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Chapter 11
Application for Locational Intelligence and Geospatial Navigation (ALIGN): Smart Navigation Tool for Generating Routes That Meet Individual Preferences

Ge Zhang, Subhrajit Guhathakurta, Jon Sanford, and Bon Woo Koo

Abstract Efficient mobility and high accessibility to urban services are critical for residents' quality of life and health. The outdoor environmental barriers, such as uneven sidewalks and missing curb cuts, can significantly impair pedestrian mobility, especially for people with disabilities. Removing those barriers is expensive and time-consuming. The Application for Locational Intelligence and Geospatial Navigation (ALIGN) is an app for mobile devices that intelligently identifies routes that are tailored to the individual's specific needs and abilities. Since ALIGN is built on real-time or near real-time data, it can complement as well as benefit from other "smart city" related efforts. The ALIGN app is designed to provide customized routes in a city for every user and to create a repository of user behaviour that can inform policy and planning decisions in prioritizing community mobility improvement projects.

Keywords Accessibility · Pedestrian · Navigation · Real-time · Disabilities

11.1 Introduction

Although much has been written about the relationship between walkability and the characteristics of the built environment, relatively few studies have concerned the mobility of people with functional limitations to ambulatory activities. Yet,

G. Zhang · S. Guhathakurta (✉) · B. Woo Koo
Center for Spatial Planning Analytics and Visualization, Georgia Tech, Atlanta, USA
e-mail: subhro.guha@design.gatech.edu

G. Zhang
e-mail: ge.zhang@design.gatech.edu

B. Woo Koo
e-mail: bkoo34@gatech.edu

J. Sanford
Center for Inclusive Design and Innovation, Georgia Tech, Atlanta, USA
e-mail: jon.sanford@design.gatech.edu

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community mobility, from the need for basic exercise to more complex participatory behaviors such as grocery shopping, going to the doctor, and visiting friends, is an essential life activity. For individuals with disabilities, outdoor mobility is especially important to maintain independence and health (Clarke et al. 2008). An important aspect of such mobility is basic physical activity, which has been associated with numerous benefits to health and well-being, including decreased social isolation, increased strength and endurance, enhanced functional abilities, greater feelings of personal control and acceptance of disability, and increased community integration (Ditor et al. 2003; Slater and Meade 2004; Tasiemski et al. 2005). Evidence suggests that people with disabilities have a lower rate of physical activity than the general population (Boninger 2007) and that physical activity levels decline at a greater rate for people aging with a disability than those without disabilities (Boslaugh and Andresen 2006). This is not surprising since the barriers to independent mobility for people with impairments are many, including unavailability of sidewalks with curb ramps, uneven pavements, inadequate traffic control mechanisms, hotspots of criminal activity, and inadequate lighting at night, among others.

The impacts of these barriers, however, can be greatly diminished if they can be easily avoided. Put another way, the real barrier to outdoor mobility is the lack of information with which to plan safe and appropriate routes that minimize encountering those barriers. Such information is more important when we consider the fact that removing the barriers and creating more accessible environments can be expensive and time-consuming while providing information needed for route planning is relatively inexpensive and can be easily updated according to changing conditions. In this chapter, we discuss the conceptual basis and design of the Application for Locational Intelligence and Geospatial Navigation (ALIGN), an application for mobile devices designed to improve the accessibility of all with particular attention to people with mobility impairments. Built on the Google Maps and OpenTripPlanner platform, the application enables users to avoid physical barriers by intelligently identifying routes that are tailored to an individual's specific needs and abilities. The pedestrian-oriented objects on the sidewalk, such as curb cuts, traffic signals, street lights and walk signals, have been identified from Google Street View images using machine learning algorithms and image recognition technologies. We expect that the ALIGN app will create a repository of user behavior that can inform policy and planning decisions by prioritizing community mobility improvement projects.

There have been earlier efforts to craft policies and design assistive devices to remove, overcome, or avoid the mobility barriers (Venter et al. 2002; Rimmer and Rowland 2008; Gray et al. 2012; Imrie 2012). For example, new electronic interfaces have been developed to aid the blind in key mobility tasks such as obstacle avoidance, orientation, navigation and travel in urban environments (Strumillo 2010). Another example is a novel geospatial mapping service designed to identify physical barriers in urban space and provide personalized and accessible urban path to users with special needs (Mirri et al. 2014). However, the defined barriers are limited, compared to the wide range of characteristics of the built environment, which influences accessibility. Many of the policy and assistive device-oriented efforts are, however, either time-consuming to implement, or expensive, making them not suitable for many individuals with impaired mobility. Being able to access various urban services is an imperative part of life for urban dwellers, but not all can afford the expensive assistive devices nor wait for the barriers across a city to be removed.

