WheelShare: Crowd-sensed Surface Classification for Accessible Routing

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***Abstract*—Accessible path routing for wheeled mobility is an important problem given the permanent and temporary obstacles in the built environment. Existing research works have focused on identifying several obstacles as well as facilities such as crosswalks with traffic signals using smartphone based sensing or crowd-sourcing and used those knowledge to generate accessible routes. In this work, we propose WheelShare which generates an accessible route through the best possible surface depending on user and wheelchair requirements. It is 1) scalable, as it uses crowd-sensing to collect voluminous data, 2) dynamic, as the data gets constantly updated, and 3) objective, as it uses an empirical and data-centric approach.**

***Index Terms*—accessibility, smart cities, accessible routing, machine learning**

I. Introduction

Travelling is challenging for wheelchairs users plying the city roads in order to accomplice their daily tasks. Barriers are even higher in unfamiliar surroundings because of unknown obstacles in the built environment [1], [2]. Common road characteristics like cobbled city squares, uneven sidewalks, curb heights which are easily ignored by able-bodied users, often pose unsurmountable hindrances to the wheelchair users. Also, usually being less healthier, the elderly individuals are more prone to using assistance, at least while using self-propelled and non-motorized wheel chairs. Meyers *et al.* [3] interviewed 28 adult wheelchair users to find out the barriers frequently faced across the built environment and the response includes narrow sidewalks, absence of ramps or steep ramps, absence of sidewalk curb cuts, uneven sidewalk surfaces, and temporary obstructions (like discarded furniture dumped on sidewalks). Along with barriers, however, there are also various wheelchair-friendly facilities, such as, supervised crosswalks or elevators, which improve accessibility of a pathway. In order to help increase accessibility of wheelchair users, different countries have made regulations with specifications for the built environment that must be considered during their design, construction, and alteration. Most of the times, these regulations aim to provide disabled users "equal opportunities and barrier-free access" across all public places.

Developing routing applications for restricted-mobility users have gained popularity among researchers in recent times. Existing vehicle or people routing applications cannot be adapted directly for people with special needs due to the absence of detailed knowledge of the sidewalk surfaces, slopes, pedestrian crossings and curbs. Similarly, wheelchair types, age, weight, and physical fitness of the users as well as presence or absence of an aide also matters in choosing the appropriate route. So, it is non-trivial to find an accessible route for wheelchair users as it requires knowledge of a whole set of parameters. Although the surface type has been identified as an important accessibility parameter, so far, there is not enough study on the nature of accessible surfaces in a systematic manner.

In this paper, we propose the WheelShare system as an end-to-end solution for accessible routing. WheelShare uses crowd-sensed surface data gained through machine on vibration data to provide accessible routing. Further, it offers a web-based routing application that computes accessible routes based on user requirements. This paper presents the concept of the WheelShare system as well as a prototype implementation of the web-based routing application.

II. Related Work

In order to provide equal opportunities to differently abled individuals and to address their need of independent living, various apps and systems have been developed which aim to assist users with mobility disorders. Such systems can be grossly divided into two categories: (1) mobility assistants and (2) crowd-sourced accessible route recommender. Mobility assistants are applications that help users to identify mobility barriers in built environments both indoor and outdoor and several facilities/resources which are helpful. Those barriers and facilities are then used along with digital maps to generate a geo-tagged accessible map which can generate accessible routes based on user queries.

MAGUS [4], [5] is a navigation system tested for wheelchair users in the Northampton area of the UK. It collects users' age and weight as well as their feedback on sidewalk parameters, such as, slope, surface type and curb cuts and calculates impedance score of sidewalk segments using mathematical models which also consider environmental obstacles. Optimal routes are calculated using minimum barriers, fewest slopes, shortest distance, avoiding bad surfaces, and using limited number of controlled road crossings. Karimanzira *et al.* [6] developed a travel aid in Georgenthal, Germany, which uses machine learning techniques to generate routes

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for visual/limb/hearing impaired people. The effort required to overcome barriers on sidewalks were mathematically modelled by the authors and the routing was achieved using fuzzy decision systems.

