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Social Moderation and Dynamic Elements in Crowdsourced Geospatial Data

A report on quality assessment, dynamic extensions, and mobile device engagement in the George Mason University Geocrowdsourcing Testbed

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14. ABSTRACT
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Abstract

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Preface

This report is a deliverable product of Department of the Army Broad Agency Announcement (BAA) #AA10-4733, Contract #W9132V-11-P-0011. The study for this report was conducted jointly by the Engineer Research and Development Center (ERDC) technical lead Douglas R. Caldwell and George Mason University faculty and research staff, in support of the ERDC. Report author Matthew T. Rice wishes to acknowledge the support of Kevin Curtin, Rebecca M. Rice, and Sven Fuhrmann, for their proofreading and editorial support; College of Science Dean Peggy Agouris for her support; and Department of Geography and Geoinformation Science Chair Anthony Stefanidis for his direction and support. Dr. Rice also thanks Megan Rice, Manzhu Yu, Rodney Vese, Han Qin, and Ava Rice for assistance with field work.

Unit Conversion Factors

Multiply	By	To Obtain
feet	0.3048	meters
miles (nautical)	1,852	meters
miles (U.S. statute)	1,609.347	meters
miles per hour	0.44704	meters per second

1 Introduction and Background

One of the most significant contemporary trends in the geospatial sciences is the use of map-based crowdsourcing for collecting, confirming, editing, and displaying geospatial data, referred to by various practitioners and observers as crowdsourced geospatial data (CGD), geocrowdsourcing, or volunteered geographic information (VGI). Sui et al. (2013, 1)[1] describe this phenomenon as part of a "profound transformation on how geographic data, information, and knowledge are produced and circulated," an important part of the current "exaflood of digital data growth."[2] McCartney et al. (2015)[3] note that this phenomenon is permeating the most basic geographic data production strategies of the United States Geological Survey, the most prolific civilian mapping agency in the United States. Liu and Palen trace the phenomenon through a wide range of emergency response applications in the government, non-profit, and media sectors (2010), noting the influence of citizen-led geocrowdsourcing on professional practice. They advocate for an emerging environment of "interoperability between professional and participatory forms of geotechnology". [4,5]

Going back at least eight years to a time when geocrowdsourcing was just emerging, Dr. Michael F. Goodchild published a series of seminal articles outlining several significant benefits associated with this general approach; namely, the local geographic expertise of the contributors, who are more familiar with the local features being mapped; the speed with which information can be collected and mapped; and finally, the greatly reduced costs associated with what is typically a very expensive activity (2007, 2009).[6,7] Researchers at George Mason University (GMU) have

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1 Daniel Sui, Sarah Elwood, and Michael F. Goodchild, eds., *Crowdsourcing Geographic Knowledge Volunteered Geographic Information (VGI) in Theory and Practice.* (New York, NY: Springer, 2013).

2 Ibid.

3 Elizabeth A. McCartney et al., "Crowdsourcing The National Map," *Cartography and Geographic Information Science* 42, no. sup1 (2015): 54–57.

4 Ibid.

5 S. B Liu and L. Palen, "The New Cartographers: Crisis Map Mashups and the Emergence of Neogeographic Practice," *Cartography and Geographic Information Science* 37, no. 1 (2010): 69–90.

6 Michael F. Goodchild, "Citizens as Sensors: The World of Volunteered Geography," *GeoJournal* 69, no. 4 (December 2007): 211–21.

7 Michael F. Goodchild, "NeoGeography and the Nature of Geographic Expertise," *Journal of Location Based Services* 3, no. 2 (June 2009): 82–96, doi:10.1080/17489720902950374.

explored the topic of crowdsourced geospatial data extensively, through the support of the United States Army Corps of Engineer's Geospatial Research Laboratory. The results of this work have been published in a series of technical reports, conference proceedings, and journal articles documenting this work from its inception and to the present day (Rice et al. 2011, 2012a, 2012b, 2013a 2013b, 2014, Paez 2014, Qin et al. (2015a, 2015b) Rice 2015, and Rice et al. 2015)[8,9,10,11,12,13,14,15,16, 17,18] The research work from these publications has been oriented toward exploring the emerging phenomena (Rice et al. 2012b), data production techniques (2012b, 2013b), accuracy assessment methods (2012b, 2013b, 2014), fitness-for-use evaluations (2012b), exemplar applications and projects (2012b, 2014), and novel implementations (2012b, 2014). These research topics address the typical early questions associated with a nascent technological transformation, where scientists, academics, and

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8 Matthew T. Rice et al., "Integrating User-Contributed Geospatial Data with Assistive Geotechnology Using a Localized Gazetteer," in *Advances in Cartography and GIScience. Volume 1*, ed. Anne Ruas, Lecture Notes in Geoinformation and Cartography (Springer Berlin Heidelberg, 2011), 279–91, http://dx.doi.org/10.1007/978-3-642-19143-5_16.

9 Matthew T. Rice et al., "Supporting Accessibility for Blind and Vision-Impaired People With a Localized Gazetteer and Open Source Geotechnology," *Transactions in GIS* 16, no. 2 (April 2012): 177–90, doi:10.1111/j.1467-9671.2012.01318.x.

10 Matthew T. Rice et al., "Crowdsourced Geospatial Data: A Report on the Emerging Phenomena of Crowdsourced and User-Generated Geospatial Data," Annual (Fairfax, VA: George Mason University, November 29, 2012), http://www.dtic.mil/dtic/tr/fulltext/u2/a576607.pdf.

11 Matthew T. Rice et al., "Crowdsourcing Techniques for Augmenting Traditional Accessibility Maps with Transitory Obstacle Information," *Cartography and Geographic Information Science* 40, no. 3 (June 2013): 210–19, doi:10.1080/15230406.2013.799737.

12 Matthew T. Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility," US Army Corps of Engineers, Engineer Research and Development Center, US Army Topographic Engineering Center Technical Report, Data Level Enterprise Tools Workgroup (Fairfax, VA: George Mason University, September 2013), http://oai.dtic.mil/oai/oai?verb=getRecord&metadataPrefix=html&identifier=ADA588474.

13 Matthew T. Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed," Annual (Fairfax, VA: George Mason University, September 23, 2014).

14 Fabiana I. Paez, "Recruitment, Training, and Social Dynamics in Geo-Crowdsourcing for Accessibility" (Master of Science, George Mason University, 2014).

15 Han Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments," *GeoJournal*, no. 10.1007/s10708–015–9659– x (2015): 1–18.

16 Han Qin et al., "Obstacle Characterization in a Geocrowdsourced Accessibility System," *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences* 1 (2015): 179–85.

17 Rebecca M. Rice, "Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study" (Master's of Science Thesis, George Mason University, 2015).

18 Rebecca M. Rice et al., "Position Validation in Crowdsourced Accessibility Mapping," *Cartographica: The International Journal for Geographic Information and Geovisualization* 50, no. 4 (n.d.): (in press).

practitioners focus on defining the terminology, placing boundaries on the field, and exploring the early implementations and activity. The current research, conducted in 2014 and 2015, asks: "What can be done in real world settings with geocrowdsourced data?", "What are the practical limitations of the quality assessment processes?" and "Can geocrowdsourced data be used in real dynamic, field-based settings?" This report addresses these questions, which focus on practical quality control, moderation strategies, and dynamic real-world uses of geocrowdsourced data. As a vehicle to explore these issues, we present the George Mason University Geocrowdsourcing Testbed (GMU-GcT), which was developed to explore these questions and many more. The GMU-GcT is a descendent of earlier mapping systems developed to help blind, visually-impaired, and mobility-impaired individuals navigate through unfamiliar urban areas (Loomis et al. 2005, Golledge et al. 2005 and 2006, and Rice et al. 2005)[19,20,21,22]. It is also an outgrowth of earlier work on emerging technological issues associated with distributed geographic information services and information sharing communities (Goodchild et al. 2005)[23]. The context for the GMU-GcT and the purposes that it serves are briefly explained in the following section as an introduction to this report. While supplying the necessary geoaccessibility functionality, an underlying value of the GMU-GcT is what it can tell us about the dynamics of geocrowdsourcing. Where possible, these dynamics and lessons learned will be emphasized throughout this report.

The GMU Geocrowdsourcing Testbed

In many geospatial settings, the field-based collection of geospatial data is a critical task. Within dynamic environments, these data collection activities are more challenging due to the rapid updates required to maintain currency and validity. GMU, for example, produces a Physical

[19] Jack M. Loomis et al., "Personal Guidance System for People with Visual Impairment: A Comparison of Spatial Displays for Route Guidance," *Journal of Visual Impairment & Blindness* 99, no. 4 (2005): 219.

[20] Reginald G. Golledge, Matthew Rice, and Daniel Jacobson, "A Commentary on the Use of Touch for Accessing On-Screen Spatial Representations: The Process of Experiencing Haptic Maps and Graphics," *The Professional Geographer* 57, no. 3 (August 2005): 339–49, doi:10.1111/j.0033-0124.2005.00482.x.

[21] Reginald G. Golledge, Matthew T. Rice, and R. Daniel Jacobson, "Multimodal Interfaces for Representing and Accessing Geospatial Information," in *Frontiers of Geographic Information Technology* (Springer, 2006), 181–208.

[22] Matt Rice et al., "Design Considerations for Haptic and Auditory Map Interfaces," *Cartography and Geographic Information Science* 32, no. 4 (2005): 381–91.

[23] Michael F. Goodchild et al., "Report of the NCGIA Specialist Meeting on Spatial Webs" (Santa Barbara, CA: NCGIA, April 2005).

Accessibility Map each August, and publishes the map online in an attempt to highlight accessible pathways and areas of significant construction activity on what is a rapidly changing campus environment (Figure 1). Provided in static PDF format, this map is updated once a year, which makes it out-of-date virtually days after it is released. Certain features, such as walkways that meet the Americans with Disabilities Act (ADA) standard design criteria for running slope, are drawn with a green line symbol and it is these features that have some longevity. A major problem, however, emerges when these features are made inaccessible by construction fencing, temporary barricades, and other transient activity.

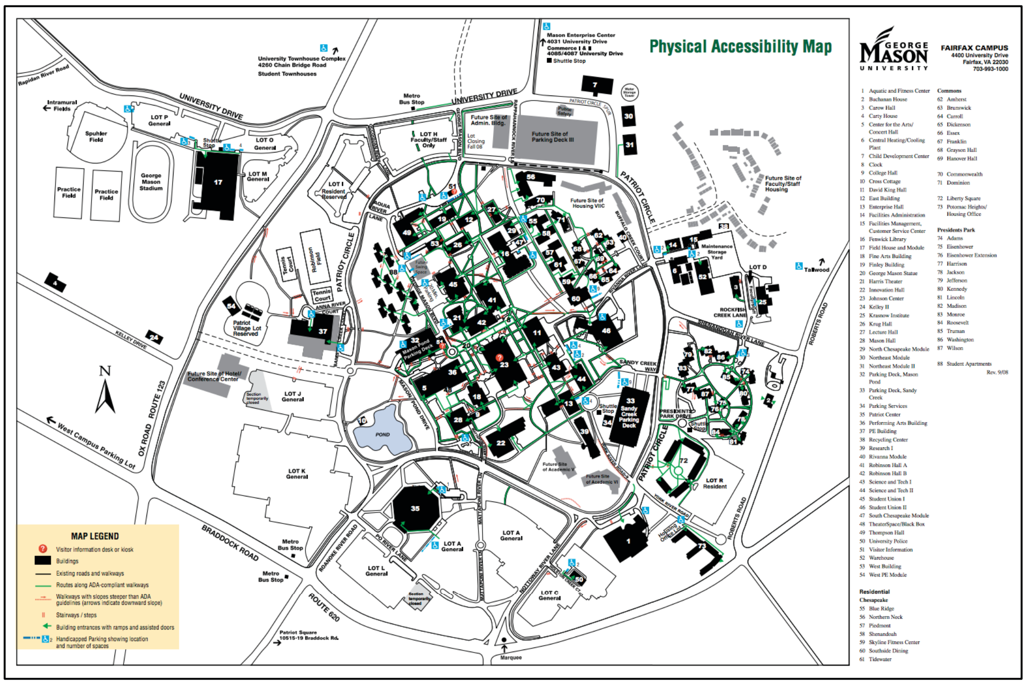

Figure 1. GMU's Physical Accessibility Map [24]

For the 250-300 blind, visually-impaired, and mobility-impaired students, faculty, and staff, changes to the GMU campus walkways can present great difficulty from the perspective of navigation and wayfinding, which involve the careful planning and repetitive use of pre-selected, accessible navigation corridors. When transient obstacles appear on navigation pathways (Figure 2), these individuals are required to improvise through backtracking and by using alternative pathways.

24 http://eagle.gmu.edu/map/pdfs/fairfax_access.pdf [accessed, August 10, 2015]

Figure 2. Transient Navigation Obstacle

Based on the seminal work of Loomis et al. (2005, Figure 3)[25], Marston et al. (2006)[26], and Golledge et al. (2006)[27]; Rice et al. (2011, 2013b)[28,29] presented the conceptual design of a geocrowdsourcing system for collecting transient obstacle information to assist blind, visually-impaired, and mobility-impaired individuals navigate through unfamiliar environments. The resulting GMU Geocrowdsourcing Testbed (GMU-GcT) has been presented and demonstrated in several previous publications, notably Rice et al. (2013a, 2013b, and 2014).[30,31,32] The purpose of the system is to build a layer of quality-checked and validated obstacle data with known positional and temporal characteristics that can be disseminated to the public through our website, distributed as a data source via KML, and used in dynamic routing and obstacle avoidance

25 Loomis et al., "Personal Guidance System for People with Visual Impairment: A Comparison of Spatial Displays for Route Guidance."

26 James R. Marston et al., "Evaluation of Spatial Displays for Navigation Without Sight," *ACM Trans. Appl. Percept.* 3, no. 2 (April 2006): 110–24, doi:10.1145/1141897.1141900.

27 Golledge, Rice, and Jacobson, "Multimodal Interfaces for Representing and Accessing Geospatial Information."

28 Rice et al., "Integrating User-Contributed Geospatial Data with Assistive Geotechnology Using a Localized Gazetteer."

29 Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

30 Rice et al., "Crowdsourcing Techniques for Augmenting Traditional Accessibility Maps with Transitory Obstacle Information."

31 Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

32 Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed."

scenarios. As discussed in Liu and Pelan (2010)[33], the future of crowdsourcing systems such as ours, will likely be as a hybrid combination of professional, authoritative elements and citizen-based neo-geographic elements.

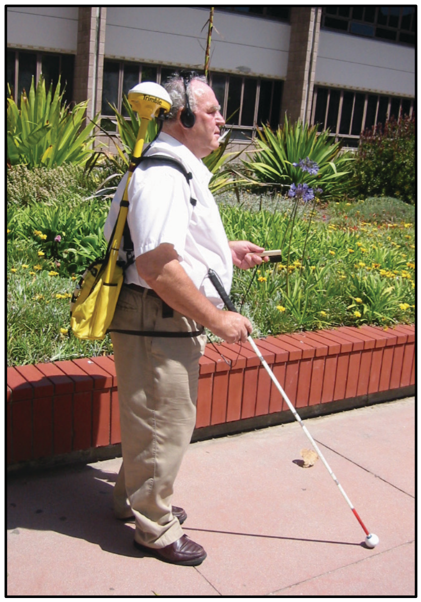

Figure 3. UCSB Personal Guidance System, circa 2003

Chapter 2 of this report provides an overview of mobile-device capabilities for geocrowdsourcing and specifically, constraints associated with mobile device global positioning systems (GPS). Chapter 3 provides a study of the social moderation process in geocrowdsourcing and what it can provide for the GMU-GcT. In Chapter 4 we look at the dynamic engagement of obstacle data with the mobile, field-based incarnations of the GMU-GcT and general positioning capabilities of GPS-enabled mobile devices. Chapter 5 explores an extension of the GMU-GcT in the area of routing analysis. The final chapter of this report summarizes selected research themes for this project and addresses what are viewed as important future issues in geocrowdsourcing. The combined retrospective and future look at geocrowdsourcing is drawn from our past technical reports and the research work presented here, as well as topics that we suggest will be important in the upcoming years.

[33] Liu and Palen, "The New Cartographers."

2 Mobile Devices and Geocrowdsourcing

In his research publications George Mason University (GMU) Associate Professor Dieter Pfoser describes an explosion of user generated content (UGC) available over the Internet (Pfoser 2011, Crooks et al. 2014)[34,35]. He describes contemporary UGC as staggering in size and growing larger at a rapid pace. His observations echo Sui et al.'s 2013 warning of an impending "exaflood" of digital information. Both authors suggest that digital geospatial content forms an important element in this tremendous growth, and a reason for this growth is the widespread availability of location-aware mobile devices used to collect data, photographs, observations, and information. Pfoser describes this geospatially-oriented UGC as a rich mixture of quantitative and qualitative geospatial information, ranging from georeferenced data collected by device GPS to text-based travel narratives, facilitated by the information collected and stored by location-aware smart phones.

This chapter looks at the primary mobile tool associated with this growing body of geospatially-oriented UGC: the GPS-enabled smart phone. We explore the use of mobile devices for many geocrowdsourcing activities, including several current applications from a variety of different domains, where the mobile device and its positioning capabilities facilitate the central functions of the application. We also present a review of mobile phone-based GPS capabilities, and a study by project collaborators on the positioning constraints of mobile phone GPS used in the field.

GPS-enabled Dynamic Geocrowdsourcing Applications

One of the most significant drivers of GPS-based data collection and GPS-embedded device production is athletics and recreation. The tracking of athletes and measures of athletic performance are of high interest to scientists and trainers, who use GPS tracking for speed and distance measurements in tennis and other court-constrained sports (Duffield et al. 2010)[36]. Applications in this area include GPS-enabled geosocial and

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[34] Dieter Pfoser, "On User-Generated Geocontent," in *Advances in Spatial and Temporal Databases* (Springer, 2011), 458–61.

[35] Andrew Crooks et al., "Crowdsourcing Urban Form and Function," *International Journal of Geographical Information Science*, no. ahead-of-print (2014): 1–22.

[36] Rob Duffield et al., "Accuracy and Reliability of GPS Devices for Measurement of Movement Patterns

geocrowdsourcing applications such as Strava (Figure 4) which track and map the running events of end-users and facilitates social interaction through a geosocial community. Strava uses mobile GPS to calculate distance, speed, rate, elevation gain, and if equipped with GPS waypoints for a pre-defined running course, can calculate distance deviations from the defined course. Strava uses a map-based and social-community based engagement strategy to encourage connections between athletes in local areas. The map-based tracking functionality using device GPS represents a key capability in the mobile tools designed for the GMU-GcT, while the geosocial functionality in this app represents an important recruitment and engagement aspect of geocrowdsourcing, addressed by Paez (2014) and Rice et al. (2014).

in Confined Spaces for Court-Based Sports," *Journal of Science and Medicine in Sport* 13, no. 5 (2010): 523–25.