Mobile devices such as smartphones and tablets have become widely available to most people. They offer a platform to help people with special needs. The Global Positioning System (GPS) and wireless network of the mobile devices make location-based services readily available, enabling various applications including social network services and location-based searching algorithms, such as nearby restaurant search (Lee et al. 2006; Zheng et al. 2009). Navigation is one of the most popular location-based applications for mobile devices (Chincholle et al. 2002). Navigation systems such as Google Maps and Here, are designed to improve the accessibility of users to urban services. However, their functions are designed mostly for automobile travel and are mostly limited to avoiding congestion. The navigating system for pedestrians in these software applications does not provide spatial information about the built environment barriers critical for people with impaired mobility, which greatly diminishes the usefulness of such systems to those with special needs.

Developing a mobile navigation application for people with impaired mobility requires a close-to-real-time, large-scale, and high-resolution spatial dataset at the street-level. The detailed pedestrian and traffic environment at a scale in which slope and unevenness of pavements can be perceived, which may not matter for vehicles, is critical for guiding people with mobility challenges. Additionally, the built environment is very dynamic. High resolution data on the street and pavement condition together with the surrounding built environment is difficult to obtain given that available data sources usually have coarse spatial resolution and the real-time data feeds often do not cover the geographic expanse of an urban region due to the limited number of the devices collecting such data. Google Street View (GSV) offers a convenient option for capturing detailed information about the built environment because it is extensive and regularly updated (Anguelov et al. 2010). Other studies have also confirmed the usefulness of GSV images (Rundle et al. 2011; Hara et al. 2013; Li et al. 2015). However, the raw GSV images are not in usable format and requires extensive pre-processing. Our approach has been to develop Machine Learning algorithms for processing Google Street View images to identify various pedestrian-related objects on the street with high accuracy (Stallkamp et al. 2012). Besides GSV, we also take advantage of open data services for some specific attributes, such as traffic volumes, that can be accessed by an application programming interface (API).

A particular challenge in developing mobile navigation systems for people with impaired mobility is the design of a functional as well as efficient routing algorithm. Algorithms for finding the shortest route are widely available and known to be efficient (Dreyfus 1969; Ahuja et al. 1990; Zhan and Noon 1998). However, most of the algorithms used in the existing navigation applications are using distance or time as the constraints. For people with impaired mobility, not only the distance but also various other built environmental factors can be significant constraints, making navigating in a city a greater challenge. To overcome the limitation of the existing routing algorithms a new cost-distance algorithm was developed, which combines the effects of the built environment barriers and distance simultaneously (Guhathakurta et al. 2013).

The goal of ALIGN is to offer individualized real-time navigation options through a mobile device to help people with mobility challenges be physically active. Increased outdoor mobility is known to improve their physical and mental health and well-being. Given that removing or overcoming the barriers in the built environment is expensive and time consuming, ALIGN can help users avoid those barriers by providing regularly updated information and turn-by-turn navigation for routes that meet their preferences.

11.2 Related Work

The relationship between physical activity and health is demonstrated in a recent study that compared the impacts of physical activity on older adults in Mexico and the United States. The study concluded that higher levels of physical activity in the U.S. were associated with fewer functional limitations in performing basic activities of daily living and greater health benefits (Gerst et al. 2011). The benefits of physical activity were also demonstrated by another study, which suggested that increased levels of physical activity among older adults were associated with a decrease in mortality rates (Hrobonova et al. 2011). Similarly, a few studies have demonstrated that when people with disabilities engage in physical activities, they realize health and functional benefit outcomes similar to those experienced by the general population, including cardiovascular and respiratory health, balance, quality of life, as well as psycho-social benefits including mood, self-esteem and emotional well-being (van den Berg-Emons et al. 2003). Unfortunately, evidence also suggests that people with disabilities have a lower rate of physical activity than the general population (Boninger 2007), particularly among older adults who use assistive devices.

Walking is an important aspect of health, given its ability to improve cardiorespiratory and metabolic fitness. A substantial body of work has established that there are measurable health benefits for individuals residing in walkable areas (Frank and Engelke 2001; Saelens et al. 2003; Lathey et al. 2009). However, people with disabilities and older adults with ambulatory limitations routinely encounter difficulties while either “walking” or “wheeling” (for those who are nonambulatory) in their communities, even on routes that are considered “accessible” under the Americans with Disabilities Amendments Act Accessibility Guidelines (US Department of Justice 2010). Barriers outside the purview of the ADAAAG, such as long distances, steep slopes, obstacles in the path of travel, high curbs, wide streets, short traffic lights and poorly maintained walkways, can deter an individual from traveling in the community, thus limiting mobility and, as a result, compromising health, independence and overall quality of life.

Route decision-making requires critical information about: (1) key environmental factors that can act as barriers or facilitators of mobility, (2) different devices used for mobility (e.g., manual or power wheelchair), and (3) crucial route and destination information about safety, length, sidewalk condition, curb cuts, shading, types of buildings and their uses, and the presence of other street furniture. The challenge to community mobility is having access to information that one does not already possess to make informed decisions about when and where to go.