Using collaborative knowledge of people was the idea of crowdsourcing [7], [8] and it is supposed to improve the quality of life of people. Crowdsourcing is a popular approach for collecting data on accessibility barriers along a path as well as for accessible route recommendation. Crowdsourcing apps for urban accessibility focuses on identifying accessible locations/services and/or barriers in built environment. WheelMap [9] and WheelMate [10] review the accessibility of different points of interest. However, they do not record the accessibility barriers. On the other hand, a crowdsourcing app is presented in [11] which lets users add photos and comments related to barriers/obstacles in sidewalks. It then integrates different types geo-tagged data for collaborative creation of accessibility maps.

Sensing applications (e.g., [12]) aim to recognize user activity, such as, using stairs (barriers) or crossing roads using traffic-light controlled crosswalk (facilities), using smartphone accelerometer data. However, it is important to have the data geo-referenced, so that the recorded barriers and facilities can be used to generate an accessible route. Authors have used specific hardware equipped with GIS and GPS in [13], to generate a network-based accessible map. Other crowd-sourced systems for accessible route generation using geo-referenced data are RouteCheckr [14] and U-Access [15]. While the former allows collaborative data annotation[1] and personalized routing, the latter generates shortest accessible route for users with different mobility levels (mobile, aided, wheelchair-bound) without personalization. Experiments show that the wheelchair accessible routes are usually quite longer than for others.

Other approaches [16], [17] focus on routing elderly users and sometimes [17] through barrier notification using phone-mounted GPS sensors. There are quite a few other crowd-sourcing schemes. A crowd-sourced safe-route generation technique was proposed in [18] after a safety perception management system was introduced in [19]. An online crowd-sourcing technique for visually impaired was presented in [20] which works with the Google Street View to identify the bus-stop landmark locations. A social platform for accessible information sharing in [21] helps disabled individuals to generate a suitable path to their destination. mPASS [22] is a system which collects and analyzes indoor and outdoor accessibility data and provide personalized paths for users customized to their preferences and needs. They have advocated for integrating sensor and crowd data and observed that the data collected about the barriers must be error-free and complete, so that, the route generated is also correct. Two other works focused on selecting the most appealing route among others based on human perceptions of quietness; happiness and beauty [23] as well as the most pleasurable route for urban walking based on crowd-voting data from social media [24].

[1] Active annotation refers to rating segments for safety, convenience, surface condition (environmental conditions) and slope; passive annotation records the user's location, orientation and movement.

Researchers have approached the problem in three different ways. (1) Several applications [4]–[6], [9], [10] have been developed that focus on specific user needs through personalization and also collect data regarding the pathway. The path information includes various barriers and facilities along the intended route. Then they suggest the user the most accessible path as per their abilities and preferences. (2) However, collecting information of barriers and facilities and updating them in a timely manner is again challenging. So, many researchers have proposed crowd-sourcing as an alternative. Various crowd-sourcing systems have been proposed for collecting and annotating accessible path information [12], [13]. While some systems require manual data input regarding presence of a barrier, others can automatically detect stairs and crosswalks from the user movement [12] using the smartphone accelerometer data. Another common approach to address the dearth of data in wheelchair routing is to use collaboratively collected geo-data obtained through the OpenStreetMap (OSM) project [25]. (3) A third type of research focuses on using the crowd-sourced data to generate the accessible route between a source and destination point for wheelchair users [14], [15].

The authors in [**?**] present a wheelchair routing algorithm that takes surface properties, slopes, and obstacles such as stairs into account. This work does not focus on the collection and classification of real world data but could make use of data collected in with our approach.

Relevant research works [26]–[31] and projects such as OpenRouteService [32], [33] and Wheelmap [9] have shown that collaboratively collected geo-data (also known as Volunteered Geographic Information (VGI) [34]) can be a reliable data source for pedestrian and wheelchair routing.

