70	0.67	0	0.67	0.61	0.34	0.48
8	Graben 29	0	0	0	0.26	0.15	0	0	0	0.03	0	0.01

Note: α denotes the facade size, β facade shape, γ color, δ visibility, $\in$ cultural importance and ζ identifiability.

The next intersection again includes *Haas Haus*, but no longer *Stephansdom*. At this intersection *Haas Haus* gets the highest score because of its size, shape deviation, visibility and cultural importance. Note, however, that the large value for the shape deviation is due to a modeling error. Shape deviation was computed from rectified images. The facade of the *Haas Haus*, however, is cylindrical, thus applying planar rectification results in distortions. On the other hand, a high score for shape deviation is definitely warranted for the *Haas Haus*, as its cylindrical shape certainly deviates from an ordinary plain facade. However, if calculated this way the magnitude of the shape deviation depends largely upon the focal length of the lens and the distance from which the picture was taken.

The results for the intersection 7 (*Graben/Dorotheergasse*) are shown in Table 1. In this case, the facade *Graben 10* is selected mainly because of its high semantic attraction: It is a well known art nouveau building. However it also consistently receives high scores on all measures for visual attraction, except visibility.

At intersection 8 (*Dorotheergasse/Stallburggasse*) the facade with the highest score belongs to the church *Lutherische Stadtkirche*. The measure with the highest influence is again the shape deviation followed by the cultural and historic attraction.

The last intersection is *Stallburggasse/Bräunerstraße*. Here the facade of the building *Stallburggasse 5* is selected, because of its semantic attraction. This building, which was completed in 1569, formerly contained the royal stables and part of the royal art collection. The street name *Stallburggasse* is derived from this building, the *Stallburg*. Today, it is part of the *Spanische Hofreitschule*, and it houses a museum and a library. It also features a renaissance style courtyard with arcades.

5 Human Subject Test on Feature Salience

To test the results of the computation, a test with human subjects was conducted. For this purpose, a web-based questionnaire was designed. First each subject was asked to specify age, gender and overall familiarity with Vienna's first district. Then, each person was shown 360° panoramic images of each intersection in an interactive viewer. The viewer shows 90° of the image at a time, and starts immediately upon loading an automatic sweep of the image. The user also had the possibility to set the viewing direction directly using either keyboard or mouse. The intersections were not presented in order of the route, and no two adjacent intersections were presented consecutively to suppress the influence of context.

The question asked was: "Which is, in your opinion, the most prominent facade?" The following text was given as an additional instruction in the introduction: "The facades in the panoramas are marked with numbers. Find the most prominent facade. It could also be the one that you would quote when giving directions, or the one that is the easiest to describe." Additionally, each person was asked to comment on his or her choice, and specify the familiarity with each individual intersection.

Of the forty persons that completed the questionnaire, sixteen were female, twenty-four male. Thirty-three were between 20 and 40 years old and seven were over 40. No one under 20 was able to complete the questionnaire. Twenty-four persons said they were not at all familiar with Vienna's first district, nine were somewhat familiar and seven said that they were very familiar. The sample size of these groups is too small, however, to find significant differences between the groups.

The familiarity with individual intersections differed most from the overall familiarity for persons that said they were somewhat familiar with the area. Among the intersections are some that are well known, those around *Stephansplatz* and *Graben*, and others that are not so well known. Subjects only somewhat familiar with the first district said they knew the former well and the latter not at all, whereas subjects that were not at all familiar with the area rarely said they knew one particular intersection. Persons who said they were overall very familiar with the area were somewhere in between.

Table 2 gives an overview of the computed salience measures and peoples' choices in the survey for each intersection. Maxima (the 'selections') are highlighted. These results are discussed in the following in detail.

At the first intersection, most subjects chose the facade of a jeweler's store. The reason most frequently given was a large protruding clock. Second was the facade of a large and for Viennese well-known bookstore. Subjects that said they were familiar with this intersection chose the bookstore by 56% (5 of 9), compared to only 29% (9 of 31) for subjects unfamiliar with the intersection. In the very familiar group even 60% chose the bookstore and only 20% the clock.

