Smart Surface Classification for Accessible Routing through Built Environment - A Crowd-sourced Approach

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ABSTRACT

In order to provide individuals with restricted mobility the opportunity to travel more efficiently, various systems have proposed modeling techniques and routing algorithms that handle accessible navigation through the built environment which is otherwise dotted with mobility barriers. Such systems use data gathered from smartphone sensors or crowd-sourcing to pinpoint the location of the barriers as well as the facilities, such as crosswalks with traffic signals or access ramps to curbs. Though the previous works have identified the type of surface and incline to be important features to determine accessibility, no extensive empirical research exists on how these parameters affect navigation. In order to address this problem, we propose to build a novel system called *WheelShare*, which uses machine learning to classify surfaces into accessible or otherwise and uses that knowledge to generate accessible routes for wheelchair users. We have trained our system with accelerometer and gyroscope data obtained from 26 different surfaces found frequently in indoor and outdoor environments across Europe and USA. More data is collected by the system through crowd-sourcing based contribution from interested users. Our evaluation shows that *WheelShare* can achieve an accuracy of up to 96% in identifying surfaces in one of the 5 different accessibility classes. Overall, *WheelShare* is a novel, scalable and data-centric approach to objectively identify the accessible features of a surface and can generate end-to-end routes for wheelchair users using frequently updated crowd-sourced information.

KEYWORDS

accessibility, smart cities, accessible routing, machine learning

ACM Reference Format:
Md Osman Gani[1], Vaskar Raychoudhury[1], Janick Edinger[2], Valeria Mokrenko[1], Zheng Cao[1], Ce Zhang[1]. 2019. *Smart Surface Classification for Accessible Routing through Built Environment - A Crowd-sourced Approach* . In *BuildSys '19: The 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, November 13–14, 2019, New York, NY, USA.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3360322.3360863

BuildSys '19, November 13–14, 2019, New York, NY, USA

ACM ISBN 978-1-4503-7005-9/19/11…$15.00
https://doi.org/10.1145/3360322.3360863

1 INTRODUCTION

Accessible routing for wheelchair users through the built environment, both indoor and outdoor, poses significant challenges for the users as well as the researchers. Obstacles and barriers, both temporary and permanent are strewn around the familiar surrounding and even more challenging, if encountered in unfamiliar environment [10, 42]. Features, such as uneven or broken sidewalk surfaces, cobbled city squares, steep inclines, and high curbs without access ramps, often pose unsurmountable hindrances to the wheelchair users. Difficulties are even more for elderly individuals with ailments like spinal cord injuries or arthritis. A survey conducted by Meyers et al. [25] by interviewing 28 adult wheelchair users revealed that they often face the following barriers, like - 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). However, the users also reported the presence of various accessible facilities, such as, supervised crosswalks or elevators. To address this issue and to control the building structures, many countries have introduced acts and regulations [3, 8] for constructing accessible public facilities which will ensure disabled users "equal opportunities and barrier-free access".

Existing research has concentrated on finding and tagging barriers of accessibility along the route through crowd-sourcing [6, 45], GIS [4, 15] or GPS [23] modeling and through smartphone sensors, including data from accelerometers and gyroscopes [7, 16, 38, 40]. 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 [32, 37]. There are multiple research works [19, 27, 29–31, 46] which are relevant. Also, several routing applications [43] have been developed in recent times for restricted-mobility users that focus on specific user needs (wheelchair types, age, weight and physical fitness of the users). Although the surface type has been identified as an important accessibility feature [4, 15], so far, there is not enough study on the nature of accessible surfaces in a systematic manner. In an earlier research we have shown how the accessible route generation works through crowd-sensed surface classification using a proof-of-concept [12].

In this paper, we propose an accessible routing solution which works by actively learning the characteristic vibrations induced by different surfaces in the built environment during wheelchair movement. In order to train our model, we have collected vibration data from 26 different reference surfaces using a manual wheelchair and 2-4 Android smartphones containing basic accelerometer and gyroscope sensors. 11 of our 26 surfaces are found in Europe (Austria, France and Germany) and the rest are found in USA. We have further collected data in India and China as well. Based on the surface vibration information and a low-resolution video acting as the ground truth, we have extracted 22 features and used them to classify the baseline surfaces into a total of five accessibility categories. WheelShare also employs crowd-sourcing to collect plethora of surface vibration data from willing contributors which can further enhance the accuracy of surface classification. The knowledge about accessibility of a surface is then used to generate accessible routes between a pair of locations upon request of a querying user.

In summary, Wheelshare presents the first ever machine learning based surface classification for accessible route generation. The contributions include:

- An extensive machine learning based classification system that is able to classify 26 surfaces found around our built environment (across Europe and USA) into accessible or inaccessible with an accuracy of up to 96%.
- A crowd-sourcing technique to accumulate location-tagged accessibility information across large areas to enable us to build an accessibility map.
- An efficient routing algorithm for wheelchair users considering various accessible features of the built environment.

2 RELATED WORK

The purpose of accessible systems is to equate the varying mobility levels of individuals and grant them the ability to navigate to their desired location as efficiently as possible. There has been much development into applications and systems that aim to adequately assist such needs. Ultimately, the needs of the users and the knowledge of the environment are considered in the construction of the system in order to create a personalized route. The systems belong to either one or both categories: mobility assistants or crowd-sourced recommendation systems. Mobility assistants rely on open information to identify possible barriers in the environment or locations that are accessible and this data is gathered and verified before it is used in the application. Crowd-sourced recommendations rely on the users who use the application to annotate obstacles and points of interests (POI)s and rank which paths are the most accessible. Users can send queries to either type of system and would receive a valid, accessible route.

