A GIS data model for landmark-based pedestrian navigation
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Landmarks provide the most predominant navigation cue for pedestrian navigation. Very few navigation data models in the geographical information science and transportation communities support modeling of landmarks and use of landmark-based route instructions for pedestrian navigation services. This article proposes a landmark-based pedestrian navigation data model to fill this gap. This data model can model landmarks in several pedestrian navigation scenarios (buildings, open spaces, multimodal transportation systems, and urban streets). This article implements the proposed model in the ArcGIS software environment and demonstrates two typical pedestrian navigation scenarios: (1) a multimodal pedestrian navigation environment involving bus lines, parks, and indoor spaces and (2) a subway system in a metropolitan environment. These two scenarios illustrate the feasibility of the proposed data model in real-world environments. Further improvements of this model could lead to more intuitive and user-friendly landmark-based pedestrian navigation services than the functions supported by current map-based navigation systems.

Keywords: pedestrian navigation system; landmark-based data model; geographical information system for transportation

1. Introduction

Data model is a critical research topic in geographical information science (GIScience). A data model defines the representation of geographical phenomenon and supports spatial analysis for geographic applications. Currently, few geographical information system (GIS) data models offer adequate functions to represent landmarks for pedestrian navigation services. The motivation of this article is to propose a landmark-based pedestrian navigation data model (LPNDM) to support the modeling of landmarks and use of landmark-based route instructions augmented on photograph for pedestrian navigation services.

Pedestrian navigation can be viewed as an approach of guiding pedestrians to their destinations by means of verbal or written directions using digital maps on personal digital assistant devices or mobile phones. Pedestrian navigation is gaining attention in the mobile phone industry (Hile et al. 2008, Roger et al. 2009). One key requirement of pedestrian navigation services is to guide pedestrians efficiently and effectively with a

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minimal spatial cognitive burden on the users. Many studies have investigated the usefulness of landmarks in offering cues to enhance wayfinding instructions (Sorrows and Hirtle 1999, Raubal and Winter 2002, Elias 2003, Goodman et al. 2004, Beeharee and Steed 2006, Li 2006, Bessho et al. 2008, Roger et al. 2009, Waters and Winter 2011). For example, research by Parush and Berman (2004) shows that ‘navigating with landmarks may acquire better route knowledge of their environment’ (p. 391). Rehrl et al. (2010) find that ‘participants clearly preferred landmark-enhanced instructions’ (p. 189). Much research has been conducted to build landmark-based pedestrian navigation applications due to their advantages such as easy-to-follow landmark cues (Goodman et al. 2004, Ross et al. 2004, Elias and Paelke 2008, Hile et al. 2008), less cognitive load with landmark-based route instructions (Furlan et al. 2007, Spiers and Maguire 2008, Schellenbach et al. 2010), and time savings (Goodman et al. 2004). In addition, Narzt et al. (2006) presents a route visualization paradigm based on augmented reality for vehicle-based navigation applications. However, few studies have addressed the importance of integrating landmarks into pedestrian navigation data models. Traditional map-based navigation data models cannot effectively integrate landmarks into pedestrian navigation instructions; therefore, they often lead to inconsistent or incorrect spatial cognitive processes (e.g., wayfinding errors) in pedestrian navigation scenarios (Lin and Chien 2010), which in turn could cause confusion to pedestrians and lead to less efficient routes than the route instructions provided by landmark-based navigation systems (Elias and Paelke 2008, Hile et al. 2008, Ishikawa et al. 2008).

Despite the increasing diversity of literature on data models such as Shared Data Access Library (SDAL) (Navigation Technologies Corporation (NAVTEQ) 1999), KIWI (Kiwi-W Consortium 2000), multidimensional location referencing system (MDLRS) (Transportation Research Board–National Research Council 2001), geographic data files (GDFs) (International Organization for Standardization 2004), and the recent multiscale, multimodal GIS for transportation (GIS-T) data model (Chen et al. 2011) for vehicle- and pedestrian-based navigation applications, few studies have addressed the challenges of developing an LPNDM to support a low-cognitive-load environment and provide easy-to-follow landmark-based route instructions for pedestrian navigation services. These landmark-based instructions should enable pedestrians to efficiently comprehend the visual prominence, semantic salience, and structural significance of landmarks (Sorrows and Hirtle 1999, Raubal and Winter 2002, Klippel and Winter 2005, Caduff and Timpf 2008, Spiers and Maguire 2008, Peters et al. 2010, Roger et al. 2011). The objective of this article is to propose an LPNDM and implement landmark-augmented route instructions to fill this gap. This landmark-based approach for pedestrian navigation is an extension of Narzt et al.’s (2006) augmented reality-based visualization paradigm presented for vehicle-based navigation applications. The contributions of our study can be summarized as follows:

1. This study proposes an LPNDM for modeling the nature and use of landmarks in common pedestrian navigation environments (e.g., buildings, open spaces, multimodal transportation systems, and urban streets).
2. This study presents an approach of augmenting sequential landmark information presented on photographs for pedestrian guidance based on the proposed landmark-based navigation data model.
3. This study uses two real-world scenarios to demonstrate the feasibility of the proposed data model that can facilitate pedestrian navigation services using landmark-based guidance.
The remaining parts of this article are organized as follows: Section 2 discusses previous research related to pedestrian navigation data models. Section 3 presents a landmark-based multimodal pedestrian navigation data model. Section 4 introduces a computational implementation of the proposed data model and an approach of augmenting sequential landmark information on photographs for pedestrian guidance in two typical pedestrian navigation scenarios. The final section offers conclusions and future research directions.

