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Passive Pedestrian Walkway Accessibility Data Collection with Scooter Riders

THESIS

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for the degree of

MASTER OF SCIENCE

in Computer Science

by

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DEDICATION

To

my family and friends

in recognition of their unconditional love and support

and

my heavenly Father

for upholding me with His hand,
comforting my heart,
answering my prayers,
and giving me strength and perseverance

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ABSTRACT OF THE THESIS

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Master of Science in Computer Science

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Robert A. and Barbara L. Kleist Professor Gillian R. Hayes, Co-chair

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Pedestrians, especially those with disabilities, rely on mobile map applications to plan their daily trips and navigate unfamiliar spaces. Yet, many of these applications do not provide crucial real-time information for pedestrians, including foot traffic, semipermanent and permanent obstacles, sidewalk accidents, and other barriers common to pedestrian spaces. Over the past decade, researchers and engineers in academia and industry have explored accessible navigation in a variety of mobile applications. Despite significant effort, accessible navigation features can only provide limited real-time information to select major metropolitan areas. One substantial obstacle preventing real-time accessible navigation from being more informative and deployed to more places is the expensive and manual process of regularly collecting and updating pedestrian walkway data. This thesis presents an initial feasibility study with eight student volunteers who commuted with scooters regularly at the University of California, Irvine. Data collected through custom GPS modules and the follow-up survey revealed insights about the plausibility of extracting real-time pedestrian walkway accessibility information from scooter riders' travel patterns.

My work calls for future researchers working on accessible maps to delve deeper into travel patterns of different human-controlled or autonomous wheeled devices, not just wheelchairs, on pedestrian walkways. Only when pedestrian walkway data collection becomes less manual and costly can updates happen often and more areas be covered.

Chapter 1

Introduction

According to the World Health Organization (WHO), "[a]n estimate of 1.3 billion people - or 1 in 6 people worldwide - experience significant disability" [21]. WHO also reported that People with disabilities (PWD) "find inaccessible and unaffordable transportation 15 times more difficult than those without disabilities" [21]. Although navigating as pedestrians has been made easier by digital map applications, such as Google Maps and Apple Maps [34] [53], these applications still cannot provide obstacle-free point-to-point navigation, particularly for PWD. Sometimes, these applications even direct pedestrians to dangerous routes, such as dark and deserted paths [31], paths without sidewalks [36], or paths that require users to cross the streets without traffic lights or even highways [65]. These navigation applications calculate the estimated time of arrival for pedestrians by treating every user as the same (e.g., assuming everyone has the same body conditions and travels at a constant speed) and optimize for getting users to their destinations the fastest without considering their abilities and preferences.

Data on pedestrian walkways is also lacking (e.g., no information about real-time traffic and obstacles) and updated less frequently than their vehicle counterparts because of the manual and expensive data collection process. For example, Google Street View (GSV) collects sidewalk data by driving in cars equipped with cameras that capture panoramic images and stitching them together [69]. For pedestrian walkways that are not sidewalks, data collectors must carry the cameras on their backs and walk around to collect the images [69]. Google Maps also retrieves data about public transportation and walkways through transit agencies and volunteers called Local Guides, who answer five questions about the paths they use every day [45][46]. While another competitor, Apple Maps, uses data from OpenStreetMap [57], a web-based map crowdsourcing platform for infrastructure information, and data collected by a contractor TomTom to provide navigation [8]. Both Google Maps and Apple Maps rely on active crowdsourcing and outsourcing to contractors to collect pedestrian walkway data. The laborious, manual, and expensive data collection for pedestrian walkways makes gathering and updating the data regularly challenging. Moreover, the conditions of pedestrian walkways also change frequently because of foot traffic, construction, landscape projects, pop-up events, and more. The uncertainty about walkway conditions makes it difficult for pedestrians, especially PWD to navigate unfamiliar locations.

Over the past decade, researchers and engineers in academia and industry have searched for cheaper ways to collect data more efficiently. Prior research sought to tackle this problem can be divided into three main streams: (1) crowdsourcing and crowdsensing with mobile applications [18, 54, 56, 62], (2) labeling accessibility issues on Google Street View (GSV) [41], and (3) attaching computing units with cameras, GPS devices, and machine-learning computing devices to motorized mobility devices to capture and analyze sidewalk conditions [78]. All three streams of works have not been scaled up yet because of various constraints or concerns. First, the crowdsourcing mobile applications struggled to achieve and maintain a critical mass of users to collect and update data regularly. Second, GSV data is only updated every few months or years [35], so it would not be possible to label temporary or semi-permanent obstacles. Last, attaching computing units to motorized mobility devices could raise concerns about privacy and operating and adjusting the systems. Many users of motorized mobility devices are also PWD who are underprivileged and may not have the knowledge or ability to reset or adjust the computing units when needed.

This thesis approaches data collection for accessible maps in a novel manner by answering the question: how feasible is it to collect pedestrian walkway accessibility data passively by studying scooter riders' travel patterns? I recruited eight student volunteers from an HCI (Human-Computer Interaction) class and attached GPS modules to their scooters and had them collect data in two-day intervals, and conducted a survey afterward to address my research question from both technical and social aspects.

Through basic data analysis, I discovered three informative traveling patterns that datasets collected by the volunteers on scooters shared: traveling at consistent speeds, slowing down, and speeding up at common sections of paths. Scooters traveling at consistent speeds on a path likely indicates that there are point-to-point wheel-accessible paths between all points along the path. Various reasons can cause scooters to decelerate or accelerate. When scooter riders decelerate, it could mean they are running into heavy traffic, temporary or semipermanent obstacles, traveling on inclines, catching up with others, etc. In contrast, scooter riders accelerate when they are in a hurry, traveling on declines or sparse paths. Finally, the volunteer survey revealed a general willingness to participate in similar future data collection opportunities, a slight change of mind and perception about route accessibility and conditions after data collection, concerns about data security and privacy, and suggestions for policies to protect data collectors' identities and their locations. Lastly, in section 5.1, I discussed some limitations of this work, including data privacy concerns and hardware limitations.

This thesis explored a passive approach to collect scooter riders' travel patterns and analyze them for pedestrian walkway accessibility data. Similar techniques have only been applied to mapping roads for vehicles. The results also suggest that travel patterns of scooters on pedestrian walkways could indicate different conditions of the path: wheel-accessible paths, dynamic or static obstacles, sparse or unobstructed paths, and etc. Therefore, researchers should continue exploring travel patterns of human-controlled or autonomous wheeled devices on pedestrian walkways in the future.

Chapter 2

Related Works

In this chapter, I separated related works into four subtopics to gradually reveal the research gap of passive data collection to be addressed in the rest of this thesis. Firstly, I discussed the systemic and deeply-rooted ableism in urban planning. Secondly, I introduced the challenges in implementing accessible maps and the expectations from PWD. Thirdly, I reviewed existing technologies for pedestrian walkway data collection and rudimentary personalized navigation proposed by both researchers in industry and academia. Last, I examined how Google Maps applied passive crowdsourcing of drivers' navigation data to provide real-time road conditions to users.

2.1 Ableism in Urban Planning

In the United States, more than 1 in 4 adults with disabilities that prevent them from performing daily social activities, according to the Centers for Disease Control and Prevention (CDC) [20]. Nonetheless, most cities were not developed for PWD. Many urban development plans showed cities were primarily designed for "a man (not a woman) in the prime of life, and at the peak of his physical fitness" [39] or "an average human being" [30] without considering the needs of PWD and people's wide range of abilities and body conditions [39, 66].

There is also a lack of literature about PWD in urban planning. A recent literature review in urban planning revealed that only 36 papers related to PWD were published in five mainstream English urban planning journals over their existence, which spans over a century[70]. Only 20 of the 36 papers focus on PWD [70]. Many of these papers also noted that city councils attributed the lack of accessible infrastructure to their lack of financial resources [70,]. Propositions for accessible infrastructure were also put aside because accessible infrastructures were deemed as "the extension of a privilege" that does not come with legal liability [39]. Researchers and allies should continue urging city councils to listen to the voice of PWD and allocate more resources to accessible infrastructure development.

Fortunately, more and more researchers in urban planning have been including PWD in their work and learning about their lived experiences through photovoice, a process that allows underprivileged people to reflect on their experience through videos or images [75], and walk-along/go-along, a qualitative interview method where the interviewers visit the interviewees' familiar spaces with them to understand their perspectives better [19], over the last two decades [70]. Nevertheless, more work is still needed to fight the deep-rooted ableism in urban planning.

Infrastructures form around policies and legislations [39], so government must implement and enforce policies that push for accessible infrastructure. A study conducted in 2020 reviewed 401 government agencies, of which 54 had implemented any Americans with Disabilities Act (ADA) transition plans, and only 7 met the minimum ADA requirements

[25]. These policies and legislations need to be better enforced [39, 66, 70] because of the need for more resources allocated for policy enforcement.

When urban planners considered PWD's needs and existing policies for accessible infrastructure, they developed areas where PWD found refuge because they felt "less disabled" and free to navigate through the space without struggling [66]. To avoid losing navigation freedom and autonomy, many PWD limit their activities to areas where they feel more comfortable [39]. For example, some PWD navigate in their cars more often because of the lack of barriers and staring from other pedestrians [39]. Regardless, not all infrastructure is accessible, and not all places are reachable by cars. Breakthrough improvements in urban infrastructure accessibility will not happen any time soon. Researchers should investigate using technology to help PWD gain the autonomy to navigate unfamiliar spaces by mitigating obstacles and providing more navigation options.

2.2 Challenges and Expectations of Accessible Maps

As discussed in section 2.1, PWD usually experience more difficulties navigating urban spaces as pedestrians than driving in cars on streets [39, 66]. The increased difficulty in navigation is not only due to the lack of familiarity with urban walkways but also PWD's everchanging range of abilities and less predictable walkway conditions. There are digital navigation applications such as Google Maps, Apple Maps, and Waze that provide live traffic information and road conditions to drivers [34, 53, 22]. Yet, applications that offer equivalent real-time information to pedestrians do not exist. The absence of accessible pedestrian maps is likely due to a dearth of regularly updated walkway data.

Generally, municipalities perform street audits manually, which is costly, time-consuming, and labor-intensive [27, 28]. The high cost of data collection makes it difficult for cities to perform regular street audits and maintain updated data [17, 28]. For instance, a 2017 audit covering 2,300 miles of sidewalk in Seattle was conducted by 14 people for $400,000 [28]. In addition to the above challenges, street audits are also not available for the public or research communities to access or contribute to [17, 27, 28], which makes it harder to carry out studies pushing for accessible maps applications. Even if accessibility audits become public, treating or evaluating the data collected by different municipalities equally would be difficult because the data could be outdated and of various formats. The data discrepancy exists because there are no open standards for the types of data to collect and their formats [17, 27, 28]. Researchers in the field of accessible navigation have been investigating developing open standards for accessibility data collection and exploring different ways to collect and represent these data [17, 28]. Ultimately, these efforts aimed to provide personalized and independent navigation experience to PWD with varying abilities and preferences.

In two recent user studies, PWD proposed some features for accessible navigation applications [38, 40]. In the participatory design portion of the user study conducted by Hara et al., the participants with mobility impairments suggested features they wished to integrate into ALTs (Assistive Location-based Technologies). These features include (1) “street-level accessibility visualization,” a color-coded map that notes all accessibility issues (e.g., missing curbs, sidewalks), (2) “point-of-interest accessibility rating,” numeric ratings left by other PWD, (3) “detailed description about the accessibility of a place,” (4) the accessibility features the place provides (e.g., accessible restrooms, ramps, and wide spaces for wheelchairs and other mobility devices), (5) “[indoor] floor plan,” a layout map of all the facilities of the location, (6) “visual accessibility inspection of [outdoor and indoor spaces],”3-D virtual tours or pictures of the outside and inside of the location, (7)“user-generated reviews [for accessibility],” short text reviews left by other PWD, (8)“search and filter places based on accessibility attributes” (e.g., accessible restrooms, changing stations, quiet rooms to escape sensory overload), (9)“[multimodal accessible] routing,” (e.g., accessible navigation to drive to a parking lot or a park-and-ride to get on public transit), and (10)“[accessible] transportation, ” (e.g., buses with ramp and straps for wheelchair/walker users or subway stations with elevators) [40]. The participants also indicated that different PWD need different accessibility information for navigation [40].