III. The WheelShare System

In this section, we introduce WheelShare, an accessible routing system that calculates routes for wheelchair users through a series of accessible surfaces. The WheelShare system uses machine learning to classify standard surfaces often encountered in the built environment into accessible and inaccessible surfaces depending on the vibration data (geo-tagged accelerometer and gyroscope readings) of a wheelchair that moves through them. The routing algorithm then finds the best route between a pair of source and destination points through the accessible pathways and sidewalks. WheelShare enriches surface classification reliability using wide-scale crowd-sensed surface information contributed by volunteering wheelchair users who themselves benefit from the application. The data is used to add an overlay to the existing map application that shows the accessibility of the sidewalks and pathways. These overlays are well-known from live traffic features.

A. System Architecture

The WheelShare system operates in two phases - the training phase and the live phase. In the training phase, we collect

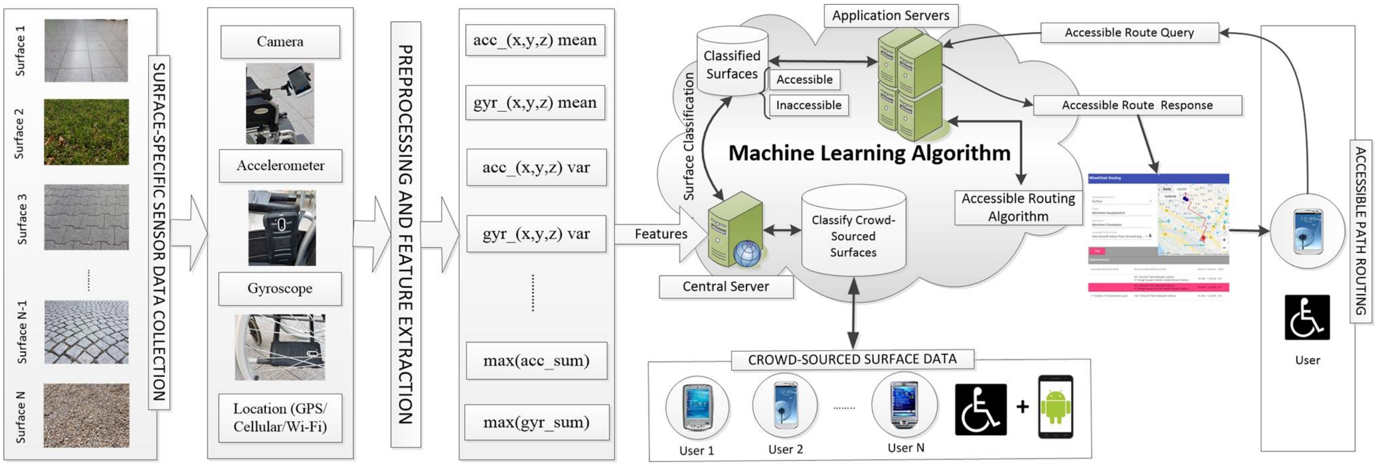

Fig. 1. The WheelShare system architecture. The core of the system is a surface classification model that has been trained with acceleration and gyroscope data from different surfaces. The data was collected by smartphones mounted on a wheelchair that was pushed through these surfaces. Further data is retrieved by a crowdsensing application that allows every wheelchair user to contribute. The data can be used by our accessible routing web application.

geo-tagged accelerometer and gyroscope data while pushing a wheelchair over different types of common surfaces. We use the recorded sensor data to train a classifier. This classifier allows us to infer about the accessibility of a surface in a quantitative manner, depending on the vibration induced by it, and is further utilized in the live phase. In the live phase, two types of participants use the system: contributors and route requesters.

The contributors are the core of the crowd-sensed system and they contribute surface vibration data collected through their smart devices attached to their wheelchairs while on the move. To facilitate this process, we provide an application that makes data collection straightforward and convenient. Contributors forward the collected geo-tagged acceleration and gyroscope data to our central server which classifies them according to the previously learned model. We then add the classified waypoints to the accessibility overlay. Thus, with the help of crowd-based data collection we can gradually enrich the overlay.