Although there are some assistive software packages available for individuals with mobility challenges, most current applications are focused primarily on accessibility to transit stops. While these applications tend to be system-specific web-based applications, a few, such as TransitTimes+, are mobile applications that provide accessibility information of subway, bus, and train stops in selected cities. TransitTimes+ indicates whether a transit stop is accessible or not by using international symbols. One drawback of these applications is that the criteria for conceptualizing and evaluating accessibility are not standardized or specified.

In contrast to TransitTimes+, HopStop provides users with online information about stroller-friendly and wheelchair-accessible transit routes in the New York metropolitan area based on the accessibility to transit and station entrances and exits. For mobile users, the HopStop app indicates whether a route is accessible by displaying icons.

A potential model for ALIGN is https://Walkit.com, which provides an "urban walking route planner" for cities across Great Britain. Although it does not include route accessibility and barrier information, it is a customizable application based on aggregating real users' preferences. Rather than simply providing route information, Walkit empowers users to select their own route based on themed walks, walking tours, walking for health, walking to lose weight, walking to work and walking to school. Walksinthecountry is another customizable application that uses the user's last known location and satellite image data to plan potential routes to the nearest places of interest. Although the application does not fully incorporate user preferences in its operation, it offers another example of an app that collects real time data about users' navigation choices.

To date, Rollstuhlrouting (wheelchair routing) is the only existing online application that includes environmental factors in route planning. Although it is limited in that it focuses on wheelchair users in Germany and that it includes only a few key environmental barriers, this application provides users with information on slope, surface material and height of curbs, and hazards.

Using OpenStreetMap, Google Maps, or Bing Map as their base, various mapping systems have been developed to evaluate accessibility using built environment characteristics (e.g., Walk Score) (Carr et al. 2010). One example is a high-resolution (10 m) bikeability map for the Metro Vancouver region, developed by Winters and colleagues, which was based on density of bicycle facilities, the separation from motor vehicle traffic, the connectivity of bicycle-friendly roads (local streets, bicycle routes, and off-street paths), slope, and density of destination locations (Winters et al. 2013). It provides a powerful visual aid to identify zones where changes are needed to support sustainable travel. Although these tools allow users to create a rough plan for their trips, they are designed for people with average mobility, and the special requirements of people with disabilities on the pedestrian-built environment have not yet been considered. Also, it is hard to use those tools in actual navigation because they do not provide a turn-by-turn navigation function. Additionally, the factors and algorithms for assessing the accessibility are predefined and fixed, not allowing users with mobility challenges to tune them according to their needs.

Navigation systems such as Google maps, Here, and many others have been developed to improve the accessibility to urban services. For example, an eco-routing navigation system was designed to find a route that requires the least amount of fuel and/or produces the least amount of emissions between a trip origin and a destination (Boriboonsomsin et al. 2012). However, those tools are mainly designed for the motorized vehicular traffic. Real-time information about the pedestrian environment is unavailable in those tools, and pedestrian routes, when available, are usually generated using distance as the sole parameter. Navigation systems with a crowdsourcing component, such as Waze and route information sharing (RIS) system, are designed to collect additional real-time traffic information, such as traffic congestion and vehicles on the side, to improve accessibility (Amin-Naseri et al. 2018). A cooperative car navigation system with RIS uses a crowdsourcing system to reduce the travel time (Yamashita et al. 2005). In the RIS system, each vehicle transmits route information (current position, destination, and route to the destination) to a central server, which estimates future traffic congestion using that information and feeds it back to all vehicles. Despite the innovations, the crowdsourcing components in these systems still lack considerations for pedestrian-related built environment features.

Among the navigation systems designed for pedestrians, Navitime, a mobile phone-based navigation service stands out in popularity. With around 2 million Japanese users, Navitime incorporates various modes of transportation including pedestrian navigation in the real world (Arikawa et al. 2007). uNavi is another example of a pedestrian navigation system developed to associate information services to the places of human interest (Bessho et al. 2008). This system provides landmark-based routing instructions that are generated by the locally-stored spatial semantics. For a special case of indoor spaces, a positioning system for indoor pedestrian navigation services was developed by Inoue et al. (2009), which operates with a user's mobile terminal and battery-driven beacon devices in a server-less environment (Inoue et al. 2009). Another method is to use a building information model (BIM) as an input for indoor pedestrian navigation especially in complex buildings (Lertlakkhanakul et al. 2009).

There have been limited efforts to develop navigation systems for people with disabilities. One such example is a mobile-cloud collaborative traffic lights detector system that was designed for individuals with low eyesight (Angin et al. 2010). Völkel and Weber (2007) developed a concept of multimodal annotation of geographical data for personalized navigation for people with impaired mobility. This concept, in conjunction with the crowdsourced geographical data, helps in finding suitable routes even in unknown territories (Völkel and Weber 2007). The direct inputs from users and the observations from the users' LOM-Modality (Location, Orientation, and Movement) are aggregated to enhance the spatial information in these systems.