Furthermore, every PWD’s navigation preferences vary. An accessibility issue for a PWD might not be problematic for another PWD. In an interview study by Gupta et al., twenty-seven participants with varying degrees and types of disabilities reflected on their navigation experience. The interview study revealed similarities and divergences in PWD’s navigation preferences. While most participants avoided busy areas to circumvent moving obstacles, noises, unwanted help, and overstimulation, some preferred crowded paths over empty paths for safety reasons and “the option of asking for navigation assistance” [38]. While most participants with mobility impairments tend to avoid stairs and use ramps instead, some prefer stairs instead of ramps because ramps could be tortuous, steep, or uneven [38]. Some participants also favored scenic and enjoyable routes over efficient routes [38]. In the end, the participants also reported on common and varying navigation obstacles they ran into, such as construction, furniture, decorations, tree roots, icy roads, noises, etc. [38]. The differences in PWD' lived experiences and preferences calls for researching and developing personalizable accessible navigation tools. Nevertheless, researchers must address the manual and costly process of walkway data collection first.

2.3 Technologies for Pedestrian Walkway Data Collection and Rudimentary Personalized Navigation

Since the early 2000s, researchers have been trying to understand different types of obstacles that PWD run into and generate routes for PWD that avoid as many obstacles as possible with machine learning techniques such as neural network analysis [13]. However, collecting and updating walkway data remains a manual and tedious process.

Over the past two decades, as technology advances, more work has been done in industry and academia to facilitate walkway data collection using crowdsourcing, crowdsensing, machine learning, geographic information system (GIS), portable computing devices, or a combination of these methods (e.g., [46, 63, 78]).

Google Maps introduced a feature in 2018 that provided wheelchair-accessible directions to public transportation users. Still, this feature was only available to major cities like London, New York, Mexico City, Boston, Sydney, etc. [46]. Even five years after the feature debut, it is still unavailable in many cities and suburban areas. This feature has yet to be widely available because it relies on data collected by transit agencies and volunteers called Local Guides, who answer five questions daily about places they visit [45, 46]. These manual data collection efforts require active participation from a large community. Another global community powered by OpenStreetMap is making a similar effort to label accessibility features and issues through crowdsourcing [57]. OpenStreetMap is also making the crowdsource data open and accessible to the public, which inspired many projects, including Wheelmap and OsmAnd maps. Wheelmap is a web and mobile application that crowdsources and provides information about wheelchair-accessible places worldwide [76]. Wheelmap also contributes data collected to OpenStreetMap [55]. These data about wheelchair-accessible places facilitated the development of a navigation application, OsmAnd maps, in 2017 [58]. OsmAnd Maps allows users to avoid routes with stairs and unpaved roads [58]. OsmAnd Maps also updates their maps by syncing with the OpenStreetMaps API every hour [58], allowing more accurate directions. Another open-sourced web application, AccessMap, also uses data from OpenStreetMap and other public sources, such as municipalities data sources and the United States Geological Survey (USGS), to provide customized point-to-point directions in three cities in Washington State [16]. When providing directions, AccessMap only uses walkways with inclines/declines within the acceptable preset ranges of users [3]. AccessMap is a significant first step toward personalized navigation. Still, the data used by the above tools are too coarse to provide the features many PWD proposed, and current data collection processes remain manual, costly, or tedious. Fortunately, more works have been looking into collecting more detailed data with fewer resources.

In 2013, Hara et al. conducted a study to evaluate the feasibility of collecting sidewalk obstacles with untrained crowd workers from Amazon Mechanical Turk and GSV [41]. The accuracy of the labels created by crowd workers on a set of GSV images went from 81% to 93% after implementing two forms of quality control that eliminated crowd workers and labels based on crowd workers' performance and crowdsourced verification of the labels [41]. This study later evolved into Project Sidewalk, an open-source project allowing volunteers to label sidewalk obstacles on an interface with a GSV panorama [63]. Project Sidewalk also provides detailed information about different obstacles and instructions on labeling them in the interface [63]. Hara et al. continued to explore scaling the GSV data labeling process with a system named Tohme [42]. In addition to allowing crowd workers to collect and verify data, Tohme used web scrapping to identify intersections, computer vision to recognize curb ramps, and machine learning to organize the workflow of crowd workers [42]. Tohme was able to speed up the data labeling process of each GSV image by 12 seconds [42]. A recent study by Duan et al., which shared the same mentor, Jon Froehlich, with the two papers published by Hara et al., continued to explore scaling and automating the GSV data labeling process with machine learning. Duan et al. discovered that a deep-learning model trained with sidewalk obstacle data collected in other cities could be used to label sidewalk obstacles in other cities where sidewalk data is not available with high accuracy [24]. A major limitation of using GSV images to collect sidewalk data is that GSV data is not frequently updated. According to Google Maps, GSV data "could be anywhere from a few months to a few years old" [35], which means the data collected from GSV might not reflect recent and temporary or semipermanent updates to sidewalks.

Zhang et al. also explored collecting sidewalk accessibility data with machine learning-based image recognition. Furthermore, they proposed attaching portable computing units with stereo cameras, GPS sensors, and GPUs for deep learning to capture and process the data to motorized mobility devices [78], which facilitates data updates. However, attaching cameras to Personal Mobility Devices (PMD) could invade the users' privacy, which could be a significant deal breaker when recruiting more volunteers to scale up data collection. The stereo camera used by Zhang et al. is also the most expensive component of the computing unit, costing $399-499 each [68], which could be another obstacle in achieving a critical mass of data collectors. Additionally, many PMD users are also underprivileged PWD, who might not be well-versed in the technology used to reset or adjust the computing units when needed, which could limit data collection opportunities.

Smartphones have become ubiquitous and equipped with many sensors, such as GPS sensors, accelerometers, gyroscopes, magnetometers, and LiDAR sensors, commonly used for activity and event detection and mapping. Several groups of researchers have suggested using smartphones to collect manual user feedback and sensor data for mapping and rating pedestrian walkways for accessibility [18, 54, 56, 62]. In 2013, Researchers at IBM Research proposed an idea for a mobile app data collection system with two parts, Citizen Sensing and Breadcrumb [18]. Citizen Sensing refers to active data collection from users, while breadcrumb refers to the system that collects mobile sensor data in the background

[18]. Later in the same year, Mourcou et al. introduced a prototype mobile application to provide accessibility ratings of walkways called Wegoto. Wegoto collected feedback through user input and data from cameras, microphones, and sensors, including a gyroscope, an accelerometer, a magnetometer, and a GPS sensor [56]. Wegoto then filtered and analyzed sensor data by recognizing common patterns to detect events in real-time and rated different portions of the route taken based on events detected [56]. However, in a trial run of Wegoto with a wheelchair user, the user's smartphone had to be fixed horizontally in the middle of the wheelchair to reduce noise in data [56], which could limit the user’s access to their phone and hinder Wegoto’s feature of manual feedback. In less than a year, Prandi et al. also proposed a mobile application prototype, mPass, that collects data about aPOI (accessibility points of interest) from users, administrators, and smartphone sensors to provide personalized navigation to PWD [36, p. 593]. The mPass app also allowed users to set up their preferences about different aPOI, including stairs, gaps, crossing facilities and barriers, obstacles, parking, and other characteristics of walkways such as pavements, width, and slopes [36, pp. 593-594]. Later, Prandi et al. also tested mPass with a group of PWD to gather suggestions for mPass [54]. The PWD suggested some information and features to improve mPass, including unidirectional sidewalk and street directions, landmarks in the routes, constructions, resting areas, Wi-Fi areas, and exploitable comment sections allowing users to trace comments of others with similar navigation preferences [54]. Nevertheless, as Prandi et al. noted, data scarcity caused by the lack of an active, diverse, and growing user base is still a significant problem that prevented mPass from being available at a larger scale and providing the features suggested by the PWD [54].

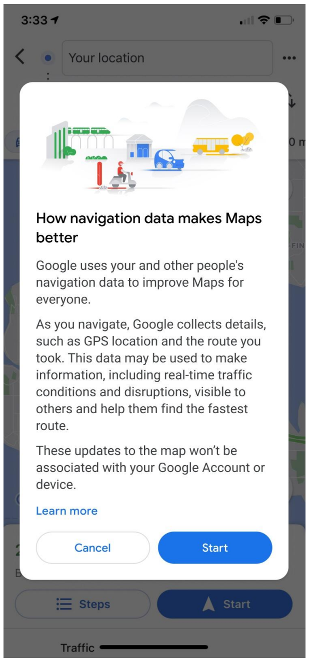
These proposed mobile applications could be solutions to personalized navigation if they achieve a critical mass of users to increase data density. Researchers must address some eminent concerns to attract more users. Many potential users are already used to mobile navigation applications like Google Maps and Apple Maps, which means there will be a learning curve switching to other mobile applications. Sensors used by these mobile applications to collect data, such as accelerometers, gyroscopes, magnetometers, and GPS sensors, are also power-hungry [47, 48]. Using these mobile applications can cause cell phones to run out of battery sooner, preventing users from contacting their families and friends for help or emergency. Finally, the types of data collected by these mobile applications also pose security concerns. Since users already share so much data with commercial applications like Google Maps, they might be reluctant to share more data with other mobile applications unless the benefits of these applications surpass or do not overlap with other existing applications.

2.4 Passive Crowdsourcing for Real-Time Road Conditions

Despite many of these works suggesting collecting data for accessible maps in the background with attachable computing modules or mobile applications, few works, if any, focus on collecting travel patterns of PMD users passively and extracting pedestrian walkway data from the patterns, which has been applied to mapping roads and highways by Google Maps for more than a decade [1]. As shown in a screenshot taken from Google Maps in Figure 1, to use Google Maps, users must give consent to Google Maps to collect and use their navigation data (e.g., GPS locations and paths taken) [49]. Google Maps uses these crowdsourced data to provide real-time road conditions to users, as well as localize advertisements for monetization [44, 49]. As personal mobility devices gained popularity, I was intrigued to see if passive data collection with drivers for mapping roads could be translated to map pedestrian walkways. This thesis explored the feasibility of using scooter riders as passive data collectors to gather pedestrian walkway data.

Figure 1

Google Maps Crowdsourcing Statement



Note. A crowdsourcing statement Google Maps displayed (See Appendix A for full screenshot).

Chapter 3

Methods

In this chapter, I dived into the implementation and details of the two-part feasibility study I conducted. I started by reviewing the first part, data collection, which included the building process of custom GPS modules and an overview of the data collection procedure. Secondly, I discussed how I explored the GPS data collected through basic visualization with Python. Last, I examined the survey to learn about volunteers' experience and opinions on passive data collection with scooters.

3.1 Data Collection

To begin data collection, I built four GPS modules by following a tutorial and built custom 3-D printed cases to protect them. After building and testing the GPS modules, I implemented a data collection help document with data collection procedures and a few hardware troubleshooting tips for volunteers to refer to.

3.1.1 GPS Module Setup

Many electric scooter rental companies use GPS sensors to track their scooters and prevent theft [15, 50]. The rising popularity of rental scooters inspired me to explore what GPS data collected by scooter riders passively can tell us about walkway conditions to aid the process of accessible maps production. To start data collection, I first built a GPS module following a tutorial by Eli the Computer Guy [10]. The GPS module consisted of all the components, as seen in Table I, and some jumper wires, bringing the total price of each GPS module to $160.34. As explained in the tutorial, the WiFi version of Arduino Uno was used instead of just the regular version because the WiFi version provided more accurate data than the regular version [10]. Since the Arduino Uno WiFi Rev 2 requires an In-Circuit Serial Programming (ICSP) header, the Arduino Ethernet Shield 2, instead of a regular data logging shield, has to be used with it to store data in the SD card [10]. Lastly, a CR 1220 battery is attached to the Arduino GPS sensor to decrease its starting time, the period it takes for the GPS sensor to start getting stable signals.