Initial systems were mobility assistants that focused on simply creating models for users using GIS modeling and testing occurred in one small area. MAGUS [4, 15] was among the first that created a GIS model and interactive GUI for users of varying fitness levels in the Northampton area in the UK. MAGUS assigned an impedance score using network analysis tools for different route recommendations that were based on minimum barriers, shortest distance, fewest slopes and tough surface terrain as well as limiting the number of road crossings. One of the first applications of Machine Learning to accessibility routing came from Karimanzira et al. [20]. A fuzzy decision systems was used to create routes for visual/limb/hearing impaired individuals in Georgenthal, Germany. Another system, U-Access [41], considers many different types of environmental objects that can affect which routes are chosen depending on the physical ability of the user and was tested in University of Utah. Mobility assistants would often use GIS and GPS software [23] to create a network-based accessible map that would have clear barriers and accessible POIs such as facilities or stairs. Several systems [7, 16, 38, 40] require the use of smartphone gyroscope, accelerometer and location information about the journey experience from the user that can identify vibrations or travel on crosswalks or heavy traffic roads.

The interest of using crowd-sourced information in navigation had originated from the emergence of mobile phones. The first use of using pictures in pedestrian navigation was by Hile et al. which created an adaptive database for storing online gathered geotagged pictures in order to be used in navigation instructions [5]. Crowd-sourcing [6, 45] is provided by a community of people and allow for continuous information on barriers, obstacles and points of interest both indoors and outdoors. The RouteCheckr system [43] enables collaborative data annotation and creates personalized routes for users. Mobile Pervasive Accessibility Social Sensing (mPASS) [33] is a system that creates personalized routing paths based on data gathered from crowdsourcing as well as sensory data from geo-referencing. Crowdsourcing and making data annotation easier has been an interest in research for the last decade [18]. Several crowdsourced platforms exist for data accessibility [1, 2, 44]. One of the most up-to-date, collaborative providers of crowd-sourced data is OpenStreetMap [32, 37], whose data was incorporated in route calculation for systems such as eNav [11]. Crowd-sourced data has gained momentum in pedestrian navigation because systems cannot solely rely on information on surface and sidewalk condition from governmental or commercial records. However due to the limit of information from crowd-sourcing on street information [9], there has been significant efforts to incorporate an additional tool called the OSMatrix for determining the accuracy of available information for route calculation [26]. Collaborative systems such as [19, 27, 29–31, 46] have shown that the collection of geo-data (also called Volunteered Geographic Information (VGI) [14]) can be a reliable data source for navigation.

The challenge with modeling accessible routes comes from the unpredictability of the objects that can affect accessibility. Routes may be temporarily flooded, or too steep and have an uneven surface which may deem uncomfortable travel if the slope is beyond one-in-twenty or path narrower than 915mm [3]. One algorithm focused on creating a routing network based on multiple criteria on accessibility gathered from OpenStreetMap data [28]. However, the decision for routing algorithms cannot depend on the data alone, as a flexible system would have to communicate with the user's preferences and adjust the route accordingly. The ability for a system to perceive the environment that includes the device it is on as well as the user who is interacting with it is called context-awareness. Kawabata [21] proposes context-adaptable pedestrian navigation system, which create user preferred routes by considering the path as context dependent over the objectives of the user and specific area conditions. However the system considers specific objects such as stairs and road surface and not other characteristics about the path, such as slope. Rahaman et al [35] proposed a network graph that does consider slope, a measure for evaluating path accessibility and an algorithm for accessible path routing. This was done by a context-aware active transport trip planning framework (CoAcT), a contour-based graph and query-based adaptation scheme, the inclusion of two metrics (vertical distance and maximum slope) and the use of a multi-objective A* search algorithm (CAPRA) [36] and reports distance and elevation. Sahelgozin et al created the optimization method, Ubiquitous Pedestrian Way Finding Service (UPWFS) [39], and defined four criteria that needs to be met for a personalized path that suits users: length, safety, difficulty and attraction. Personalized multicriteria routing is based on using equally weighted and normalized criteria values gathered from user rating on a specific path. Another system created personalized routes that appeals to human preferences of quietness, beauty and happiness [34]. Though there are no standard criteria for determining the most preferred paths, the system would have to generate a safe route for the path to be usable in the first place. A method for generating a path based on safety criteria alone has been proposed by Elsmore et al. through the creation of a vector-based diffusion and interpolation matrix [13]. The algorithm creates a rating matrix of features in one spatial region and it is used to create a route according to which features correspond with safety. Determining criteria is important for understanding whether there is enough geo-data to make a valid and accurate decision on the route for the user. For example, Berlin has approximately 28% complete information on the surface of the sidewalk as compared with 44% for Riga [28]. The reoccurring criteria for determining safety include the identification of surface types, slope, the age, weight and physical ability of the user, and wheelchair type and this information is useful in crowdsourced systems.