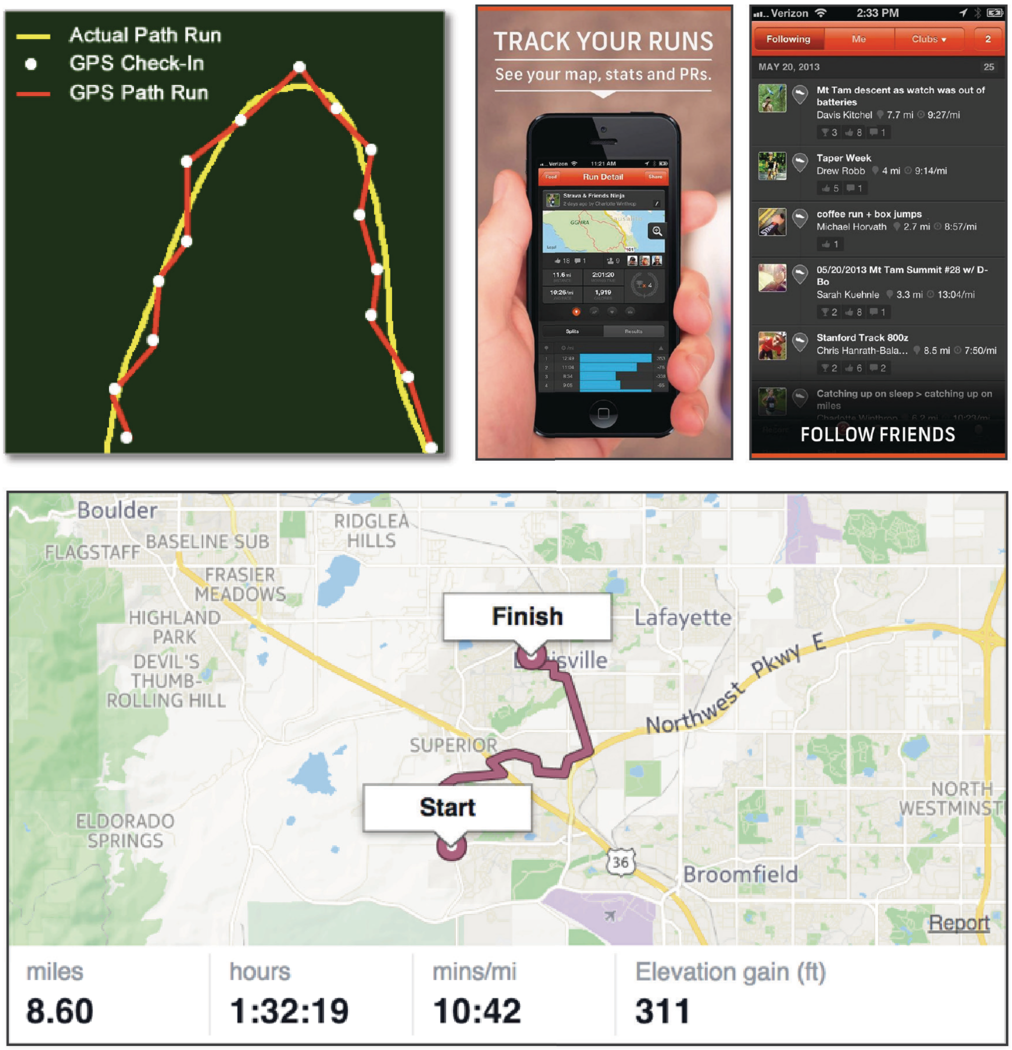

Figure 4. GPS-enabled geosocial athletics and run-tracking applications[37]

Geocaching is the modern incarnation of a treasure hunt game, where GPS-enabled mobile devices are used to locate hiding places, called 'caches' and track items left in the cache and carried to other caches by participants. The most popular mobile geocaching application, produced by Groundspeak, Inc. and distributed through the Apple App Store as "Geocaching," contains map-based and GPS-based searching capabilities, with orientation and distance displays, including an uncertainty estimate for GPS, popup reminders about device GPS capabilities and the current search radius (Figure 5). There are more than 2 million geocaches hidden

[37] https://www.strava.com/ [accessed August 23, 2015]

in 184 countries world-wide, and an estimated user base of 3-4 million.[38,39] The spatial searching functionality in the Geocaching App and focus on distance between user and object using mobile device GPS is similar to functionality in mobile GMU-GcT tools discussed in this report.

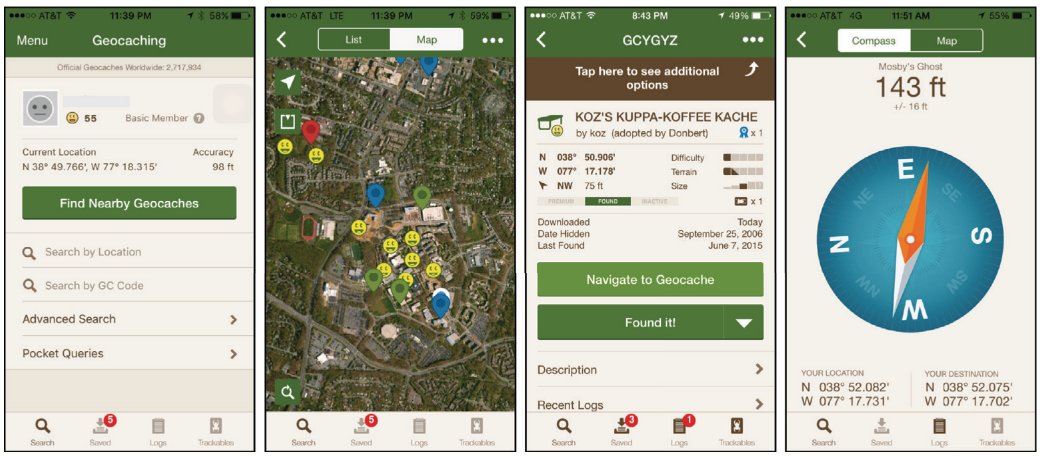

Figure 5. Geocaching GPS-enabled mobile application

Many contemporary geocrowdsourcing applications are transportation-related, which reflects the view expressed by Pfoser and others, that one of the most significant emerging trends in current geocrowdsourcing is the generation of tracking data used for transportation analysis and related transportation and logistics activities. The combination of dynamic data collection and analysis is at the foundation of the mobile GMU-GcT activities profiled in this report, where we focus on the interaction of end-users and moderators with location-aware mobile devices that both contribute and receive geocrowdsourced data from the field.

The local public transportation network serving the City of Fairfax and GMU includes signage with QR codes that when scanned with a mobile device, opens a dynamic bus tracking service that provides distance and time estimates between a user's location and the bus's location (Figure 6). This tracking data is dynamically updated through a web application and a GPS bus tracking system. On the back end, the next bus service can analyze the patterns associated with service requests generated from

[38] http://www.geocaching.com/blog/2013/02/celebratin-two-million-geocaches-list-by-country/ [accessed August 23, 2015]

[39] http://forums.groundspeak.com/GC/index.php?showtopic=241632 [accessed August 23, 2015]

specific QR codes, and provide information to public transportation providers about location-specific queries, which could be used to improve infrastructure or focus service on locations with high QR code scanning activity.

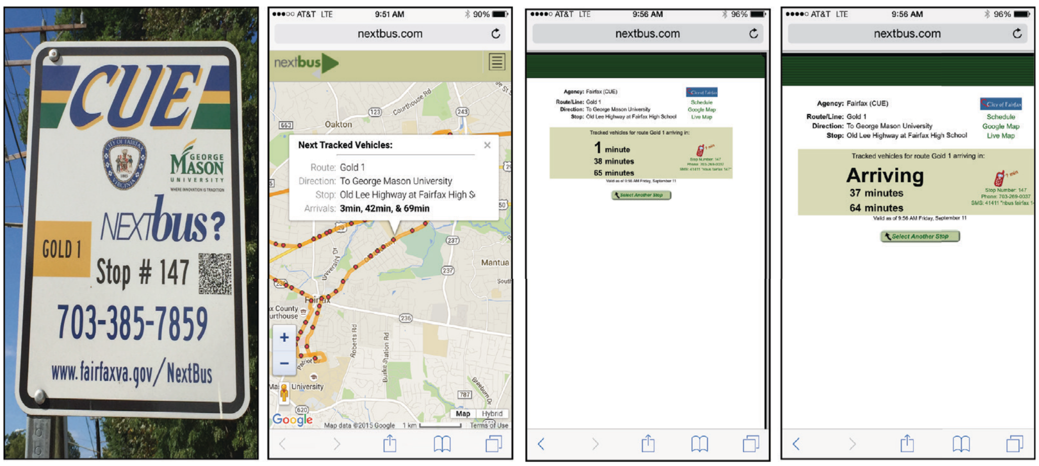

Figure 6. Sign-mounted QR code for City of Fairfax CUE bus tracking through the NextBus Service[40]

The GPS Alarm Clock application (Figure 7) is a novel application for travelers and public transit riders, similar to the accessibility application developed by Barbeau et al. (2010),[41] to provide notification of proximity to a planned stop. This is targeted toward inattentive or sleeping passengers, as well as disabled travelers who need advanced warning of an approaching stop. The application uses the built-in GPS device uncertainty estimates, provided as a blue bubble around the present GPS location, as well as a distance threshold for triggering warnings. The functionality in this application is directly relevant to our interest in providing mobile obstacle notifications through the GMU-GcT.

[40] https://www.nextbus.com [accessed August 23, 2015]

[41] Sean J. Barbeau et al., "Travel Assistance Device: Utilising Global Positioning System-Enabled Mobile Phones to Aid Transit Riders with Special Needs," *Intelligent Transport Systems, IET* 4, no. 1 (2010): 12–23.

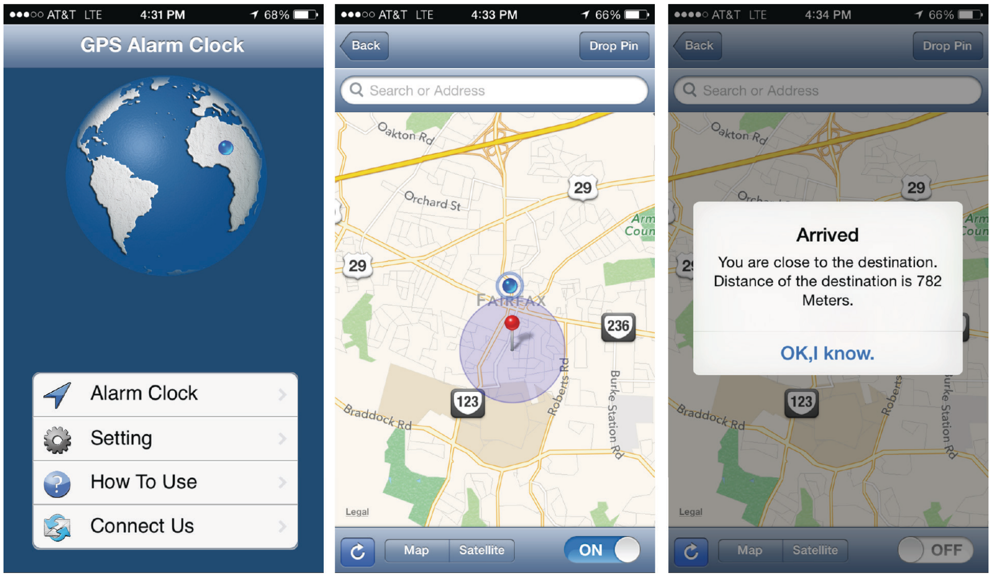

Figure 7. Location and scale-sensitive GPS Alarm for commuters

Finally, Yik Yak is a geosocial application that has received a great deal of attention over the last two years, due to the anonymous nature of the interactions among end-users. The concept of the geosocial application is a geographically-defined user community, which includes all users within a specific radius of the end-user. This user community dynamically changes based on the location of the device. As a useful dynamic element, the application shuts down when it detects that it is located near to or inside of the footprint for a public school facility, other than colleges and universities, where it operates freely (Figure 8). This geofencing functionality was implemented to curb the anonymous trolling and anti-social elements that became widespread among younger users. This novel method for controlling mobile device interaction using geographic location highlights the capabilities for device-based GPS to be a part of fundamental interaction in geocrowdsourcing and geosocial media. Figure 37 shows the application being shut down due to proximity to Fairfax High School.

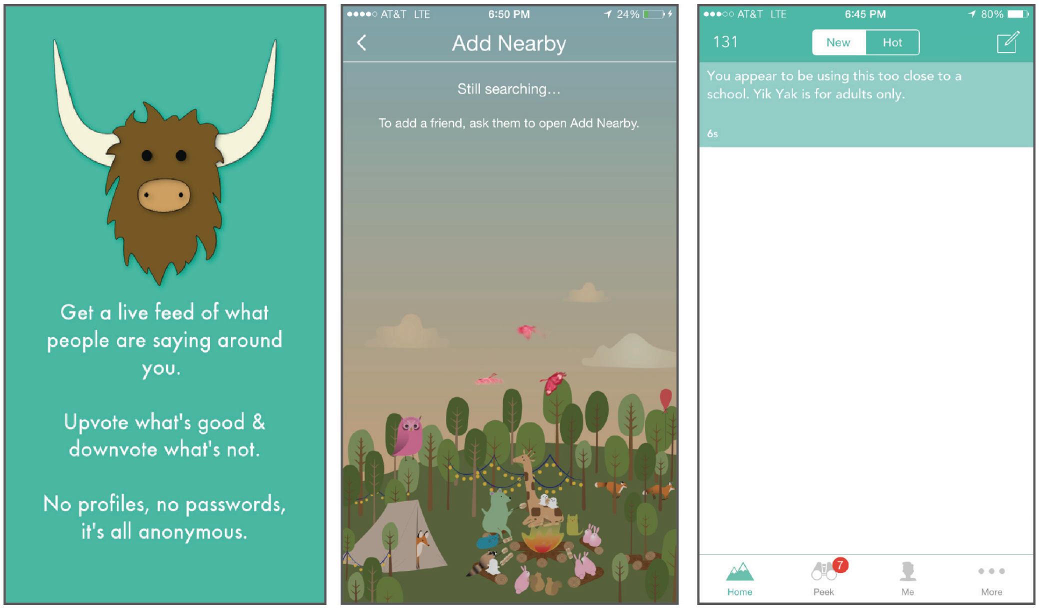

Figure 8. Yik-Yak geosocial mobile app with geofencing capabilities[42]

Mobile Device GPS Accuracy Studies

In a 2009 study of the iPhone 3G, Zandbergen studied the horizontal error patterns for mobile device GPS, finding a Root Mean Square Error (RMSE) of 8.3 meters, and a maximum error of 18.5 meters (Figure 9)[43]. The Garmin GPS device used as a control had a maximum error of 1.4m and an RMSE of 1.0 meters.

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42 http://www.yikyakapp.com/ [accessed August 23, 2015]

43 Paul A. Zandbergen, "Accuracy of iPhone Locations: A Comparison of Assisted GPS, WiFi and Cellular Positioning," *Transactions in GIS* 13, no. s1 (2009): 5–25.

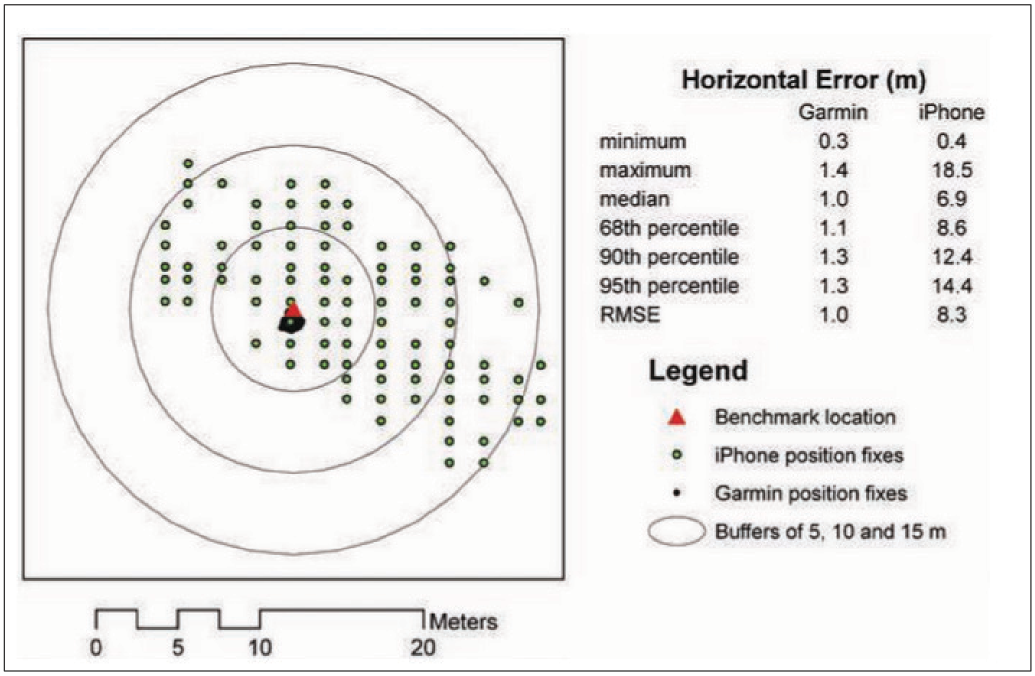

Figure 9. Horizontal error plot for Garmin and iPhone GPS, from Zandbergen (2009)

An earlier study by Modsching et al. (2006)[44] looked at GPS accuracy for travelers and tourists in a medium-sized city. They found error rates for four different consumer-level GPS receivers to be between 2.5 meters (for open areas such as public squares) and 15.4 meters (for urban streets with four story buildings on each side, Figure 10). The Modsching et al. study provides estimates for GPS accuracy in the type of public spaces and buildings heights encountered by end-users of the GMU-GcT.

[44] Ibid.

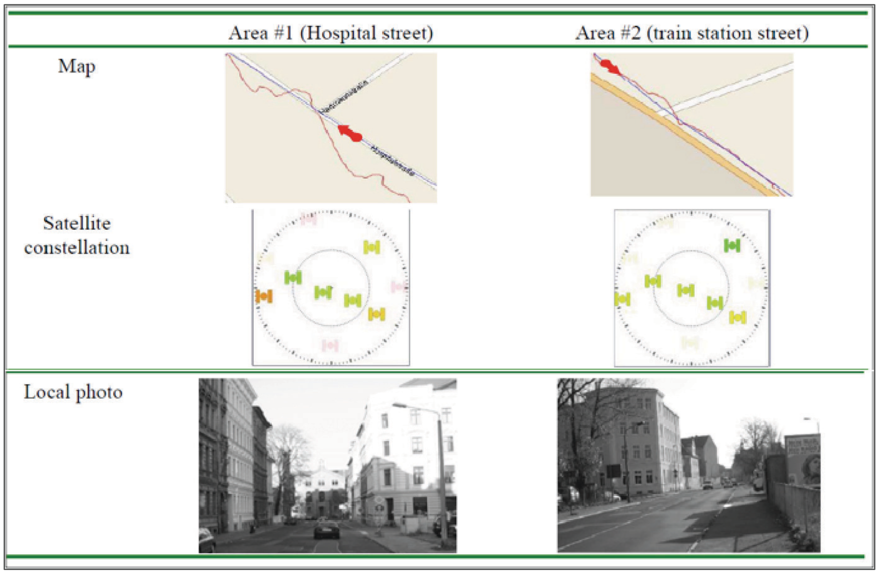

Figure 10. GPS accuracy study for two urban settings, from Modsching et al. (2006)

GMU Geocrowdsourcing Testbed Mobile Device GPS Accuracy Study

GMU Doctoral student and research collaborator Rodney Vese has been an instrumental part of the State of Maryland's public mapping and GIS efforts, with responsibility for studying the feasibility of citizen-based mapping of public trails. In order to understand how to conflate trail data geocrowdsourced with mobile devices, and provide quality assessment for position, Rodney has begun a large study of consumer-device capabilities under a variety of conditions and circumstances. Some of his preliminary data is presented here, along with error estimates that confirm the estimates of Zandbergen (2009)[45] and Modsching et al. (2006)[46].

Vese uses methodology based on the Frechet distance, which is a measure for the distance between two curves, proposed by Frechet (1906)[47]. In a much later study, Alt et al. (1995)[48] gave an algorithm for the computation. A popular illustration of the Frechet distance is the following: Suppose a person is walking his dog, the person is walking on the one curve and the

45 Ibid.

46 Marko Modsching, Ronny Kramer, and Klaus ten Hagen, "Field Trial on GPS Accuracy in a Medium Size City: The Influence of Built-Up," in *3rd Workshop on Positioning, Navigation and Communication*, 2006, 209–18.

47 M. Maurice Fréchet, "Sur Quelques Points Du Calcul Fonctionnel," *Rendiconti Del Circolo Matematico Di Palermo (1884-1940)* 22, no. 1 (1906): 1–72.