Table 1

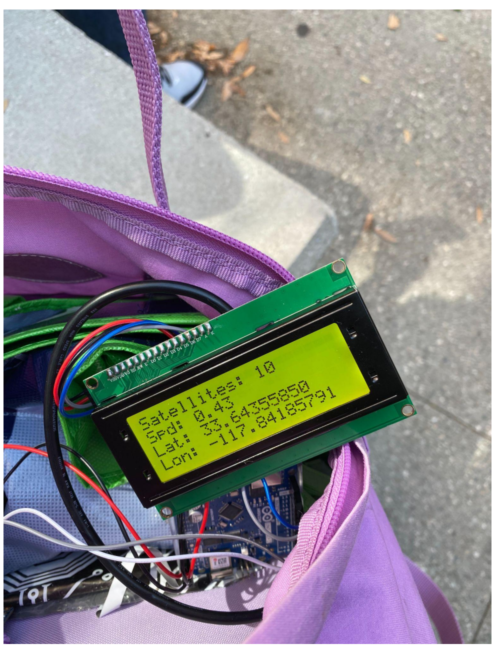
Components of The Custom GPS Module and Their Costs

Components	**Price on Mar 3, 2023**
Arduino Uno WiFi Rev 2	$53.80 [11]
Arduino Ethernet Shield 2	$29.80 [9]
HiLetgo 2004 20x4 LCD Display	$9.99 [6]
Adafruit Ultimate GPS Breakout - 66 channel w/ 10 Hz updates - PA1616S	$29.95 [4]
16 GB microSD Card	$9.14 [64]
500mAh Power Bank	$26.96 [5]
CR 1220 Battery	$0.70 each [7]

The code loaded onto the modules contained an infinite loop that collected data samples with the UTC timestamp, the traveling speed, and the GPS coordinate (latitude and longitude) in degrees every 2 seconds and updated the LCD screen to reflect the new data. I also modified the code so that only data samples collected with five or more satellites were recorded into the SD cards to obtain more accurate data since it usually takes around four satellites to obtain precise GPS coordinates [74]. To test the GPS module, I carried it in my backpack, as shown in Figure 2a while walking from Donald Bren Hall at the University of California, Irvine (UCI) to Chick-fil-A at the University Center. The GPS module required approximately two minutes to get stable signals and record data to the SD card. Figure 2b shows all the GPS coordinates collected by the GPS module during the trip. Overall, the data samples were accurate except for a few outliers that were 2-3 meters off, which was expected and noted in the specification of the Adafruit GPS sensor [4].

Figure 2a

GPS Module Prototype Working



Note. The GPS prototype in my backpack displaying a data sample.

Figure 2b

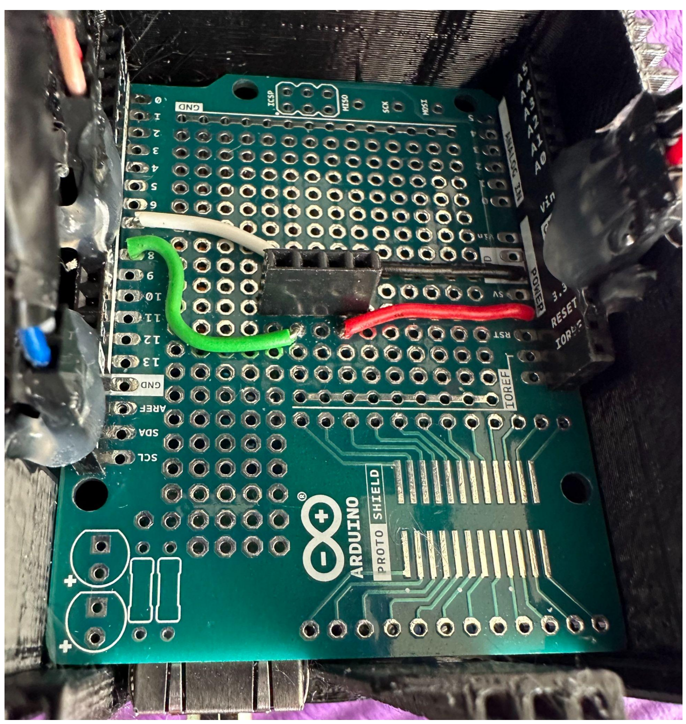
GPS Coordinates Collected from a Test Walk

Note. GPS coordinates collected from my test walk plotted with Google My Maps.

After testing the first GPS module, I made another three modules and tested them separately to ensure they worked properly. I attempted to make the GPS module more compact and the connections between the Arduino and the GPS sensor more stable by replacing the flexible male-to-male jumper wires shown in Figure 2a with soldered connections made with breadboard jumper wires and a 4-pin header socket as shown in Figure 3. Unfortunately, the Adafruit sensor could not detect any satellites when connected to the Arduino through the header sockets, so I kept the original design.

Figure 3

Soldered Jumper Wire Connections the GPS Sensor

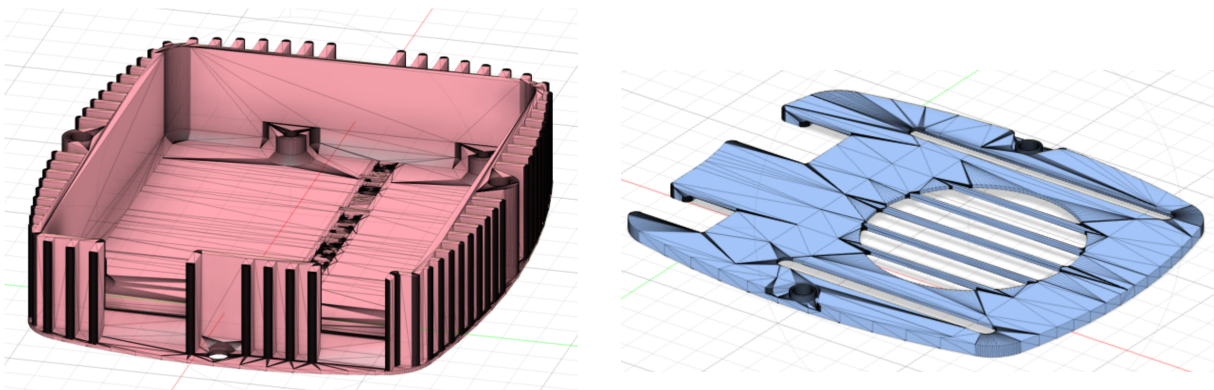


Note. A 4-pin header socket for the GPS sensor with soldered jumper wire connections to their designated pins.

To better protect the GPS modules, I created custom 3D-printed cases for them. I browsed through Thingiverse and found a design for an Arduino Uno R3 case, as shown in Figure 4 [71], and modified it in Autodesk® Fusion 360 [29] with the mesh modification feature to fit the GPS module.

Figure 4

Original Arduino Uno R3 Case Design on Thingiverse

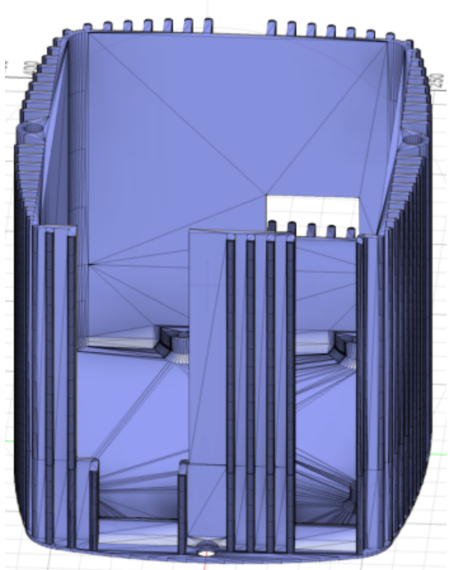


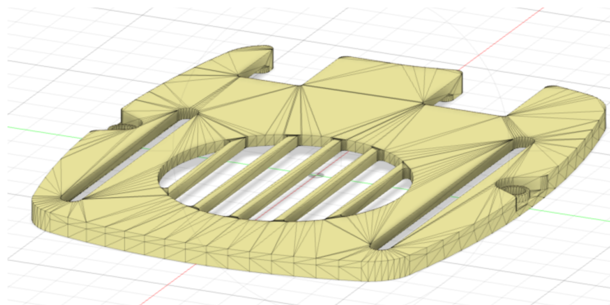
Note. The red design on the left is for the main case. It comes with slots for the power jack and USB-B connector. The blue design on the right is for the lid. It comes with two long thin slots for jumper wires and a hollow top for ventilation.

I extruded the top surface of the case to make it taller and widened the dimension of the slot to accommodate both the Arduino and the Ethernet Shield. I also made the lid thicker to be more sturdy to protect the extra components. Ultimately, I made a slot for the SD card slot on the Ethernet Shield in the back of the case. The new design and all changes made are shown in Figure 5.

Figure 5

Modified Arduino Uno R3 Case Design for the GPS module





Note. The blue design on the left is for the modified main case. It was taller, had wider slots at the front, and an added slot in the back for the SD card. The yellow design on the right is for the lid, which was thicker than the original.

After making cases for all of the GPS modules, I printed three more cases for the LCD screens with a design I found on Thingiverse [72]. Figure 6 shows the completed GPS module. The Arduino and the Ethernet shield were enclosed in the modified case. The flexible male-to-male jumper wires connecting the GPS sensor and LCD screen to the Arduino were bound together with electrical tape. The ends of the connections were hot-glued to ensure stability. The finished GPS modules were put into small lunch bags so volunteers could put the loops of the lunch bags through the handles of their scooters.

Figure 6

Completed GPS Module

Note. The completed GPS module with the GPS sensor, the case-enclosed LCD screen, and the power bank attached.

3.1.2 Data Collection Procedure

After building the GPS modules, I recruited volunteers from an HCI class I taught. I incentivized students to participate in the data collection process by rewarding volunteers with a 1% extra credit on their total grades, which would not change the volunteers' percentage grades dramatically but could improve the students' letter grades if they were at the border between two letter grades. However, only students, who regularly commute on the UCI campus with scooters, were allowed to collect data. To ensure every student had an opportunity to receive the extra credit, we also provided another option for students to produce visualizations with the data collected by the students who participated in the data collection process to receive the extra credit. Eight students volunteered for data collection and twenty-seven students signed up to produce data visualizations of the data collected. Only the GPS module data collected was used in this thesis, not the visualizations produced.

I created a help document that provided some background information about the project and instructions on using and troubleshooting the GPS modules during data collection but intentionally left out information about what types of routes they should take to keep data collection as passive as possible. The instructions for using the GPS modules included:

- Make sure the GPS module is always on during your time outside of any buildings while on campus.
- Disconnect the power bank to the GPS module when you are no longer outdoors or on campus.
- Charge the power bank connected to your GPS module during the evening so you will have enough power for the next day.
- Make sure that the SD card is detected when collecting data. (You will see a line that says “SD Card Not Found” on your LCD display if it is undetected).

The instructions for troubleshooting included:

- If the SD card is not detected, you can just eject the SD card and insert it again.
- If the LCD screen is not bright enough, you can use the potentiometer on the back to adjust the brightness.
- If you are having any other problem with anything else or with troubleshooting the issues listed above, contact Stella Lau through Zulip or email at ytlau1@uci.edu

Other than following the procedures for using and troubleshooting the GPS modules, the data collectors were not told to visit any specific areas or take routes they did not intend to take, which ensures passive and voluntary data collection.

I announced the extra credit opportunity in the class discussion forum. The announcement included a link to the document with project specifics and a link to a Google form allowing users to sign up for different data collection periods that lasted two days each. The two-day data collection periods provided cushion time for charging the power banks and solving possible hardware problems. After each round of data collection, the data collected in the SD cards were transferred to my laptop and deleted from the SD cards.