2. Related work

2.1. Navigation data models

Although several international organizations have introduced navigation data models to organize navigation-related data and define file formats to store the data for offline navigation or real-time navigation using mobile communications, very few navigation data models support the modeling of landmarks and use of landmark-based route instructions for pedestrian navigation services. For example, the International Standards Organization (2004) released a data interchange standard of GDFs that provides models and rules for capturing, representing, and cataloging standard features, attributes, and topological relationships. Many map vendors (including NAVTEQ, Tele Atlas, GeoSmart, and Automotive Navigation Data) provide navigable maps in GDF format to support navigation applications of global positioning system vehicle navigation systems (e.g., Tom Tom and Garmin) and portable navigation systems (e.g., Google Maps Navigation for mobile, T-Mobile’s NaviGate, and Nokia’s Smart2go system). In particular, Kiwi-W Consortium’s KIWI navigation system data file format defines a navigation data model and provides byte-based physical storage organization for navigation data and the associated information. NAVTEQ (1999) offered a fully open digital navigation database specification (SDAL) to organize navigation map data for enabling sophisticated vehicle navigation systems (e.g., map display, vehicle positioning, geocoding, route calculation, and route guidance) and other smart transportation applications.

Besides these navigation data models, the GIS-T community and the location-based services (LBS) community also conducted studies of multimodal transportation data models for navigation services, transportation planning, and management. Goodchild (1992) reviewed the geographical data models available in spatial databases and discussed the time dependency of these models. Miller and Shaw (2001) systematically discussed various data models for GIS-T applications (e.g., node-arc network model, linear referencing system data model of the National Cooperative Highway Research Program (NCHRP), and Dueker/Butler enterprise data model; see Miller and Shaw 2001, pp. 53–76). The multimodal, MDLRS data model introduced by the Transportation Research Board’s NCHRP Report 460 (2001) illustrates conceptual schematics that are central to transportation features (such as multimodal transportation systems, linear referencing systems, and spatiotemporal changes) and establishes logical schematics to express the spatiotemporal data structures of transportation data. Based on the NCHRP Report 460, Koncz and Adams (2002) introduce a transportation-based multidimensional data model which describes characteristics of the essential elements of transportation location referencing systems in support of navigation applications and temporal GIS. The Environmental Systems Research Institute (ESRI)’s transportation model (Butler 2008) implements transportation data models (e.g., NCHRP 20–27, Federal Geographic Data Committee (FGDC) data exchange standard, and Unified NEtwork-TRANSportation (UNETRANS)) to support transportation features, multimodal transportation, and multiscale representations of transportation data (Xia and Wei 2008). Recently, a multiscale, multimodal GIS-T data
model (Chen et al. 2011) has been introduced to support sustainable urban transportation policies. This model provided several data management and integration functions, such as integration of multimodal public and private transportation networks and multilevel data representations.

Most of the models focus on the organization of navigation routes and navigation instructions and ignore the cognitive load in the process of finding routes. For example, navigation data models (e.g., Kiwi, SDAL, and GDF) focus on route-specific guidance data (e.g., point of interest (POI), road network, and public transportation system) and navigation instructions (e.g., distance, turn direction, and voice instruction). Transportation data models (e.g., NCHRP and MDLRS), on the other hand, concentrate on transportation features, multimodal transportation systems, and multiscale representations of transportation data. These transportation data models do not pay close attention to the route-specific guidance data. Both kinds of data models pay little attention to the nature of route-finding process using landmark-based route instructions. Landmark salience represents relatively distinct, prominent, or obvious features compared to other features in the surrounding environment (Caduff and Timpf 2008). Previous data models generally fall short of modeling landmark salience (i.e., visual prominence, semantic salience, and structural significance) or using landmarks in pedestrian navigation environments that involve buildings, open spaces, multimodal transportation systems, and urban streets. They therefore cannot adequately support an effective landmark-based route-finding process in pedestrian navigation environments. To overcome the above shortcomings, this article presents an LPNDM that considers landmark salience and uses landmarks to assist pedestrian navigation.

2.2. Landmark-based instructions

Studies have been conducted to provide pedestrian navigation instructions based on landmarks and assess the effect of landmark-based instructions (e.g., Elias et al. 2008, Roger et al. 2009, Fang et al. 2011). However, these studies did not present a landmark-based data model to integrate the salience (i.e., visual prominence, semantic salience, and structural significance) of landmarks into route instructions when developing landmark-based pedestrian navigation applications.

Previous studies have shown that landmarks are by far one of the most predominant cues for pedestrian navigation (May et al. 2003). Landmarks and globally available cues can be used to improve wayfinding and geographic orientation (Waters and Winter 2011). Landmark-based pedestrian navigation systems are considered to be a promising solution to provide pedestrian navigation aids in unfamiliar places. May et al. (2003) investigated the landmark information requirements for pedestrian navigation aids within an urban navigation context. Millonig and Schechtner (2007) analyzed the requirements of importing landmark information into navigation services for pedestrians.