48 Helmut Alt and Michael Godau, "Computing the Fréchet Distance between Two Polygonal Curves," *International Journal of Computational Geometry & Applications* 5, no. 01n02 (1995): 75–91.

dog on the other. Both are allowed to control their speed but they are not allowed to go backwards. Then the Frechet distance of the curves is the minimal length of a leash that is necessary for both to walk the curves from beginning to end. Figure 11, from Brakatsoulas et al. (2005)[49] provides a visual example of the Frechet distance for two curves, Q and P.

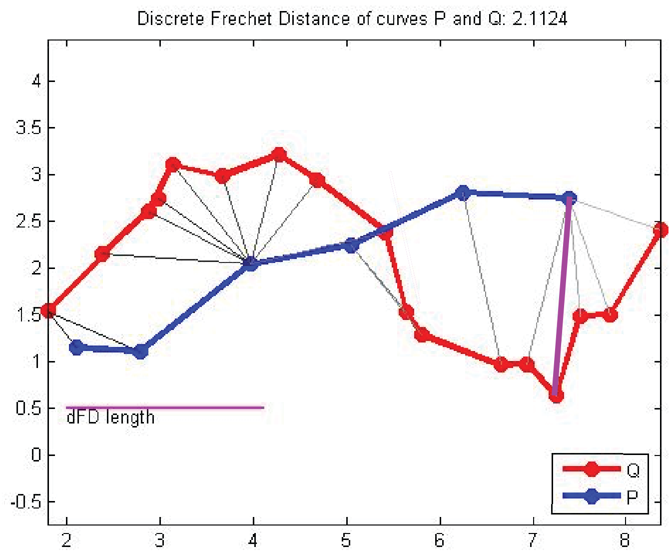

Figure 11. Frechet Distance for curves P and Q, from Brakatsoulos et al. (2005)

This general methodology is used to compare the curve generated by a survey-grade Trimble GPS with iPhone4, iPhone5, and iPhone6 GPS curves. The mobile devices utilize Collector for ArcGIS to automatically stream device GPS coordinates to ArcGIS Online while being carried along trails or pedestrian pathways. The mobile GPS data is collected and stored using editable feature service layers from Esri's Spatial Database Engine (ArcSDE), with double precision coordinates preserved through the entire processing chain. Additional post-processing routines are used to check data consistency and add calculated Frechet distances to each segment. An excerpt from these mobile device tracks is shown in Figure 12 and Figure 13 (below), as part of a large data collection transect through our study area. The transect began in the center of the GMU campus, proceeding 1.5 miles to the center of the City of Fairfax, and returned on the same path, using the sidewalks.

[49] Sotiris Brakatsoulas et al., "On Map-Matching Vehicle Tracking Data," in *Proceedings of the 31st International Conference on Very Large Data Bases* (VLDB Endowment, 2005), 853–64.

Figure 12. Ground-level view of mobile device GPS tracks, Fairfax, Virginia

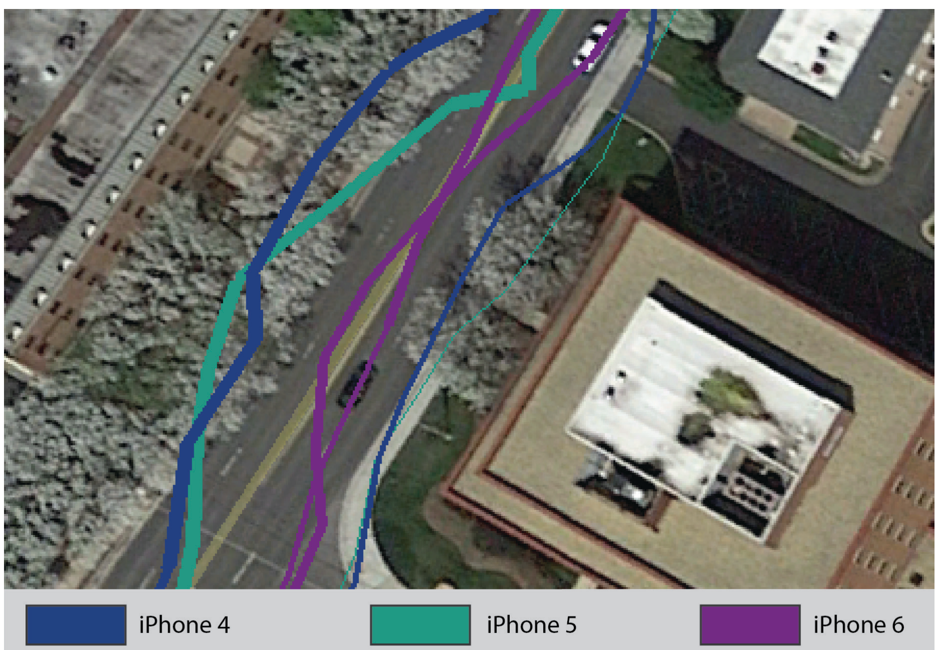

Figure 13. Overhead view of mobile device GPS tracks, Fairfax, Virginia

After the data collection transect is finished, Frechet distances are calculated and stored as attributes of each curve segment using post-processing routines in MATLAB. Average Frechet distances for each device are calculated for 30-second time intervals and stored separately. Figure 14, Figure 15, and Figure 16 (below) show average Frechet distances for a section of this transect near the north side of the GMU campus, with the iPhone 4 have a Frechet distance of 6.42 meters, iPhone 5 having a Frechet distance of 5.62 meters, and iPhone 6 having a Frechet distance of 4.75 meters.

Table 1 has a summary of average Frechet distance for each device along 3 component tracks of the larger transect, and an average Frechet distance for the total observations from all tracks. In this case, the average Frechet distance for the iPhone 4 is 10.51 meters, the iPhone 5 is 6.72 meters, and the iPhone 6 is 5.92 meters.

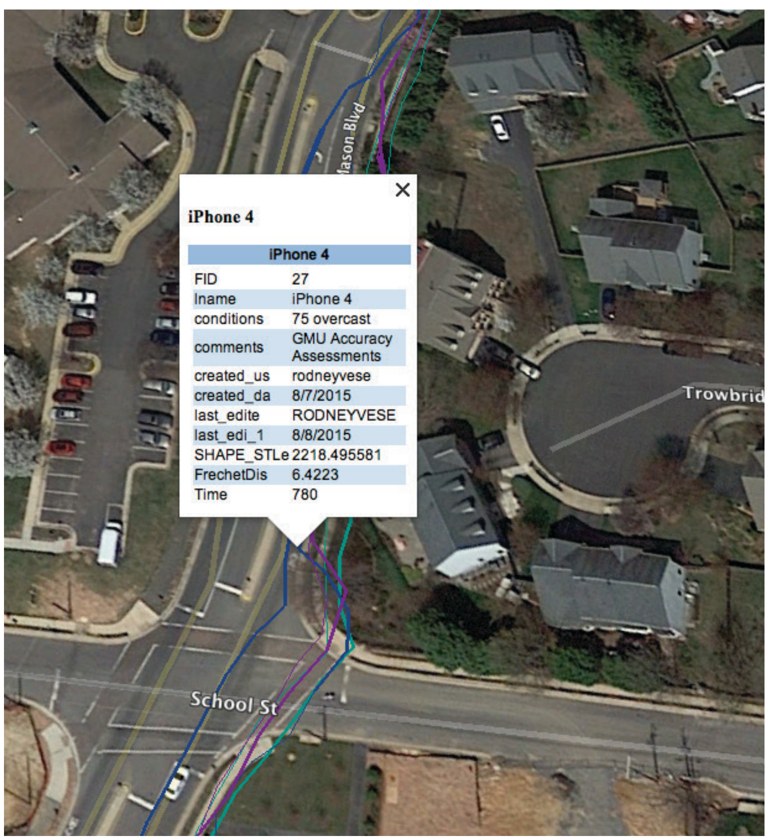

Figure 14. Mobile GPS tracks and average Frechet distance for iPhone 4

Figure 15. Mobile GPS Tracks and Average Frechet Distance, iPhone 5

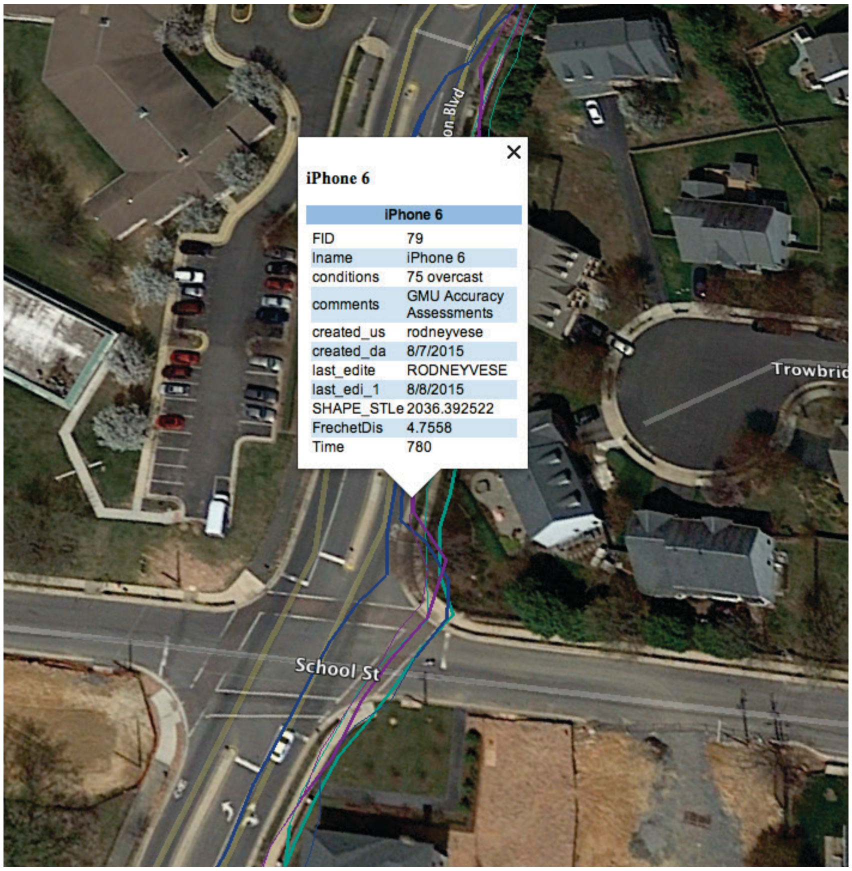

Figure 16. Mobile GPS Tracks and Average Frechet Distance, iPhone 6

Table 1. Average Frechet distances for mobile device GPS (meters) with weighted average.

Average Frechet Distances

		Frechet Distance	Weighted Average
iPhone 6	Track 1	5.89	**5.92**
	Track 2	5.11	
	Track 3	7.94	
iPhone 5	Track 1	5.26	**6.72**
	Track 2	6.68	
	Track 3	10.44	
iPhone4	Track 1	8.71	**10.51**
	Track 2	11.32	
	Track 3	13.15	

In addition to average Frechet distances, the mobile device GPS accuracy study conducted for this research project looked at the type of canopy cover (or alternatively), land use/land cover as a factor responsible for significant variation in GPS accuracy. The Modsching study (2006) found mobile device GPS to be more accurate in open areas, such as public squares, and less accurate near tall buildings. Preliminary work by Vese in the state of Maryland confirms this general trend. In the local study area, Vese found mobile device GPS tracks to have more variation in areas with tall buildings, likely due to multipath error, where the signal received by the mobile GPS is being reflected from tall structures. Figure 17 shows this dynamic, with all GPS tracks within 6.62 meters of each other near the City of Fairfax City Hall, which is characterized as 'Open Canopy'. The area just 1/3 mile north on University Drive, near the GMU Commerce building shows mobile device tracks spreading to a width of 23.16 meters, where larger 5-6 story buildings predominate.

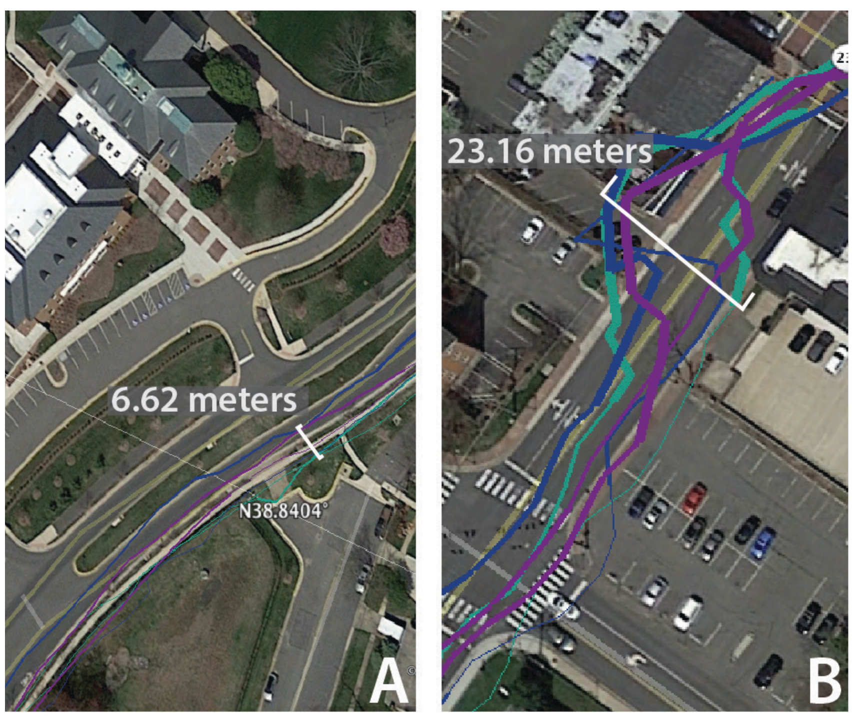

Figure 17. Mobile GPS tracks, Open Canopy (A) and Urban (B)

A thorough analysis of canopy coverage types and average Frechet distance is presented in Figure 18, Figure 19, Figure 20, Figure 21 and Table 3, from a collection of multiple data transects through the State of

Maryland. The average Frechet distance for areas with Open Canopy was 7.53 meters, Partial Canopy was 7.07 meters, Heavy Canopy was 9.47 meters, and Urban Canopy (including taller buildings) was 14.83 meters. Each of these average Frechet distances were calculated across multiple transects with thousands of individual observations. An analysis of variance (ANOVA) for the four canopy types (Table 3) shows an F-statistic of 6.02 and an associated p-value of 0.0014. The critical F-statistic value for this test (with 3 and 49 degrees of freedom and alpha = 0.05) is 2.794. Based on these numbers, we can conclude that the null hypothesis, suggesting no significant variation between treatment groups (canopy types), can be rejected. For the four canopy types, at least one of them is different than the others.

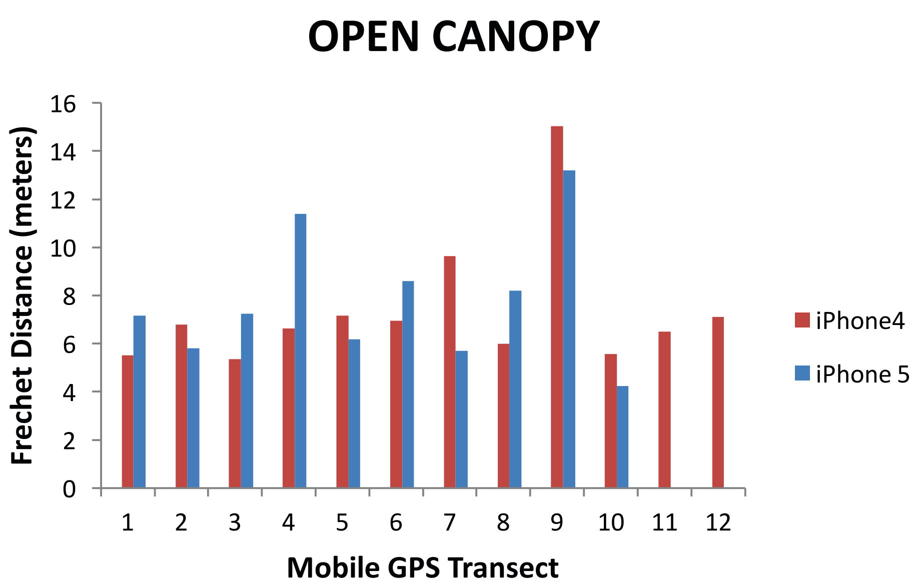

Figure 18. Mobile GPS data transect with average Frechet distance (Open Canopy)

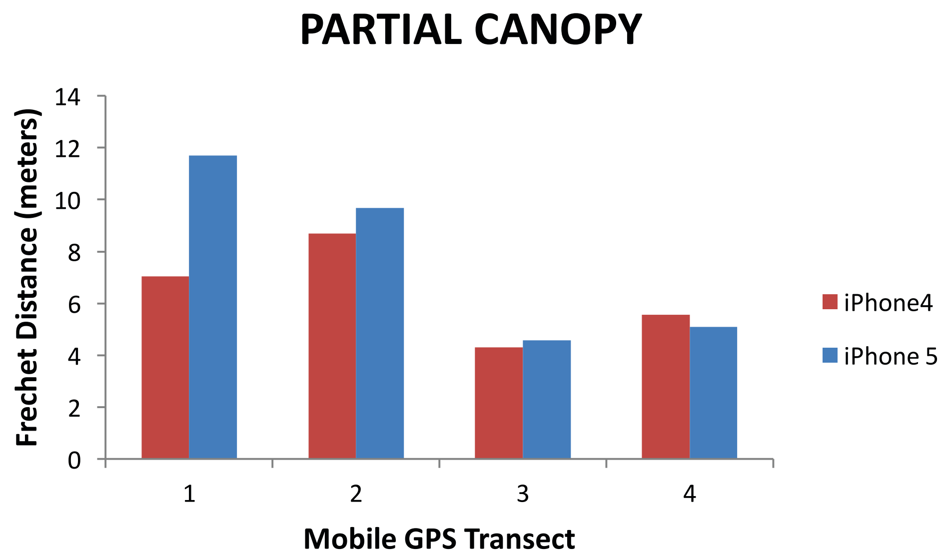

Figure 19. Mobile GPS data transect with average Frechet distance (Partial Canopy)

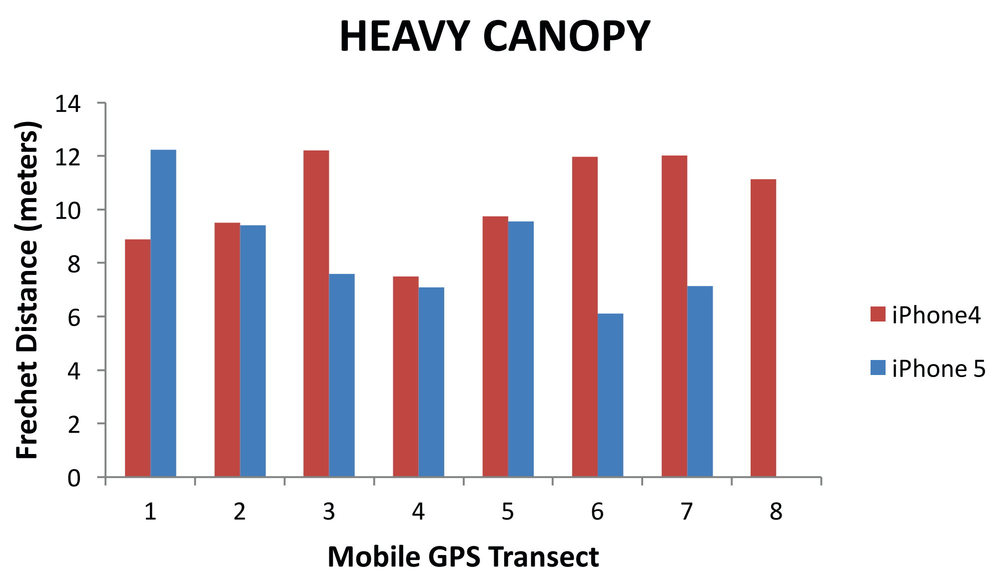

Figure 20. Mobile GPS data transect with average Frechet distance (Heavy Canopy)

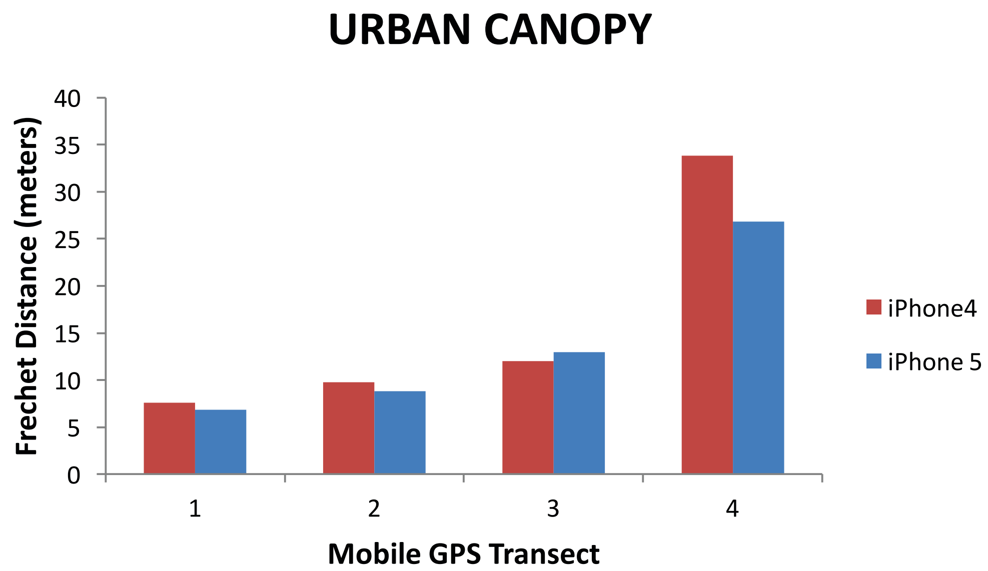

Figure 21. Mobile GPS data transect with average Frechet distance (Urban Canopy)

Additional pairwise tests for the average Frechet distances by canopy type (Table 3 and Table 4), with the Bonferroni correction, indicate that only the Heavy Canopy type is different than the Open and Partial Canopy. All other pairwise comparisons yield results where the null hypothesis (equality of means) cannot be rejected. It is important to note that the Urban Canopy type (Figure 21, Table 2, Table 3, and Table 4) has a much larger variance than the other types, and therefore cannot be distinguished as different during the pairwise tests for means. The shape of the graph for Urban Canopy in Figure 21 reflects the same variation seen in Figure 17(B), where tall buildings result in interference, likely from multipath error.