3.2 Data Exploration

After receiving the data samples, I plotted the datasets by colors on Google My Maps [2] to look for path overlaps. I then explored the data with pandas [60], a Python data analysis library, to see what information I could extract. Each data entry included a timestamp, a speed snapshot in miles per hour (mph), and a set of GPS coordinates. The GPS coordinates were then plotted with pyplot, a data visualization library in Python, in a Google Colab [32] notebook as points colored by the speed recorded at the coordinates on a map background image downloaded from OpenStreetMap [57]. The faster the speed was, the darker the point of the GPS coordinates. Each dataset was plotted separately on different figures, allowing me to observe sections of paths where speed changes occurred.

I also incorporated the timestamps in the GPS coordinate plots to see if time affected the scooter's speed in certain areas. Since all timestamps are in Coordinated Universal Time (UTC), I first had to convert them to Pacific Standard Time (PST), the local time at UCI. I then extracted the hour of the day (0-24) when the data was recorded. For each dataset, I found the minimum and maximum hours of the day when it was recorded using pandas.DataFrame.describe, a pandas method that generates descriptive statistics, including the count, minimum, maximum, mean, standard deviation, and data types of data samples [59]. I then plotted the datasets so that the color of data points recorded within the same hour was the same for each dataset, making it easier to observe any common patterns.

3.3 Volunteer Survey

My brief chats with volunteers after data collection led me to dive deeper into their data collection experiences and their opinions on voluntary GPS data collection. I designed a survey on Google Forms [33] to distribute to all volunteers. The survey included primarily open-ended questions. There were a total of nine questions, which are all required, in the survey. The survey (see Appendix B) collected the volunteers' email addresses, so it is possible to associate their responses with their datasets. I also gathered the difficulties that volunteers experienced during data collection and whether they would be willing to participate in similar data collection opportunities. The survey also examined whether volunteers perceived routes differently or changed their traveling behaviors when carrying GPS modules. Since GPS data is sensitive, the survey asked the volunteers' opinions on scooters with GPS and other sensors for collecting accessible map data, if they would share the data with third parties, and if the intended use would change their minds. Finally, the survey asked the volunteers for suggestions on policies for scooters equipped with sensors that collect data to build accessible maps. After collecting all the responses, the data were analyzed to observe trends in volunteers' experiences and opinions.

Chapter 4

Results

Through basic analysis of the GPS data collected, I discovered three travel patterns of scooter riders worth exploring: traveling at consistent speeds, decelerating, and accelerating. While the volunteer survey revealed concerns about data security and privacy when sharing data with third parties and a slight change of mind in data collectors that led them to be more conscious of walkway conditions and opt for more accessible paths.

4.1 Scooter Travel Patterns and Their Implications

After sending the announcement about the data collection opportunity, eight students volunteered. There ended up being three rounds of data collection. Three students participated in the first and third rounds, and two students participated in the second round. The three rounds of data collection resulted in six usable samples as seen in Table II, there were two datasets from each round. There were only six usable samples because one of the GPS modules failed to detect satellites during the first and third rounds of data collection. After reloading the program onto the problematic GPS module, it worked when tested but failed to detect satellite signals during the last round of data collection.

Table 2

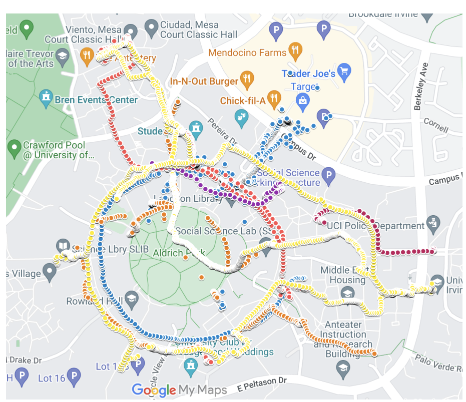
Datasets Summary

Dataset	Collection Round	Color (Figure 7)	Color (Figure 8 and 9)	Marker (Figure 10)
#1	1	blue	blue	circle
#2	1	orange	orange	triangle
#3	2	coral	black	square
#4	2	purple	yellow	plus
#5	3	maroon	purple	diamond
#6	3	yellow	red	star

First, I imported all the datasets into Google My Maps to check for overlapping paths taken by different volunteers, as shown in Figure 7 and Table 2, plotted with different colors: blue (dataset 1), orange (dataset 2), coral (dataset 3), purple (dataset 4), maroon (dataset 5), and yellow (dataset 6).

Figure 7

GPS Datasets Plotted on Google My Maps

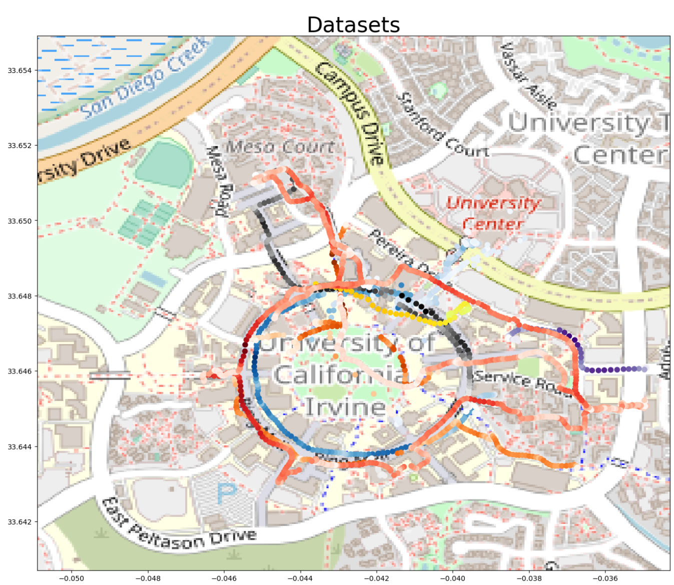


Note. GPS data sets plotted by Color according to Table 2 (See Appendix B for full picture).

As I described in section 3.2, I plotted each data point from the six datasets by traveling speeds with pyplot, as shown in Table II, Figure 8, and 9. The slower the speed when the data point was recorded, the lighter it is colored. Datasets 1, 2, and 6 shared paths on the bottom half of the outer ring road. For a section of shared path captured by a dashed black rectangle in Figure 8, the three datasets all showed a traveling speed ranging from 2 to 8 mph. For datasets 1 and 2, both scooters slowed down during that section. The scooter in dataset 6 sped up a bit in that section, but its speed was also within the same range. There are other similar patterns in the datasets shown in Figure 8. For example, scooters from datasets 3, 4, and 6 all sped up on the top of Ring Mall right after passing the dashed blue line, in the area captured by a blue circle. The six datasets in Figure 8 also show continuous paths from points to points that are wheel-accessible because the scooters did not halt while traveling on those paths.

Figure 8

GPS Datasets Plotted by Color according to Traveling Speed



Note. All GPS datasets plotted by color according to traveling speed and Table 2

Figure 9

Individual GPS Datasets Plotted by Color according to Traveling Speed

Note. Individual GPS datasets plotted by color according to traveling speed and Table 2

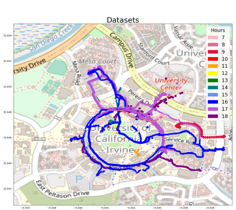
(See Appendix D for full images and descriptions of subfigures).

As mentioned in section 3.2, to observe if time also contributes to the accessibility of paths, I plotted each data point from the six datasets labeled with different markers by the hour of the day when it was recorded, as shown in Table II, Figure 10, and 11 (See Appendix D for full images and descriptions of subfigures). Two pairs of datasets, dataset 1 and 6, and dataset 3 and 6, shared paths during the same hours. Thus, more information could be extracted from the common patterns in speed observed between these pairs of data that shared both paths and traveling time. For example, in the context of a university campus, these common patterns could indicate when and where larger classes are dismissed, which can help users who would like to avoid crowds steer clear of crowded paths.

The above findings suggest many PMD travel patterns are worth exploring to extract real-time information about pedestrian walkways. The findings also demonstrated the feasibility of collecting PMD travel patterns passively and extracting pedestrian walkway accessibility information from the data.

Figure 10

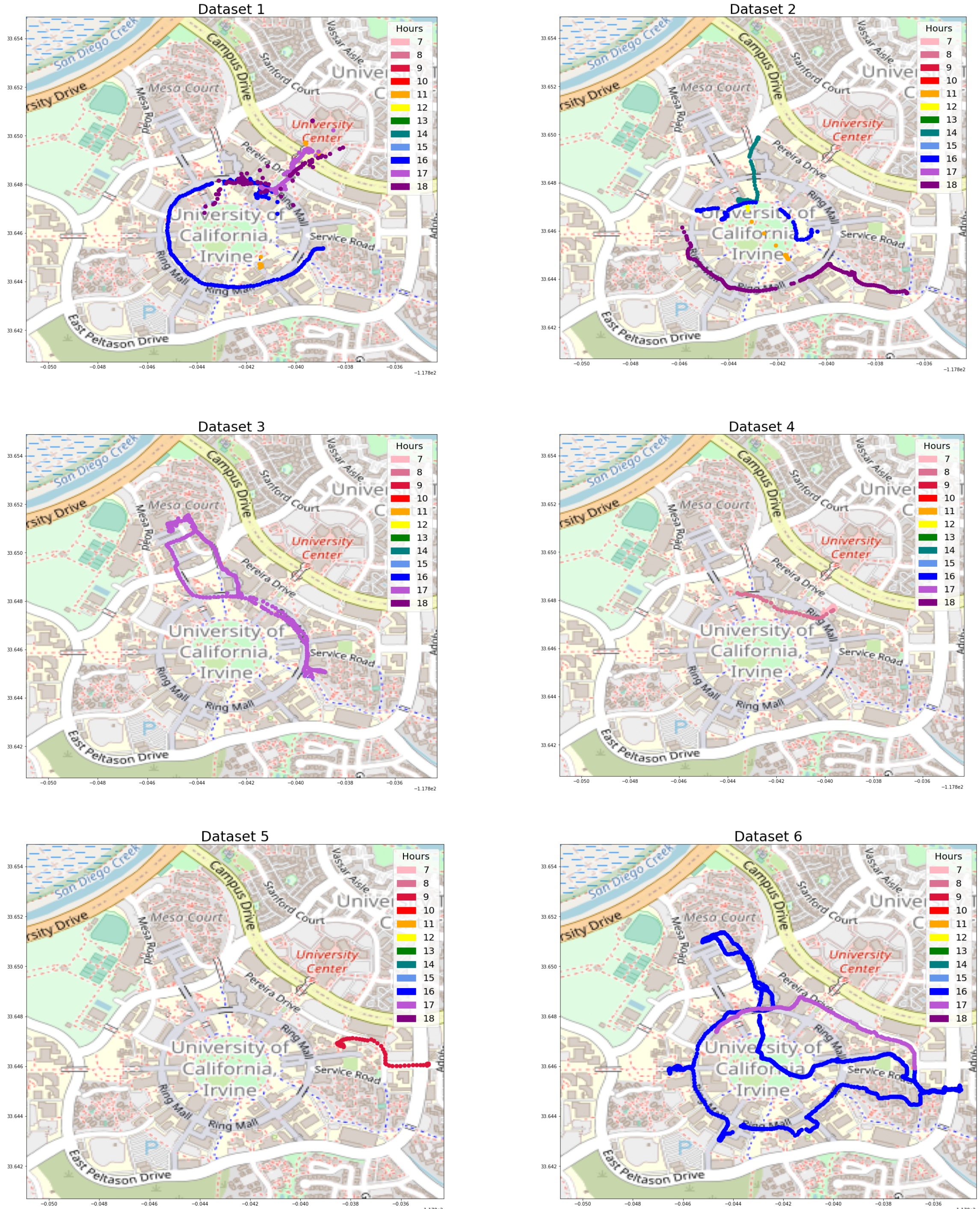
GPS Datasets Plotted by Color according to Traveling Time



Note. All GPS datasets plotted by color according to traveling time and Table 2 (See Appendix E for full image).

Figure 11

Individual GPS Datasets Plotted by Color according to Traveling Time



Note. Individual GPS datasets plotted by color according to traveling time and Table 2

(See Appendix D for full images and descriptions of subfigures).