11.3 App Design and Method

The ALIGN app consists of three main components: (1) a geographic information system, (2) a routing system, and (3) the geo-visualization (mapping) application. The overall framework of ALIGN is shown in Fig. 11.1. The geographic information system is a geospatial database that stores the pedestrian-related built environment data. The routing system has two parts, a mobility score module and a routing module. The mobility score module generates a score for each street segment using the geospatial database and the cost-distance algorithm, which is used as the constraints in the routing module. The preference system in the mobility score module provides users an option to select a set of parameters that are important to each user. Using these information, the routing module computes the most accessible route based on the street network between the origin and destination points using Dijkstra algorithm (Dreyfus 1969). The mapping system is built on Google Maps and geo-referenced for users to identify locations on the map. Finally, the computed routes are displayed on the map and the turn-by-turn navigation is provided as the user travels along the chosen route.

11.3.1 Data Requirements

Previous studies have examined several built environment parameters to assess the ease of mobility and accessibility of the pedestrian environment (McKinnon et al. 2009; Ewing and Cervero 2010). Based on these studies, the ALIGN project uses the following data categories for evaluating the pedestrian environment:

1. Sidewalk: This category records the presence of sidewalk and whether the street segment has adequate width, shade and slope. If a street segment has a sidewalk or shade, the value of the parameter for that segment would be marked as 1.

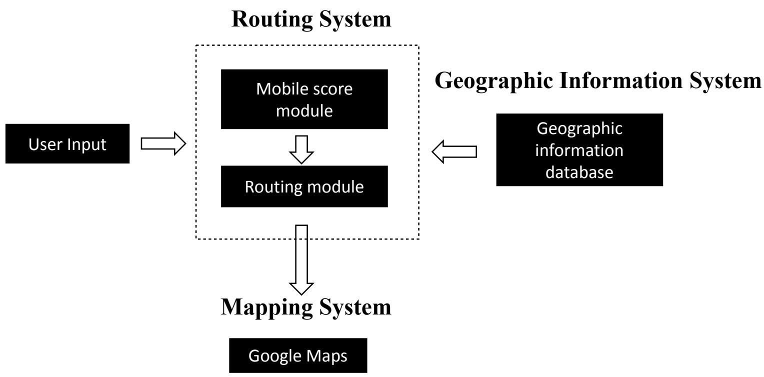

Fig. 11.1 Framework of the ALIGN

Otherwise, it would be marked as 0. The adequate width of the sidewalk is also a binary data with a threshold of 3 ft. If the width of the sidewalk of a street segment is above 3 ft, the parameter would get a value of 1. Otherwise, it would be 0. Slope is normalized such that a larger value indicates that the street segment has a steeper slope while a smaller value represents a gentler slope.

2. Traffic control: The presence of traffic lights and stop signs at intersections are important for traffic safety. If there is either a traffic light or a stop sign at the intersection, the value of this parameter for the street segment around that intersection is 1. Otherwise, it would be 0.
3. Street Crossing: The presence of curb cuts, pedestrian signals, crosswalks, and intersection density are recorded under this category. The density of the intersections in the block is calculated based on the number of intersections and the size of the block and is assigned to the street segments within that block. For the presence of curb cuts, pedestrian signals, and crosswalks, the respective parameters are coded as 1 if they are present on the street segments around that intersection. Otherwise, they would be assigned 0.
4. Building density: Both residential density and business density are computed. Residential density represents the density of the population of the block. The value of the parameter at the block level would be assigned to the street segments within the corresponding block. Business density is the density of businesses in the block. The street segments in the corresponding block would be assigned the same value.
5. Safety: The presence of street lights, low traffic volume, and low crime rate would constitute a safe street environment for pedestrians. If the street segment has a street light, the value of the street light parameter would be marked as 1. Otherwise, it would be 0. The traffic quality is an index defined by HERE Maps traffic API which is between 0 and 10. Higher value means slower traffic. The crime rate is the number of the crime incidents in the block, and each street segment in the block would share the same value.
6. Resting Areas: Resting areas in this case are specifically bus shelters. If there is a bus shelter on the sidewalk, the value of the parameter for that street segment would be marked as 1. Otherwise, it would be 0.

Various open data services and Google Street View images have been used to build the spatial database. The presence and the width of sidewalks were collected and computed through a GIS shapefile provided by the local government. The slopes of sidewalks were calculated using the digital elevation model (DEM) data acquired from the United States Geological Survey (USGS). The pedestrian-related objects on the sidewalk and intersections, including curb cuts, traffic lights, stop signs, pedestrian signals, crosswalks, and street lights were extracted from Google Street View images using object detection and machine learning technologies (Fig. 11.2). The residential density was calculated from the recent US census information and the business density was generated from the ESRI Business Database. The crime data was obtained from the local police department and the traffic data was provided by