Route requesters use our routing application to retrieve an accessible path to their destination. The routing application uses the overlay data to evaluate the accessibility of multiple alternative routes. It provides graphical and textual information about the routes and sorts them based on a utility function before presenting to the requester. Route requesters can then select their preferred route. Participants can be contributors and route requesters at the same time.

Figure 1 shows the architecture of the WheelShare system. Here, we briefly describe the components of the system as well as the communication between them.

Reference Surfaces: To learn which surface produces which pattern of acceleration and gyroscope data, we collected sensor data from different surfaces common to most built environment. The analysis of the surface data is out of scope of this paper.

Surface Model: We use multiple machine learning algorithms to train a model that classifies the accessibility of surfaces based on labeled acceleration and gyroscope data. We train the model with the data from the reference surfaces where we, literally, know the ground truth. When further sensor data are collected in the live phase of the system, this model is used to infer the accessibility of those surfaces - thus replacing subjectivity from the nature of a surface with objective and empirical sensor data based machine learning models. Building this model is out of scope of this paper.

Crowd-Sensing Application: Wheelchair users can contribute to WheelShare by collecting and sharing sensor data. Therefore, they use their own smartphone and our Android-based crowd-sensing application. While they are moving through the city, the application collects geo-tagged sensor data and stores them on the phone. In addition to the acceleration and gyroscope data, the collected GPS information allows us to relate the sensor data to a physical location on the city map. The smartphone opportunistically connects to the WiFi hotspots and and transmits the data to the data server.

Data Server: The data server stores the surface model and receives data from the crowd-sensing application. It classifies the data, stores them in a database, and periodically sends updates to application servers, which perform the routing. The updates contain tuples that store the accessibility level of the path or sidewalk at a certain location.

Application Server: Application servers respond to route requests that users send via the routing application. They retrieve updates from the data server and store all known accessibility information. Upon request, they compute possible routes for the user and evaluate them based on their accessibility as available through the constituent surfaces.

Routing Application: The web-based routing application provides an easy-to-use interface to get wheelchair accessible routes. It sends queries to the application server with the origin and the destination. The application server responds with multiple routes. The web application displays these routes and adds an overlay that illustrates the accessibility level. Further, it provides textual information about the routes in form of a utility value and ranks the alternatives. The users can then select their preferred route based on their capability and the wheelchair capability.

B. Design Considerations

The separation of the WheelShare system into the training and the live phase requires a comprehensive data collection and analysis before the first wheelchair user can send an accessible route request through the web-application. Further, when the live phase starts, the available data is limited to the results from the initial data collection performed by a small group of researchers. However, this design has multiple advantages that will be discussed in the following.

Scalability: Even though the amount of the initial data collection is limited, crowd-sensing surface data makes the system scalable. As users of the system themselves can contribute in the recording of the data, the workload is distributed to a large group of people who have an intrinsic motivation to gather as much data as possible. The greater the amount of data, the more each person benefits from the system. The crowd-sensing application makes contributing straightforward and requires only little user interaction to start and stop the recording. We chose not to automatically trigger the data collection in order to respect the user's privacy even though the collected data is anonymized.

Up-To-Dateness: Crowd-sourcing surface data is not only beneficial in terms of the amount of data that can be collected. Rather, the information stays up-to-date as data will be collected for the same sidewalks and paths repeatedly over time. More current data will replace outdated measurements which accounts for temporary or permanent changes. Collected data could even 'evaporate' over time which would identify routes that become unusable at some point in time as no current data can be collected there.

Objectivity: Crowd-sourcing is prone to human errors and subjective interpretation. Moreover, accessibility of a route varies depending on the physical ability of the user as well as aids such as walking sticks, crutches or different types of wheelchairs. However, the WheelShare system can counter those subjective error propagation using our robust classifier that has been trained with a large dataset for multiple surfaces, any subjective component is eliminated. In addition, the crowd-sourcing application standardizes the data collection process.