As for implementation of landmark-based pedestrian navigation systems, some studies have been performed to integrate landmarks into route instructions. For example, Caduff and Timpf (2005) proposed a ‘landmark spider’ approach to compute an optimal landmark-based route; this approach is the first effort to integrate distance, orientation, and salience of landmarks into the route guidance process and to represent landmark knowledge for wayfinding tasks. Richter (2007, 2008) developed generation of unambiguous, adapted route directions (GUARD) to generate context-specific route instructions using landmarks in which the route instructions adapt to route properties and environmental characteristics. For example, the GUARD can generate route instructions by considering the circular order that the branches of a decision point form and the order of events in route following
that is induced by the directedness of a route’ (p. 387). Hile et al. (2008, 2009) developed a prototype system to generate landmark-based pedestrian navigation instructions and implemented an image-based live-matching navigation mode for pedestrian navigation. Winter et al. (2008) evaluated a hierarchy of landmarks for generating landmark-based granular route directions. Duckham et al. (2010) presented an algorithm to generate route instructions with references to landmarks from commonly available data and existing web-based mapping environments.

Moreover, several efforts have been done to assess the effect of landmark-based instructions. For example, Roger et al. (2011) examined the effect of landmark use in route instructions on navigation efficiency and the level of satisfaction with speech-based over-the-phone guidance systems. Tenbrink et al. (2010) investigated the strategies people use to convey route information in relation to a map by reinterpreting landmarks in the context of human–human and human–computer interactions. Peters et al. (2010) evaluated landmark identification theories in a virtual environment by analyzing the characteristics of human participants and proposed a weighting method for navigation services to generate human-like route descriptions.

In short, although some studies have developed landmark-based pedestrian navigation instructions in multimodal transportation systems, buildings (Millonig and Schechtner 2007), and urban streets (Spiers and Maguire 2008, Hile et al. 2009), designing a robust landmark-based navigation data model remains a challenge research question in GIScience, transportation science, and LBS. This article presents a landmark-based navigation data model that integrates landmark-based route instructions in several typical pedestrian environments involving buildings, open spaces, multimodal transportation systems, and urban streets.

3. Conceptualization of an LPNDM

3.1. Requirements

Identification of model requirements is one of the most important steps in developing an LPNDM. Besides the requirements of multidimensional data management (Adams et al. 2000, Koncz and Adams 2002) for multimodal transportation systems (NCHRP Report 460 2001, Huang and Peng 2008, Chen et al. 2011), the salient features and service functions of landmarks should also be integrated into a pedestrian navigation data model because of the usefulness of landmarks in offering clear cues to enhance navigation instructions. The more closely a data model represents the landmark-based guidance process, the more easily pedestrians can achieve their navigation objectives. The requirements of a pedestrian navigation data model therefore should include the following elements:

3.1.1. Landmarks

Landmarks play an important role in supporting the clarification of specific routes and ensuring efficient and reliable navigation (Caduff and Timpf 2005, Klippel and Winter 2005, Spiers and Maguire 2008). The salient features of a landmark include three important attributes (i.e., visual, semantic, and structural attributes) according to the landmark theory (Sorrows and Hirtle 1999). A comprehensive pedestrian navigation data model needs to support the modeling of visual, semantic, and structural components of landmark salience. The wayfinding theory contributed by Klippel et al. (2005) stresses the integration of landmarks in the cognitive aspects of route knowledge. This theory requires a
conceptualization of wayfinding actions (Sester and Elias 2007) as related to landmarks for user-centric navigational supports. Therefore, this pedestrian navigation data model must meet the modeling of landmark salience and wayfinding actions to provide landmark-based navigation services.

3.1.2. Walking environment

A comprehensive pedestrian navigation data model should support the modeling of walking environments such as building complexes, urban streets, open spaces, and walking spaces in multimodal public transportation systems. In particular, this model needs to support pedestrians to identify their feasible connections among different transportation systems (e.g., bus, subway, and car). These connections are critical for pedestrians to make transfers between different transportation lines.

3.1.3. Route instructions

A comprehensive pedestrian navigation data model should also support the generation of route instructions, which are central to pedestrian guidance. For instance, route instructions should integrate landmark-based guidance information as well as distances, directions, and turns in support of navigation applications. The challenge of transforming landmark salience into navigation cues (i.e., route instructions) as described by Millonig and Schechtner (2007) requires a comprehensive pedestrian navigation data model to accomplish and facilitate this task with the aid of GISs.

These three requirements are essential components in pedestrian navigation applications. Landmarks are crucial objects that help pedestrians identify their routes in a walking environment. Route instructions, on the other hand, use the salient landmarks in a walking environment to facilitate navigation cues. Consequently, a pedestrian navigation data model should be able to support multiple data representations and address pedestrians’ needs for landmark recognition and route guidance. This data model requires a concise and comprehensive set of objects, properties, and relationships for implementation. The landmark-based multimodal pedestrian navigation data model proposed in this article therefore uses the Unified Modeling Language specification (Object Management Group 2007) to represent the above three requirements and their relationships.

3.2. Conceptualizing an LPNDM

Central to an LPNDM is the integration of landmark-based instructions into an abstraction of the pedestrian navigation process. This process not only involves the landmark features but also references the walking environment associated with multimodal public transportation systems. Landmarks can help pedestrians understand local spatial relations through a combination of information such as ‘greater familiarity, visually dominating nearby locations, visible from a distance, and of greater cultural importance’ (Sadalla et al. 1980, Sorrows and Hirtle 1999, p. 40). Therefore, this study proposes a conceptual LPNDM (Figure 1) using an object-oriented approach (Borges et al. 2001, Malinowski and Zimányi 2008). The LPNDM defines a set of objects and relationships to model the landmark salient features and the ways pedestrians use landmarks for navigation in a walking environment. This model focuses on the objects and their relationships that describe the visual, semantic, and structural salience of landmarks. The Landmark, a core object in the LPNDM (Figure 1), has close relationships with the walking environment and route instructions. The
LPNDM offers a salience measure for all landmarks by integrating the visual, semantic, and structural salience into the landmark salience object. This measure supports the selection of landmarks for generating landmark-based route instructions. These three saliencies are described in the following paragraphs.