Table 2. Single factor ANOVA for Canopy Type

Single Factor ANOVA for Canopy Type

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Open	22	165.8593	7.539061	6.988686
Partial	8	56.63584	7.079479	7.269384
Heavy	15	142.0906	9.472703	4.346086
Urban	8	118.6585	14.83231	99.13493

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	351.206	3	117.0685	6.022817	0.001414	2.79395
Within Groups	952.438	49	19.43751			
Total	1303.64	52				

Table 3. Test for Equality of Variances for Average Frechet Distance by Canopy Type. Green figures show homoscedastic pairs, red figures show heteroskedastic pairs.

Equalilty of Variances (F-tests, Observed / Critical)

	Open	**Partial**	**Heavy**	**Urban**
Open		1.04 / 2.48	1.61 / 2.38	14.19 / 2.49
Partial	1.04 / 2.48		1.67 / 2.76	13.64 / 3.79
Heavy	1.61 / 2.38	1.67 / 2.76		22.81 / 2.76
Urban	14.19 / 2.49	13.64 / 3.79	22.81 / 2.76	

Table 4. Pairwise T-Tests for Average Frechet Distance by Canopy Type. Green figures show means with statistical equality, orange figures show means with inequality.

Pairwise T-tests (T-value, P-value | T-critical at 0.05)

	Open	**Partial**	**Heavy**	**Urban**
Open		0.419, 0.678 | 2.04	2.37, 0.023 | 2.03	2.045, 0.080 | 2.364
Partial	0.419, 0.678 | 2.04		2.369, 0.027 | 2.07	2.125, 0.066 | 2.306
Heavy	2.37, 0.023 | 2.03	2.369, 0.027 | 2.07		1.505, 0.176 | 2.364
Urban	2.045, 0.080 | 2.364	2.125, 0.066 | 2.306	1.505, 0.176 | 2.364	

For GPS-based mobile device positioning, we can assume that positioning will vary based on whether or not the end-user is near tall buildings, or perhaps under heavy canopy. Zandbergen cites a GPS horizontal accuracy figure of 8.3 meters (RMSE) with a maximum of 18.5 meters. Modsching et al. found the GPS horizontal accuracy to vary between 2.5 and 15.4 meters, based on whether the location was open or near tall buildings. Vese's GPS study yields confirmatory results, with average Frechet distances between 7.52 and 14.8 meters generally, and for our specific study area, between 5.92 meters and 10.51 meters, depending on the device used. The Vese GPS study, and earlier studies by Zandbergen and Modsching et al. suggest that mobile devices have approximate accuracies between 2.5 meters and 15.4 meters, likely somewhere between. Applications with a need for higher accuracy, i.e., transportation and navigation, often employ additional methods to snap the device's map-based position to the nearest network, an item explored by Karagiorgou, et al. (2012), Pfoser (2000), Pfoser et al. (2003, 2005), and Brakatsoulas et al. (2005)[50, 51, 52, 53, 54]. For the GMU-GcT, the dynamics for obstacle interaction will be guided by additional uncertainty and interaction buffering, and for moderator search, the mobile GPS accuracy will place the moderator well within the normal visual identification distances.

The quality of the obstacle positioning in the GMU-GcT is based both on the device GPS accuracy (for reports submitted by end-users) as well as map-based positioning and multiple aspects of moderated position validation, as discussed in Chapter 3 of this report, Rice (2015)[55], and Rice et al. (2015)[56]. For the GMU-GcT, we use information from GPS accuracy studies summarized above to control the interaction distances between end-users and moderators with mobile devices, and obstacles in our

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50 Sophia Karagiorgou and Dieter Pfoser, "On Vehicle Tracking Data-Based Road Network Generation," in *Proceedings of the 20th International Conference on Advances in Geographic Information Systems* (ACM, 2012), 89–98.

51 Dieter Pfoser, "Issues in the Management of Moving Point Objects" (Department of Computer Science, the Faculty of Engineering and Science, Aalborg University, 2000).

52 Dieter Pfoser and Christian S. Jensen, "Indexing of Network Constrained Moving Objects," in *Proceedings of the 11th ACM International Symposium on Advances in Geographic Information Systems* (ACM, 2003), 25–32.

53 Dieter Pfoser and Christian S. Jensen, "Trajectory Indexing Using Movement Constraints*," *GeoInformatica* 9, no. 2 (2005): 93–115.

54 Brakatsoulas et al., "On Map-Matching Vehicle Tracking Data."

55 Rice, "Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study."

56 Rice et al., "Position Validation in Crowdsourced Accessibility Mapping."

system. Figure 22 shows a conceptual drawing of an end-user with some positioning uncertainty (based on his/her mobile GPS device positioning error, summarized in this chapter) traversing a path with obstacles, each of which has some final position uncertainty associated with the quality of the social moderation process (summarized in Chapter 3 of this report).

This chapter suggests that the position uncertainty for mobile device users in this scenario is between 5.92 and 10.51 meters, depending on the device used and the presence of tall buildings and heavy canopy (Table 2). The analysis presented in Chapter 3 of this report, and in Rice (2015) suggests that the uncertainty in obstacle positioning in the GMU-GcT is between 2.12 meters and 5.55 meters. The combination of the two uncertainty ranges (shown conceptually as dashed concentric buffers in Figure 22, is 8.04 meters and 16.06 meters. This suggests that in circumstances where a GMU-GcT user has a mobile device with the best positioning (iPhone 6, 5.92 meters) and obstacles have been optimally moderated for position (2.12 meters), the average uncertainty between positions is expected to be approximately 8.04 meters.

Mobile devices with less accurate GPS capabilities and GMU-GcT obstacles with less accurate moderated positions may lead to distances of 16 meters or more. For GMU-GcT moderators interacting with unverified end-user reports with positional error (summarized in Rice et al. 2014 as having an average positional error of 18.36 meters), the uncertainty in position between the moderator (with a mobile device have between average positional uncertainty of 5.92 – 10.51 meters) and the obstacle interaction distance would be 24.28 – 28.87 meters. The interaction distance formulations discussed above are summarized in Table 5 (A) for interaction with moderated obstacles, and Table 5 (B) for mobile interaction with unmoderated reports.

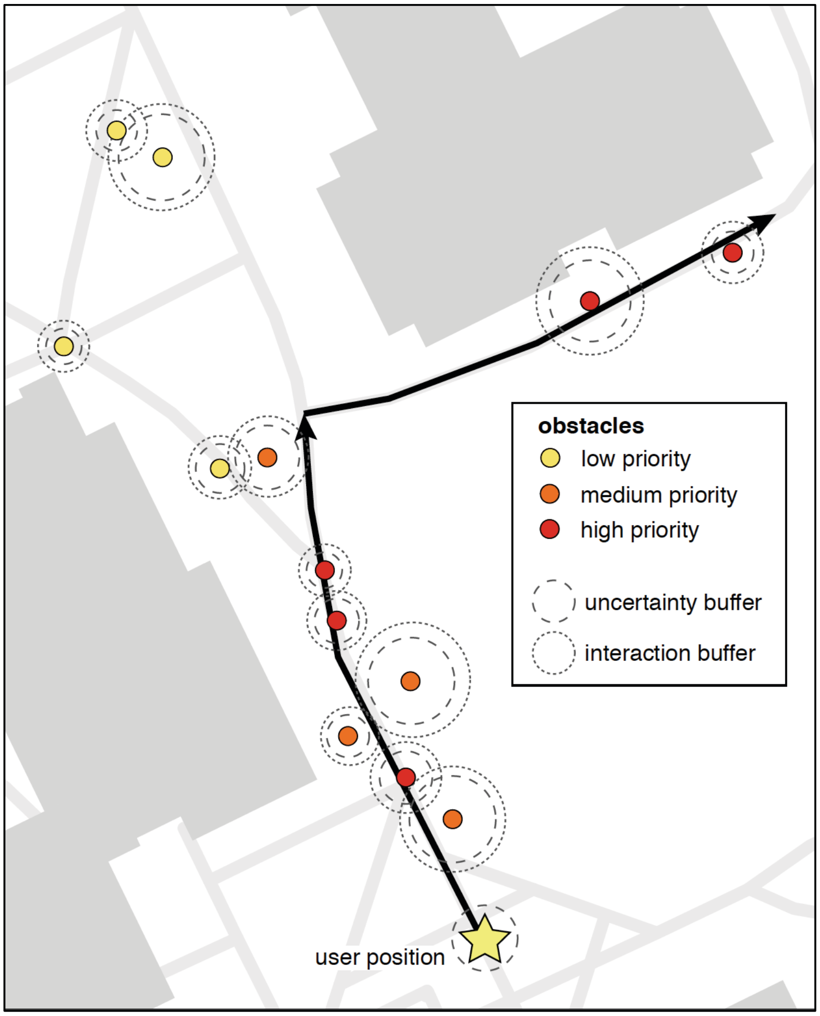

Figure 22. Conceptual diagram of the Interaction between end-user and obstacles in the GMU-GcT

Table 5. Interaction distances for moderated obstacles and for field moderation

A). Interaction distance estimates for moderated GMU-GcT obstacles		
	iPhone 6	**iPhone 4**
Position uncertainty of moderated GMU-GcT obstacles	2.12	5.55
Position uncertainty from Mobile device GPS	5.92	10.51
Interaction Distances (meters)	**8.04**	**16.06**
B). Interaction distance estimates for GMU-GcT field moderation		
	iPhone 6	**iPhone 4**
Position uncertainty of unmoderated reports:	18.36	18.36
Position uncertainty from Mobile device GPS:	5.92	10.51
Interaction Distances (meters)	**24.28**	**28.87**

Mobile Field Moderation in the GMU-GcT

The moderation activities in the GMU-GcT, covered in detail in Rice et al. (2014)[57], Rice et al. (2015)[58,59], and Qin et al. (2015a), have in the past involved a hybrid desktop and mobile interaction paradigm, where information is collected via mobile device and entered into a desktop-based moderation dashboard. Project researchers have decomposed the basic functionalities of this moderation dashboard (presented in Rice et al. 2014)[60] and deployed them to a mobile Web Application design for use on a mobile phone. The benefits of this moderation paradigm have been immediate and clear. The GMU-GcT mobile field moderation tools allow moderators to see and inspect obstacles, collect photographs, and document their properties while viewing the original obstacle reports. This in-situ moderation activity is not only more efficient and satisfying, as reported by project moderators, but is quicker, due to all moderation being done in the field rather than on separate computers over a period of hours. We provide a description of the tool and the mobile moderation workflow here.

The GMU-GcT mobile moderation portal uses the same PostgreSQL database, PHP code, and JavaScript as our desktop moderation dashboard, but uses a JQuery Mobile framework to develop the mobile interface and functionality. Direct connections between our GMU-GcT native mobile application and the mobile moderation portal are provided through HTML links, so that a moderator can use the more responsive native mobile application while in exploratory mode or routing mode, but switch to the web application for mobile moderation. Figure 23 shows two preliminary obstacle selection screens (a single screen with finger scrolling functionality displayed here as two images). This screen is used by moderators to select and preview reports, and contains the key fields for obstacle reports, including User ID, Report ID, Location, Obstacle Description, Obstacle Type, and the contributed images. Experimentation with the mobile moderation tools and the reorganization of the

[57] Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed."

[58] Rice et al., "Position Validation in Crowdsourced Accessibility Mapping."

[59] Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

[60] Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed."

moderation workflow underscored the importance of having the Obstacle Image and map-based location as key elements on the first screen as an essential part of the preview. In our former moderation paradigm, obstacle position was moderated several steps before an image of the obstacle was moderated, but for mobile moderation, the obstacle image needed to be part of the first screen. As we discuss in the final chapter of this report, obstacle images are the primary 'commodity' and future focus on the GMU-GcT.

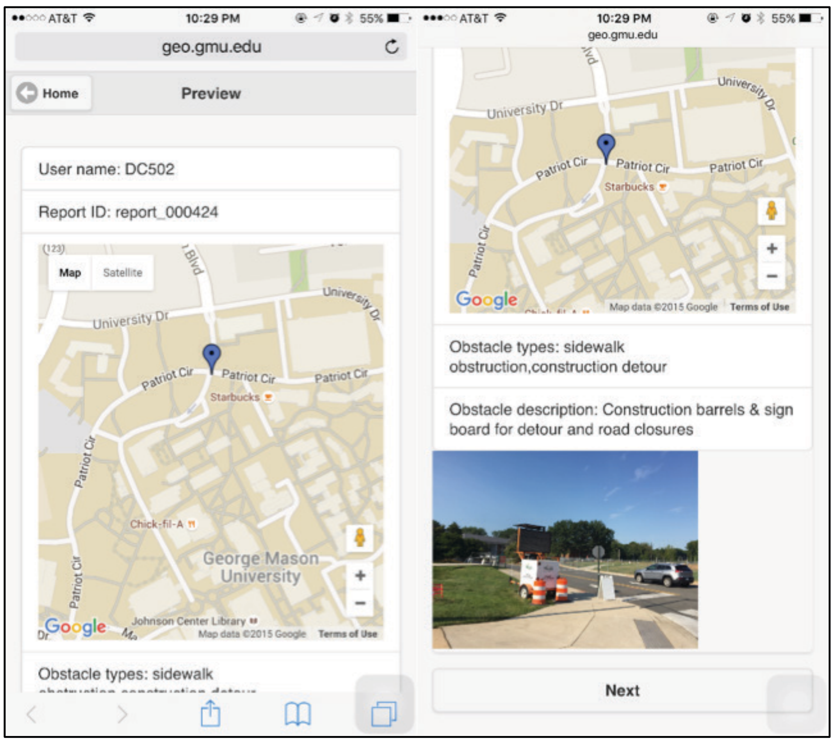

Figure 23. Obstacle selection and preview screen of the GMU-GcT Mobile Moderation Portal

After an obstacle preview, the moderator taps the 'next' button at the bottom of the page. At this point, the moderation tools switch to a non-linear structure with six different screen areas representing different aspects of moderation (Figure 24). The six moderation areas can be visited in sequence or out of order with a single tap.

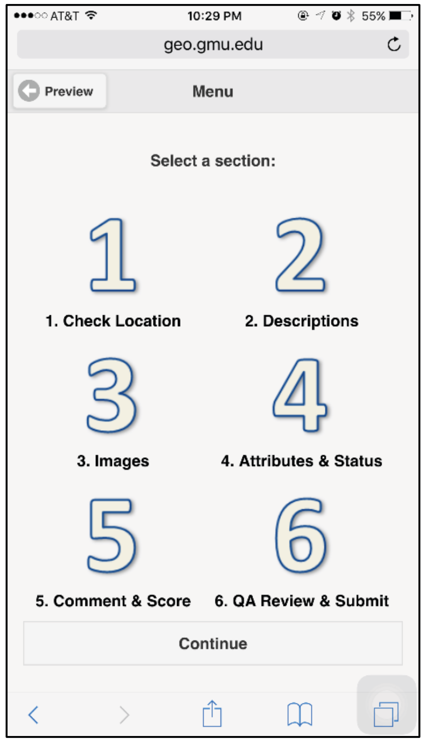

Figure 24. Main Moderation menu of the GMU-GcT Mobile Moderation Portal

Figure 25 shows the location validation functionality, (accessed through tapping #1, Figure 24), which opens a screen with a map-based obstacle position that can be zoomed, and obstacle position updated with a click-drag action. Positional accuracy for the report (calculated with a Haversine-based distance calculation between the reported location and the moderated location) is displayed and stored in our PostgreSQL database.

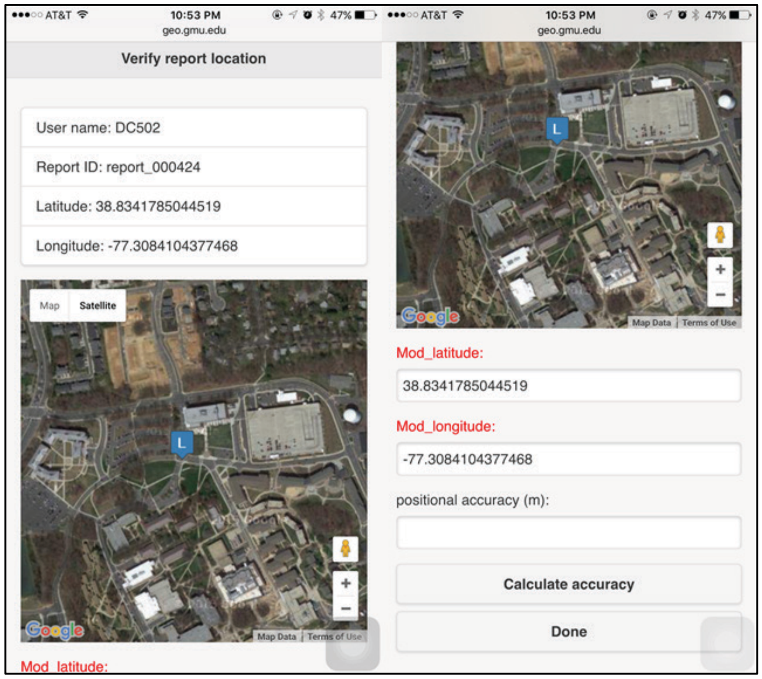

Figure 25. Location validation in the GMU-GcT Mobile Moderation Portal

Figure 26 contains the moderation menus for checking and updating location description, obstacle description, obstacle type, and obstacle impact, which are accessed by tapping #2, Figure 24). The moderated values are stored in our PostgreSQL database.