3 THE WHEELSHARE SYSTEM

The WheelShare system aims to classify usual indoor and outdoor surfaces found in the built environment into accessible or otherwise, using machine learning techniques. The classification is aided by accelerator and gyroscope readings characteristic of different surfaces generated through a wheelchair movement (see Figure 5). Once capable of generating end-to-end on-demand routes, WheelShare is also tested by multiple users for generating voluminous crowd-sourced surface acceleration information. The obtained data is used to further train the system for even better route generation customized to the user requirement.

3.1 System Architecture

The WheelShare system works in two phases. The first one is called the *training phase* during which we collect the surface vibration information using accelerometer and gyroscope readings and train a classifier using that. The classifier makes quantitative decision regarding the accessibility of a surface. The second phase is called, the *execution phase* during which multiple users use the system. The users who wishes to contribute their collected data are identified as the contributors and the rest just send route requests and receive the responses. In order to facilitate data contribution, an Android app is shared with the contributors which automatically records the vibration induced by their wheelchair and communicates to our central server for classification. Our routing algorithm (Section 5) uses the classified waypoints for accessible route generation based on incoming user requests. Multiple routes are returned for a single query using both textual and graphical means and they are ordered based on a utility score (see Section 5) from which the user chooses their preferred one.

Figure 1 shows the architecture of WheelShare system along with its principal components. We shall briefly elaborate the functions of the major components.

Reference Surfaces: In order to determine characteristic vibration patterns of different surfaces usually found across the built environment, both indoor and outdoor, we collected accelerometer and gyroscope readings from total 26 different surfaces across Austria, France, Germany and USA (see Figure 4). Many of the surfaces we have categorized together due to their similar vibration patters.

Automated Surface Classification: Several machine learning algorithms are used to train a model that classifies the accessibility of the reference surfaces based on their labeled acceleration and gyroscope data. During the execution phase, live data from the contributors are used to determine the surface accessibility using the previously trained model. This helps us to achieve objective determination of surface accessibility using standard machine learning approach.

Crowd-Sensing Application: As explained earlier, contributors can enrich the WheelShare system by collecting and sharing surface vibration information during their everyday navigation through city streets. An Android app has been developed to facilitate their contribution and they can use their personal smartphone. The collected data is geo-tagged to easily relate it with the actual physical location and for building the city-wide accessibility map. The data collected by the contributors is transmitted to the server in an opportunistic manner whenever high-bandwidth WiFi connectivity is available.

Data Server: Our data server stores the surface model and data received from the contributors. 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 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 surface types and related factors, such as presence of access ramps to curbs, presence of pedestrian crosswalks, etc.

Routing Application: The routing application provides an easy-to-use interface for the users requesting accessible routes. It sends queries to the application server along with a pair of source and destination locations and receives the corresponding response(s). The resulting routes are then ordered by their accessibility scores and presented for the user to choose.

3.2 Design Considerations

The two-phase separation of the WheelShare system requires a comprehensive data collection and analysis before a reasonable route response can be generated for wheelchair user during the execution phase. Although this is restricted by the limited amount of data collected only by the researchers, this design technique has certain advantages as elaborated below.

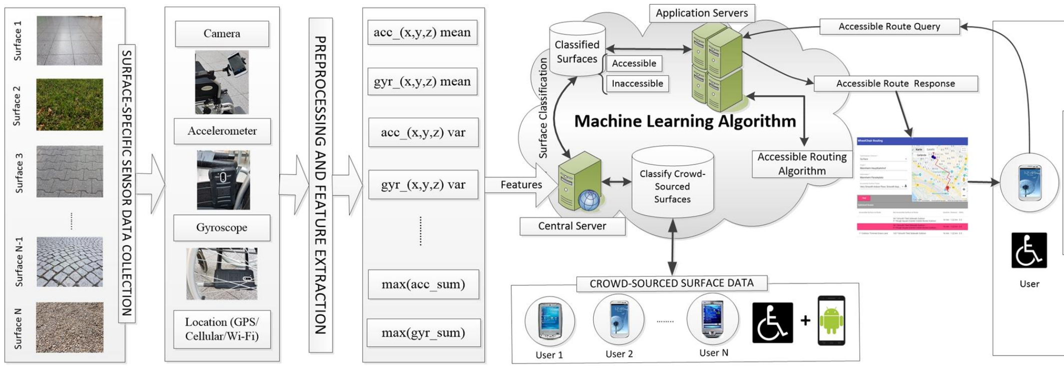


Figure 1: The WheelShare system architecture ([anonymized source])

Scalability: Crowd-sourcing enhances the scalability of the WheelShare system and distributes the data collection responsibility to a large number of users, even though the amount of the initial data volume is limited. With more and more users, the system performs better and better and the contribution is made easy through our easy-to-use app with mere start-stop functionalities. Data collection is not automated, in order to protect the user privacy, and all user identifier's are removed from the contributed data.

Data Freshness: The crowd-sourcing feature of the Wheelshare system will not only lead to large volume of contributed data, but it will also help the data to remain up-to-date. Data from same location are repeatedly collected by multiple users and will eventually replace outdated information. This process will turn out to be helpful for identifying temporary obstructions in the built environment (such as, building materials or discarded furniture dumped in sidewalk) or the addition of a new feature (e.g., elevator to a footbridge). Also, routes which ran into disrepair can be identified and gradually removed from the system for future users. 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.