4.2 Volunteer Survey Findings

After analyzing the volunteer survey results, I extracted five notable findings: (1) all participants experienced difficulties with cold-starting the GPS modules, (2) most participants were not against participating in future passive data collection, (3) half of the participants observed an unintentional change in their assessments about route accessibility and traveling behaviors, opting for accessible routes, (4) most participants shared concerns about sharing data with third parties, (5) all participants proposed policies to ensure data security and privacy.

4.2.1 Difficulties with GPS Modules

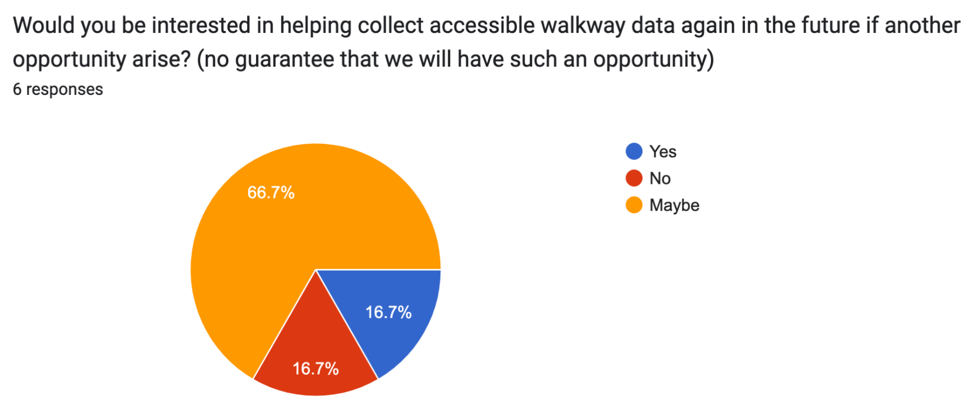
After emailing the eight student volunteers asking them to fill out the survey discussed in section 3.3, I received six responses (75% response rate). All six volunteers who responded reported that they experienced difficulty starting the GPS modules. Three volunteers (50% of respondents) mentioned the GPS modules take a few minutes to detect enough satellites for data collection, leading to missed opportunities to collect data. One volunteer noticed an unknown and indecipherable message on the LCD screen. The illegible message was likely due to the brightness-adjusting potentiometer being tempered by outside forces (e.g., being dropped several times) or malfunctioning. The other two responses brought up how the GPS modules sometimes fail to detect enough satellites over an extended period.

4.2.2 Willingness to Participate in Future Data Collection

As shown in Figure 12, more than 80% (5 out of 6 respondents) of survey participants were not opposed to participating in similar accessible walkway data collection opportunities, which could be due to the ease of data collection and how it was incorporated into their daily life.

Figure 12

Participants' Willingness to Participate in Future Data Collection



Note. A pie chart that shows the percentages of participants who would say yes, no, or maybe to future data collection opportunities.

4.2.3 Tendency to Opt for Accessible Paths during Data Collection

Three volunteers (50% of respondents) noticed they started to assess routes they take differently than before when collecting accessible pathway data. Two volunteers found they had to avoid some popular paths or stop and carry their scooters because of the steps. At the same time, two volunteers found that wheel-accessible routes usually take longer to traverse than regular routes. One student, in particular, realized that many paths have hidden ramps that are hard to find and inconvenient to use. Four out of six respondents observed no change in their traveling behaviors. They stopped and carried their scooters when needed. In contrast, two volunteers decided to avoid all stairs when collecting data.

4.2.4 Concerns and Opinions Towards Sharing Data with Third Parties

When asked about their opinions on equipping scooters with accessible map data collection sensors, all respondents expressed privacy concerns when sharing data with third parties. Three respondents were worried about being tracked everywhere they went. One of these three respondents was especially concerned about exposing their home addresses. In comparison, one respondent was comfortable with having the sensors embedded in their scooters if the data stayed private and was only available for their use (e.g., locating their scooters). Another two students mentioned they were also fine with having sensors on their scooters if they were only for use in public areas such as university campuses or if the users could control when and whether to turn the sensors on. Half of the respondents reported being uncomfortable sharing scooter sensor data with a third party, such as government agencies, commercial applications, or open-source projects, because they worried about their data being misused or abused by the third party. A respondent said they would be willing to share their data with a non-commercial third party only if the third party would compensate them. Another student is only comfortable sharing data with specific communities like university campuses. The last respondent would only be okay with sharing data with open-source projects because the data could contribute to and inspire meaningful projects for the greater good. When asked if who uses and how they use the data would change respondents' minds about sharing data with a third party, five out of six of them answered yes.

All survey respondents expressed varying levels of concern about exposing their personal and navigation data to third parties. Therefore, to expand the scope of passive data collection, concerns about data security and privacy must be addressed and enforced with policies to reassure data collectors that their data should be anonymized and not misused.

4.2.5 Suggestions for Scooter Data Collection Policies

Participants recommended some rules and policies for scooters equipped with sensors that collect GPS and other sensor data, mainly on improving data security and privacy. Three participants (50% of participants) suggested that the data be anonymized, and no demographic information about the data collectors should be associated with the sensor data or shared with commercial applications for targeted monetizations. Another participant suggested that the sensors should only be limited to collecting data in specific public settings/communities like university campuses. A participant also mentioned there should be a policy that restricts how much battery the sensors could drain so the data collection does not hinder people's daily commute.

These proposed policies reflect and echo the concerns about data security and privacy raised by participants in section 4.2.4. Government entities should adopt and impose similar policies to third parties to ensure the anonymity, security, and privacy of the data collected.

Chapter 5

Discussion, Limitation and Reflection, and Conclusion

5.1 Discussion

Researchers have sought to develop accessible navigation applications over the past decade. However, one of the most prominent challenges researchers face is collecting enough data and frequently updating it to keep their applications relevant. Researchers mainly collected accessibility data about pedestrian walkways through crowdsourcing information from users and/or crowdsensing, which requires users' active participation and consistent efforts, making it hard to sustain a large enough user base for data collection and updates. Thus, to collect accessibility data about pedestrian walkways at a larger scale, it is crucial to explore passive data collection, which requires less manual effort to perform regularly. My findings extracted from my two-part feasibility study led me to further discuss five topics this section that can motivate future research in accessible maps: (1) travel patterns of PMD users and their indications, (2) privacy concerns and potential solutions, (3) raise awareness of accessible walkways through data collection, (4) different scooter policies across the United States, and (5) ideas for future research to explore.

5.1.1 Travel Patterns of PMD Users to Explore

In this thesis, I explored the travel patterns of scooter riders on pedestrian walkways and their connections to the conditions of the walkways. The first type of pattern I noticed was paths where the scooters were traveling at a consistent speed, which could indicate that there are point-to-point wheel-accessible paths between all points on the path. However, some sections of these paths might not be accessible to larger PMDs (e.g., wheelchairs, rollators, or mobility scooters) since the electric scooters used by volunteers are much narrower.

The second type of pattern to explore was when and where different scooters traveled at slow speeds. Many reasons can cause scooters to slow down, such as heavy traffic, inclines, obstacles, catching up with acquaintances, and dismissals of larger classes on university campuses. Some obstacles, like construction and large landscaping projects, can cause walkway blockages for an extended period, while some obstacles in other scenarios would resolve quickly. For short-term walkway traffic or blockages caused by routine events such as regular landscaping maintenance, large class dismissals on campus, lunch breaks at office buildings, or common times for people to get to and off work, I also found it informative to explore their occurrence patterns. While the causes of these routine short-term walkway obstacles may matter less to pedestrians than the time of their occurrences, the same cannot be said for occasional semipermanent obstacles. Since semipermanent obstacles do not happen regularly, their causes of them can be actively crowdsourced to help pedestrians assess how long the path could stay obstructed.

Finally, the last type of pattern is when and where scooters traveled faster than usual. The scooter riders could be rushed and/or just traveling on declines or sparse paths when traveling fast. The occurrence patterns of this type of pattern should also be examined since the paths may become busier during different times of the day. This information could be helpful to pedestrians with varying preferences on walkway crowdedness described in section 2.2 from work by Gupta et al.. Pedestrians who want to avoid crowds because of moving obstacles might prefer these paths during less busy hours [38]. In contrast, some pedestrians might also want to avoid these paths because they feel less comfortable traveling on deserted paths since it would be harder to ask for help when they want to [38].

This section discussed potential implications on pedestrian walkway conditions that could be inferred from three types of travel patterns of scooter riders. More interesting travel patterns could be revealed if a larger number of data sets were available. I would be particularly interested in examples where datasets demonstrate similar patterns on a common path during the same time, which the six datasets of this study did not exhibit due to lack of overlaps in data collection time.

5.1.2 Privacy Concerns to Address

All survey participants in section 5.2.1 expressed some privacy concerns about being tracked during data collection and sharing data access with third parties. Some participants suggested a few policies that could address their concerns and make them more willing to collect and share data with third parties. A few policies proposed by participants revolve around letting data collectors control where, when, and how frequently data collection happens. Others advocated for transparency about what data is collected and who or what organizations can access the data. Several participants also preferred donating data to third parties such as universities or open-sourced projects. To ease data collectors' minds, researchers could also experiment with implementing mechanisms that give the data collectors autonomy over when and where to collect data.

Indeed, these privacy concerns raised are to be expected and understandable. Yet, they made me wonder what made us agree to the privacy policies of mobile applications and accept the use of cookies on different websites in our daily life without pondering. As a 2011 study conducted by Beresford et al. showed many mobile applications require users' consents to surrender a wide range of sensitive data to access full functionalities [14]. When the convenience and benefits of these tools outweigh our concerns about data collection transparency, data privacy, and data security, we could be more likely to sacrifice our privacy. In future studies, it would be worthwhile to delve deeper into what types of incentivization could be both sustainable and appealing to data collectors or users of accessible navigation applications.

5.1.3 Raising Awareness of Pedestrian Walkway Accessibility

OpenStreetMap and other organizations have also been hosting mapathons, "coordinated mapping event[s]," in the United States and worldwide over the past decade to draw attention and interest in mapping [52]. Still, mapathons happen far less frequently than pedestrian walkway conditions change. Most mapathons occur at set locations and take up a whole weekend of participants' time, which can be a reason that dissuades people from taking part in one. For instance, I have previously attended a two-day virtual mapathon, many participants who attended the first day did not show up on the second day. There should be more opportunities that allow people to participate in mapping or data collection more easily.

In this thesis, I explored passive data collection by incorporating it into data collectors' daily life. The data collectors did not need to collect data actively, kept their daily routines, and ignored the GPS modules for the most part. At the same time, some survey participants also noticed changes in their conceptions about paths and their traveling behaviors during data collection. Participants were more conscious and aware of the accessibility and conditions of the paths they took when collecting data. Perhaps, making data collection ubiquitous and integrated into everyday life and less troublesome and demanding could lead to a slight change of mind in data collectors, which could raise awareness about pedestrian walkway accessibility and encourage more to participate in data.

5.1.4 Policies Divergences and Safety Concerns of Electric Scooters

While working on this thesis, I found significant divergences in electric scooter policies across different states that could hinder the use of scooter riders as data collectors for mapping. Two states, Hawaii and West Virginia, do not have any set regulations for electric scooters [26]. There are also Idaho and Oregon that only impose some rules in their largest cities, Boise and Portland. Many municipalities in the same states can also have different electric scooter regulations [26]. Seven out of fifty states, including Nebraska, New Hampshire, South Carolina, New Mexico, Oklahoma, and Rhode Island, allow cities to set up all or part of their electric scooter policies [26]. There are also three states, Missouri, Nebraska, and Pennsylvania, with no clear regulations for electric scooters [26]. Some states, which include those where electric scooters are the most popular such as New York and California, impose more substantial restrictions and regulations on riders.