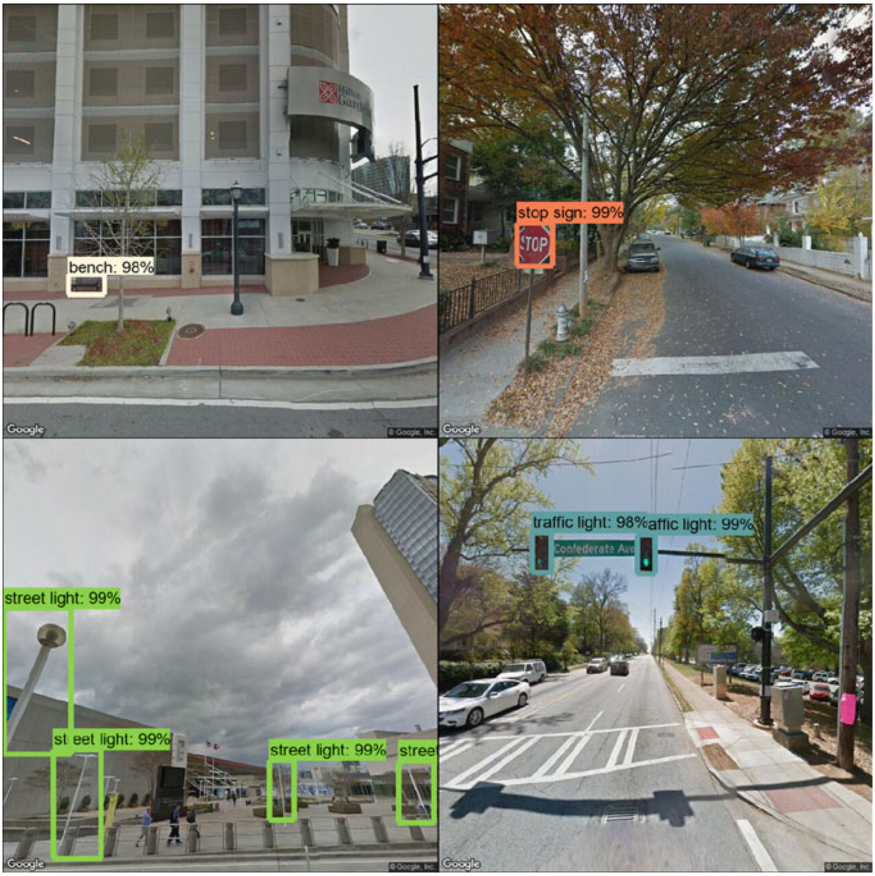

Fig. 11.2 Samples of sidewalk objects detection from google street view images

the HERE Maps traffic API. The street density was calculated from the TIGER road shapefile and census block boundary from US census.

11.3.2 The Design of the Spatial Database

Sources of real-time data are limited because the installation of data collection devices and the maintenance of the data infrastructure are expensive. As an alternative, the Google Street View API is a popular open data source that provides reasonably detailed information about the streetscape. We used a convolutional neural network (CNN) built with the TensorFlow platform to detect the objects in the Google Street View images. The detected objects were located on the map using the geo-tags of the Google Street View images. For the city of Atlanta, we collected around

600,000 geo-tagged street images from Google Street View image API, covering every street segment in the city. We created around 200 annotated images for each object as the training data, and we tested the performance of the trained model on 500 annotated images for each object category. The maps of the traffic lights, stop signs, walk signals, street lights, cross walks, and curb cuts were generated based on those models and then transformed to parameters at the street level.

11.3.3 Design of Algorithm for the Routing Module

The routing service is the core component in the navigation application, as the final output of the navigation is the preferred route generated based on various constrains, such as distance and time and Dijkstra algorithm (Dreyfus 1969). In this case, a mobility cost of street segments was used as the constraints to reflect various needs of people with impaired mobility. The mobility cost for each street segment is calculated using the following equation:

$$MC_j = \frac{D_j}{\sum_{i=1}^{n}(V_{ij}W_i) + 1} \tag{11.1}$$

where MC_j is the mobility cost of the street segment j; D_j is the length of the street segment j; n is the number of the attributes of mobility chosen by the user; and V_i and W_i are the value and the weight for the attribute i, respectively. V_i is a normalized value based on the values of all the possible routes between origin and destination. As described above, the application provides users an option to select a set of parameters that are important to each user. This is to ensure that the routes generated by the app are tailored to the specific needs and preferences of each user. For example, if a user is a person in a wheelchair, they might consider the existence of curb cuts along the route as the most important factor whereas another user with impaired vision might think the audible pedestrian signal is a more important consideration when navigating a city. Users can also define whether the selected parameters are essential or secondary. The essential parameters are considered to be ten times more important than the secondary parameters when the routing system calculates the optimized routes.

11.3.4 Interface Design for Users Input and Visualization

The interface was built based on Google Maps and provides the functions for users to select preferred parameters, input the origin and destination points, review the computed routes, experience the turn-by-turn navigation, and report the trouble spots.