At the second intersection, 16 subjects chose the facade of the *Dombeisl*, a restaurant. The dominant reason was that it was a restaurant (9 mentions in 12 comments). This justifies the high value of restaurants for the measure of identifiability. Twelve persons chose a facade with a large sign. Another facade was chosen 9 times by the subjects. The reasons were more varied, but most referred to the structuring of the facade. Most notable is that no one familiar with Vienna chose this facade. The reason might be that elaborate facades like

Table 2
Computed Salience Measure (first line) and the Responses of the Subjects (second line) for each Intersection

IS	FNo 1	FNo 2	FNo 3	FNo 4	FNo 5	FNo 6	FNo 7	FNo 8
1	3.6	1	4.7	**10.9**	5.4	3.2	5.3	NA
	14	0	2	5	0	**17**	2	NA
2	**10.8**	NA	4.8	1.3	3.3	9.3	1.3	8.8
	16	NA	0	9	0	12	0	3
3	2.4	2.2	**16.4**	10.5	NA	NA	NA	NA
	3	1	**35**	1	NA	NA	NA	NA
4	3.4	NA	2.7	3.2	**10.5**	NA	3.4	NA
	3	NA	0	0	**22**	NA	15	NA
5	4.1	2.5	7.8	5.4	4.2	3.2	**17.1**	NA
	0	0	**31**	0	0	0	9	NA
6	12.5	0.7	4	4.2	**17.8**	NA	NA	NA
	3	1	0	2	**34**	NA	NA	NA
7	5.3	0.5	4.1	NA	**12.4**	5.1	4.8	0.1
	1	0	6	5	**26**	1	1	0
8	4.7	4.5	**5.7**	5.4	3.9	3.7	NA	NA
	10	0	**12**	11	2	4	1	NA
9	**12.9**	2.2	0.7	6.6	1.5	11.9	12.9	NA
	20	1	0	9	2	5	3	NA

that are quite common in Vienna, so persons familiar with Vienna will not notice.

For the next three intersections, the choice of the subjects is almost unanimous: the *Stephansdom*. The reasons given are mostly saying that a large medieval cathedral easily qualifies as most prominent landmark. One subject, however, who said to be very familiar with this intersection, said that although the cathedral is certainly prominent, the *Dombuchhandlung*, a bookstore, is more characteristic of the location. The last of these intersections includes *Haas Haus* as well. It is chosen nine times by the subjects.

At intersection 6, the *Stephansdom* is still visible, however, it was not included as an option. The *Haas Haus* was chosen 34 times by the subjects. More or less, all referred to its distinctive architecture, and consequently, to being the most extraordinary building.

At intersection 7, the decision is surprisingly clear. The image shown to the subjects and the results of this intersection are given in Figures 2 and 3, respectively. The choice was the facade of a building called *Ankerhaus*, built by the famous architect Otto Wagner in 1894. The reason most often cited (nine mentions) was the contrast between the upper and lower part. The subjects often referred to it as a contrast between old (the upper part in apparent art nouveau

Figure 2. Intersection 7 (*Graben/Dorotheergasse*).

style), and modern (the glass facade in the lower part). However, this is deceptive, because the entire facade is, apart from recently added signs, in its original state. The reason second most often given was the most prominent placement of text (seven mentions). Finally two persons mentioned the building as the only building standing alone.