Twenty-four states, close to half of the United States, impose speed limits ranging from 15 to 35 miles per hour (mph) on electric scooters [26]. Out of these twenty-four states, eighteen, more than half impose a speed limit of 20 mph and under [26]. Only six states allow scooters to go over 20 mph [26]. Most data collectors for this thesis stayed under 20 mph, which matches this speed limit pattern. Nine states also require electric scooter riders to obtain licenses, permits, and DMV registrations [26]. California and Kansas require driver's licenses. Alabama, Alaska, Maine, Massachusetts, and South Dakota require electric scooter riders to hold other classes of licenses and permits [26]. In South Dakota, electric scooter riders also need to have insurance in addition to licenses [26]. In Illinois, only people under 17 need to have licenses to operate electric scooters [26]. Finally, all electric scooters in North Carolina must be registered at the DMV [26].

After diving deeper into policies about electric scooters on pedestrian walkways, I found nine states that strictly prohibit electric scooters from being on sidewalks [26], including California and New York, two states with relatively high electric scooter popularity [73].

While the other states allow scooters to be on sidewalks, Colorado and Washington D.C. impose strict speed limits on electric scooters on sidewalks [26]. Colorado's speed limit for electric scooters on sidewalks is 6 mph [26]. Electric scooters on sidewalks in Washington D.C. have to travel under 10 mph and stay out of the business district [26]. In Florida and Georgia, electric scooters can only stay on bike lanes [26]. Delaware, Pennsylvania, and two cities in Alabama even prohibit electric scooters from traveling on public roads [26].

A major reason some states ban electric scooters on sidewalks is the security concerns they pose when sharing paths with other pedestrians [51]. Badeau et al. reviewed and analyzed all injuries related to electric scooters processed by two emergency departments in Salt Lake City, Utah, from June to November of 2017 and 2018. In these five months of 2017, the two emergency departments reported only eight electric-scooter-related injuries [12]. Electric-scooter-related injuries increased by more than five times to fifty in those five months of 2018 as electric scooters gained more popularity in Salt Lake City [12]. Twenty-two of these fifty injuries were caused by incidents on sidewalks [12]. Another study in 2020 also revealed the victims of electric scooter accidents are primarily young children and seniors [77], who probably could not dodge PMD users fast enough on narrow sidewalks.

The deviations in electric scooter regulations across the country and the safety concerns electric scooters pose could hinder collecting accessibility information about pedestrian walkways with scooters on a larger scale, e.g., in metropolises. Therefore, the data collection method used in this study might only be valid on university campuses or other public spaces with wide and spacious walkways shared by pedestrians and PMD users.

5.1.5 Suggestions for Future Passive Pedestrian Walkway Data Collection

As discussed in section 2.4, many navigation applications collect and learn from vehicle travel patterns to predict traffic and road conditions. Researchers could also follow suit by collecting and delving into the travel patterns of pedestrian walkway users in more sustainable and creative ways. For instance, autonomous delivery robots are a data collection channel worth delving into. Autonomous delivery robots are rising in popularity on campuses, neighborhoods, and urban areas. Over the past few years, more than twenty universities in the US adopted Starship robots for meal delivery [67]. Starship even started collaborating with GrubHub last year to expand its meal delivery program with more options to five more universities in the US [37]. Another robotic company, Cartken, also started working with Uber Eats and deployed autonomous sidewalk delivery robots in Miami, Florida, at the end of last year [43, 61].

Furthermore, researchers are also looking for ways to help autonomous sidewalk robots navigate crowded sidewalks better. In 2019, Du et al. proposed a navigation system for autonomous sidewalk robots that allowed them to mimic and adopt pedestrian travel behaviors by following different pedestrian groups heading in the same direction as they are during their trips [23]. The navigation system would optimize for the best group of pedestrians for the robots to follow, which could change from time to time [23]. Deep Reinforcement Learning was also applied to guide the robots to avoid collisions with static or dynamic obstacles, including other pedestrians that the robots were not imitating [23]. These mechanisms and efforts help autonomous sidewalk robots share paths with pedestrians safely. Additionally, collecting data with autonomous sidewalks robots would pose fewer privacy concerns than collecting data with actual humans like PMD users. These qualities of autonomous sidewalk robots could make them more suitable as passive data collectors for accessible maps, especially if they were to be programmed to imitate pedestrians. Therefore, more researchers working on accessible maps should consider exploring using autonomous sidewalk delivery robots to collect data passively.

5.2 Limitations and Reflection

This thesis explored the feasibility of passively collecting accessible pedestrian walkway data using scooter riders as data collectors. Feasibility was informed through quantitative measurements of scooter rider traveling behaviors and qualitative assessment of rider experience. Although this thesis offers a compelling proof of concept, there are several limitations to consider for future study. While the number of datasets and the varieties of data examined are too narrow to conclusively identify accessibility information about the paths taken, they suggest that accessibility issues and barriers can be identified through passive crowdsourced data collection of PMD users' travel patterns.

The study was limited due to low participation caused by my recruitment method. A few factors contributed to the small number of participants. First, there was little time or resources to recruit and incentivize participants outside of the HCI class I taught. Second, only some students in the class commute regularly with scooters. Third, if the students are already doing well in the class, they might not be interested in the data collection opportunity. The was also a limited number of data samples collected for each dataset, which could be due to the extended cold start time and the instability of the satellite detection feature of the custom GPS modules. The cold start time and stability of GPS modules can be significantly improved if using commercially produced GPS modules in networks, which can mitigate this limitation and improve the data collection experience and results.

The dearth of data samples also prevented further data exploration with machine-learning approaches, such as unsupervised learning to extract potential features of interest from the data collected. If I were to have more time and resources for another round of data collection, I would recruit around twenty students with scooters from different departments with different classes and commute routines to cover more paths on campus. Since UCI is on a quarter system and each quarter lasts for around ten weeks, I would ask the students to collect data for three weeks. Other than just collecting timestamps, GPS coordinates, and traveling speeds with a GPS module, I would also incorporate a gyroscope and an accelerometer to capture the movements of scooters and the inclinations of walkways. The data would also need to be analyzed more vigorously and thoroughly to extract potential features to build and train machine-learning models that would recognize similar patterns in different GPS datasets. Nonetheless, the machine-learning models trained on the UCI campus might not perform as well in other settings or on campuses with different terrains. Varying levels of retraining are needed to apply the models elsewhere. It would be interesting to see how well machine-learning models trained on one campus would perform on another with similar terrain.

In the future, I hope more researchers will continue to explore collecting different types of travel data passively at a larger scale and analyzing travel patterns to extract accessibility information about pedestrian walkways, as well as raising awareness among allies about pedestrian walkway accessibility through data collection.

5.3 Conclusion

For this thesis, I assessed the feasibility of collecting data for accessible maps passively with scooter riders. I built GPS modules and had volunteer students attach them to their scooters and carry out their daily routines on campus. After performing basic visual analyses of the data collected, a few prominent patterns that could indicate different pedestrian walkway conditions were discovered. Nonetheless, more data was needed to discern the potential causes of the observed patterns, which calls for more data samples, breadth in data variety, and depth in data analysis in future research.

A voluntary survey was also conducted to evaluate volunteers' experience and opinions about passive data collection. The survey results showed a few volunteers ran into difficulties cold-starting the GPS modules. The volunteers were also not opposed to participating in future data collection. Their tendency to opt for accessible paths during data collection was also revealed in the survey. This could mean that people might be more willing to volunteer for data collection if it is made easier and incorporated into their daily life. At the same time, collecting data for accessible maps could also bring the accessibility of pedestrian walkways to volunteers' attention. In the latter half of the survey, the participants raised different levels of concerns surrounding data privacy and security when sharing data with third parties because they were worried about leaking personal information and being tracked for monetization. Finally, the participants suggested some policies for future data collection projects with scooters that addressed the privacy concerns raised by ensuring data anonymity and limiting data collection to public communities. Therefore, future research or projects that plan to collect data on a larger scale with scooter riders should also implement policies protecting volunteers' personal information and privacy.

Through working on this thesis, I learned that current commercial navigation applications do not address the different needs and preferences of pedestrians, especially PWD. While navigation applications provide real-time traffic information to drivers, they do not for pedestrians. Unlike the uniformity in vehicle functionality and road conditions, the abilities of human bodies and conditions of pedestrian walkways are much more diverse. Pedestrians, especially PWD could use more real-time information for trip planning. Regular data collection and updates are necessary to provide relevant real-time accessibility information to pedestrians. Current pedestrian walkway audits and data collection are manual, tedious, and costly, which prevents them from being conducted often. Existing technologies for pedestrian walkway data collection also mainly focus on active crowdsourcing, which requires achieving a highly active and engaged critical mass of data collectors. Navigation applications have been passively crowdsourcing drivers' navigation data for more than a decade to produce real-time traffic information. However, pedestrians', particularly PMD users' travel patterns have been overlooked. My work suggests there exists a great potential in extracting real-time accessibility information about pedestrian walkways from wheeled mobility devices' travel patterns. As more human-controlled or autonomous wheel devices are starting to share spaces with pedestrians, researchers should continue investigating collecting pedestrian walkway accessibility data passively with these devices.

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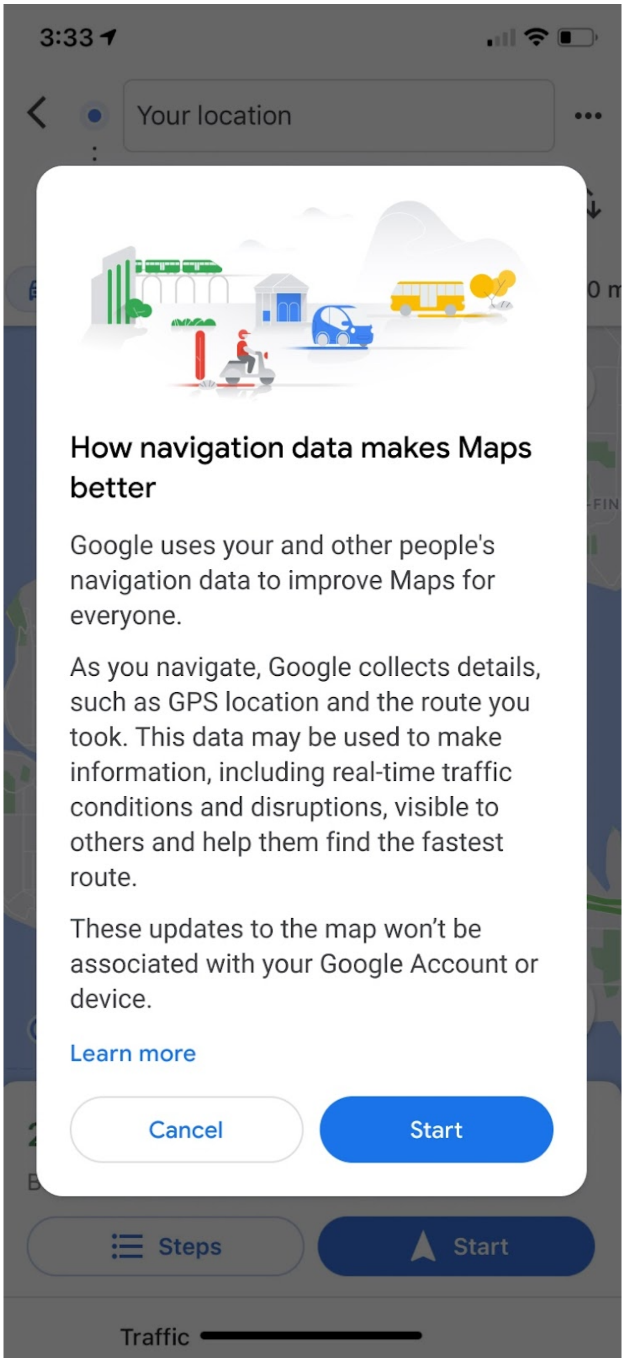
Appendix A