IV. Routing Application

We use the captured surface data to build an accessible routing application. Wheelchair users can use the application to compute accessible routes based on the crowd-sensed surface data. The application contains two parts: a frontend for visualization and a backend server for performing the calculation.

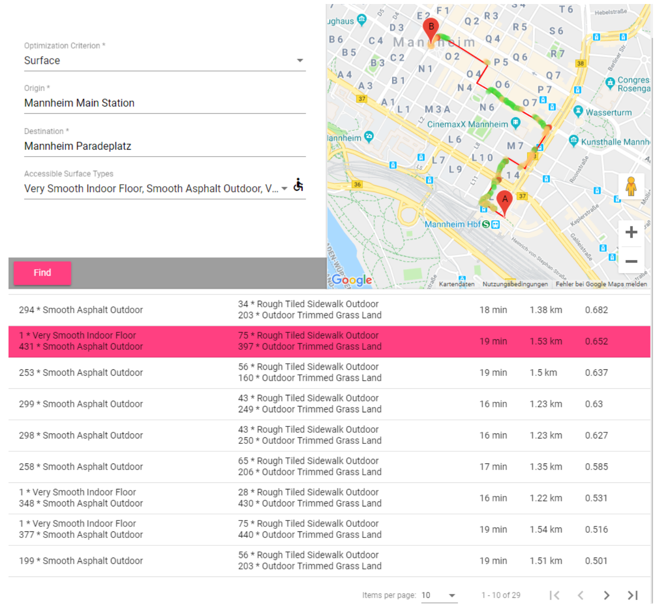

Fig. 2. Screenshot of the web-based accessible routing application. The application provides textual and graphical support for the user. Further, routes are ranked according to a utility function that is computed based on the accessibility of the route.

A. Design

The frontend is designed with the *Angular 4* framework in *Material* design and is available as a Web application. The user interface (UI) includes input fields as well as a map where the surface overlay and the route is displayed. Initially, a kind of heatmap is shown in the area of the map which shows the collected surface data in different colors to distinguish the surface types. Application users search the map for accessible paths and get further surface information when they point the mouse at classified locations. For displaying a route and the surface information, we integrate the Google Maps JavaScript API. Users can enter their preferences, find routes, and select a route from a presented list of routes on the bottom part of the UI. The chosen route is highlighted in the list and visualized on the map. Further, the application provides textual information about which surfaces will be encountered on the route. Figure 2 shows the web application. We plan to implement native apps for Android or iOS and merge the crowd-sensing application with the routing application.

The backend of the prototype is implemented in *Java 8* and the *Spring Boot* framework which eases the creation process of services. The implemented algorithm in the backend calculates an optimal path by using the *Google Maps API* for loading routes and by analyzing them based on the given input data by the user and the constraint for optimization. Frontend and backend communicate via *REST* calls.

B. Accessible Routing Algorithm

The backend receives the input from the client as a *JSON* request. The input consists of the origin and the destination for the route in natural language as well as a selection of

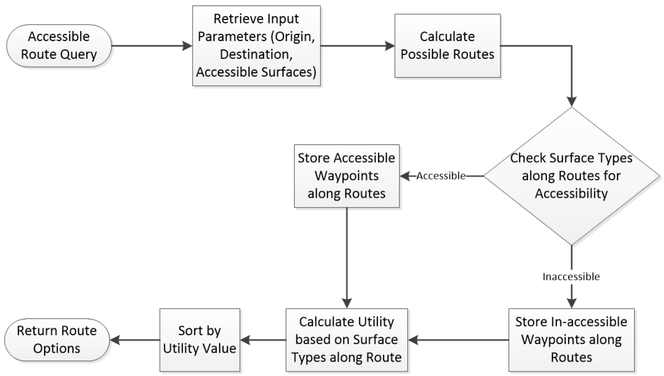

Fig. 3. Flow representation of the route calculation algorithm.