Objectivity: Despite the questionable nature of crowd-sourced data due to their dependence on user perception and interpretation, often the contributions are of quality usage. 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 26 different surfaces, any subjective component is eliminated. In addition, the crowd-sourcing application standardizes the data collection process.

4 SURFACE ANALYSIS

Existing research has identified the nature of sidewalk and road surfaces as a major concern for accessibility. Researchers have pointed out that uneven sidewalk surfaces in combination with various environmental effects, such as rain or snow, render the surface inaccessible. In order to help increase accessibility of public areas, different countries have made regulations with specifications for the built environment that must be complied with during design, construction and alteration phases.

Figure 2: Wheelchair equipped with four smartphones to collect sensor and video data.

The ADA 2010 [3] accessibility specifications for floor and ground surfaces specifies that accessible floor and ground surfaces "*must be stable, firm, and slip resistant [like, concrete, asphalt, tile, or wood and unlike gravel or grass]. Stable surfaces resist movement, while firm surfaces resist deformation by applied forces.*" Rough surfaces like cobblestones or Belgian blocks are "*unsuitable for wheeled mobility aids due to the vibrations they cause.*". Smoothness of the surface is also important provided it generates adequate friction. Similarly, the DIN 18024-1 [8] also specify that accessible paths "*shall be easy, with low-vibration and safely accessible in each weather condition*" without any particular quantification of different parameters. As per the subjective specifications, surfaces made of gravel or grass do not qualify as accessible and hence, should not be suggested as a path to the users.

4.1 Data Collection

We have experimented with two different sets of data collected in Europe (Austria, France, and Germany) and in USA. Two different

Table 1: Subjects Used for Data Collection in Europe

Subject	Gender	Age Grp.	Weight (KG)	Health
1	Male	70-75	75	Frail
2	Male	35-40	60	Frail
3	Male	30-35	78	Healthy
4	Male	25-30	64	Frail

light-weight manual wheelchairs were used. In order to analyze the nature of a surface, we decided to capture the vibration induced by the movement of a wheelchair carrying a user.

4.1.1 Data Collection in Europe. Data collection in Europe was carried out across multiple cities (see Figure 3) and 4 subjects were used for the same. For data collection, we used four smartphones

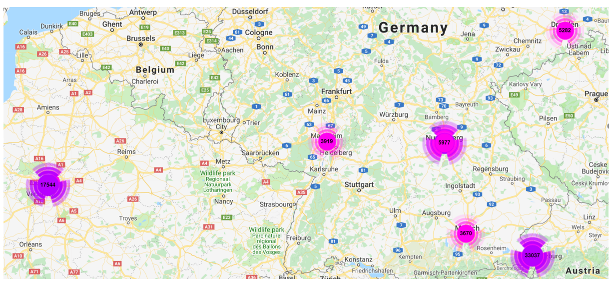


Figure 3: Places in Europe used for data collection

of the type 'Motorola G4 Plus', equipped with 1.5 GHz Octa-Core processors. Three smartphones were attached to the wheelchair in different positions and angles as shown in Figure 2. This approach has two advantages. First, we can learn how the sensor recordings differ over the three positions on the wheelchair. The recordings might be affected by how close the smartphone is to the ground, which part of the wheelchair it is connected to, and which direction it faces. Second, we can train our model with all different recordings to make it more robust. The latter is important for the crowdsensing when wheelchair users use their own devices to collect data. They might attach the phone to any part of the wheelchair and leave it with any possible orientation. The three smartphones that were attached to the wheelchair measured acceleration and gyroscope data with 50Hz and GPS data with 5Hz. The idea is as follows: An uneven surface would produce more vibration in the wheelchair than a smooth surface. This vibration can be quantified by fast changes and higher peaks in the acceleration and gyroscope data. Similar surfaces would result in similar sensor data pattern and can thus be trained and classified by machine learning algorithms. We mounted a fourth smartphone to a selfie stick that is attached to the arm rest of the wheelchair. This smartphone takes a video of the surface to capture the ground truth.

4.1.2 Data Collection in USA. Data collection in USA was carried out in the town of Oxford, Ohio within the campus of Miami University and in the Oxford town centre. We have used a manual wheelchair (similar to the one in Figure 2) and 22 subjects with the age and weight statistics described in Table 2. There are 13 male subjects and 9 females among whom 5 are of generally frail health, 1

Table 2: Subjects Used for Data Collection in USA

Parameters	Mean	Median	Mode	Min	Max
Age	26.14	22.5	22.5	20	50
Weight (KG)	73.05	71	72	54	120

more uses wheelchair all the time and another one used wheelchair for quite some time. We have used three different phones for data collection and attached them to the wheelchair at different heights with latex bands. The phones were Samsung Galaxy S9+, Samsung Galaxy S7 edge, and Samsung Galaxy J7. At any time, we have used any two of them for data collection.