Figure 11.3 shows the parameter list from which users can choose their preferred features. Users can input the addresses or directly tap the screen to set up the origin and

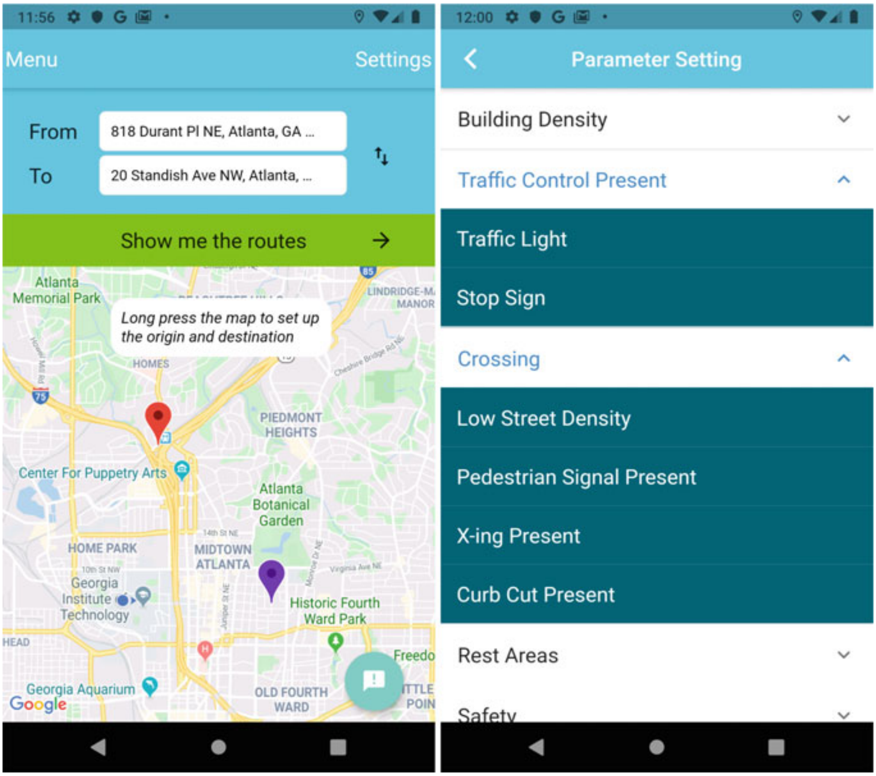

Fig. 11.3 Landing page and parameter setting in the app

destination points. Figure 11.3 also shows the address of the origin and destination points and their locations on the map.

Based on the user input, an overview of the computed routes is generated for review prior to turn-by-turn navigation (Fig. 11.4). In this case, while the preferred route generated by the application is 0.11 miles longer than the shortest route and needs two more minutes for traveling, it can provide greater accessibility by meeting the needs of the user.

11.4 Implementation and Evaluation

The ALIGN app integrates the following tasks in its operation: (1) identify and validate key real-time, street-level environmental barriers; (2) calculate the mobility score for each street segment based on user's input and the location-based data; (3) calibrate the routing algorithm based on the mobility scores; and (4) provide map-based visualizations of the best route and the shortest route for each trip.

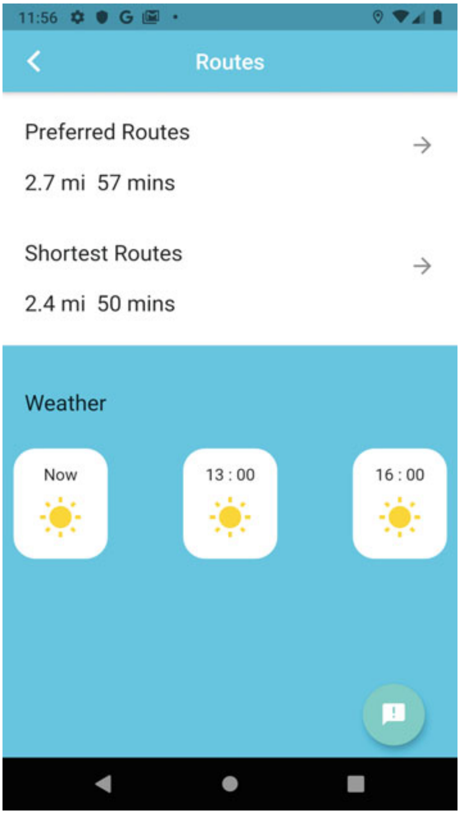

Fig. 11.4 Overview of the preferred route in the app

Here, we demonstrate the performance of the application using three hypothetical users with various needs who navigate in the city of Atlanta. For this demonstration, we used a geographic information system database hosted on a local server as a data storage. For the routing service, we built a Java back-end based on the OpenTripPlanner running on a local server. The sequential process from the user input to the final display of the computed route is as follows: Once the user input from the front-end interface is confirmed, a request is sent to the back-end server. The back-end server retrieves the data from the database, computes the preferred route based on the user's input, and sends the preferred route back to the front-end platform. The front-end translates the route information to a line on the map.