Figure A1

Google Maps Crowdsourcing Statement

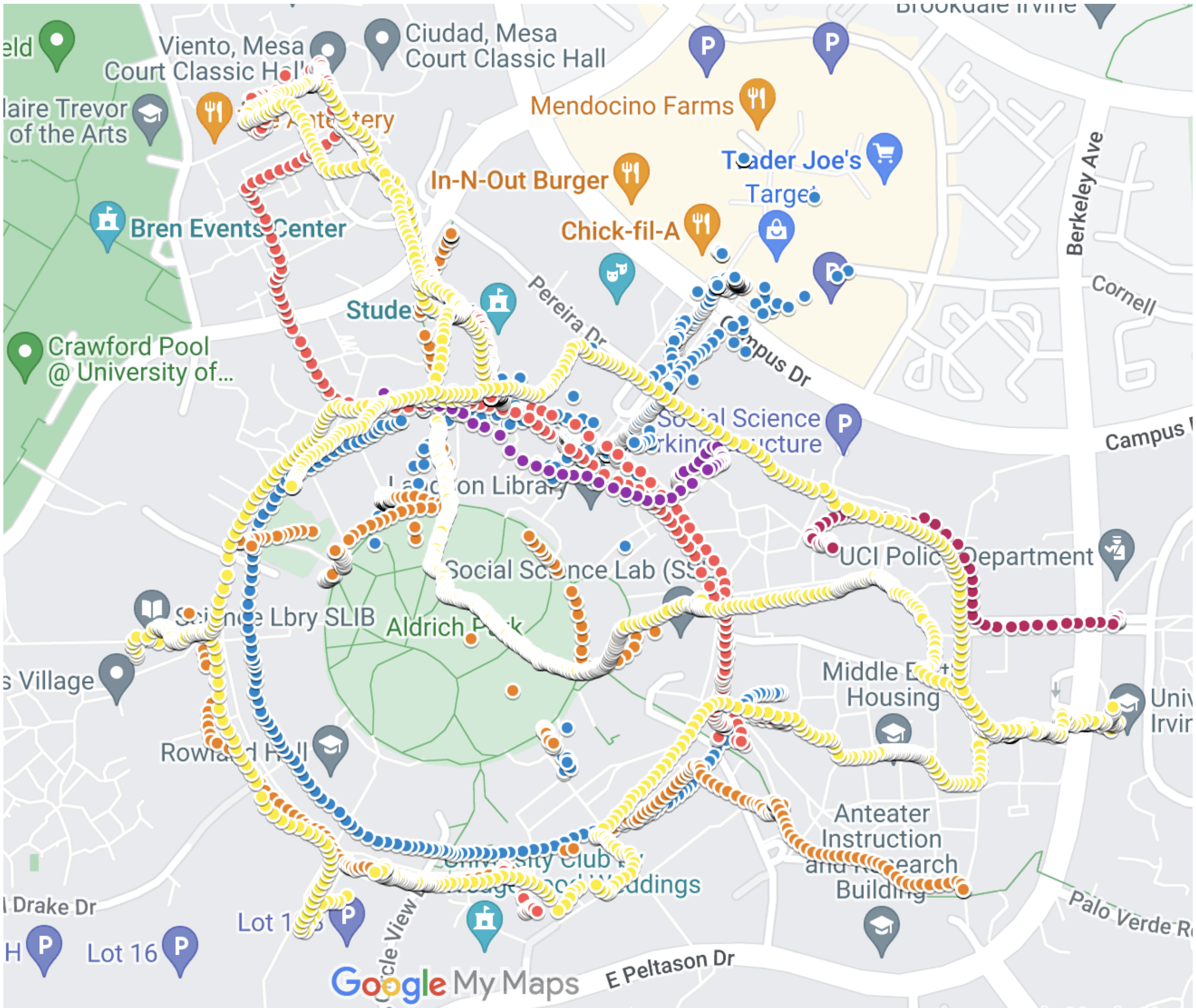


Note. A crowdsourcing statement Google Maps displayed

Appendix B

Figure B1

GPS Datasets Plotted on Google My Maps



Note. GPS Data Sets Plotted by Color according to Table 2

Appendix C

Accessible Maps Data Collection Survey

Thank you all for helping me collect accessible walkway data last quarter! Below are a few questions about your experience collecting data. I will really appreciate your participation in this survey!

* Required

1. What's your UCI email address? (e.g. panteater@uci.edu) *

2. What were some difficulties, if any, that you ran into while collecting the data with the GPS module? (e.g., GPS modules taking longer than a few minutes to start recording data because they could not yet detect enough satellites) *

3. Would you be interested in helping collect accessible walkway data again in the future if another opportunity arise? (no guarantee that we will have such an opportunity) *

   Mark only one oval.

   - Yes
   - No
   - Maybe
   - Other: ____________

4. How, if at all, did you perceive routes differently when you were collecting data? (e.g., realizing a route you take frequently is not accessible for wheelchair users) *

5. How, if at all, did carrying a GPS module around change your traveling behaviors? (e.g., avoiding stairs/steep slopes) *

6. What would you think if your scooters came with sensors that collects GPS and other data for the purpose of developing accessible map? Are there any concerns you might have? (e.g., privacy and security issues) *

7. Assuming that your scooters came with sensors that collects GPS data, how comfortable would you be with sharing the data with a 3rd party (e.g., Government agency, commercial applications, open source projects) and why? *

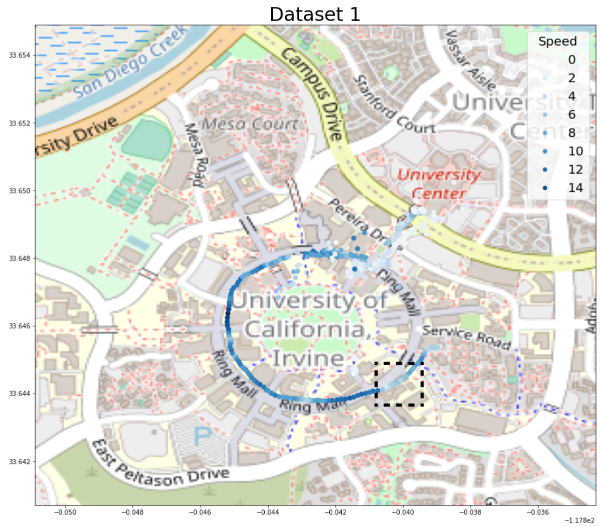
8. Does your answer to question 7 change depending on who uses it (e.g., developing accessible maps versus tracking location to generate ad revenue)? *

9. What rules do you think should be in place if new scooters come with sensors that collect GPS and other data? *

Appendix D

Figure D1a

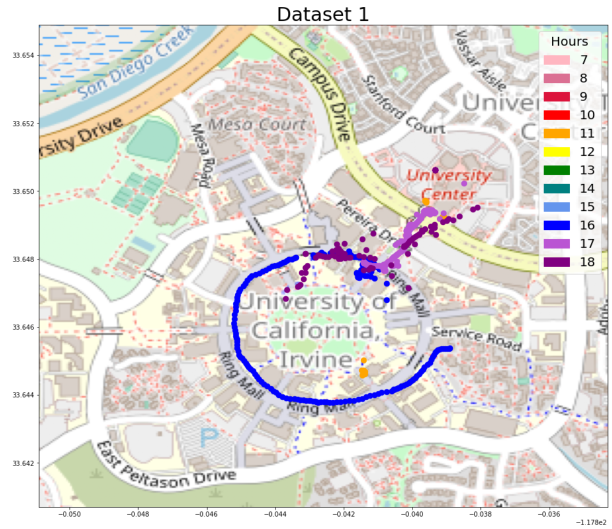
Dataset 1 Plotted by Travel Speed



Note. GPS coordinates collected by the first volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of blue the data point is.

Figure D1b

Dataset 1 Plotted by Travel Time

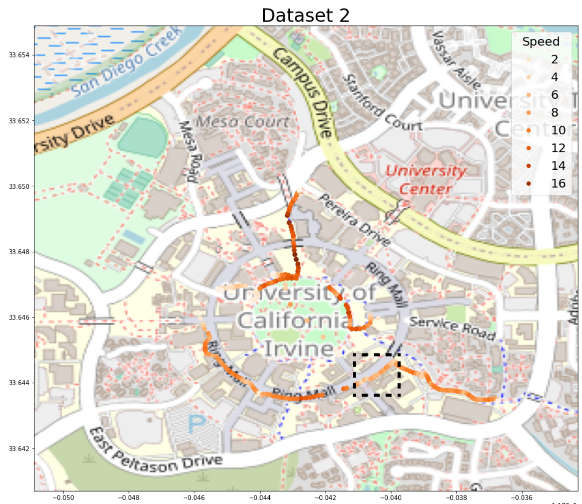


Note. GPS coordinates collected by the first volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D1a and D1b, the first volunteer started data collection at around 4-5 PM in the Middle Earth student housing area. They slowly merged into Ring Mall and made their way around it in the direction of Java City Kiosk. They gradually accelerated but slowed down when approaching intersections. Finally, they reached the University Center for some errands and returned to Anteater Learning Pavilion at around 6-7 PM. The data collection session lasted for about three hours.

Figure D2a

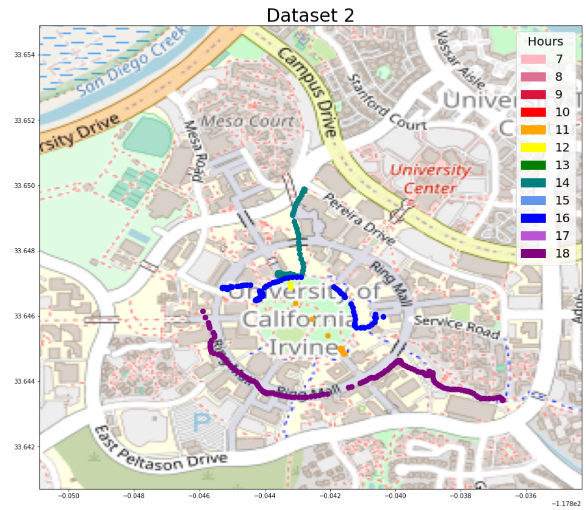
Dataset 2 Plotted by Travel Speed



Note. GPS coordinates collected by the second volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of orange the data point is.

Figure D1b

Dataset 1 Plotted by Travel Time



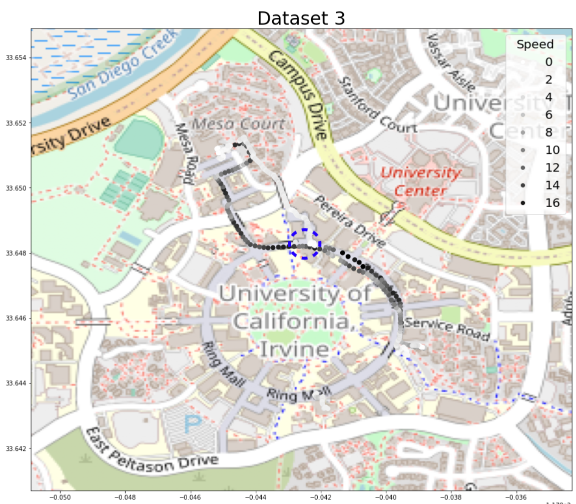
Note. GPS coordinates collected by the second volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D2a and D2b, the second volunteer started data collection at around 2-3 PM in the Student Center area. They started picking up their speed and decelerating before crossing Ring Mall and arriving at Anteater Learning Pavilion. After around 1-2 hours, they exited Anteater Learning Pavilion, accelerated, and traveled to the social science buildings on the opposite side of Inner Ring Road. They then traveled in the same direction they came and traveled to parking lot #7. During this section of their travel, some data points were missing, likely due to an insufficient number of satellites being detected.

Starting at around 6 PM, they left the parking lot and headed toward Middle Earth's Elrond Hall before stopping data collection. Like the first volunteer, the second volunteer slowed down before crossing intersections on Ring Mall. The second volunteer collected data across four hours.