The first set of objects in the LPNDM focuses on the visual salience of landmark. In Figure 1, the objects of visual salience, visual features, visibility, facade area, shape color, image, and image property shown in orange color are related to the visual salience of landmark. The visual salience represents ‘the distinct subjective perceptual quality which makes some items in the world stand out from their neighbors and immediately grab our attention’ (http://www.scholarpedia.org/article/Visual_salience). The visual features represent the shape, color, facade area, and visibility (Lerasle et al. 2003, Hayet et al. 2007) of landmarks that visually dominate nearby locations. The visibility of a landmark, which is derived from surrounding landmarks within its neighboring environment, represents the extent of visible prominence of each landmark. Visual salience can be derived from these visual features. For example, a visual salience model was implemented in the iLab Neuromorphic Vision C++ Toolkit (http://ilab.usc.edu/toolkit/). This toolkit can calculate the visual salience of landmarks in a complex scene (Itti and Koch 2000, 2001). Images (photographs) can be used as an easy-to-understand way of guiding pedestrian navigation. Each image containing landmarks is taken from a specific viewpoint (Zinger et al. 2010)
with reference to a fixed azimuth angle (Shibayama and Wiegand 1985) and a set of orienta-
tion elements (Corten 1959). The use of an image in pedestrian navigation is based
on its basic image property values (e.g., location of viewpoint, azimuth angle, and orienta-
tion elements) that can support the presentation of augmented information (e.g., direction
arrows, boundary boxes, and highlighted text) around landmarks.

The second set of objects in the LPNDM deals with the semantic salience of land-
marks. The semantic salience, semantic features, cultural and historical (CH) importance,
and explicit mark objects shown in gray color are used to represent semantic salience of
landmarks. The semantic features object includes cognitive information about a landmark
such as its CH importance, explicit markings, and its name and category. For example, the
type (i.e., hotel, store, or restaurant) and name of a landmark represented in route instruc-
tions can help pedestrians reference and use landmarks. The explicit mark represents those
marks such as signs on the front of a building that explicitly specify its semantics to
the wayfinder’ (Raubal and Winter 2002). The semantic salience represents the standing
semantic functions (e.g., their use and meaning) as well as cultural significance, which
are dependent on the semantic features of the landmark. The semantic salience can be
calculated based on a landmark weighting and scoring system (Duckham et al. 2010)
that is based on expected average properties (e.g., ubiquity, familiarity, and the length of
name or introduction description) of the categories of points of interests in Yellow pages
(e.g., hotels, restaurants, parks, and museums) according to their suitability of serving as
landmarks.

The third set of objects in this proposed model focuses on the structural salience.
The structural salience of a landmark describes how its location is cognitively easy to
conceptualize in route instructions. The structural salience is determined by geometric
characteristics of landmarks, the structure of walking networks, and local route depen-
dence (Klippel and Winter 2005). Klippel and Winter (2005) introduced an approach of
measuring the structural salience of landmark by considering the location relative to a route
(e.g., at nodes or in between nodes) and the turning direction for pedestrians to follow in
a walking network. A walking network consists of links available for pedestrians to walk
in two typical categories of walking environments. The first category of walking environ-
ment includes building complexes, open spaces (i.e., parks and squares), and urban streets,
which are shown in green color in Figure 1. In this data model, junctions (points), walking
links (lines), and areas (polygons) are the three basic objects used to model the elements
in a walking environment from a geometric perspective (Balley et al. 2004). The junction
object represents features such as the entry and exit points in a subway system, rooms and
elevators in a building, and transfer points in a public transit system. The walking link
object is used to model links between pedestrian footpaths and streets in road networks,
linear pedestrian facilities (e.g., pedestrian bridges, crosswalks, and walkways in subway
stations), and staircases and corridors in building complexes. The area object represents
open areas such as halls and squares. The building object containing walking networks is
for walking paths in simple or complex building environments.

The second category of walking environment is for multimodal transportation systems
that are represented by the objects shown in purple color in Figure 1. To accommodate the
walking environments for four different public transportation modes (i.e., air, rail, subway,
and bus), this proposed LPNDM includes six object classes (i.e., public transport (PT)
point, PT line, PT way, PT way segment, station, and platform) to support the modeling of
pedestrian navigation between different transportation modes. Each transportation mode
consists of transportation lines and stations. A PT line is a directed path consisting of a
sequence of PT points (e.g., bus stations) and PT way segments. A PT line may have two
public transportation ways (e.g., from and to traffic) or a loop public transportation way. A public transportation way contains several public transportation way segments. A public transportation way segment connects two PT points which may or may not be adjacent stops or platforms. A platform is a boarding site along public transportation lines. Each station has at least one PT point. The station object represents an abstraction of airports, railway stations, subway stations, or bus stops that offer a walking environment. For example, an ‘airport’ station provides a walking environment for pedestrians to reach their gates in the terminals or pick up their luggage after arrival. In the proposed data model, activity points are related to the locations where pedestrians conduct certain activities during their navigation. Examples of activity points include ticket counters, security check points, information services (e.g., kiosks, timetables, and floor maps), and stores in a station. ‘A point of interest is a specific point location that people may find useful or interesting’ (http://en.wikipedia.org/wiki/Point_of_interest). The activity points in a station or building, the platforms in public transportation systems, and various POIs are well suited to serve as landmarks in pedestrian navigation applications. In particular, landmarks in public transportation systems play an important role in assisting pedestrians to find their way when they need to make transfers between public transportation lines.