To make the comparison between the optimized routes for different needs and preferences of the three hypothetical users comparable, the same origin and destination points which were randomly selected in the city are used for all three hypothetical users. Only the number and weights of the parameters representing the preferred features of the built environment on the routes are different.

The first user is a visitor from a different city who is not familiar with the City of Atlanta. As a visitor, this user wants to visit some famous places in the city to

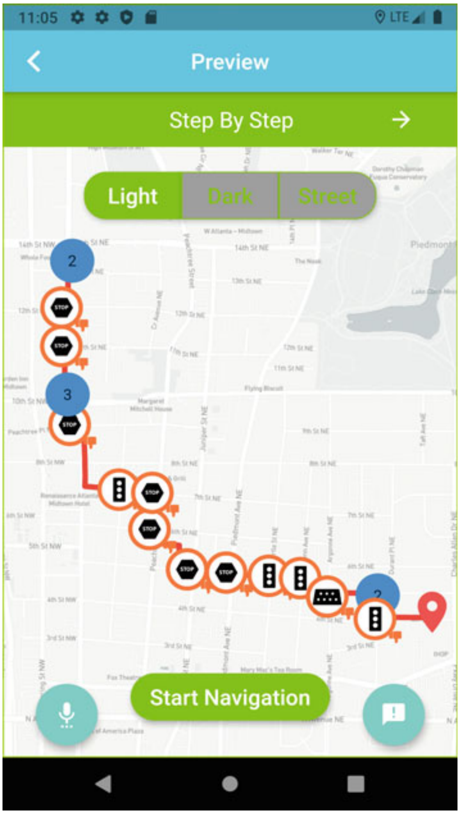

Fig. 11.5 Routing maps with residential density, sidewalk present and crime as the primary parameters while business density and sidewalk width as the secondary parameters

experience its most popular parts. Also, the landscape on the way to the destination is a consideration since the city is known for its tree canopy. In addition, the user also wants to make sure the trip is safe and comfortable as public safety can be a concern in big cities and pedestrian infrastructure is not always available in the city of Atlanta. In this case, the full range of preferred parameters includes residential density, business density, sidewalk present, sidewalk width, and crime. We use residential density, sidewalk present and crime as the primary parameters while business density and sidewalk width as the secondary parameters in this experiment. Figure 11.5 shows the calculated route based on this setting.

The second hypothetical user of our application is a resident of Atlanta who wants to exercise during the weekend. In general, doing exercise, such as walking or running, requires that the trip be long in distance or time (e.g., a few miles and/or over 30 min). The user also prefers streets with tree canopy or shelters that can provide shade. The traffic condition is also an important safety consideration for the user. The application needs to find the street with less traffic volume or road with enough traffic control devices such as traffic signal, walk signal, crosswalk, and stop sign. The sidewalk is necessary for exercising. For this second hypothetical user, the preferred

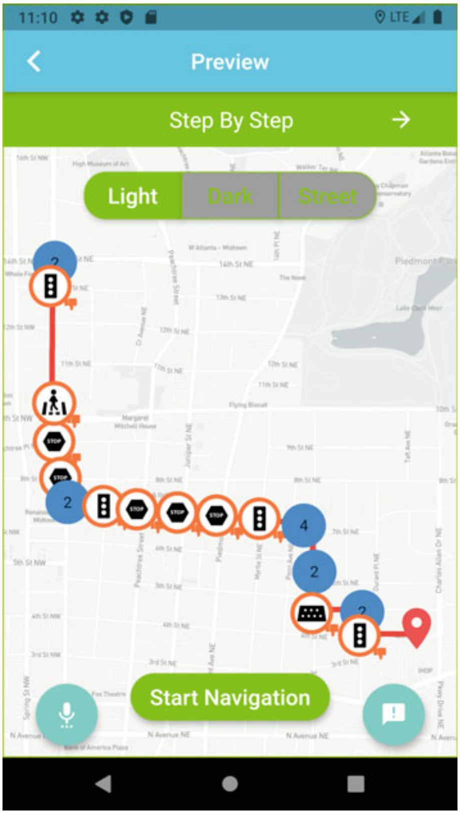

Fig. 11.6 Routing maps with shade and sidewalk present as the primary parameters while traffic signal and crosswalk as the secondary parameters

parameters can include traffic signal, crosswalk, tree canopy, and sidewalk. We use shade and sidewalk as the primary parameters and traffic signal and crosswalk as the secondary parameters. Figure 11.6 shows the calculated route for this experiment.

The last hypothetical user of our application wants to plan a trip through a hilly neighborhood at night. Walking or running at night is challenging and unsafe if the street is not well lit, and the location of street light can be an important factor in choosing a route. The hilly topography in the city of Atlanta can also make the trip more challenging, and the user is interested in finding streets with gentle slope. For the final hypothetical user, the preferred parameters can be street light and slope. In this demonstration, we use street light and slope as the primary parameters. Figure 11.7 shows the calculated route for this purpose.