4.2 Surface Selection

Before we collected baseline data to train our surface model, we identified those surfaces that are usually encountered around the built environment both indoor and outdoor. Based on that, we selected 11 different surface types in Europe and 15 in USA (see Figure 4). They range from smooth marble floor to grass and very rough irregular cobble stones. We traveled continuously through those surfaces for 5-8 minutes per surface in order to get a set of consistent vibration patterns. This resulted in more then 90,000 data points for each surface. Our experiences show that gravel is the most difficult surface to push a wheelchair, since the surface deforms with pressure and does not produce enough firmness to maintain a contact acceleration. Grass surface is also difficult for wheelchair navigation. However, the most painful navigation is caused by surfaces paved with Belgian blocks with large gaps in between each block. Vibration caused by most of the typical surfaces are shown using the accelerometer and gyroscope readings presented in Figure 5. After the data collection, we processed the European and American data separately. However, in both the cases, we merged some of the groups as they did only marginally differ in their accessibility. For the European data, we combined 11 different surfaces into 7 categories which was further reduced to 5 categories (see Table 3). We argue that slight differences in the accessibility would not affect the quality of the route. However, too many categories introduce a complexity that renders the routing application less useful. Similarly, for American data, we combined 15 different surfaces into 10 initial categories which was further reduced to 7 categories and then down to 5 categories (see Table 4).

4.3 Feature Extraction

For the feature extraction of both the datasets, we used a windows-based approach [24]. Each window has a size of one second which corresponds to about 50 data points for the acceleration and gyroscope traces. For each window we computed 22 commonly used features that are listed in Table 5. For the European data, we created five distinct sets of features, F1 to F5. F1 contains all 22 features and is expected to result in the most accurate prediction when machine learning algorithms are applied. As the smartphones to collect the sensor data are attached always in the same positions in our data collection process, x, y, and z values can be used for the classification. However, we argue that this is not a realistic assumption for the crowd-sensing scenario as contributors might not place their smartphones in the same orientation as one of the three phones

Figure 4: Surfaces that were selected for the baseline data collection in USA and in Europe. This selection represents those surfaces that are usually encountered around the built environment. For each surface, more than 90,000 data points were collected.

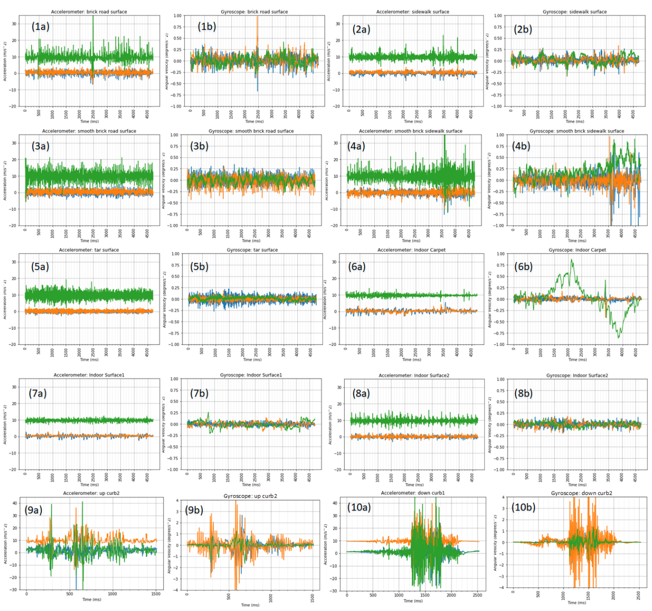


Figure 5: Accelerometer (a) and Gyroscrope (b) readings of 10 surface types listed in Table 4 found among 15 broader ones in USA.

used in the baseline data collection. Thus, for F2 to F4, we excluded all features that rely on a single direction. For F3 we further removed all features that were based on the mean magnitude of the signal to account for different levels of damping which flattens the signal. In F4, we only considered features that were based on the sum of the absolute values of the x, y, and z data to make sure that positive and negative values do not cancel each other out. Finally, in F5, we applied the strictest rules and only selected the variance of the sum of the absolute values of the directional measures. For the American data we decided to only use the feature sets F1 and F2. We also computed the average latitude and longitude for each window to be able to locate the collected data on the map.

Table 3: The initial 11 surface categories were merged into 7 categories (S2) and 5 categories (S3) - Data from Europe

	Surface	S1	S2	S3
1	Very smooth indoor floor	A	A	A
2	Smooth asphalt floor	B	B	B
3	Rough tiles sidewalk	C	C	B
4	Trimmed (2 inch) grass land	D	D	C
5	Very rough irregular cobble stones	E	E	D
6	Rough irregular cobble stones	F	F	E
7	Smooth tiled sidewalk	G	C	B
8	Rough regular square cobble stones	H	F	E
9	Very smooth stone tiled sidewalk	I	C	B
10	Rough rectangular cobble stones	J	F	E
11	Deep (2-3 inch) gravel	K	G	C
	Number of categories	**11**	**7**	**5**

Table 4: The initial 15 surfaces were identified into 10 categories which were merged into 7 categories (S2) and 5 categories (S3) - Data from USA

	Surface	S1	S2	S3
1	(Rough) Brick road	A	A	A
2	Sidewalk	B	B	A
3	Smooth brick Road	C	C	B
4	Smooth brick sidewalk	D	D	B
5	Asphalt	E	E	C
6	Indoor carpet	F	F	D
7	Indoor surface 1	G	F	D
8	Indoor surface 2	H	F	D
9	Upward curb	I	G	E
10	Downward curb	J	G	E
	Number of categories	**10**	**7**	**5**

Table 5: Features extracted from acceleration and gyroscope data. Different sets of features have been evaluated (F1-F5)