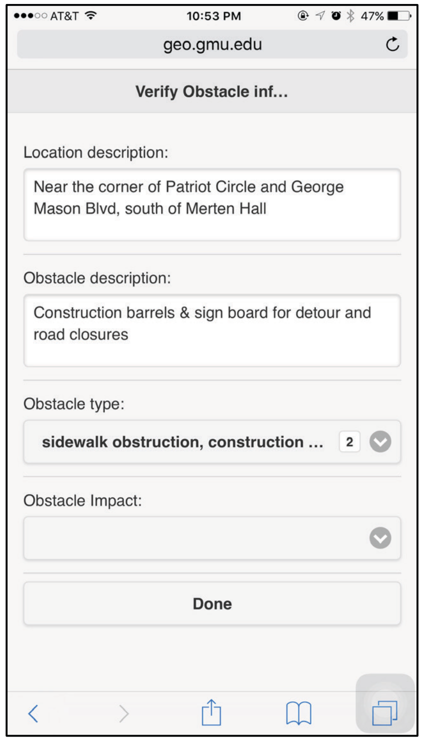

Figure 26. Obstacle descriptions update in the GMU-GcT Mobile Moderation Portal

Image validation (Figure 27) is accomplished through the tools behind item #3 from Figure 24. The screen allows moderators to quickly view and replace images of an obstacle, and provide an assessment of image quality from our Moderator Rubric (discussed in Rice et al. 2014 and Rice 2015)[61,62].

[61] Ibid.

[62] Rice, "Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study."

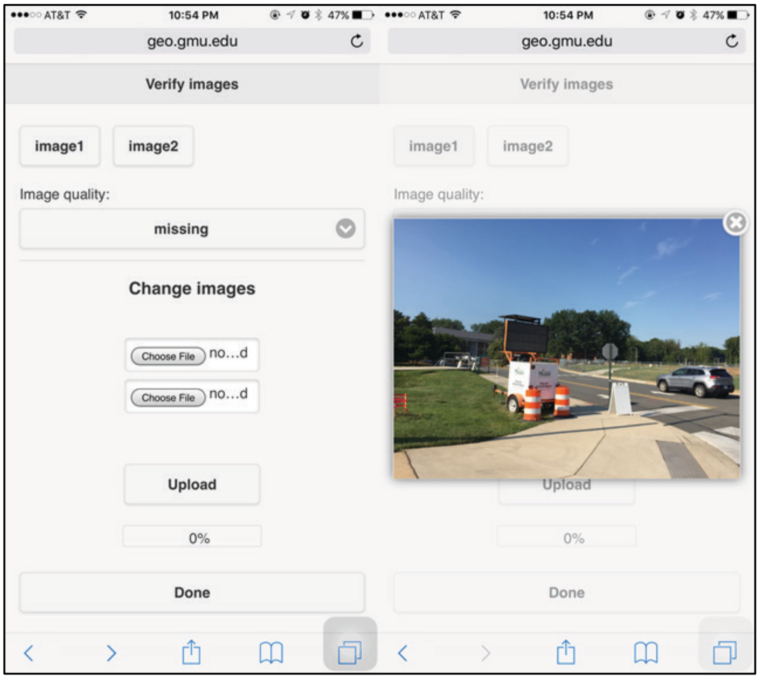

Figure 27. Image validation in the GMU-GcT Mobile Moderation Portal

The remaining screens (accessed through tapping #4, 5, 6 from Figure 24) take the moderator through an assessment of obstacle attributes, including duration, urgency, and status code (Figure 28); moderator comments, report quality scoring, and obstacle lifetime extensions (if needed, Figure 29); and general moderation overview (Figure 30). These items are followed by a confirm / submit process, where quality assessment statistics are displayed and final moderation submission is made (Figure 31).

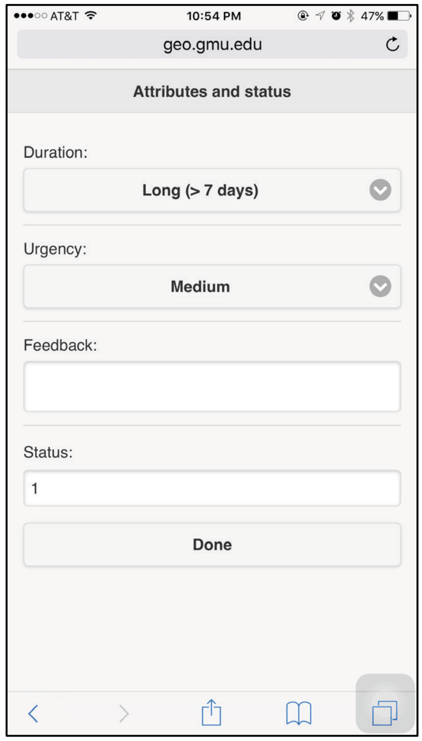

Figure 28. Attributes and status, GMU-GcT Mobile Moderation Portal

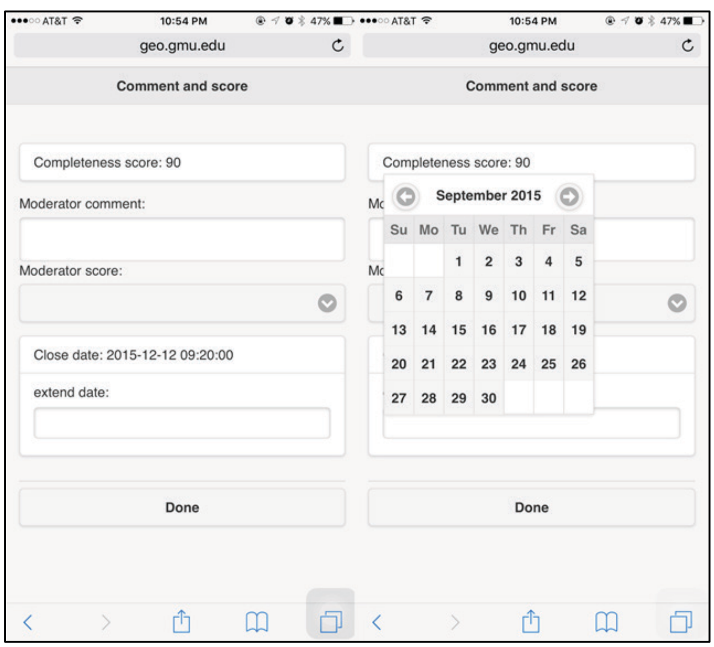

Figure 29. Moderator comments, scoring, and obstacle longevity

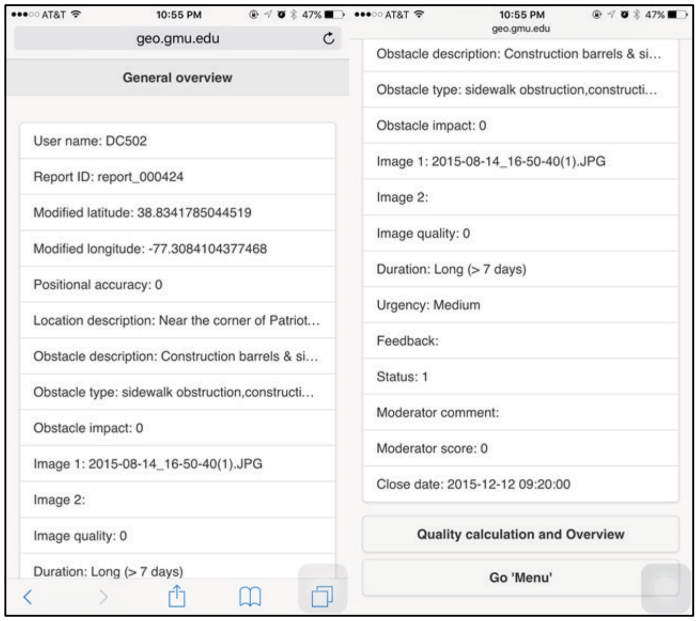

Figure 30. Obstacle moderation overview, GMU-GcT Mobile Moderation Portal

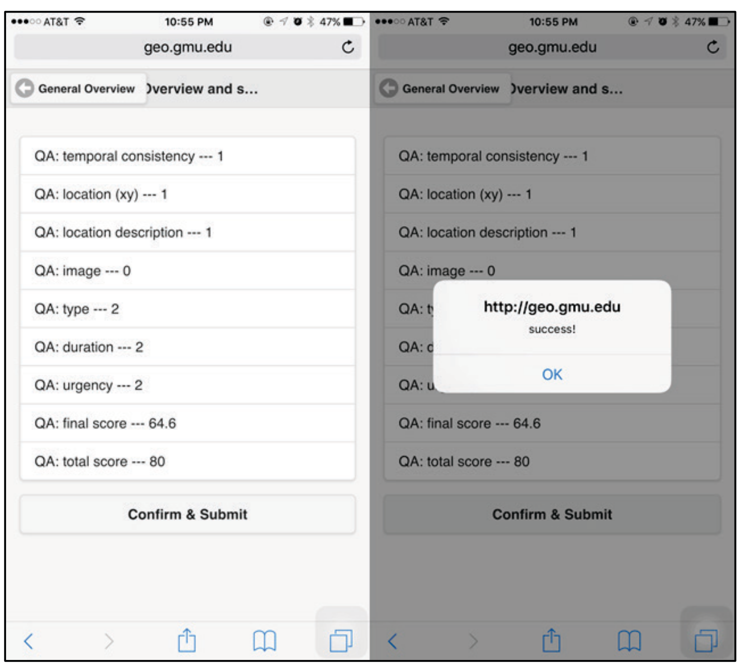

Figure 31. Quality assessment statistics and moderation overview with submit

The following chapter presents an important overview and study of the social moderation process, which is at the heart of the quality assessment for the GMU-GcT, and represents one of the principle quality assessment techniques outlined by Goodchild and Li (2012) for geocrowdsourcing applications.[63]

[63] Michael F. Goodchild and Linna Li, "Assuring the Quality of Volunteered Geographic Information," *Spatial Statistics* 1 (May 2012): 110–20, doi:10.1016/j.spasta.2012.03.002.

3 Social Moderation for Crowdsourced Geospatial Data

Quality assessment and social moderation processes in geocrowdsourcing

Though crowdsourced geospatial data (CGD) has proved to be useful in providing up-to-date information, the quality and the reliability of these datasets are two areas of concern. In the Phase 3 report (Rice et al. 2014)[64], several approaches to ensuring geocrowdsourced data quality were reviewed, along with the approach for data quality assessment used by the GMU Geocrowdsourcing Testbed (GMU-GcT). Large web service platforms such as Wikipedia and OpenStreetMap (OSM) rely on a large contributor base to find and correct errors (a crowdsourced approach), resulting in continuously improved database quality. However, the GMU-GcT cannot solely rely on this approach, due to its smaller contributor group. Since the GMU-GcT produces a reasonably small dataset, with an average contribution rate of ten reports per week, we apply what Goodchild and Li (2012)[65] refer to as the *social approach* to geocrowdsourced quality assessment. This approach relies on a group of team leaders to act as moderators in validating incoming data.

The use of moderators to validate data is necessary when there is no authoritative data source to authenticate geocrowdsourced information, though it is uncertain how accurate this method is. The GMU-GcT utilizes a team of moderators who are thoroughly trained in project details, obstacle classification, and precise methods for moderating reports including field-checking. The aim is for consistency amongst one another in order to establish authority as the ground-truth. However, there is the concern regarding the extent to which the moderators are consistent with one another, as well as if they are a sufficient source for the ground-truth. This section will report on an analysis of the consistency and adequacy of multiple moderators in assessing the quality of GMU-GcT data in both positional location and obstacle characterization. For position, we base

[64] Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed," 201.

[65] Goodchild and Li, "Assuring the Quality of Volunteered Geographic Information."

adequacy on consistency with previous findings in other geocrowdsourced data quality studies, such as Haklay (2010)[66], Girres and Touya (2010)[67], and Ramm et al. (2011) [68], who find that positional error is typically within 5-6 meters in OSM studies (as summarized in Table 6). We also use Camponovo and Freundschuh's (2014)[69] research on prior knowledge of categorical accuracy of geocrowdsourced data. The data used in Camponovo and Freundschuh (2014) is from the Ushahidi Project, a humanitarian relief project that took place during the 2010 Haiti earthquake, where emergency responders were asked to categorize incoming messages into a series of primary and secondary categories. The accuracy rates for placement into primary categories were 50% and subcategories were only 27%. The tasks being performed by emergency responders were difficult and in some cases, unfamiliar, and the messages being categorized involved language translation, which presents further difficulty. Nevertheless, the Camponovo and study highlights the need for analysis of uncertainties associated with categorization by individuals involved in geocrowdsourcing. The GMU-GcT involves several opportunities for contributors to characterize attributes and select categories. Other than the preliminary study by Paez (2014) and this study by Rice (2015), we have not pursued the quality issues associated with errors in categorization to the same depth as presented in the Camponovo study.

66 Mordechai Haklay, "How Good Is Volunteered Geographical Information? A Comparative Study of OpenStreetMap and Ordnance Survey Datasets," *Environment and Planning. B, Planning & Design* 37, no. 4 (2010): 682.

67 Jean-François Girres and Guillaume Touya, "Quality Assessment of the French OpenStreetMap Dataset," *Transactions in GIS* 14, no. 4 (August 2010): 435–59, doi:10.1111/j.1467-9671.2010.01203.x.

68 Frederik Ramm, Jochen Topf, and Steve Chilton, *OpenStreetMap: Using and Enhancing the Free Map of the World* (UIT Cambridge Cambridge, 2011), http://library.wur.nl/WebQuery/clc/1958758.

69 Michael E. Camponovo and Scott M. Freundschuh, "Assessing Uncertainty in VGI for Emergency Response," *Cartography and Geographic Information Science* 41, no. 5 (October 20, 2014): 440–55, doi:10.1080/15230406.2014.950332.

Table 6. Summary of positional accuracy findings for various OpenStreetMap datasets.

Reference	Datasets Analyzed		Positional Accuracy		
	OpenStreet Map	Reference Dataset	Points	Lines	Buffer used
Girres and Touya 2010	France, 2009	Ordnance Survey	6.65 m	Hausdorff distance = 13.57m Average distance = 2.19m	
Haklay 2010	England, 2008	Ordnance Survey		5.83m	3.75m and 5.6m
Arsanjani et al. 2013	Germany, 2012	Federal Agency for Cartography and Geodesy (BKG)			3m, 5m, 10m, 15m
Ciepluch et al. 2010	Ireland, 2010	Google Maps	Used a point system to measure number of errors for road types		
Ramm et al. 2011			Generalizes that data contributed by users using GPS is within 5m		

Moderator Consistency Study

In evaluating moderator consistency, a study was conducted as a part of Rebecca Rice's Master's Thesis (2015). Ms. Rice designed a study in which datasets of three project members who acted as GMU-GcT moderators were tested for consistency. First, the three moderators were trained in the use of moderator tools by Rebecca, the study designer. Each moderator received a rubric, carefully created by the project leader, providing detailed instructions on how to adequately position reports to reflect the actual obstacle location as well as how to correctly classify obstacles. Then the study designer reports a series of obstacles to separate customized versions of the GMU-GcT website, enabling simultaneous blind moderation by all three moderators. As soon as new reports were added to the separate databases and appeared on each moderator's web map, each moderator was asked to field-check, confirm, and quality assess the report. Due to the transient nature of the obstacles being reported, moderators were asked to field-check and moderate reports on the same day the reports are were contributed. Once each of the moderators completed their set of reports for the day, we created a "ground-truth" version of each reported obstacle by making a joint decision with the two study designers and project leader through careful moderation of the report, based on the rubric created by the project leader. This ground-truth version acted as the basis for comparison in evaluating moderator accuracy. The workflow of the study is outlined in Figure 32.

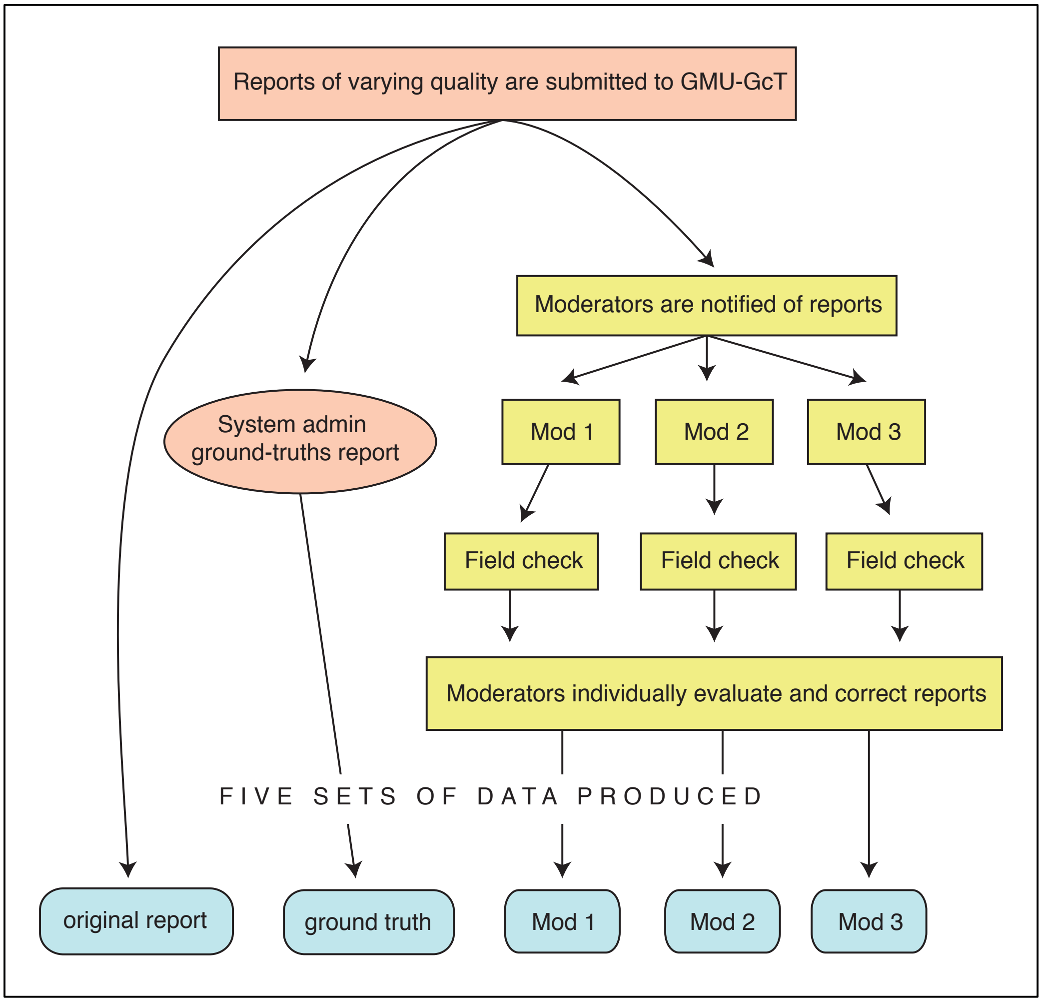

Figure 32. Framework outlining the process for evaluating moderator consistency

Data Collection

Over the course of three weeks in April 2015, a set of 33 reports with varying quality were contributed to the test GMU-GcT database being used for the study by Rebecca, project leader and study designer. Between four and seven obstacles were reported per day, twice a week, and then copied to the three moderator PostgreSQL databases. The moderators were then notified that there were reports to field-check, moderate, and validate. Figure 33 highlights the study area as well as the location of the reported obstacles.

Figure 33. Obstacles report to the GMU-GcT for the moderator consistency study (33 total)

Evaluating Positional Accuracy

Because the GMU-GcT uses its data for obstacle-avoidance in routing, positional accuracy is critical, as demonstrated by Figure 34. Once moderated, obstacles are expected to intersect with the GMU-GcT's pedestrian network. To evaluate positional accuracy, the position of each moderated report was compared to the ground-truth report for each obstacle. The "near" tool in ArcMap was used to calculate the distance from one feature to its nearest feature based on the projected coordinate system of the data, resulting in the distance of each moderated report from the actual obstacle. These distances are analyzed to determine the overall positional error and gain insight into moderator accuracy in positioning reports.