The routes generated for the three users demonstrate the performance of the application in generating routes that serve various needs and preferences. The results show that the application is sensitive to the changes in the parameters, whether they are the number of parameters or weights therein. The preferred route is noticeably different from the shortest route, indicating that the shortest route may not always be the optimal route for people with varying needs and preferences.

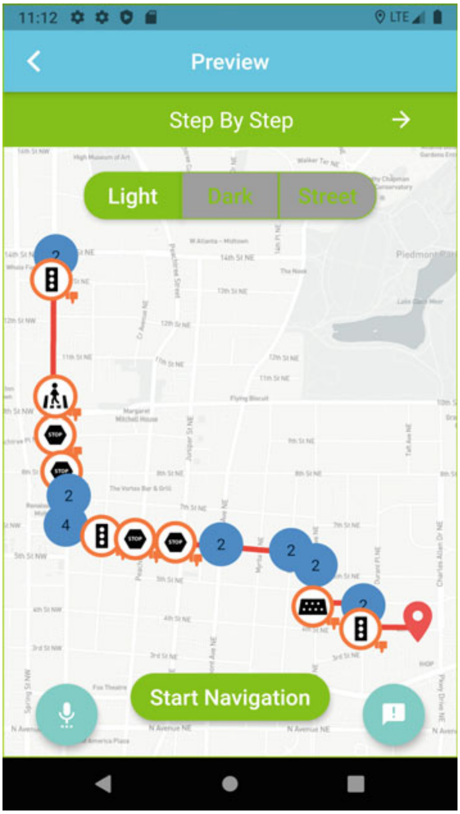

Fig. 11.7 Routing maps with street light and slope as the primary parameters

11.5 Discussion and Conclusions

The traditional navigation and mapping tools have successfully assisted users with average mobility. However, for people with disabilities and special needs, those tools are limited as they often lack critical information about the environmental barriers, such as missing curb cuts and pedestrian signals. The ALIGN app can generate customized routing based on the user input for people with different physical challenges, such as impaired vision, hearing, and mobility. Unlike the traditional tools, ALIGN utilizes comprehensive data on the built environment ranging from the presence of various pedestrian-related objects on the sidewalk to building density and safety at a block level, all of which can impact the accessibility of the people with disabilities. The real-time or near real-time aspect of the data powered by the Google Street View will improve the performance of the app by updating the database and maintaining it as an accurate representation of the real-world as best as possible.

It is important to note that some real-time data have been operationalized in the app. For example, HERE map, hosted by Microsoft, provides the real-time traffic data service, which is used to update traffic volume in the ALIGN database. The Atlanta police department updates their crime report every two weeks and this crime data is open to the public. This data has been used to update the crime rate in the database. However, some pertinent information about the pedestrian environment were left out due to problems of acquiring accurate data. For example, the data on the location of benches was a part of the initial data collection process using the Google Street View images and an object detection model developed by Google. This attempt did not meet our expected accuracy and was therefore left out of the data infrastructure. The next major update to the app may include this location parameter if we are successful in developing better object detection models.

Another important component of the ALIGN app is a crowdsourcing system that captures user contributed data about conditions of street segments as the user experiences it in real-time. Crowdsourcing applications are drawing attention in various fields, such as disaster management and marketing as well as navigation system development (Whitla 2009; Ni et al. 2016; Chincholle et al. 2002). It has been used to verify the existing data and fill data gaps when the number of samples are limited and survey is out-of-date. The advantage of crowdsourcing is that there is no installation and maintenance costs for the data collection sensors because people reporting the data are treated as "sensors". However, the quality of the data collected by the crowdsourcing system is not guaranteed to be usable because the reporters are not always professionally trained, suggesting that a great amount of data may be needed in order to remove the marginal errors caused by the low quality of the data inputs. Nonetheless, given the significant advantage, a crowdsourcing system was developed for the application to verify the existing spatial data capture system and to update it when new events occur. Users can report the missing objects such as curb cuts and crosswalks by tapping on the application screen. Considering that the data we collected are from multiple sources with the potential to have errors, a crowdsourcing component in the application is necessary to keep the data accurate and current.

The ability to save user profiles is another useful component of the ALIGN app. This functionality helps those who want to save their personal settings for a more customized service. The users can sign up through their emails and get access to their saved personal setting at any time and any place. The personal setting includes saved addresses, saved parameters and saved routes. The profile system allows users to easily reload the parameters used in the last trip and make changes to it based on their current preference and previous experience. This makes it easy to test various parameter settings thereby allowing users to find more optimized routes quickly and efficiently.

Although the current app is limited to the City of Atlanta, its design can be replicated for any city in the U.S. that maintains the data used in the app. Note that the full set of data is not an absolute requirement for the cost algorithm used in the app. Cities that do not have the full set of data discussed in the data requirements section can still apply the app's system by simplifying the required data or by replacing the preference parameters based on the unique context of each city.

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