accessible surface types specified by the user. The origin and the destination are used to calculate possible pedestrian routes via the Google Maps API. As the Google Maps API returns only three alternative routes, we apply an approach similar to a genetic algorithm. Therefore, we split up each route into two sections by defining one waypoint in the middle of the path. In a first step, this new waypoint is used as the new destination of a new route. As a result, the Google Maps API returns up to three alternative routes from the origin to the waypoint. In a second step, the waypoint is used as the new origin and routes to the original destination are computed. This, again, results in up to three routes. The algorithm generates new routes by combining these partial routes. With this algorithm we are able to compute multiple alternative routes from an origin to a destination. This is an important extension of the API, as the most accessible route might not always be the shortest path and might not be among the original three suggestions of the Google Maps API. For each route, a utility value is calculated based on its accessibility. Afterwards, all possible routes are sorted by their utility values and returned as *JSON* response. The returned route options consist of the route for navigation, the calculated utility value, a list of all accessible and inaccessible waypoints along the route as well as additional data, like the total travel time and distance. Figure 3 shows the process for the calculation of routes.

C. Utility Computation

The utility function distinguishes between accessible and inaccessible waypoints. The users themselves can define which surface they consider to be accessible. Thus, we can account for multiple types of wheelchairs as some can be used on rather rough surfaces while others require a smooth sidewalk. Each route is checked based on the classified surface types and all accessible and inaccessible waypoints lying in a radius of around ten meters along the route are stored. Based on the information about the surface types along the route, a utility function is applied to calculate a comparable score for each route r_i. The utility function is composed of two parts: (i) a *score* for the accessible waypoints ($w_{accessible}$) along the route and (ii) a *penalty* for the inaccessible waypoints ($w_{inaccessible}$)

The utility values are each normalized based on a min-max formula to the bounds [0,1].

$$score[r_i] = \frac{w[r_i]_{accessible} - min(w_{accessible})}{max(w_{accessible}) - min(w_{accessible})} \quad (1)$$

Equation 1 depicts the *score* for wheelchair accessible waypoints *w* along the route where the route with the highest number of accessible points $max(w_{accessible})$ receives a utility value of 1. The route with the smallest number of accessible waypoints gets assigned the value of 0.

$$penalty[r_i] = \frac{w[r_i]_{inaccessible} - max(w_{inaccessible})}{min(w_{inaccessible}) - max(w_{inaccessible})} \quad (2)$$

The *penalty* function (Equation 2) assigns a penalty value of 1 to the route with the highest number of inaccessible points $max(w_{inaccessible})$ and a penalty of 0 to the route with the fewest inaccessible points.

$$utility(r_i) = max\left(0, score[r_i] - penalty[r_i]\right) \quad (3)$$

Eventually, the *utility* of the route r_i is computed as the difference between the *score* and the *penalty* (see Equation 3). The lowest possible utility is 0.

V. Conclusion and Future Work

Accessible path routing for wheelchair users is a well-researched problem. Many researchers have focused on using the users' smartphones for crowdsourcing information regarding barriers and facilities in the built environment and then used those information for designing an accessible route. While all the research works have identified the nature of the road or sidewalk surface (even/uneven) as a major accessibility concern, there is no in-depth research regarding how the accessibility varies from surface to surface or which surfaces are more accessible than others. So far, the accessibility of surfaces were treated more subjectively rather than empirically.

In this work, we have proposed the concept of the WheelShare system to clearly separate accessible surfaces from the rest using a purely objective and data-centric approach. We have further used collected surface data for generating accessible route suggestions for wheelchair users. The accessibility of the route is evaluated depending on user settings and the surface information along the route. Further, we did first experiments on the identification of the surfaces using machine learning. The presentation of the automatic identification of surfaces is out of scope of this paper.

For future work, we plan to include other vehicles such as strollers or wheeled walkers into the system. Using this variety of data, we will provide a prototype implementation of the whole WheelShare system. Therefore, further baseline data has to be collected and models must be extended to be able to classify for these vehicles as well. We further plan to implement the routing tool as native smartphone applications and integrate them with the crowd-sensing appliation. Finally, we will improve the utility function to produce more accurate route predictions.

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