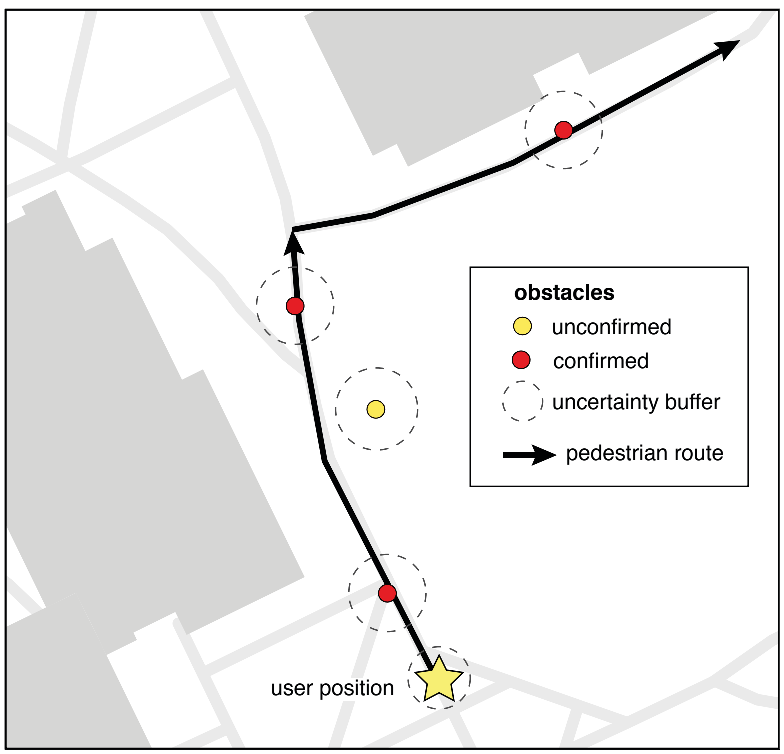

Figure 34. Obstacle avoidance in routing for the GMU-GcT. Obstacles are buffered to facilitate interaction through routing and mobile exploration. An unconfirmed report may not intersect with the pedestrian network.

Evaluating categorical consistency for obstacle type

Because the GMU-GcT is meant to be useful for end-users with varying accessibility needs, it is important that obstacles are correctly categorized. The classification system for obstacle type is outlined extensively in the rubric given to the moderators. The GMU-GcT uses six main categories to classify obstacles: sidewalk obstruction, construction detour, poor surface condition, entrance/exit problem, crowd/event, and other. Moderators can select one or multiple obstacle types during the validation process. The reports evaluated by the moderators in this study contained varying data quality, meaning that some reports did not need obstacle type changes, while other reports needed considerable attention. After the data collection, all moderator databases were analyzed, and each obstacle report was given a score based on consistency with ground truth. Reports received a “2” for a complete match, a “1” for a partial match, and a “0” for no match. Averaging all of the reports scores for each moderator provided a final score on overall categorical consistency for the obstacle type category.

Results

Thirty-three obstacles were reported during the course of this study, resulting in a total of 132 data entries for quality analysis. The study area, campus sections 1-4, containing the ground-truth location of the obstacles along with the position chosen by each of the moderators, is shown in Figure 35, Figure 36, Figure 37, and Figure 38, while Table 7 summarizes the positional measures for the 33 collected reports. The average positional error amongst the three moderators is 5.55 meters, with a standard deviation of 2.86 meters. Out of the 33 obstacle reports, 54.5% of reports were positioned within three meters of the obstacle’s actual location, which is well within the expected distance as laid out by previous research. 69.7% of the reports were positioned within 6 meters of the obstacle’s actual location, which is in congruence with similar findings regarding positional accuracy of VGI. Figure 39 is a representation of two reports that were positioned very well by the moderators, which is ideal in the realm of geocrowdsourced data quality. An analysis of variance (ANOVA) for comparing the mean positional accuracy figures for the three moderators (Table 8) indicates that there were no significant differences between them (F-statistic 1.5735, p-value 0.2162). An analysis of the type of obstacle (point, areal) indicates that the mean positional accuracy for point features (2.12 meters) is significantly different from the mean positional accuracy for areal features (12.54 meters). This comparison is based on a Student's T-statistic with heteroskedastic variance and an unequal sample size, results in a t- value of 4.817, a p-value of 0.00002, with 38 degrees of freedom (Table 9).

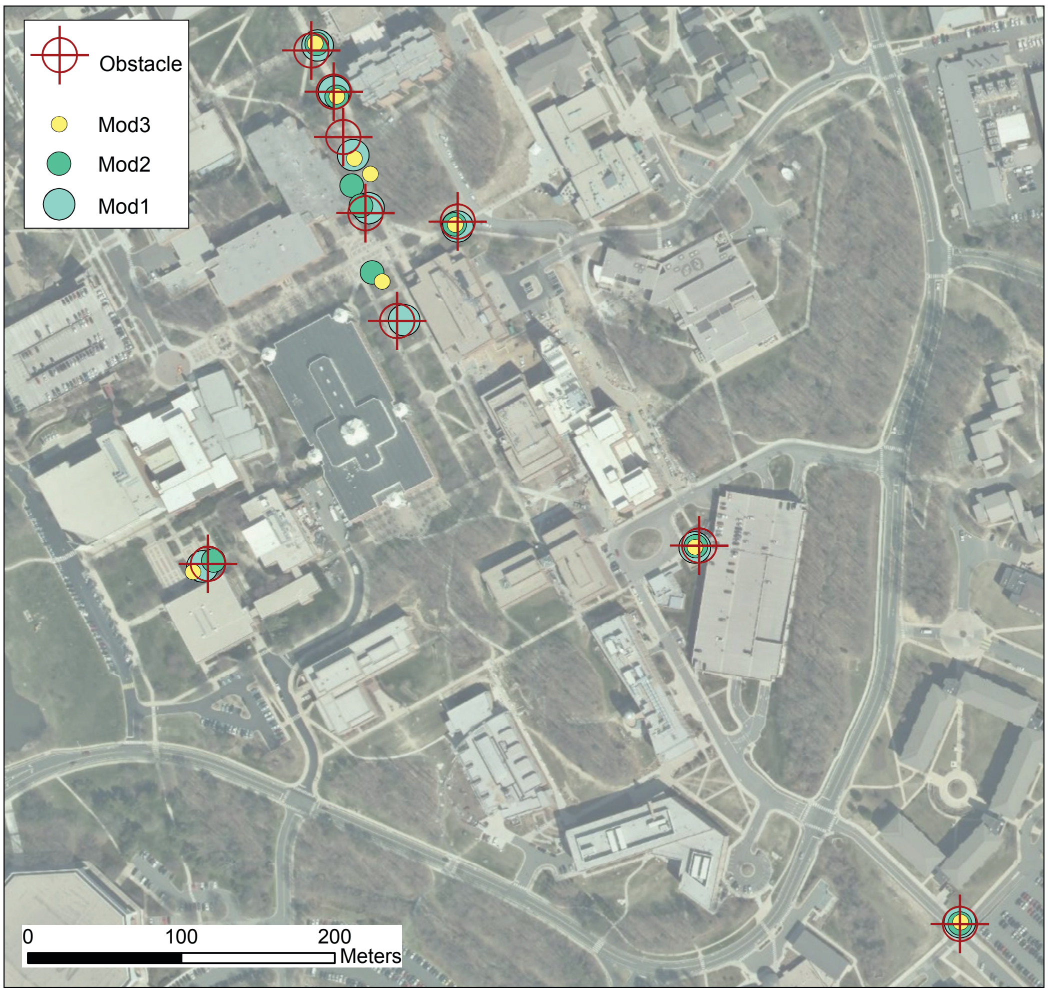

Figure 35. Obstacle reported to the GMU-GcT for the moderator consistency study, including the obstacle's actual report location and the locations chosen by moderators. South GMU Campus

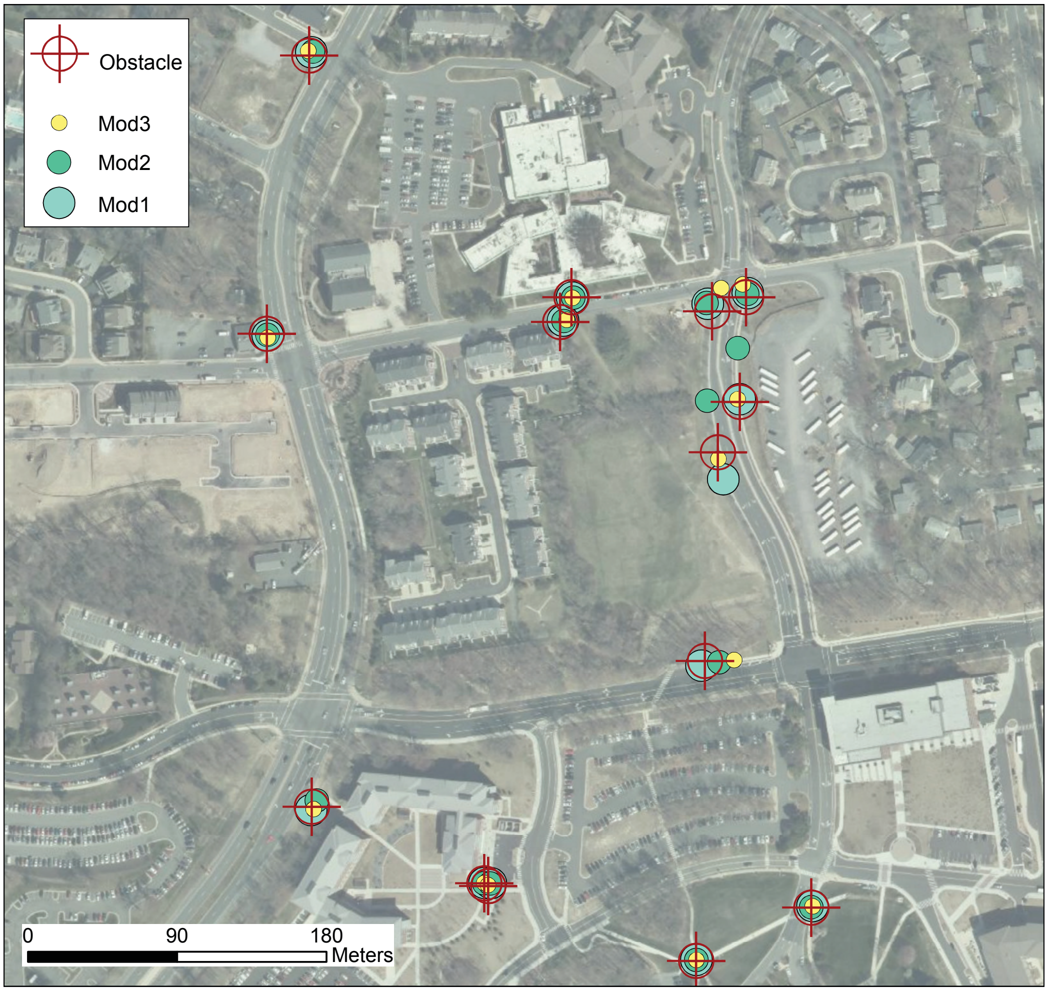

Figure 36. Obstacle reported to the GMU-GcT GcT for the moderator consistency study, including the obstacle's actual location and the locations chosen by moderators. North GMU Campus

Figure 37. Obstacle reported to the GMU-GcT for the moderator consistency study, including the obstacle's actual location and the locations chosen by moderators. Old Town Fairfax

Figure 38. Obstacle reported to the GMU-GcT for the moderator consistency study, including the obstacle's actual location and the locations chosen by moderators. North Fairfax.

Table 7. Positional error for each report, based on the location determined by each moderator. Positional error is calculated as the difference between the moderator position and the confirmed ground truth position.

Positional Errors of Moderated Reports						
Report	Mod1	Mod2	Mod3	AVG PE	STDEV	Areal Feature?
report_0001(mod)	2.25	0.65	1.14	1.35	0.82	
report_0002(mod)	3.59	3.69	0.16	2.48	2.01	
report_0003(mod)	2.74	2.80	3.38	2.97	0.35	
report_000365(mod)	15.79	20.21	13.55	16.52	3.39	Y
report_000366(mod)	11.35	4.07	4.27	6.56	4.15	Y
report_000367(mod)	0.66	1.10	0.42	0.73	0.35	
report_000368(mod)	1.07	0.48	0.94	0.83	0.31	
report_000369(mod)	17.36	8.43	3.63	9.81	6.97	Y
report_0004(mod)	2.98	2.24	3.18	2.80	0.50	
report_0005(mod)	1.77	4.72	2.20	2.90	1.59	
report_0007(mod)	27.48	35.71	4.45	22.55	16.20	Y
report_0008(mod)	5.17	5.61	5.12	5.30	0.27	
report_0009(mod)	14.93	6.12	5.32	8.79	5.33	Y
report_00010(mod)	7.97	2.03	2.57	4.19	3.28	Y
report_00011(mod)	3.98	2.06	1.77	2.60	1.20	
report_00012(mod)	3.00	3.38	2.39	2.92	0.50	
report_00013(mod)	1.00	2.22	3.79	2.34	1.40	
report_00014(mod)	3.52	2.60	1.26	2.46	1.13	
report_00016(mod)	8.28	1.56	5.44	5.09	3.37	Y
report_00017(mod)	4.09	19.70	16.59	13.46	8.26	Y
report_00018(mod)	2.22	26.95	1.53	10.23	14.48	Y
report_00019(mod)	4.26	2.64	16.46	7.79	7.55	Y
report_00020(mod)	5.71	55.14	4.73	21.86	28.83	Y
report_00021(mod)	9.09	0.37	1.89	3.78	4.66	
report_00022(mod)	4.10	4.83	1.86	3.59	1.55	
report_00023(mod)	0.72	0.76	0.57	0.69	0.10	
report_00024(mod)	0.93	5.05	0.76	2.25	2.43	
report_00025(mod)	4.17	0.25	0.25	1.56	2.27	
report_00026(mod)	25.87	5.79	3.70	11.79	12.24	Y
report_00027(mod)	0.36	0.59	0.51	0.49	0.12	
report_00029(mod)	0.27	0.13	0.17	0.19	0.07	
report_00030(mod)	1.07	0.37	1.07	0.84	0.41	
report_00031(mod)	0.60	1.83	2.07	1.50	0.79	
Average Positional Error	6.01	7.09	3.55	5.55	2.86	
Average Positional Error (Areal Features Removed)	2.53	2.18	1.66	2.12	4.15	

Table 8. Analysis of Variance for Moderator Positional Accuracy

Analysis of Variance (One-Way)

Summary

Groups	Sample size	Sum	Mean	Variance
mod1	33	198.35048	6.01062	48.85601
mod2	33	234.07044	7.09304	141.05155
mod3	33	117.13823	3.54964	17.54808

ANOVA

Source of Variation	SS	df	MS	F	p-level	F crit
Between Groups	217.62105	2	108.81052	1.5735	21.26176%	3.09119
Within Groups	6,638.58048	96	69.15188			
Total	6,856.20152	98				

Table 9. T-Test for Obstacle Type (point, areal)

T-Test: Positional Accuracy for Obstacle Type

Descriptive Statistics

VAR	Sample size	Mean	Standard Deviation	Variance
point	63	2.12136	1.78096	3.17183
areal	38	12.54855	13.27182	176.14116

t-test assuming unequal variances (heteroscedastic)

Degrees of Freedom	38
Hypothesized Mean Difference	0.
Pooled Variance	67.81694
Test Statistics	4.81707

Two-tailed distribution

p-level	0.00002	*Critical Value (5%)*	2.02439

One-tailed distribution

p-level	0.00001	*Critical Value (5%)*	1.68595

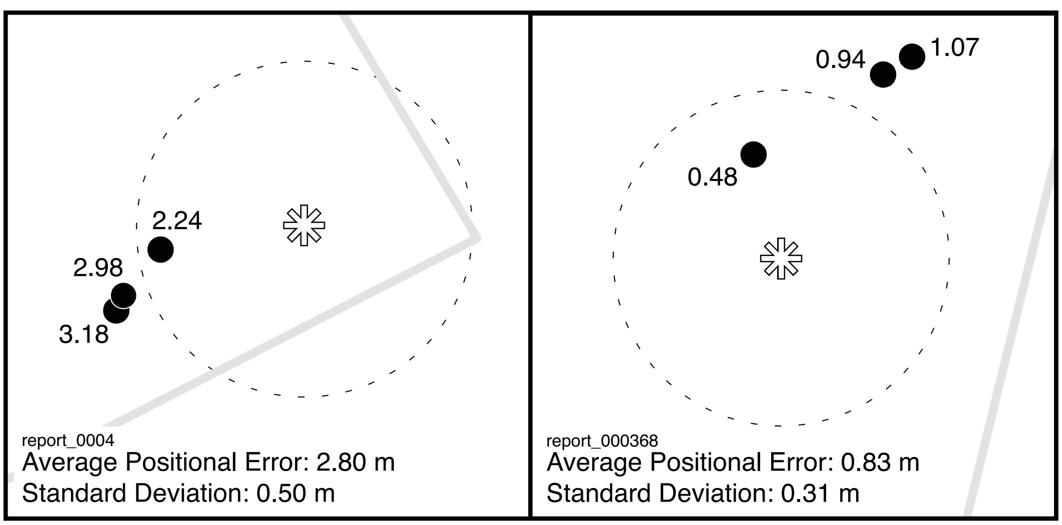

Figure 39. A representation of the positional errors associated with two obstacle reports. The black circles represent the obstacle location chosen by the moderators, while the asterisk represents the obstacle's actual location, as determined by the project managers.

Six of the ninety-three moderator obstacle reports had positional errors of greater than 20 meters. This can mainly be attributed to some obstacles not being adequately represented by a point location, which is the type of feature used to represent obstacles in our system, rather than a line or polygon representation. This presents an issue for obstacles that are very large, as demonstrated by Figure 40. In many cases, the obstacles reported to the GMU-GcT consisted of a large construction area or a large segment of sidewalk that was closed, which would be best represented by a polygon feature. The moderators for this study were instructed to assign the position of the obstacle report directly in the center of the obstacle, but the resulting variances in spatial perception associated with georeferencing became a factor in selecting the accurate position of the obstacle. Report_0007 (Figure 41) is an example of such scenario, which explains the positional error of 22.55 meters. Because of this discrepancy Table 7 has a column indicating whether an obstacle was an areal feature, and the overall positional error was recalculated with areal features removed, with an average positional error of non-areal features being 2.12 m.

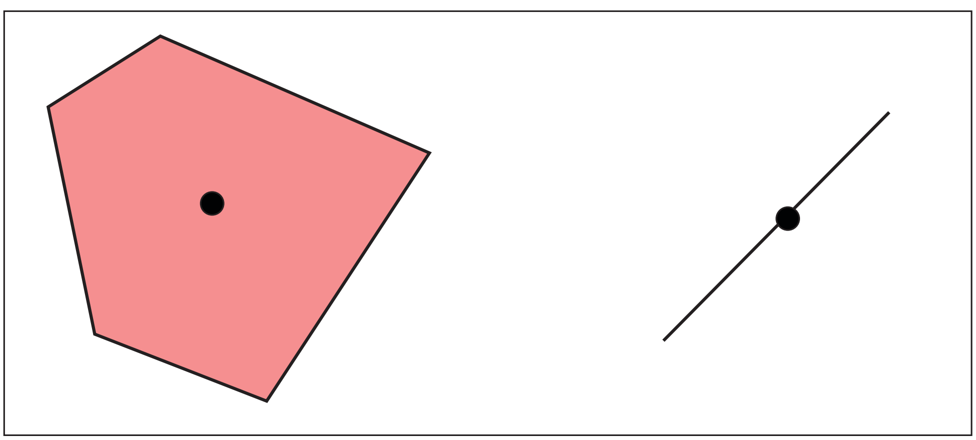

Figure 40. A representation of the limitations presented by assigning position as a point location rather than assigning position to encompass a larger area, as a line or polygon.