In addition, the geometric features support the representation of the location, shape, size, and reference region of landmarks and networks in multimodal public transportation systems. Specifically, a reference region, which is ‘a region associated with the use of a landmark in communication’ (Winter et al. 2008), is dependent on the size, shape, and height of the landmark and its surrounding environment. A general rule for defining a reference region is that the nearer the landmark is to a pedestrian, the more likely the pedestrian will refer to it. The reference region therefore determines the choice and filtering of POIs and landmarks for navigation. In practice, these geometric attributes are influenced mainly by the real-time status of pedestrians (Bertozzi et al. 2007, Oliveira et al. 2010, Schindler et al. 2010) and the reference regions. For example, the real-time status of pedestrians determines the visible field of the walking environment from a specific viewpoint, the update frequency of the visible field during movements, and the walking direction of pedestrians.

The last set of objects in the LPNDM is related to route instructions. The route instruction in the LPNDM is defined to describe the navigation cues of a route for pedestrians. The route instruction represents the turning directions of the route and the sequential landmarks near a route by virtue of augmenting these landmarks on images with landmark and route information in the walking environment. Each route instruction provides an interface for pedestrians to navigate in an unfamiliar environment. A route usually contains a sequence of walking links intended to connect a location to a destination. A route is identified step by step by pedestrians using sequential route instructions in real-world navigation applications.

4. Implementation

This section introduces a prototype system that implements the proposed data model. We also demonstrate the feasibility of the proposed data model with two typical pedestrian navigation scenarios as described in Sections 4.2 and 4.3, respectively. The first scenario represents a pedestrian navigation situation in a multimodal traveling environment, while the second scenario represents walking environment for pedestrian navigation in a subway system. Both of the scenarios represent common pedestrian navigation situations in the real world.
4.1. Prototype system

A prototype system was developed to implement the LPNDM in order to facilitate landmark-augmented pedestrian navigation guidance. This prototype system was implemented with C# programming language using ESRI’s (Redlands, CA, USA) ArcSDE functions to access ArcGIS personal geodatabase in which the experimental data are represented according to the proposed LPNDM. This prototype system operates on a personal computer with Pentium (R) Dual-Core CPU E5200 @2.50 GHz, 2.49 GHz, and 1.96 GB of RAM.

Figure 2 shows the implementation of the class objects and the attributes of each class in the proposed LPNDM using an object-oriented approach (Yang et al. 2010, Kumar et al. 2010). Besides the objects shown in Figure 1, several additional class objects are implemented to maintain and utilize the relationships among the objects in Figure 1 for supporting the pedestrian navigation process. For example, pedestrian navigation services usually need to suggest multimodal travel routes with criteria such as the shortest travel distance or the least travel time or cost. A route consists of sequential route segments. The RouteSegment class is based on the GeometricFeature of a WalkingLink or

![Figure 2. Implementation of class objects in the proposed data model.](image-url)
**PTWaySegment** that represents a portion of a route bounded at each end by a network node. The **RouteSegmentArray** object is designed to store one or more **RouteSegments** for representing pedestrian travel routes in a multimodal transportation system. A **RouteInstruction** object is abstracted as a base class from which we can generate various types of route guidances including verbal, graphical, or gesture-based navigation instructions (Klippel and Winter 2005). The **RealTimeStatus** class object represents the status of a pedestrian, including their location, speed, and orientation. These attributes in the **RealTimeStatus** object help pedestrian navigation services to judge whether pedestrians walk along the suggested routes or not and to control the display time and frequency of the route instructions.

The **Image** (or photo) class includes the **LandmarkArray** and **ActivityPointArray** objects. The **LandmarkArray** object records all visible landmarks in an image. The **ActivityPointArray** object records all activity points within an image. These two arrays organize the essential landmarks and activities that are candidates to be included in route instructions. The **ImageProperty** class organizes the attributes related to the process of capturing and using images in navigation services. In addition, the concept of anchor point is used to represent different scales of point-based objects (e.g., landmarks, activity points, and buildings) in a walking environment.

Landmark-based pedestrian navigation services need to suggest salient landmarks for route instructions in an unfamiliar environment. The measurement method of landmark salience determines the selection of landmarks for route instructions. The overall salience value of a landmark is computed according to the Klrippel and Winter’s (2005) equation:

$$S = w_v s_v + w_s s_s + w_u s_u; \quad w_v + w_s + w_u = 1$$

where $s_v$, $s_s$, and $s_u$ are the visual salience, semantic salience, and structural salience, respectively, and $w_v$, $w_s$, and $w_u$ are the weights assigned to the three types of saliences. These weight parameters are set by users in real-world applications. Here, we set $w_v = 1/2$, $w_s = 1/4$, and $w_u = 1/4$ as an example. A higher salience value for a landmark along a route means that this landmark is more likely to be chosen for route instructions at a route decision point (Nothegger et al. 2004).