	Feature	F1	F2	F3	F4	F5
1	mean(acc x)	•				
2	mean(acc y)	•				
3	mean(acc z)	•				
4	var(acc x)	•				
5	var(acc y)	•				
6	var(acc z)	•				
7	mean(sum(acc))	•	•			
8	mean(sum(abs(acc)))	•	•		•	
9	var(sum(acc))	•	•	•		
10	var(sum(abs(acc)))	•	•	•	•	•
11	max(sum(abs(acc)))	•	•		•	
12	mean(gyr x)	•				
13	mean(gyr y)	•				
14	mean(gyr z)	•				
15	var(gyr x)	•				
16	var(gyr y)	•				
17	var(gyr z)	•				
18	mean(sum(gyr))	•	•			
19	mean(sum(abs(gyr)))	•	•		•	
20	var(sum(gyr))	•	•	•		
21	var(sum(abs(gyr)))	•	•	•	•	•
22	max(sum(abs(gyr)))	•	•		•	
$\sum$	**Number of features**	22	10	4	6	2

Table 6: Evaluation results of different machine learning algorithms applied on an 80:20 split of trainings to test data. The results show the accuracy. Grey cells indicate the maximum for each column.

Dataset		**EU-Data**					**USA-Data**	
Features		**F1**	**F2**	**F3**	**F4**	**F5**	**F1**	**F2**
ANN	**S1**	0.816	0.670	0.337	0.586	0.434	0.719	0.665
	S2	0.902	0.814	0.660	0.716	0.639	0.888	0.797
	S3	0.911	0.850	0.755	0.760	0.698	0.928	0.838
J48	**S1**	0.840	0.773	0.564	0.629	0.474	0.754	0.627
	S2	0.891	0.832	0.726	0.760	0.670	0.880	0.767
	S3	0.921	0.889	0.790	0.804	0.733	0.912	0.797
KNN	**S1**	0.859	0.780	0.533	0.616	0.403	0.719	0.659
	S2	0.922	0.880	0.689	0.759	0.575	0.831	0.791
	S3	0.940	0.892	0.750	0.785	0.661	0.859	0.824
NB	**S1**	0.399	0.406	0.363	0.372	0.356	0.404	0.390
	S2	0.420	0.419	0.424	0.444	0.408	0.454	0.578
	S3	0.551	0.602	0.579	0.571	0.558	0.518	0.603
RF	**S1**	0.914	0.834	0.617	0.728	0.433	0.856	0.745
	S2	0.931	0.895	0.765	0.819	0.637	0.944	0.849
	S3	0.954	0.919	0.826	0.856	0.712	0.960	0.869
SVM	**S1**	0.732	0.672	0.427	0.584	0.340	0.811	0.670
	S2	0.839	0.811	0.584	0.742	0.580	0.935	0.834
	S3	0.857	0.841	0.689	0.768	0.643	0.946	0.847
Avg.		**0.811**	**0.765**	**0.615**	**0.683**	**0.553**	**0.795**	**0.731**

4.4 Evaluation Using Data from Europe

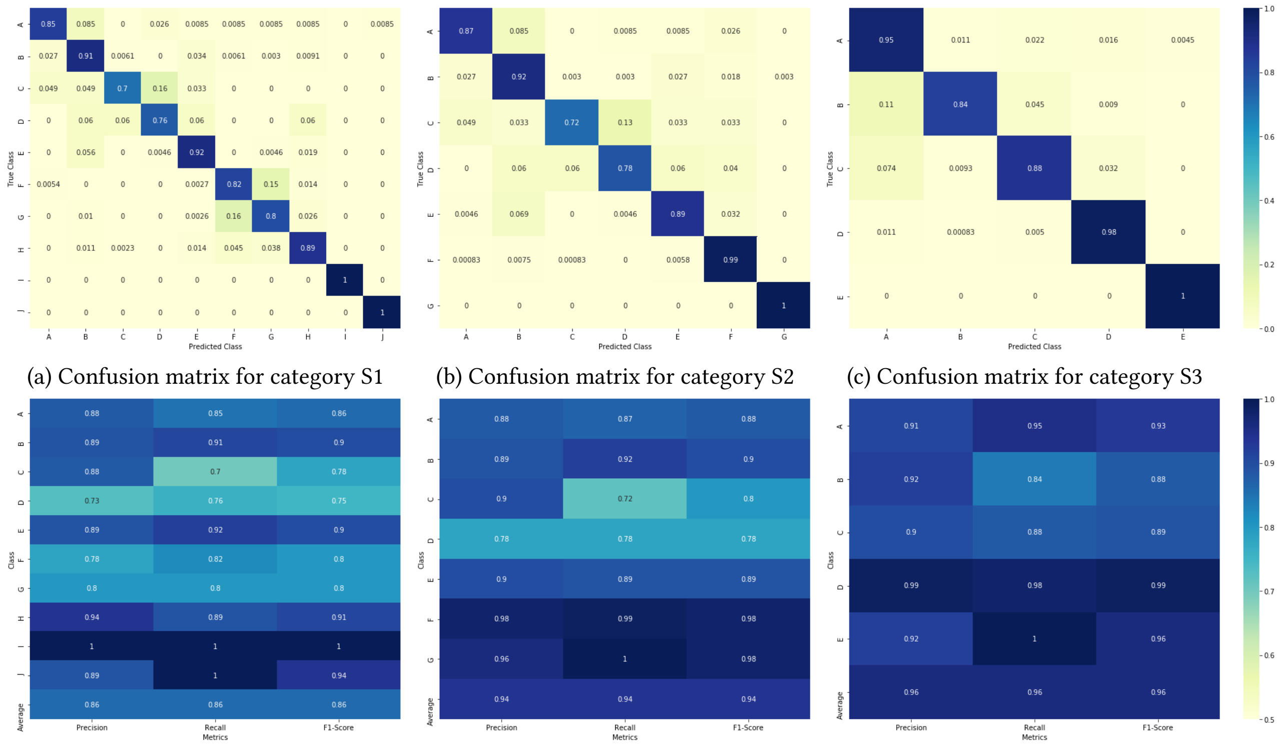
We have evaluated the surface classification using the WEKA machine learning framework [17]. The goal of the evaluation was to find out how much information is required to identify the surface at one location successfully. Therefore, we split up a set of 10562 windows at a ratio of 80:20 (8450:2112 windows) into training and test sets. We evaluated six algorithms, namely Artificial Neural Network (ANN), J48 Decision Tree (J48), k-Nearest-Neighbor (KNN), Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). Table 6 summarizes the results of the evaluation. The results show that we can classify five categories of surfaces with an accuracy of 95.4% using a Random Forest (S3, F1). Even if we do not merge the surface categories, 91.4% of all test windows are correctly classified (S1, F1). However, we argue that there is no benefit of having more than five surface categories because the accessibility between some categories does not differ much. The results also indicate that the best predictions can only be achieved, when all features are taken into account. As discussed before, we cannot assume that smartphones of crowd-sensing participants are mounted to the wheelchair in a particular way. Thus, using features set F1 with information about the x, y, and z coordinates might not be applicable for crowd-sensed data. Instead, we apply F4 where only the sum of the unsigned sensor measurements is considered. Even with this restricted set of only six features, we achieve an accuary of 85.6%. A different approach would be to estimate the orientation of the smartphone in a first step and then select a more specialized model for the prediction as introduced in [22].