Figure D3a

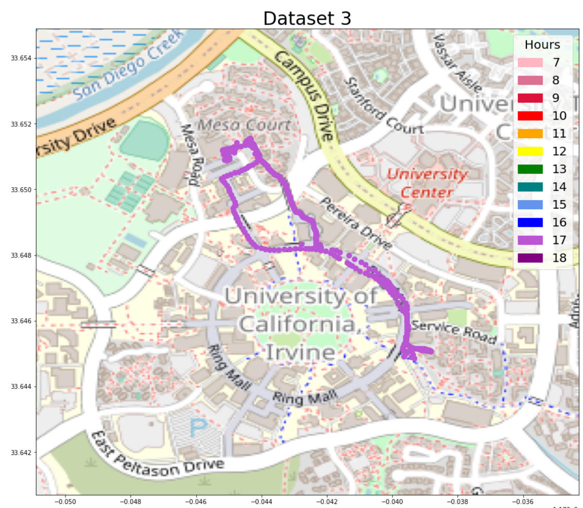
Dataset 3 Plotted by Travel Speed



Note. GPS coordinates collected by the third volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of gray the data point is.

Figure D3b

Dataset 3 Plotted by Travel Time

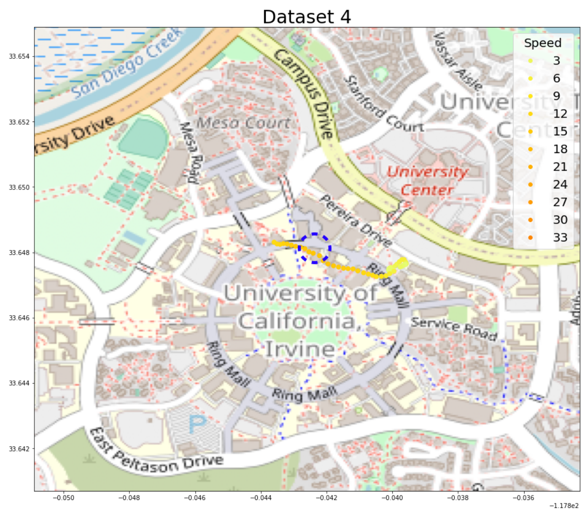


Note. GPS coordinates collected by the third volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D3a and D3b, the third volunteer only collected data for approximately an hour starting at around 5 PM. They started traveling very slowly at Mesa Court. After reading Ring Mall, they accelerated and headed toward Brandywine dining hall at a slow speed. Finally, within the same hour, they left the dining hall, accelerated and maintained a constant high speed, and headed back to Mesa Court, passing Humanities Hall on the way.

Figure D4a

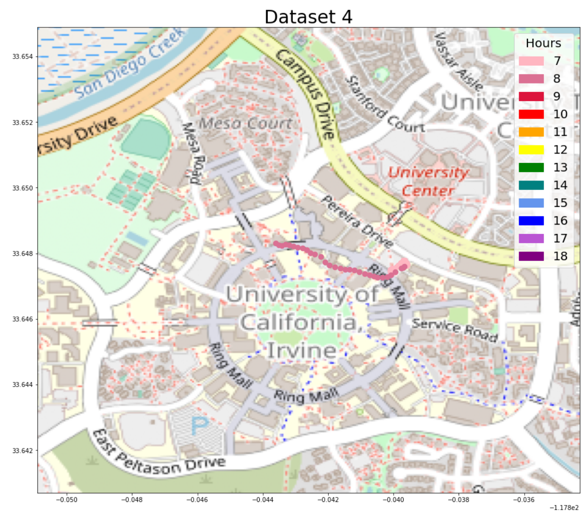
Dataset 4 Plotted by Travel Speed



Note. GPS coordinates collected by the fourth volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of yellow the data point is.

Figure D4b

Dataset 4 Plotted by Travel Time



Note. GPS coordinates collected by the fourth volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D4a and D4b, there are very few data points collected in this session. The fourth volunteer accelerated quickly and headed from parking lot #1 to Humanities Hall between 8 and 9 AM.

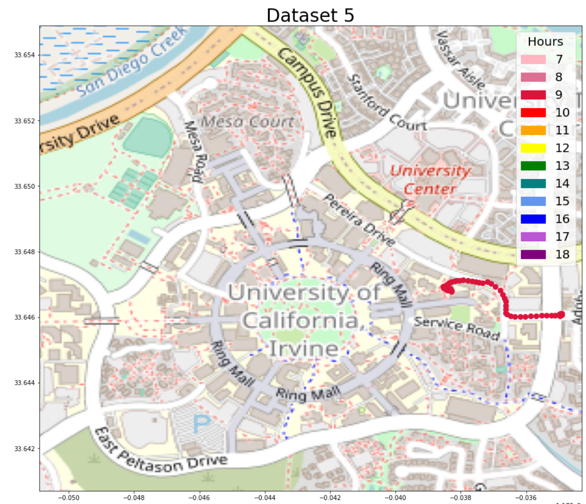
Figure D5a

Dataset 5 Plotted by Travel Speed

Note. GPS coordinates collected by the fifth volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of purple the data point is.

Figure D5b

Dataset 5 Plotted by Travel Time

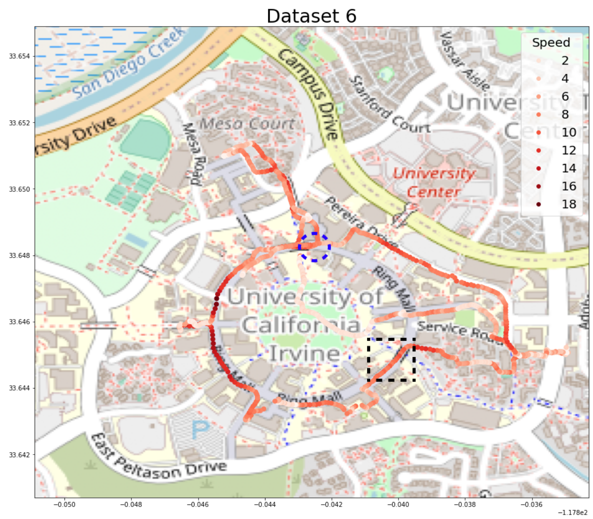


Note. GPS coordinates collected by the fifth volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D5a and D5b, the fifth volunteer slowly accelerated and headed from the UCI Transportation and Distribution Services to the Starbucks next to The Paul Merage School of Business between 9 and 10 AM. They slowed down before reaching Starbucks.

Figure D6a

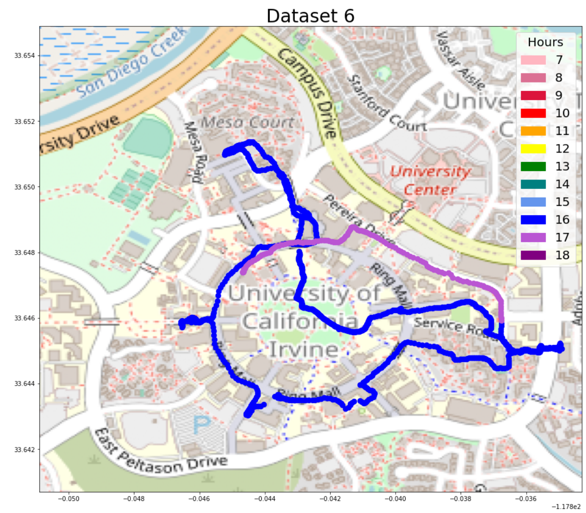
Dataset 6 Plotted by Travel Speed



Note. GPS coordinates collected by the sixth volunteer plotted by traveling speed. The faster the traveling speed, the darker the shade of red the data point is.

Figure D6b

Dataset 6 Plotted by Travel Time



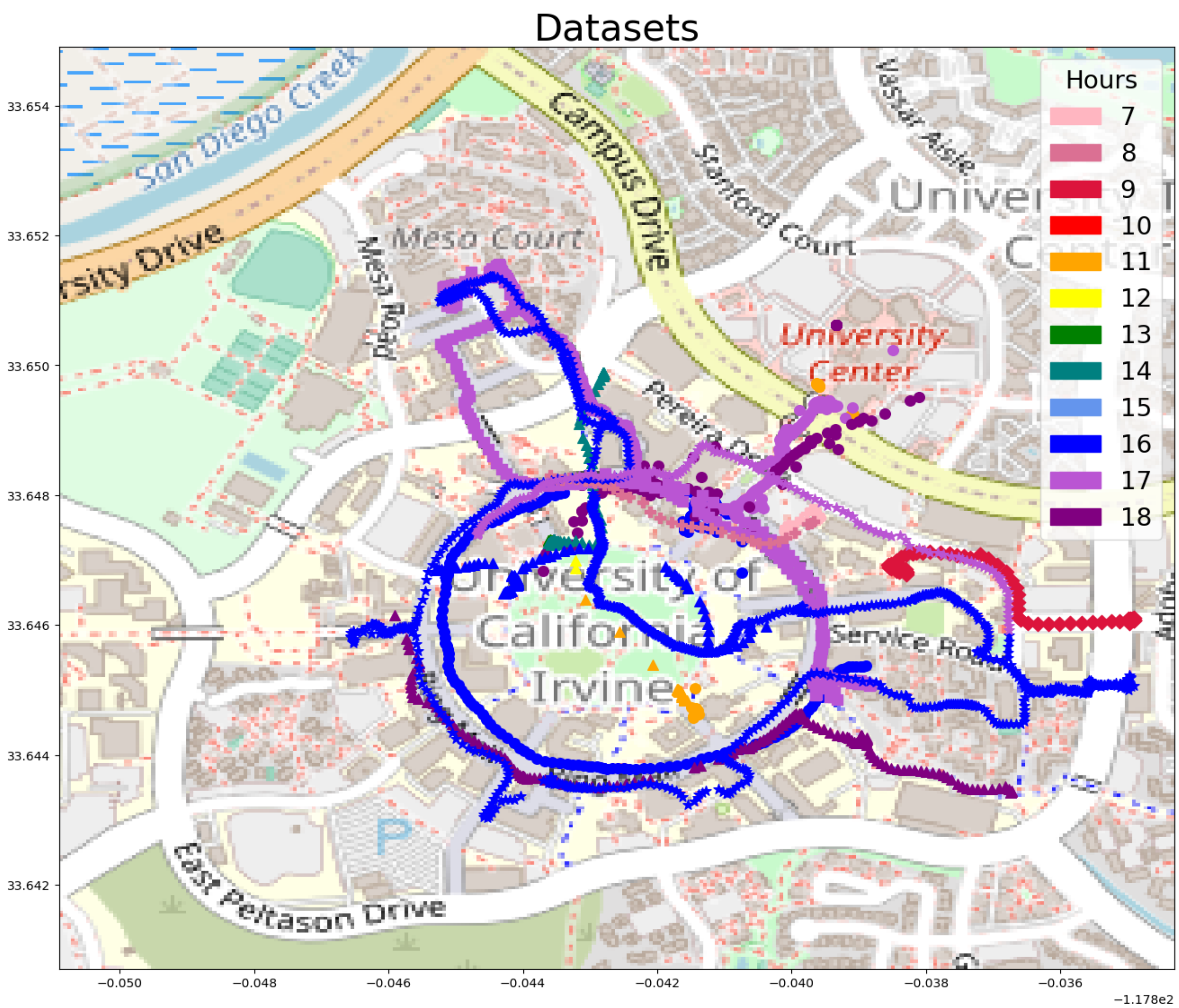
Note. GPS coordinates collected by the sixth volunteer plotted by traveling time. The color of the data point depends on the hour recorded according to the legend shown.

As shown in Figures D6a and D6b, the sixth volunteer started collecting data at around 4 PM. They started at Middle Earth's Crickhollow Hall and slowly headed to Mesa Court through Aldrich Park. Within the same hour, they left Mesa Court and accelerated toward BC's Cavern Food Court through Ring Mall. They left the food court, headed to Physical Sciences Lecture Hall, and then back to Crickhollow Hall. When it was almost 5 PM, they headed toward Anteater Learning Pavilion through Pereira Drive at a consistent pace. The entire data collection lasted for less than two hours.

Appendix E

Figure E1

GPS Datasets Plotted by Color according to Traveling Time



Note. All GPS datasets plotted by color according to traveling time and Table 2.