A visual salience value can be calculated according to a computational model for visual salience proposed by Parikh et al. (2010) or by a computational model for detecting salient regions in an image (Mundhenk and Itti 2005). In this implementation, this visual salience value is derived from the iLab Neuromorphic Vision C++ Toolkit (http://ilab.usc.edu/toolkit/) which was developed by the iLab and Laurent Itti at the University of Southern California. This toolkit includes a number of neuroscience models ready to be applied to visually guided robotics in outdoor environments. For example, the bottom-up attention model in this toolkit can simulate elements of a visual scene likely to attract the attention of human observers. This model computes a salience map, which topographically encodes for salience at every location in the visual input. The SaliencyToolbox in this toolkit is a collection of Matlab functions and scripts for computing the salience map for an image and for serially scanning the image with the focus of attention. According to this salience map, the highest value of a landmark in an image is the visual salience value of this landmark.

The semantic salience value of each category of landmarks (see Table 1) is computed based on the weighting approach of Duckham et al. (2010). The salience value is evaluated with the help of their landmark scoring system based on the landmark categories (Duckham et al. 2010) and the rating of landmark categories suggested in this article (see Table 1) for the two example implementation scenarios. This article adopts the Duckham’s
Table 1. Proposed ratings of landmark categories in the implementation scenarios.

<table>
<thead>
<tr>
<th>Category</th>
<th>Proposed suitability ratings for</th>
<th>Proposed typicality ratings for</th>
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<tbody>
<tr>
<td></td>
<td>Cultural and historical</td>
<td>Explicit</td>
</tr>
<tr>
<td></td>
<td>importance</td>
<td>markings</td>
</tr>
<tr>
<td>College</td>
<td>High</td>
<td>Ideal</td>
</tr>
<tr>
<td>Park</td>
<td>High</td>
<td>Ideal</td>
</tr>
<tr>
<td>Theater</td>
<td>High</td>
<td>Ideal</td>
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<tr>
<td>Bank</td>
<td>Suitable</td>
<td>Ideal</td>
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<tr>
<td>Restaurant</td>
<td>Suitable</td>
<td>Ideal</td>
</tr>
<tr>
<td>Hospital</td>
<td>Suitable</td>
<td>Ideal</td>
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<tr>
<td>Library</td>
<td>High</td>
<td>Ideal</td>
</tr>
<tr>
<td>Hotel</td>
<td>Suitable</td>
<td>Ideal</td>
</tr>
<tr>
<td>Station</td>
<td>Suitable</td>
<td>Ideal</td>
</tr>
<tr>
<td>Activity point</td>
<td>Never suitable</td>
<td>Somewhat suitable</td>
</tr>
<tr>
<td>Lift/elevator/staircase</td>
<td>Never suitable</td>
<td>Suitable</td>
</tr>
<tr>
<td>Signage</td>
<td>Never suitable</td>
<td>Ideal</td>
</tr>
</tbody>
</table>

scoring system to rank the landmark categories. For example, a five-point rating (from ‘ideal, ‘highly suitable,’ ‘suitable,’ ‘somewhat suitable’ to ‘never suitable’) can be used to identify the suitability of typical landmarks in a category and a five-point rating (from ‘all typical,’ ‘most,’ ‘many,’ ‘some’ to ‘few’) can be adapted to represent the frequency of typical landmarks in a category (Duckham et al. 2010, p. 38). Based on these ratings, the semantic salience value for a landmark category can be computed as follows:

\[
s_s(i) = w_{ch} \frac{ch(i)}{\text{Max}(ch(i))} + w_{em} \frac{em(i)}{\text{Max}(em(i))}\]

where \(s_s\) is the semantic salience of landmark category \(i\), \(w_{ch}\) is the weight assigned to the CH importance of landmark category \(i\), \(ch(i)\) is the ranking of the category’s CH importance, \(em(i)\) is the ranking assigned to explicit markings, and \(w_{em}\) is the weighting for explicit markings. Here, \(\text{Max}(ch(i)) = \text{Max}(em(i)) = 8\), \(w_{ch} = 0.7\), \(w_{em} = 0.3\). Again, these parameters are set by users in real-world navigation applications.

The structural salience value of a landmark for route instructions ranges from 0 to 1 and is calculated based on the approach proposed by Klippel and Winter (2005). This study uses the following three rules to define the structural salience value of a landmark.

Rule 1: If a landmark is not located on any walking link of the suggested route and this landmark is visible from a walking link of the suggested routes, the structural salience value of this landmark is in the range \([0, 0.2]\) which can be computed as follows:

\[
s_u(i) = 0.2 \times \frac{\text{dist}(i, \text{link}_i)}{\text{max}_\text{vs}(i)}\]

where \(s_u(i)\) is the structural salience of landmark \(i\). \(\text{dist}(i, \text{link}_i)\) is the distance between the landmark \(i\) and the nearest walking link, \(\text{link}_i\), of the suggested route. \(\text{max}_\text{vs}(i)\) is the maximum visible distance of the landmark \(i\). This range of \([0, 0.2]\) is defined according to the importance of landmark for guiding pedestrians.
Rule 2: If a landmark is located on a walking link of the suggested routes, the structural salience value of this landmark is in [0.2, 0.5]. If the landmark is close to the start or the end node of the walking link, the structural salience of the landmark will be higher. This value can be computed as follows:

\[
s_u(i) = 0.2 + 0.3 \times \frac{\left(\text{length}(\text{link}_1)/2 - \min(\text{dist}(i, \text{node}_{ls}), \text{dist}(i, \text{node}_{le}))\right)}{\text{length}(\text{link}_1)/2}
\]

where \(\text{link}_1\) is the walking link in which the landmark is located. \(\text{length}(\text{link}_1)\) is the length of \(\text{link}_1\). \(\text{dist}(i, \text{node}_{ls})\) is the distance between the landmark \(i\) and the start node of \(\text{link}_1\). \(\text{dist}(i, \text{node}_{le})\) is the distance between the landmark \(i\) and the end node of \(\text{link}_1\).