At intersection 8, twelve subjects chose the front, and eleven the side facade of the church *Lutherische Stadtkirche*. Ten subjects chose the facade of a shop. Several subjects indicated that the two facades of the church would have been interchangeable. The reasons for choosing the front facade of the church were: flags mounted on the facade (five times), its color (four times), and historical interest (twice). Reasons for choosing the side facade of the church were: color (six times), most beautiful (twice), elongated windows (twice). Surprisingly, no one mentioned that it was a church. This was probably hard to see, as its steeple was not in the picture. The only reason given by the subject for having chosen the facade of the shop was an unusual metal structure above the entrance. This intersection seemed to be little known. Only five persons said they had seen it

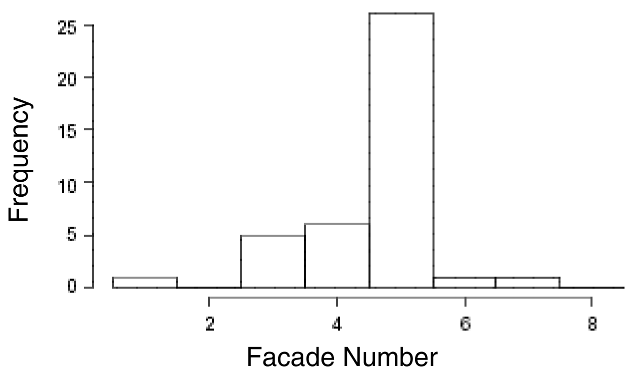

Figure 3. Responses for intersection 7 (*Graben/Dorotheergasse*).

before, and only one said that he knew it well. All subjects familiar with the intersection chose one of the facades of the church.

At the last intersection, 50% of the subjects voted for the back facade of the Stallburg as the most salient feature. 23% (9 persons) chose the facade of an art gallery and 13% chose the facade of the Restaurant Novelli. The reasons for choosing the facade of the Stallburg were: distinct architectural style (eight mentions), shape (two mentions), size (one mention). Reasons for choosing the facade of the art gallery were: the sign Galerie (three mentions), color (three mentions), contrast between lower and upper part (two mentions), and the balcony (two mentions). The facade of the Restaurant Novelli was chosen only for its sign (three mentions).

6 Discussion

Table 2 contrasts the responses from the subjects with the computed total salience. They are significantly correlated ($r = 0.58$; $n = 55$; $p < 0.001$). Of the nine intersections studied, the automatic selection of landmarks agrees with, the human selection in seven instances. For five intersections, the computation of rank correlation was possible. In four out of the five cases, both the rank correlation and the linear correlation between the automatic ranking and the ranking by the subjects is greater than 0.6.

The selections do not match at the first intersection. The facade selected by the computer is only ranked third by the human subjects, at a significant distance. Choosing the automatically selected facade in wayfinding directions is, however, not implausible, but it might not be the optimal choice. The result of the survey could be interpreted such that the visually most prominent feature is the protruding clock, whereas the semantically most prominent feature is the *Morawa* bookstore. Not to identify one of them automatically is a type I error.

At the second intersection the selections match. The main reason why the chosen facade received the highest score was because of its shape, which was also among the reasons given by humans. The second highest score also matches. The high score produced by the computer is due to a high visibility of a section of the facade. This is where the big sign is placed that is quoted by the subjects as the reason for their choice.

At the following four intersections the obvious choices *Stephansdom* and *Haas Haus* dominate the selection. The selections match for all but the intersection 5 where *Haas Haus* receives a higher score, but the subjects preferred *Stephansdom.* At intersections 7 through 9, the selections all match, and the two rankings of these intersections are highly correlated.

We were able to show that each of the individual measures is plausible by itself. Each of the measures was given by the subjects at least once as a reason for their choice. Facade size was given as a reason at intersection 9, facade shape at intersection 2, shape deviation at intersection 6, color at intersections 8 and 9, visibility at intersection 6, cultural importance at intersections 3 through 9, and explicit marks at intersections 1 to 3, 7, and 9.

Nevertheless, some measures had a consistently greater influence on the selection than others. Among the measures with great influence are the two measures of semantic attraction and visibility. The measures with a low influence on the selection are color and shape deviation. Facade color, however, has a great influence on the choices of humans. This measure could therefore be improved to be more representative.

The measures for visual attraction presented here were chosen because they are tangible: they can be measured according to objective criteria. Other visual properties, such as texture and condition are inherently subjective. Facade texture was often referred to by the human subjects. However, exactly what detail was mentioned depended heavily on the familiarity with Vienna.