4.5 Evaluation Using Data from USA

Although some of the surfaces studied in USA are similar to those in Europe, we wanted to process them separately as the wheelchair used were different (by make) and the phones were of different models. Also, in Europe we used 3 phones just for data collection, whereas we used two in USA. The results are found to be similar which proves that with plenty of crowd-sourced data, using a different brand of wheelchair or smartphone (or multiple smartphones) will not majorly impact the accuracy of the WheelShare system.

We used Python to process this dataset and to perform experiments. At first we split up data for each surface class into multiple windows. Each window contains enough information to understand surface vibration pattern. Then we split up the entire dataset at a 80:20 ratio into training and testing sets respectively. We evaluated the same six algorithms we discussed in Section 4.4 for the feature sets F1 and F2 using Scikit-learn library in python. We presented the result in Table 6. The accuracy of classification in one of the five surface categories using Random Forest (S3, F1) is 96%. For the American data we can observe that Random Forest gives the best classification results for all combinations of surface categories (S1, S2, and S3) and feature sets (F1 and F2). We have not reported results of feature sets F3, F4 and F5 as they are similar in trend to the European data. As mentioned earlier, the best predictions are achieved, when all features are taken into account.

The diagonal elements in the confusion matrices in Figure 6(a)-(c) shows the True positive rates (TPR) for the surface categories (class), S1, S2, and S3. Rest are the false negative rates (FNR). As we go from left (a) to right (c), TPR increases and FNR decreases. This is because, the similar surfaces with identical vibration patterns are combined to reduce the classifier confusion. Precision, Recall



(a) Confusion matrix for category S1 (b) Confusion matrix for category S2 (c) Confusion matrix for category S3

(d) Precision, Recall, F1-Score (cat. S1) (e) Precision, Recall, F1-Score (cat. S2) (f) Precision, Recall, F1-Score (cat. S3)

Figure 6: Performance matrices from USA data considering feature set F1

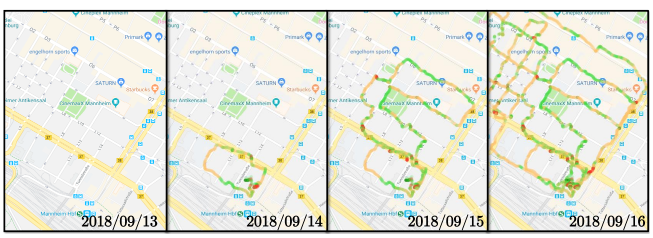


Figure 7: Progress of the crowd-sensed surface classification on the example area around the Mannheim central station. Whenever the server receives new data, the overlay gets updated.

and F1-scores are presented in Figure 6(d)-(f). Values are reported individually for each surface category as well as for the average of all categories (class). We can see that our highest accuracy obtained is 96% (average F1-score of 0.96 in Figure 6(f).

4.6 Crowd-Sensing

The crowd-sensing application is an easy-to-use data collection utility. The recording does not need to be configured by the user but by default records acceleration and gyroscope data with 50Hz and GPS data with 1Hz. The data is stored on the local device until the device connects to a WiFi network where the anonymized data is uploaded to our central data server. The server pre-processes the data and classifies each data window according to the model that has been created in the training phase of the WheelShare system. Figure 7 shows the gradual growth of an accessibility map (around the Mannheim central station) with every bit of user input.