Rule 3: If a landmark is a decision landmark (a decision landmark is a landmark that is used as a decision object for pedestrians to identify their next way point and walking direction toward their ultimate destination while they are being guided by a sequence of landmark-based pedestrian navigation instructions) near a junction of a walking environment and this landmark is on the suggest routes, the structural salience value of this landmark is in [0.5, 1]. Specifically, if the route direction does not change at this junction, the structural salience value of this landmark is in [0.5, 0.7]. If the route direction changes at this junction, the structural salience value of this landmark is in [0.7, 0.1]. Moreover, in the case of changing directions at the junction, if the pedestrian has passed the landmark before changing the navigation direction, the structural salience value is in [0.9, 1]. If the landmark is passed after changing the navigation direction, the structural salience value is in [0.8, 0.9]. If the landmark is very close (i.e., within 50 m) to the junction, the structural salience value is in [0.7, 0.8]:

\[
s_u(i) = \text{Lowerbound} + (\text{Upperbound} - \text{Lowerbound}) \times \frac{\max_{\text{vs}(i)} - \text{dist}(i, \text{node}_{\text{junction}})}{\max_{\text{vs}(i)}}
\]

where \(\text{node}_{\text{junction}}\) represents the junction near the decision landmark. The Upperbound and Lowerbound are the upper and lower limits of an interval. For example, 0.7 and 0.8 are the upper and lower limits of the interval [0.7, 0.8].

Figure 3 shows a simple example of tables in a personal ArcGIS geodatabase that implements some of the class objects shown in Figure 2. The ‘Landmark’ table in Figure 3 records the attributes that are used to define the ‘Hubei Theater’ landmark, and other tables in this figure record the values and relationships of other related landmark attributes.

4.2. Scenario 1: a multimodal navigation environment involving bus lines, public squares, and building interiors

Pedestrians often need to walk in a multimodal environment. The first example scenario is a multimodal navigation environment that involves bus lines, public squares, and building interiors to demonstrate the feasibility of the proposed LPNDM. This scenario assumes that a person at the Shouyi Square in Wuhan City of China wants to borrow a book from the Wuhan University Library. This pedestrian navigation scenario covers a multimodal traveling environment involving bus lines, public squares, and building interiors (Lammel et al. 2009). Figure 4 shows an overview map of all walking links (i.e., green lines in this figure) in this navigation environment. Three zoomed-in windows in Figure 4 display the walking paths (i.e., black lines in this figure) at the Shouyi Square, Wuhan University Campus,
Figure 3. A simple example of tables in an ArcGIS geodatabase.

and the Wuhan University Library, respectively. The first two zoomed-in windows reflect the walking paths in a two-dimensional network. The third zoomed-in window shows the walking path in a three-dimensional network within a building interior. In Figure 4, point O1 at Shouyi Square is the origin point and point D3 in the Wuhan University Library is the final destination. The complete route for this person includes three origin–destination segments (O1 and D1, O2 and D2, and O3 and D3) for pedestrian walking. In addition, the bus line #413 (shown as a red polyline in Figure 4) connects the Shouyi Square and the Wuhan University Campus. The O1–D1 segment guides the pedestrian from the origin location to the boarding stop of the public bus line #413, while the O2–D2 segment takes the pedestrian from the exit stop of public bus line #413 to the destination building (i.e., the Wuhan University Library). Finally, the O3–D3 segment guides the pedestrian to his final destination (i.e., a specific bookshelf in the Wuhan University Library). This integrated map represents the pedestrian’s walking paths in a multimodal navigation environment.

This example scenario consists of 34 decision landmarks (i.e., 8 landmarks in the Shouyi Square, 15 landmarks along the public bus line, 6 landmarks in the Wuhan
Figure 4. Implementation of a scenario involving bus lines, parks, and indoor spaces.

University campus, and 5 landmarks in the indoor environment of the Wuhan University Library) along the route that are selected to help pedestrians to confirm their location in this navigation environment.

The images in Figures 4 and 5 illustrate some landmark-augmented route instructions based on the LPNDM for a pedestrian navigation service. For example, the red arrow in image #1 points out the current walking direction for the pedestrian. This direction is derived directly from the viewpoint/direction parameters of the camera (using the Theodolite app in the iPhone system) and the location of the landmark in the image. The two landmarks in this image are augmented with their names and the distances from the viewpoint location of this image. Specifically, one landmark (Hubei Theater) in image #1 is visible while another landmark (a monument) is invisible from the current location. The orange arrow connecting two landmark information boxes indicates the next walking direction. This information is helpful for pedestrians to check their next movement. The radar diagram in each image shows the direction and the relative locations of nearby landmarks. The other four images (#6, #21, #26, and #35) in Figure 4 and the additional six selected images (#2, #7, #26, #30, #32, and #35) in Figure 5 are augmented using the same method. The image #21 in Figure 4 does not contain any direction arrow because a person riding a bus only needs to pay attention to bus stops. The sequential landmark information in the images of Figure 5 illustrates the pedestrian’s walking directions, the key locations, and turns that he/she needs to pay attention to during navigation. All images in Figures 4 and 5 highlight the salience of landmarks to support landmark-augmented pedestrian guidance in the experimental walking environment.
Figure 5. Landmark-augmented pedestrian navigation route instructions in an integrated environment.