7 Conclusions

The proposed model of salience allows to automatically identify features at decision points that are highly correlated with human choices of landmarks at these decision points. All obvious landmarks were found, and the automatic selection did not produce implausible results, or type II errors. Furthermore, we have shown that the proposed model is computable and robust.

In this paper, only one class of features in an urban environment (facades) was considered. Other classes of features are used by people (Denis, et al., 1999), or have otherwise been shown to be successful (Fontaine & Denis, 1999). Hence, they should be considered by an automatic selection process, as well. In principle, measures and averaging could be defined similarly on any class of features. However, in urban environment most other classes of features are not as frequent as facades; and sometimes it is simply their appearance at a specific location that makes them salient. Consider, for example, the class of monuments. It is the single monument that is salient, not its individual properties compared to a “mean” monument. It is an open question how to integrate other classes of features in the selection process.

Furthermore, we observed from three identified properties of landmarks (visual, semantic, structural) only the previous two. It is left open for further investigations to identify measures of structural salience for this class of features and to integrate these measures with the presented ones.

For another specific class of features (traffic network elements), Winter (2003a) has successfully proposed measures of *structural* salience. For these features, visual and semantic properties were not considered. It is an interesting question how visual and semantic criteria could be included and how they would influence an overall measure of salience.

Assume that we are approaching a general formal model of salience. If we are able to identify salient features for the use in route directions, a number of new questions arises. The model does not help in the decisions where along a route salient features shall be selected. Is it sufficient to select salient features at decision points, or are additional local salient features useful? How frequently shall they appear in route directions? How shall salient features be integrated in a formal algebra, or how shall we refer to them in directions verbally? These questions are part of our future work.

8 References

Allen, G. L. (1999). Spatial abilities, cognitive maps, and wayfinding. In R. G. Golledge (Ed.), *Wayfinding behavior* (pp. 46–80). Baltimore: Johns Hopkins University Press.

Batty, M. (2001). Exploring isovist fields: space and shape in architectural and urban morphology. *Environment and Planning B*, *28*, 123–150.

Burnett, G. E. (1998). *Turn right at the king's head: Drivers' requirements for route guidance information*. Unpublished doctoral dissertation, Loughborough University.

Burnett, G. E., Smith, D., & May, A. J. (2001). Supporting the navigation task: Characteristics of 'good' landmarks. In M. Hanson (Ed.), *Contemporary ergonomics 2001* (pp. 441–446). London: Taylor & Francis.

Daniel, M.-P., & Denis, M. (1998). Spatial descriptions as navigational aids: A cognitive analysis of route directions. *Kognitionswissenschaft*, *7*, 45–52.

Deakin, A. K. (1996). Landmarks as navigational aids on street maps. *Cartography and Geographic Information Systems*, *23*, 21–36.

Denis, M., Pazzaglia, F., Cornoldi, C., & Bertolo, L. (1999). Spatial discourse and navigation: An analysis of route directions in the city of Venice. *Applied Cognitive Psychology*, *13*, 145–174.

Downs, R. M., & Stea, D. (1977). *Maps in minds: Reflections on cognitive mapping*. New York: Harper and Row.

Elias, B. (2003). Extracting landmarks with data mining methods. In W. Kuhn, M. Worboys, & S. Timpf (Eds.), *Spatial information theory, Vol. 2825 Lecture Notes in Computer Science* (pp. 375–389). Berlin: Springer.

Emerson, J. D., & Stoto, M. A. (1983). Transforming data. In D. C. Hoaglin, F. Mosteller, & J. W. Tukey (Eds.), *Understanding robust and exploratory data analysis* (pp. 97–128). New York: John Wiley.

Ennesser, F., & Medioni, G. (1995). Finding waldo, or focus of attention using local color information. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *17*, 805–809.