5 ACCESSIBLE ROUTING

For determining accessible routes through the built environment, we first generate an overlay graph on the map of the environment. The graph (G) has a set of vertices (V) and edges (E). We set a vertex on a path whenever there is a change in surface type (Figure 8 (I)(c)). Each edge connects a pair of vertices and hence, one whole edge represents one particular surface type. Thus, a 4-way crossing receives 4 vertices (Figure 8 (I)(a)) as the sidewalk surface changes into asphalt. Also, we set vertices at sidewalk junctions like the T-crossing shown in Figure 8 (I)(b). Origin of a path, right outside of a building also receives a new vertex as the indoor surface changes into an outdoor one (Figure 8(I)(d)).

The overlay graph is generated based on the surface types in an automatic manner depending on the changes of vibrations while a wheelchair moves though those surfaces. Our algorithm for accessible route generation operates over the graph to determine *accessibility*, *safety* and *difficulty* perspectives of an end-to-end route generated between a pair of start and end vertices. Separate scores are assigned for aforementioned perspectives depending on type and nature (broken or uneven) of surfaces, steepness of slopes,

Figure 8: Accessible routing approach and features

Table 7: Road Surface Score

Road Surface Type	Score
Very Smooth indoor floor	1.0/1
Very Smooth Gray Stone Tiled Sidewalk	0.9/1
Smooth Tiled Sidewalk Outdoor	0.8/1
Smooth Asphalt Outdoor	0.7/1
Rough Tiled Sidewalk Outdoor	0.6/1
Rough Irregular Cobble Stones Outdoor	0.5/1
Rough Regular (Rectangular) Granite Cobble Stones	0.4/1
Rough Regular (Square) Granite Cobble Stones Outdoor	0.3/1
Very Rough Irregular Cobble Stones Outdoor	0.2/1
Outdoor Trimmed Grass Land	0.1/1
Deep Gravel Outdoor	0.0/1

presence of stairs, height of curbs and presence of crosswalks (with and without pedestrian crossing signals).

5.1 Assigning Accessibility Scores

If there is no high curb or the curb has accessible slope (Figure 8(II)(a) and (c)) , it will be assigned higher score for accessibility. On the other hand, stairs and steep curbs (Figure 8(II)(b) and (d)) will be considered inaccessible. *Inaccessible surface types* like a broken or uneven sidewalk surface is assigned 0 score. *Slope* of the route is a major factor in determining accessibility and the slope must be less than 3-6° or larger than -3° (or -6°) and gentle incline will always get higher score. The *width* of road segment should be larger than 90 cm. Any lower width will consider it to be inaccessible. We have found an edge having width of 87 cms and hence (Figure 8(III) discarded it. A route segment having a *crosswalk* (with pedestrian signal) receives lower score. However, absence of the pedestrian signal results in even lower score (Figure 8(IV)). Different road *surfaces* will have different scores. So far, for routing, we consider surfaces shown in Figure 8 and the scores for different surfaces are reported in Table 7.

5.2 Functioning of the Accessible Routing Algorithm

Given a pair of start (A) and end (B) points, our algorithm first finds all possible routes between them. In order to restrict the searching area (to keep a check on the generated route lengths), we search within a circle with the Cartesian distance between A-B as the diameter. In case, no routes are found within the circle, the diameter is incrementally updated by adding a certain ***value***. Generated routes are sorted by length and the top 10 are selected for further processing. While selecting the top 10 routes we wanted to do away with route duplication. If two or more routes are having majority (≈ 90%) of the edges common, we carried out a similarity check between each pair of routes on an edge-to-edge matching basis. One among a pair of similar routes is dropped while choosing the top 10 routes. After the similar check, we assign scores to the top 10 routes. Scores are assigned to each edge depending on its proportion of length w.r.to the whole route. E.g., consider a route has three edges with lengths 10m, 8m and 2m. The total length of the route is 10+8+2 = 20m. Final Route-score = (score for first edge * 10/20) + (score for second edge * 8/20) + (score for third edge * 2/20). At the end, we return the top three routes with their lengths and scores to the user for choosing one.

6 CONCLUSION AND FUTURE WORK

An accessible navigation system continues to be a popular and important topic for both research and practice. Most current systems use sensors, GPS, or GIS, but only recently has machine learning been introduced to the topic. Collecting information about the path is also unpredictable and costly. So, many systems have debated on using crowd-sourcing because information about a path can become out-of-date. Though previous researchers identified surface type as an important parameter in navigation, there has been little in-depth research on the effect of surface induced vibrations on accessibility. The WheelShare system, for the first time, uses machine learning to successfully classify 26 common surfaces from Europe and USA into 5 different accessibility classes with an accuracy up to 96%. Using crowd-sourcing enabled us to infuse more data into the system from multiple contributors which enhanced our classification accuracy. A routing engine generates end-to-end route for wheelchair users through a series of accessible surfaces classified earlier. In future, we plan to apply transfer learning to evaluate the applicability of WheelShare to other types of surfaces and mobility support devices (e.g., power wheelchair, mobility scooters, strollers, etc.). We further plan to implement the routing tool as a native smartphone application and integrate it with the crowd-sensing application. We are also considering accessing Google maps API and Open Street maps for collecting slope information of a surface.

7 ACKNOWLEDGMENTS

This work is partially supported by the Alexander von Humboldt Foundation postdoctoral fellowship and Miami University CFR Summer 2019 Research Award to Dr. Vaskar Raychoudhury. (This project has IRB approval, Protocol ID# 01738r)

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