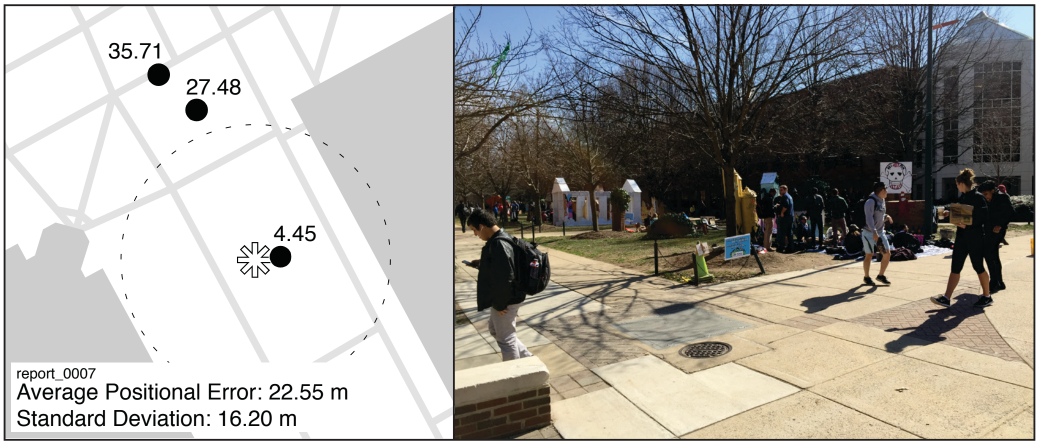

Figure 41. Demonstration of a difficult report to position with a point due to its areal nature, resulting in a high positional error.

The difference in average positional errors between the point and areal features underscores the inadequacy in simple point-based representation. This problem has been partially rectified with polygon-based obstacle footprints, but this feature is not commonly used by the public. Polygon-based obstacle footprints are enabled for regular moderation in the GMU-GcT, however, they were not implemented in this study due to its potential for creating complications with the moderating process. The regular GMU-GcT moderation process will continue to use polygon geometries to represent obstacles that are larger and inadequately represented by a point.

Another issue that caused a larger positioning error amongst moderators is the limitation of georeferencing based off of Google Maps orthoimagery, as opposed to collecting GPS coordinates of hazards when field checking. The orthoimagery provided by Google is not leaf-off, which causes issues for positioning in some cases, such as report_000365 (Figure 42). Report_000365 consisted of a wooden walkway that routed the user around a pathway that required a detour due to construction, and is not reflected in the most recent orthoimagery or in Google Maps, making the obstacle even more difficult to locate on a map.

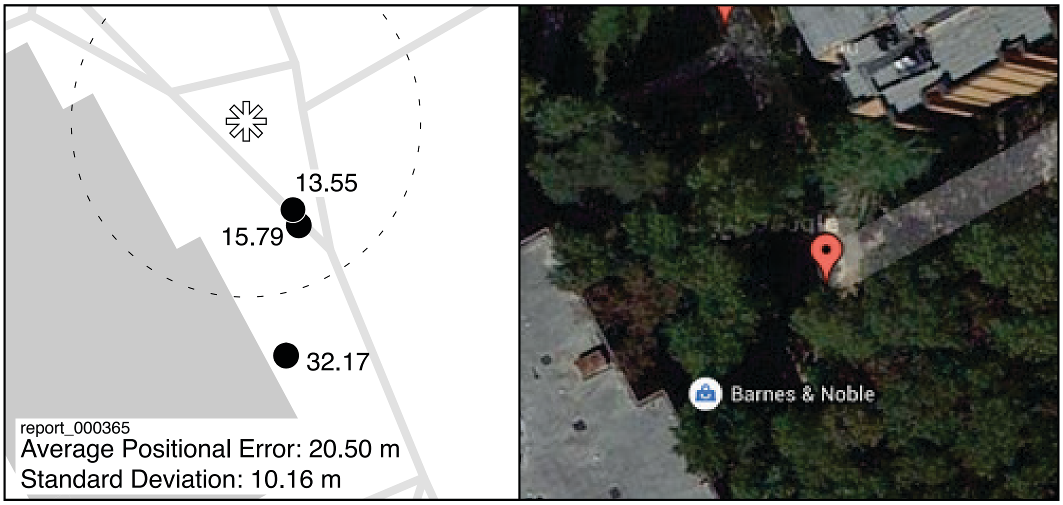

Figure 42. An example of a poorly positioned report, due to the limitations present by using Google orthoimagery to georeference an obstacle's position rather than validating position by GPS or through some other method.

In evaluating categorical consistency for obstacle type, moderators remained mostly consistent. After calculating a matching score for the category designations in each report, where 0=no match, 1=partial match, and 2=exact match, a total matching score was calculated for each moderator for all reports. The total matching score for moderators was 1.79 for moderator 1, 1.76 for moderator 2, and 1.70 for moderator 3 (Figure 43). The overall average matching score for all moderators and all reports was 1.75. This shows that the three moderators were mostly in agreement, and have an overall 76.8% exact match rate, and an overall 98.0% match rate of at least one of the appropriate categories. The match rate for each moderator compared to the ground truth is graphed in Figure 43.

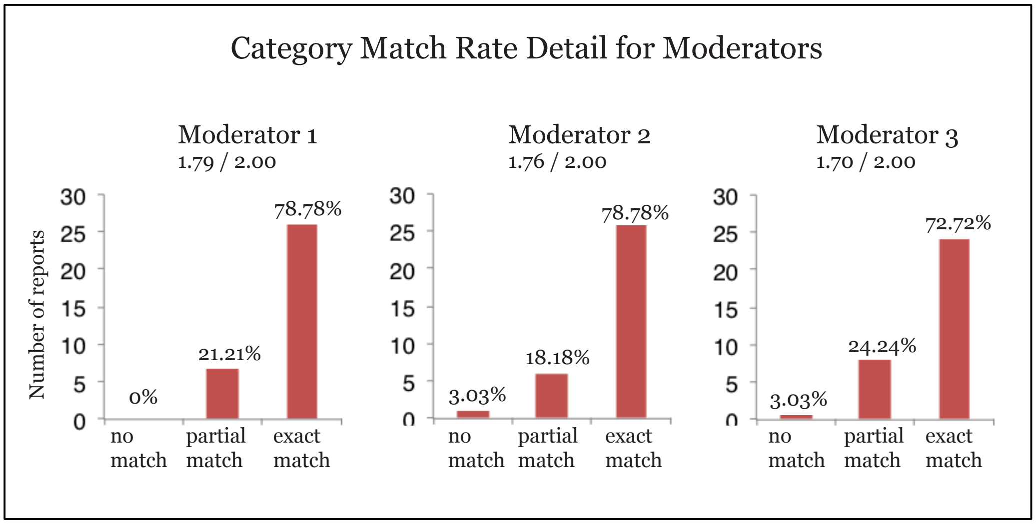

Figure 43. Overall agreement between the three moderators and the ground truth for classifying obstacles, with each moderator represented by one histogram.

While an exact match rate of 76.8% is very good, and is better than categorical accuracy found in research such as Camponovo and Freundschuh (2014), there is still some explanation necessary for some matching errors and disagreement in obstacle classification. Though the moderators are trained and given a rubric that declares the criteria for each obstacle type, there is still some ambiguity. For example, poor surface conditions and sidewalk obstructions can easily be confused if a poor surface condition begins to fully or partially obstruct a path, in which it would be a sidewalk obstruction as well. Construction detours are also sometimes difficult to classify, because there are often reports for construction-related hazards, but they do not actually culminate in a detour. This was apparent for one obstacle, in which two of the moderators resulted in "no match" for correctly classifying obstacle type. The original report contained "construction detour, sidewalk obstruction," though the obstacle would have been correctly classified as a poor surface condition. One moderator classified the obstacle correctly, while another moderator classified the obstacle as a construction detour, and another as a sidewalk obstruction. Figure 44 exemplifies some of the discrepancies for each obstacle type, with the most discrepancies being associated with sidewalk obstructions and poor surface conditions.

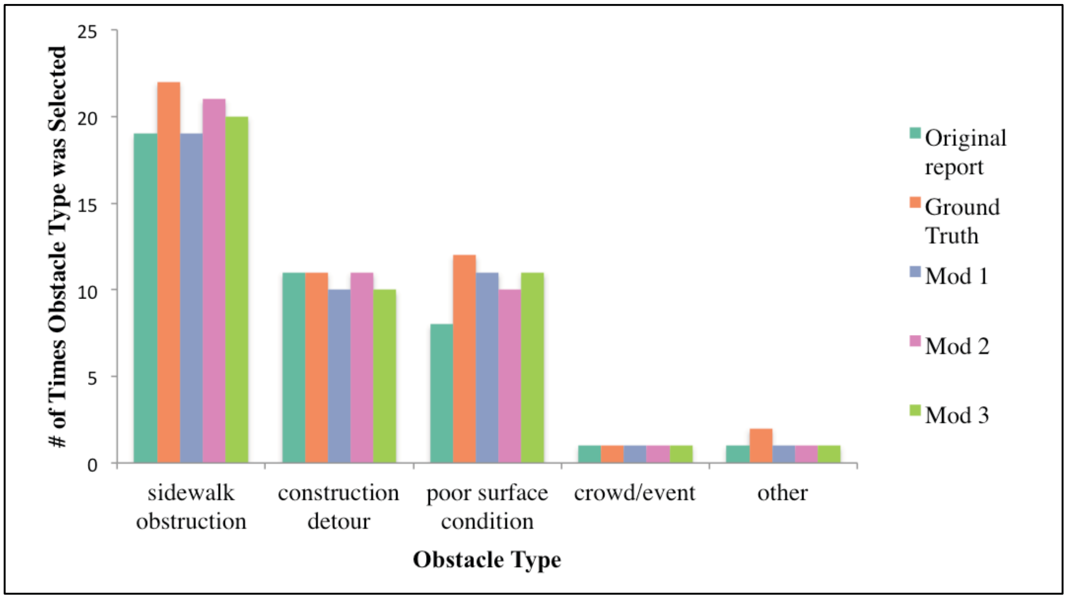

Figure 44. Total count of obstacle type selections per each moderator, compared to original reports and the ground truth.

This data quality analysis is a progressive start to assessing consistency amongst moderators and evaluating the social moderator process. We have gained much insight from this study about the role that moderators play in positioning reports, and the expected positional accuracy, which is better than the typical positional accuracies for mobile GPS reported by authors such as Zandbergen (2009), reviewed in Chapter 2 of this report.

The GMU-GcT benefits from its small area of interest and relatively small amount of incoming data in that the social approach is most appropriate for ensuring data quality. In order to assure that incoming reports are checked in a timely manner, the GMU-GcT employs a team of moderators to quality check reports. The conclusions that can be drawn from this study are that moderator positioning falls within the expected positional error of most crowdsourced data (as outlined by previous OSM study findings in Table 7), meaning that the GMU-GcT contains data that falls within the quality standard provided by other VGI quality assessment studies. While we can assert that the data contained in the GMU-GcT is quality assured, it is difficult to assert that our data is “good quality” without a set standard for VGI data quality, similar to the National Standard for Spatial Data Accuracy.

While moderators are thoroughly trained in how to field-check and validate obstacles, there is no proven method for making them 100% consistent with one another. While the reports are mainly consistent, in that their positioning is within 3 meters for all obstacles (and less than 1 meter for non-area features), and in agreement for almost all obstacle types, there is still some inherent ambivalence in selecting a location as well as for determining obstacle type. However, as the research from Camponovo and Freundschuh (2014) shows, ambivalence may be an intrinsic part of the geocrowdsourcing process. In order to improve the consistency and accuracy of moderator's decisions, it is critical that we ensure they are trained and are allowed to make joint decisions when validating incoming data. If this experiment allowed the three moderators to discuss with one another the reasoning behind their report positioning and categorical selections, they would likely be more consistent and more congruent with the ground truth. While the only categorical assessment analyzed in depth for this study was obstacle type, the many other areas of categorical assessment will be analyzed in future to gauge moderator consistency. A preliminary look at categorical designations in the GMU-GcT is reviewed in Paez (2014)[70] and Qin et al. (2015b)[71].

Multiposition Validation and Moderation in the GMU-GcT

One recent avenue of research by this team is the combination of multiple elements of positioning to provide additional guidance and help to the GMU-GcT moderators. As noted in this chapter, each report submitted by a contributor includes an asserted position, as well as a moderated position. The moderated report also includes a moderated position, which was the subject of the study in this chapter. Other report elements such as the images and description text can produce other positioning information that can be combined into a multiposition validation workflow, which is still under development. Figure 45 shows the concept of multiple aspects of position validation in the GMU-GcT. including user-contributed position from smartphone GPS and hand-selected georeferencing, as well as final validated positioning built with moderator positioning, image geotags, and geoparsed location description. This section will look at the development of experimental methods to use image geotags associated with position and orientation, as well as geoparsed location description text for multiposition validation in the GMU-GcT.

[70] Paez, "Recruitment, Training, and Social Dynamics in Geo-Crowdsourcing for Accessibility."

[71] Qin et al., "Obstacle Characterization in a Geocrowdsourced Accessibility System."

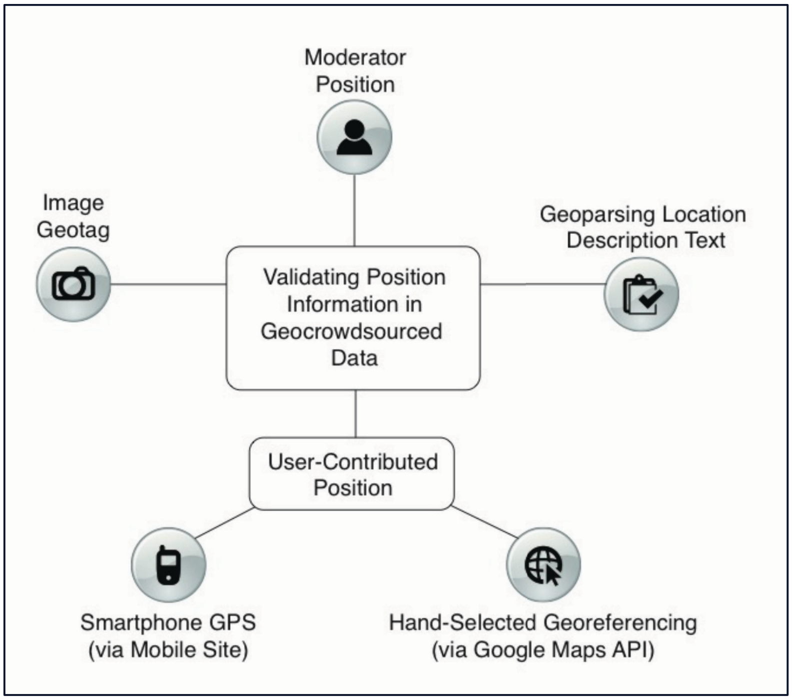

Figure 45. Multiple aspects of positioning in the GMU-GcT, and the position confirmation process

Image Geotags for Position and Orientation

Figure 46 shows typical GMU-GcT report with an attached photograph, submitted with the report. Report contributors can submit up to two photographs, while additional reports of the same obstacle can contribute additional images. Figure 47 shows a conceptual view of information that can be extracted from a collection of reports with multiple photographs of the same obstacle. The figure shows positional information and orientation vectors extracted from the image headers of three photographs, whose origin positions and intersection points would converge on the reported obstacle, whose position is being independently confirmed by the moderator.

Figure 46. GMU-GcT Obstacle Report

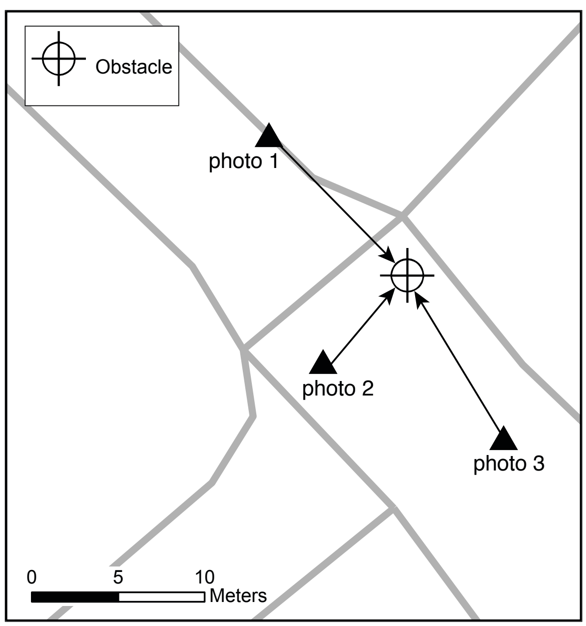

Figure 47. Obstacle photos with geotags and orientation vectors

In order to explore the possibilities represented by positional geotags and orientation geotags in the multiposition validation workflow, the authors used three different camera systems to repeatedly photograph the GMU-GcT obstacle shown in Figure 46. The three different camera systems include an iPhone 6 plus, a Nikon Coolpix S9500 (an inexpensive consumer-level point and shoot camera), and a Canon EOS 6D (a professional-level Digital SLR camera with a GP-E2 GPS attachment, which captures location and orientation). All three devices are capable of capturing position and orientation, and writing that data into image headers, which are processed with python scripts and imported into a geographic information system. The location and orientation information for all three camera systems are shown along with direction vectors in Figure 48, Figure 49, Figure 50.