Fellbaum, C. (Ed.). (1998). *WordNet: An electronic lexical database*. Cambridge, Massachusetts: The MIT Press.

Fontaine, S., & Denis, M. (1999). The production of route instructions in underground and urban environments. In C. Freksa, & D. M. Mark (Eds.), *Spatial information theory: Cognitive and computational foundations of geographic information science, COSIT '99, Vol. 1661 Lecture Notes in Computer Science* (pp. 83–94). Berlin: Springer-Verlag.

Frank, A. U. (2003). Pragmatic information content: How to measure the information in a route description. In M. Duckham, M. F. Goodchild, & M. Worboys (Eds.), *Foundations in geographic information science* (pp. 47–68). London: Taylor & Francis.

Freundschuh, S. M., Mark, D. M., Gopal, S., Gould, M. D., & Couclelis, H. (1990). Verbal directions for wayfinding: Implications for navigation and geographic information and analysis systems. In K. Brassel, & H. Kishimoto (Eds.), *4th International Symposium on Spatial Data Handling* (pp. 478–487). Zurich: Department of Geography, University of Zurich.

Golledge, R. G. (1993). Geographical perspectives on spatial cognition. In T. Gärling, & R. G. Golledge (Eds.), *Behaviour and environment: Psychological and geographical approaches* (pp. 16–46). Amsterdam: Elsevier.

Golledge, R. G. (1999). Human wayfinding and cognitive maps. In R. G. Golledge (Ed.), *Wayfinding behavior* (pp. 5–45). Baltimore, MA: The Johns Hopkins University Press.

Habel, C. (1988). Prozedurale Aspekte der Wegplanung und Wegbeschreibung. In H. Schnelle, & G. Rickheit (Eds.), *Sprache in Mensch und Computer* (pp. 107–133). Opladen, Germany: Westdeutscher Verlag.

Hirtle, S. C., & Heidorn, P. B. (1993). The structure of cognitive maps: Representations and processes. In T. Gärling, & R. G. Golledge (Eds.), *Behavior and environment: Psychological and geographical approaches* (pp. 1–29). Amsterdam: Holland.

Iglewicz, B. (1983). Robust scale estimators and confidence intervals for locations. In D. C. Hoaglin, F. Mosteller, & J. W. Tukey (Eds.), *Understanding robust and exploratory data analysis* (pp. 404–431). New York: Wiley.

Itti, L., & Koch, C. (1999). Learning to detect salient objects in natural scenes using visual attention. *Image understanding workshop (IUW)* (pp. 1201–1206). Los Altos, CA: Morgan Kaufmann.

Kuipers, B. J. (1978). Modeling spatial knowledge. *Cognitive Science*, *2*, 129–153.

Livatino, S., & Madsen, C. B. (2000). Acquisition and recognition of visual landmarks for autonomous robot navigation. *International symposium on intelligent robotic systems* (pp. 269–279). Reading, UK, University of Reading.

Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). Elements of good route directions in familiar and unfamiliar environments. In C. Freksa, & D. M. Mark (Eds.), *Spatial information theory: Cognitive and computational foundations of geographic information science, COSIT '99, Vol. 1661 Lecture Notes in Computer Science* (pp. 65–82). Berlin: Springer.

Lynch, K. (1960). *The image of the city*. Cambridge, MA: MIT Press.

Maaß, W., & Schmauks, D. (1998). MOSES: Ein Beispiel für die Modellierung räumlicher Leistungen durch ein Wegebeschreibungssystem. *Zeitschrift für Semiotik*, *20*, 105–118.

Mallot, H. A., & Allen, J. S. (2000). *Computational vision*. Cambridge, MA, MIT Press.

Merriam-Webster (2001). *Merriam-webster's collegiate dictionary*. Merriam-Webster, Inc.

Metzger, W. (1936). *Gesetze des Sehens*, Vol. VI of *Senckenberg-Buch*. Frankfurt am Main: W. Kramer & Co.