4.3. Scenario 2: a subway environment in a metropolitan area

Pedestrians also often need to navigate in a subway system that involves transfers between different lines. This study selects lines #1 and #4 in Beijing’s metro subway system to demonstrate the feasibility of the proposed data modal in a subway environment. Lines #1 and #4 in Beijing’s subway system connect at the Xidan station (Figure 6). If pedestrians want to travel from the Zhongguancun station to the National Theater, they first need to take subway line #4 for 11 stations and then transfer to line #1 and get off at the Tian’Anmen
Figure 6. Implementation of a scenario involving Beijing’s metro subway environment.

West station. A short walk will subsequently take them from the Tian’Anmen West station to the National Theater. Figure 6 shows these two metro subway lines and their stations as represented by the proposed data model in an ArcGIS geodatabase. The blue line is subway line #1 and the red line is the subway line #4. The red points on both subway lines are their stations. Three zoomed-in maps represent the landmarks, activity points, junctions, and their walking links at the three key subway stations (i.e., Zhongguancun station, Xidan station, and Tian’Anmen West station). The green lines in the three zoomed-in maps are walking links inside stations. These walking links, which connect landmarks, activity points, and junctions in a three-dimensional space, represent accessible paths for the pedestrian to walk inside these three stations. These three zoomed-in maps show detailed information about the walking environment, while the subway lines only show abstracted lines with stations. The combination of representing the zoomed-in maps and the abstract subway lines in this scenario demonstrates a multilevel representation design for pedestrian navigation services. The complete route under this scenario includes three walking paths (i.e., the paths shown in black color in the zoomed-in maps) inside the three subway stations and two segments of the metro subway lines (i.e., the red polyline from the Zhongguancun station to the Xidan station on subway line #4 and the blue polyline from the Xidan station to Tian’Anmen West station on subway line #1). The O1–D1 segment guides the pedestrian from the origin location to the platform of subway line #4 in the Zhongguancun station, while the O2–D2 segment takes the pedestrian from the platform of subway line #4 to the platform of subway line #1 inside the Xidan station. Finally, the O3–D3 segment guides the pedestrian from the station of the subway line #1 inside Tian’Anmen West station to his/her final destination (i.e., the National Theater).

This scenario covers 26 landmark-augmented images from the origin to the final destination. Four of these landmark-augmented images (#1, #5, #9, and #26) are shown in
Figure 6 for illustration purpose. Similar to Figure 4, the landmarks, radar maps, and red arrows in these images provide useful cognitive information for the pedestrian to comprehend his/her environment and identify his/her route toward the final destination. Also, the images (#1, #4, #8, #17, #18, and #26) in Figure 7 show the selected landmark-augmented pedestrian navigation route instructions in Beijing’s metro subway environment. Specifically, image #4 in Figure 7 augments three sequential visible and invisible landmarks. The first augmented landmark is a ticket vending machine which suggests...
the pedestrians to buy ticket. The second augmented landmark is a signage which indicates the subway line the pedestrian should take. The third augmented landmark reminds the pedestrian to go through a turnstile as the next move. These augmentations help pedestrians to confirm their routes in a complex Beijing’s metro subway environment. This scenario highlights the usefulness of a landmark-augmented representation based on the LPNDM for pedestrian navigation in a subway environment. The above two example scenarios demonstrate the feasibility of the proposed LPNDM in providing landmark-augmented route instructions for pedestrian guidance in two different environments.

5. Conclusions and future work

This article proposes an LPNDM to model the salience and use of landmarks in pedestrian navigation environments (e.g., buildings, open spaces, multimodal transportation systems, and urban streets). In this data model, landmarks are represented as a specific class object that differentiates the LPNDM from previous approaches such as GDF, KIWI, SDAL, NCHRP, and MDLRS. The LPNDM has three specific capabilities: (1) the ability to describe landmarks in mixed indoor and outdoor spaces for pedestrian navigation; (2) the ability to support the salience measure of landmarks, and the landmark-based augmentation for route instructions in different walking environments; and (3) the representation of activity points in multimodal transportation systems with reference images or photos. The two example scenarios presented in this study demonstrate the implementation feasibility of the proposed LPNDM in the ArcGIS environment. A major limitation of the proposed data model is the lack of components dealing with the cognitive load of recognizing landmarks in pedestrian navigation environment. These components would be very helpful in pedestrian navigation services to minimize cognitive load associated with following navigation instructions.

We plan to further improve the proposed data model in several directions. First, it would be useful to model the cognitive load of recognizing landmarks in different walking environments. Second, there is a need to develop an efficient indexing method for organizing landmarks in a large pedestrian navigation area. Also it would be valuable to investigate if people would feel comfortable of using landmark augmentations suggested in this study in order to improve the design of the proposed LPNDM. Further improvements in these aspects will enable pedestrian and vehicle navigation systems to provide useful landmark-based navigation instructions in various environments.

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