Michon, P.-E., & Denis, M. (2001). When and why are visual landmarks used in giving directions? In D. R. Montello (Ed.), *Spatial information theory: Foundations of Geographic Information Science, COSIT '01, Vol. 2205 Lecture Notes in Computer Science* (pp. 292–305). Berlin: Springer.

Montello, D. R. (1993). Scale and multiple psychologies of space. In A. U. Frank, & I. Campari (Eds.), *Spatial information theory: A theoretical basis for GIS, COSIT '93, Vol. 716 Lecture Notes in Computer Science* (pp. 312–321). Berlin: Springer.

Nicklas, D., Großmann, M., Schwarz, T., Volz, S., & Mitschang, B. (2001). A model-based, open architecture for mobile, spatially-aware applications. In C. S. Jensen, M. Schneider, B. Seeger, & V. J. Tsotras (Eds.), *Advances in spatial and temporal databases, Vol. 2121 Lecture Notes in Computer Science* (pp. 117–135). Berlin: Springer.

Pradhan, S., Brignone, C., Cui, J.-H., McReynolds, A., & Smith, M. T. (2001). Websigns: Hyperlinking physical locations to the web. *IEEE Computer Journal*, *34*, 42–48.

Raubal, M., & Winter, S. (2002). Enriching wayfinding instructions with local landmarks. In M. J. Egenhofer, & D. M. Mark (Eds.), *Geographic information science, Vol. 2478 Lecture Notes in Computer Science* (pp. 243–259). Berlin: Springer.

Siegel, A. W., & White, S. H. (1975). The development of spatial representations of large-scale environments. In H. W. Reese (Ed.), *Advances in child development and behavior, Vol. 10* (pp. 9–55). New York: Academic Press.

Sorrows, M. E., & Hirtle, S. C. (1999). The nature of landmarks for real and electronic spaces. In C. Freksa, & D. M. Mark (Eds.), *Spatial information theory: Cognitive and computational foundations of geographic information science, COSIT '99, Vol. 1661 Lecture Notes in Computer Science* (pp. 37–50). Berlin: Springer.

Treisman, A. (1985). Preattentive processing in vision. *Computer Vision, Graphics, and Image Processing*, *31*, 156–177.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*, 97–136.

Tversky, B. (1993). Cognitive maps, cognitive collages, and spatial mental models. In A. U. Frank, & I. Campari (Eds.), *Spatial information theory: A theoretical basis for GIS, COSIT '93, Vol. 716 Lecture Notes in Computer Science* (pp. 14–24). Berlin: Springer.

Wandell, B. A. (1995). *Foundations of vision*. Sunderland, MA: Sinauer Associates.

Weiss, W. M. (2002). *Wien*. DuMont Reisetaschenbücher. Dumont Reiseverlag.

Werner, S., Krieg-Brückner, B., Mallot, H. A., Schweizer, K., & Freksa, C. (1997). Spatial cognition: The role of landmark, route, and survey knowledge in human and robot navigation. In M. Jarke, K. Pasedach, & K. Pohl (Eds.), *Informatik '97* (pp. 41–50). Berlin: Springer.

Wertheimer, M. (1925). Über Gestalttheorie. *Philosophische Zeitschrift für Forschung und Aussprache*, *1*, 39–60.

Winter, S. (2003a). *On network topology and structural salience* (Technical report). Institute for Geoinformation, Technical University Vienna.

Winter, S. (2003b). Route adaptive selection of salient features. In W. Kuhn, M. Worboys, & S. Timpf (Eds.), *Spatial information theory: Foundations of Geographic Information Science, COSIT '03, Vol. 2825 Lecture Notes in Computer Science* (pp. 320-334). Berlin: Springer.

Wolfe, J. M. (2000). Visual attention. In K. K. de Valois (Ed.), *Seeing: Handbook of perception and cognition* (pp. 335–386). San Diego, CA: Academic Press.

Yeh, E. (1995). *Toward selecting and recognizing natural landmarks* (Yale Technical Report 9503). Center for Systems Science, Yale University.