Figure 48. iPhone 6+ image geotag positions and orientation vectors

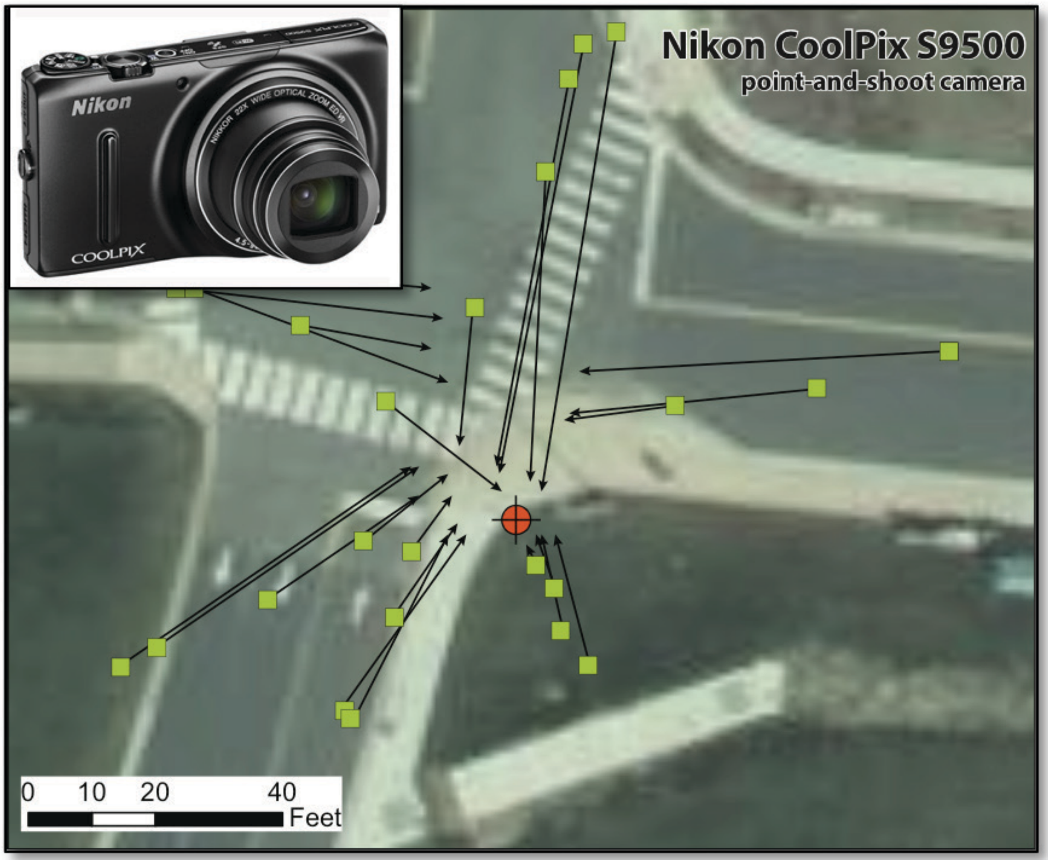

Figure 49. Nikon CoolPix S9500 image geotag positions and orientation vectors

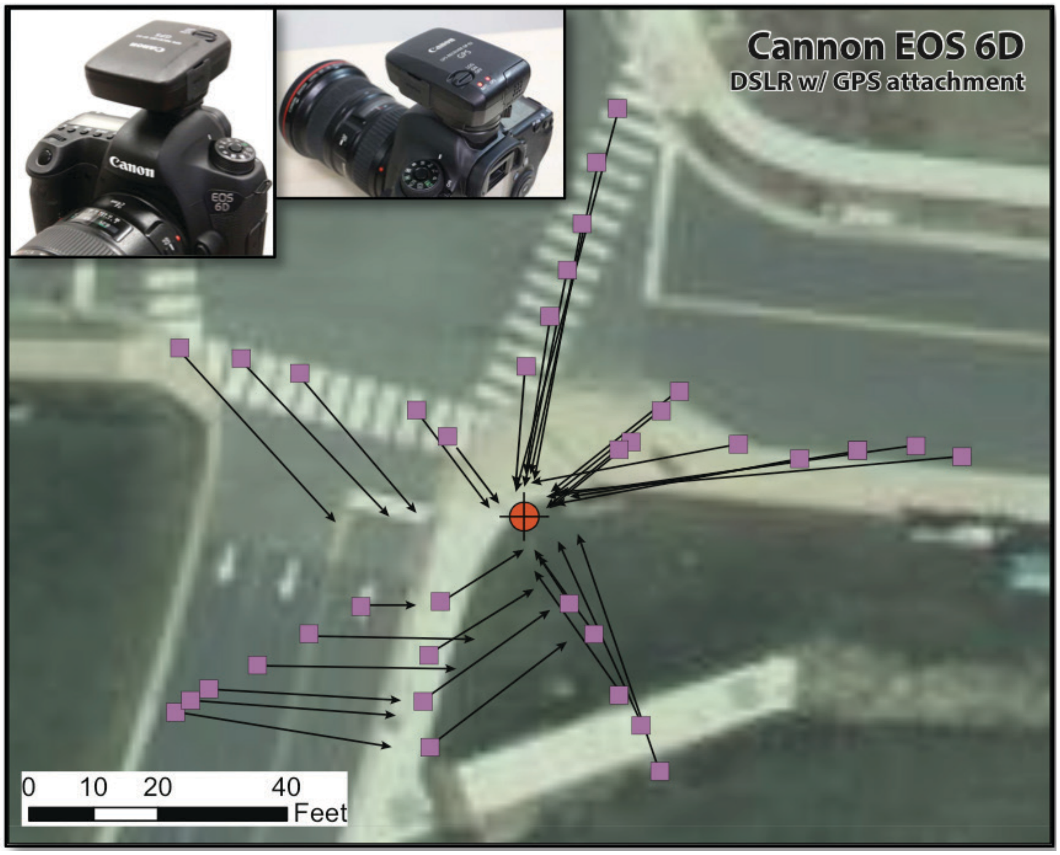

Figure 50. Canon EOS-6D + GP-E2 geotag positions and orientation vectors

As is evident from the Figures, results are mixed. The Canon EOS6D + GP-E2 and Nikon Coolpix S9500 produce good results and show how geotag positions and orientation vectors could be used to assist a moderator confirm the position of a report. In cases where the contributed report is mis-positioned due to contributor error, as has been seen in the GMU-GcT and discussed in Pease (2014) and Rice et al. (2014), this additional element of validation would be useful in performing a correction to report position. The image geotag positions from the iPhone 6+ are in approximately the right places, consistent with what we have discussed about mobile device GPS constraints in chapter 2, but the orientation vectors are incorrect, and in fact, show a systematic error in the wrong direction. This error appears to be a device and operating system-specific error in the processing of electronic compass information and embedded EXIF tags.[72] If future technology has the same trend toward improvement

[72] https://discussions.apple.com/thread/6649249?start=0

as it has in the past, we can expect to see the same quality from the Canon EOS 6D + GP-E2 being integrated into the iPhone and other less expensive consumer level devices. The Nikon Coolpix S95000, a moderately priced consumer level device manufactured in 2013, has excellent quality and good results, with respect to image geotag positions and orientation. Future incarnations of GMU-GcT may be able to use image geotags and orientation vectors, as shown here, to provide a quick automatic validation to position.

Geoparsed Location Description Text in the GMU-GcT

Rice et al. (2012a) and Rice (2015) contain details about a methods being integrated into the GMU-GcT, which involves the automatic generation of a geospatial footprint from the placenames, directions, distances, and location descriptions in an obstacle report. Project collaborator Ahmad Aburizaiza has continued work with gazetteer-based geoparsing presented in Rice et al. (2011) and Rice et al. (2012a), and has substantially increased its functionality. Using open source web-mapping tools MapBox, TURF.js, JQuery, and Bootstrap, Aburizaiza has demonstrated the ability to quickly derive a footprint from geoparsed text, and represent it on a map as a convex or concave hull, as shown in Figure 51, where references to two GMU campus buildings are matched using a gazetteer, and whose geometry is then used to automatically construct footprints.

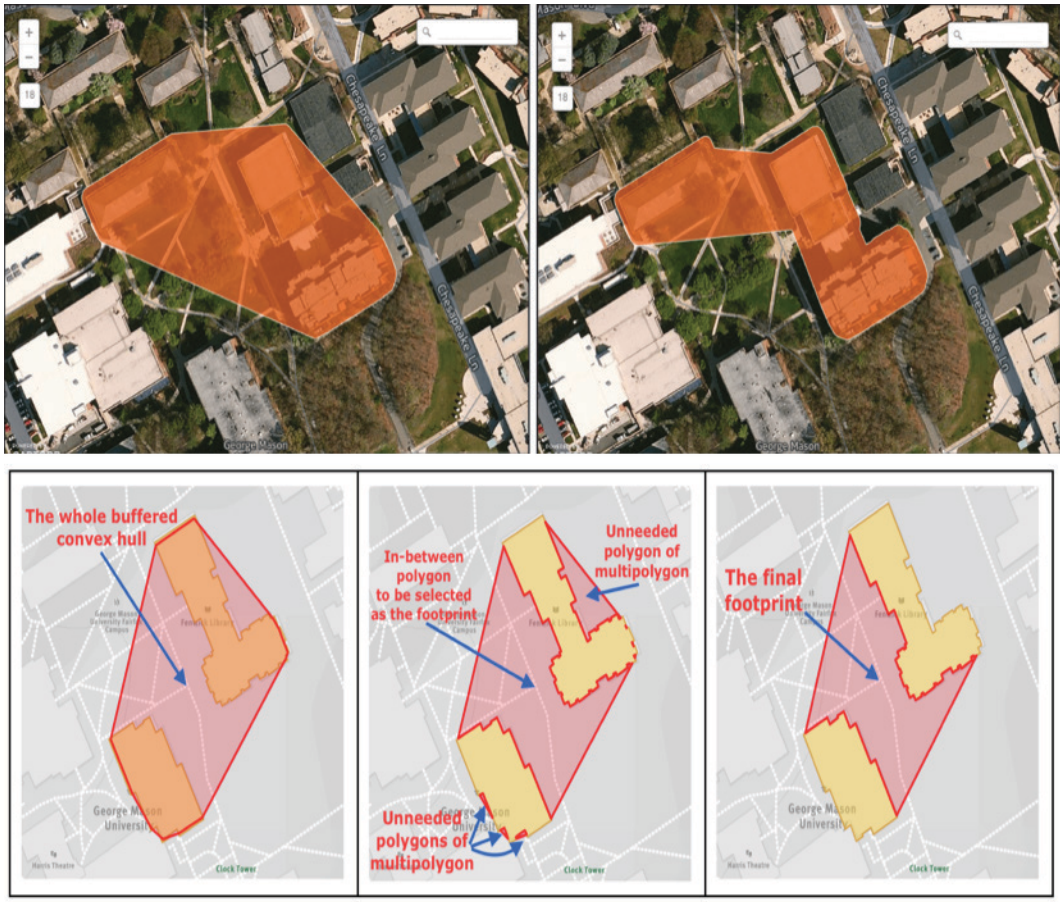

Figure 51. Convex (upper left) and concave (upper right) hull geometries associated with two campus buildings. Hull geometry is refined (bottom) to include only areas between the named features.

Aburizaiza has developed automatic geoparsing code to construct footprints for many generic instances of obstacle description text, including named street intersections (Figure 52), walkways between named buildings (Figure 53), areas between named streets and nearby buildings (Figure 54), directional indicators associated with buildings (Figure 55), and street segments in between two other street segments (Figure 56).

Figure 52. Footprint for the intersection of two streets

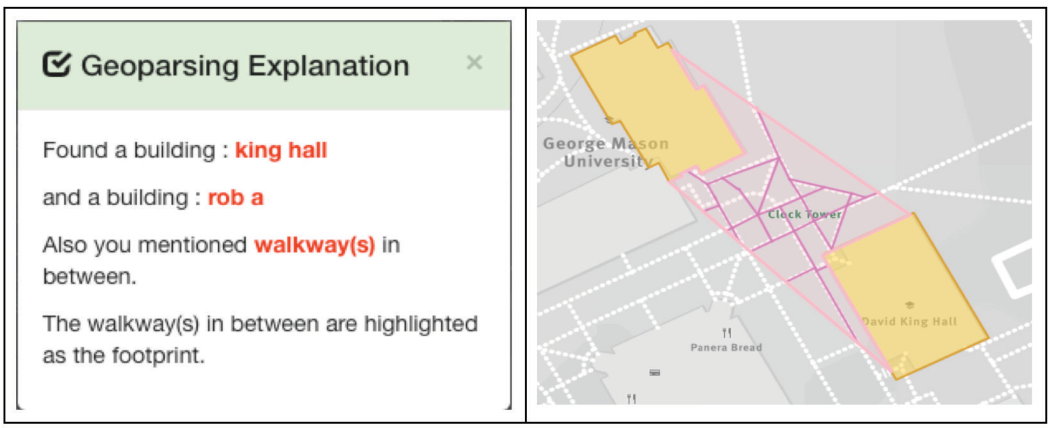

Figure 53. Walkways between named buildings

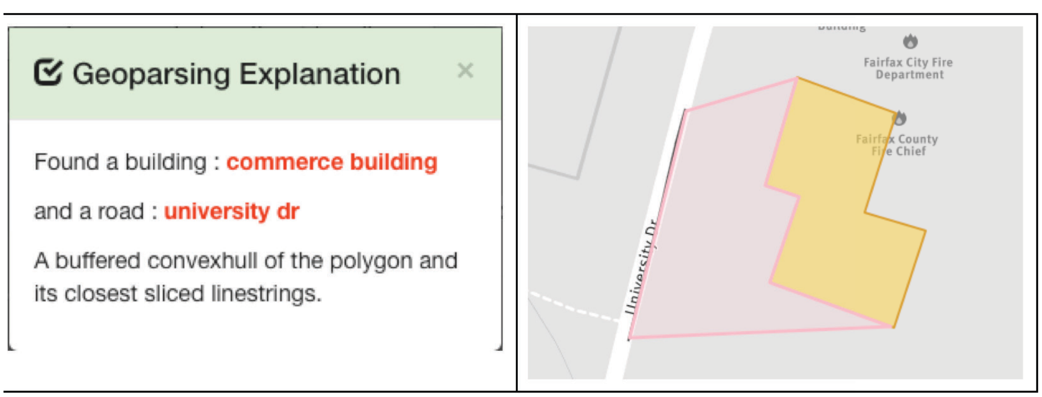

Figure 54. Footprint for the area between a named street and a named, nearby building

Figure 55. Footprint for the area associated with a directional word and a named building

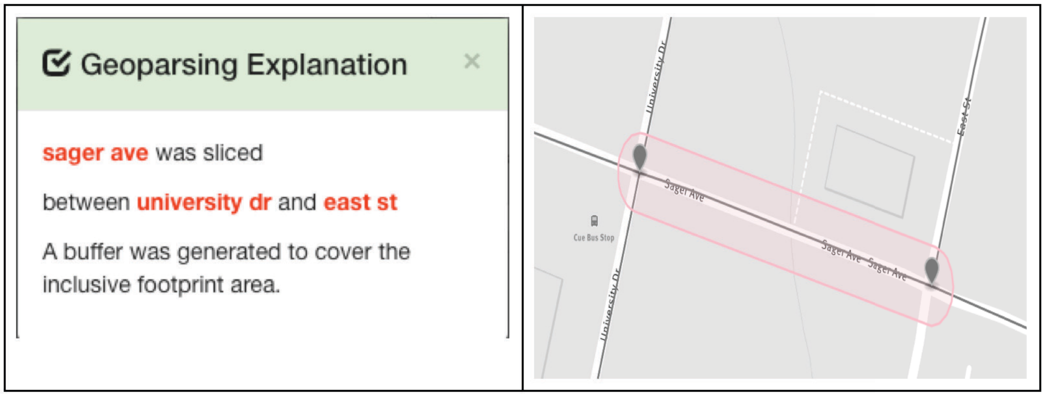

Figure 56. Footprint for the area associated with a street segment between two other streets

The processing for the examples shown can be done automatically for any location descriptions with named features from our gazetteer meeting any of the general patterns shown. Augmenting the capability of the GMU-GcT to include more elaborate and complex geospatial relationships and importantly, to resolve ambiguities when they arise, is a goal of future work. With the capabilities presented here to process image geotags and extract location and orientation, and to automatically create footprints from geoparsed location descriptions, future moderators in the GMU-GcT will have many sources of positioning information to identify, confirm, and validate reports. The final goal of this work is a dashboard, under development, containing information such as Figure 57, which combines the various existing forms of position information together into a single window that can be used by moderators in their validation and quality assessment workflow.

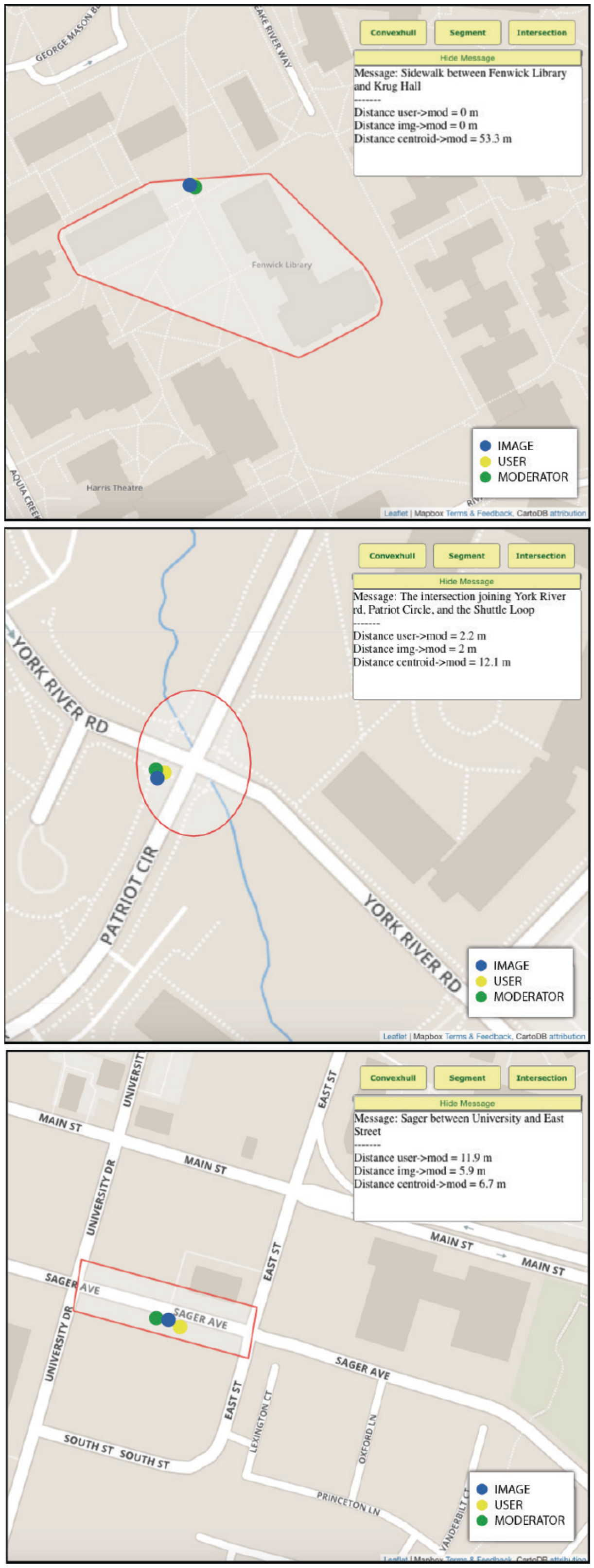

Figure 57. GMU-GcT moderator multiposition validation dashboard (under development)

The next chapter looks at obstacle engagement with mobile devices, which represents an important augmentation of the GMU-GcT and reflects some of the important dynamic elements of geocrowdsourcing discussed in Chapter 2.

4 Dynamic Obstacle Engagement with Mobile Devices

One of the most important emerging aspects of geocrowdsourcing is the focus on mobile devices as both the platform for participation by end-users, and as a platform for authoritative entities to manage, quality check, and facilitating geocrowdsourcing activity. Chapter 2 looked at the dynamic elements of geocrowdsourcing, where with Dr. Dieter Pfoser described the commoditization of GPS technology and its integration in mobile phones as a major element in dynamic geocrowdsourcing. This dynamic, device-based focus has resulted in vast amounts of tracking data that can be used in applications such as traffic prediction and road condition reporting. Chapter 3 looked at the ability of moderators to field check reports and establish position, through a hybrid mobile and desktop paradigm. This chapter focuses on how mobile devices can be used for geocrowdsourcing engagement and GMU-GcT functionality.

Authors such as Muehlenhaus (2013)[73] see mobile devices as a new center of information exchange. He articulates the important cartographic design principles for mapping on mobile devices, including dynamic display elements and interfaces that are "chubby-finger friendly" (ibid, 23). Dillemuth (2005)[74], seeing the future importance of widespread mobile map use, designed studies of pedestrian route-following with mobile devices, offering cartographic advice and cognitive-design guidelines for small devices that would be used in dynamic, field-based settings. Hupfer and colleagues (2012)[75] developed software for mobile devices to facilitate simple, rapid construction and deployment of geocrowdsourcing applications. Thatcher (2013)[76] suggests that the focus on mobile devices

[73] Ian Muehlenhaus, *Web Cartography: Map Design for Interactive and Mobile Devices* (CRC Press, 2013).

[74] Julie Dillemuth, "Map Design Evaluation for Mobile Display," *Cartography and Geographic Information Science* 32, no. 4 (2005): 285–301.

[75] Susanne Hupfer et al., "MoCoMapps: Mobile Collaborative Map-Based Applications," in *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work Companion* (ACM, 2012), 43–44.

[76] Jim Thatcher, "From Volunteered Geographic Information to Volunteered Geographic Services," in *Crowdsourcing Geographic Knowledge*, ed. Daniel Sui, Sarah Elwood, and Michael F. Goodchild (Dordrecht: Springer Netherlands, 2013), 161–73, http://www.springerlink.com/index/10.1007/978-94-007-4587-2_10.

is a way to extend the static world of volunteered geographic information into a realm of volunteered geographic services, where mobile devices place the user in the field and links him or her in time and space with other users. The mobile device becomes the link between embedded end-users, who share volunteered geographic information and volunteered geographic services.

Haklay, in his highly cited 2010 paper asked, “How good is volunteered geographic information”? Given the current 2015 context of what we know about VGI and CGD data quality (explored in detail in Girres and Touya 2010[77], Ruitton-Allineau 2011[78], Rice et al. 2013b[79], Rice et al. 2015[80], and Rice 2015[81]), we extend the question to ask, “How capable are mobile devices in facilitating dynamic geocrowdsourcing?” This focus on the mobile platform is an important theme in dynamic geocrowdsourcing and explores the interaction between a mobile device user and obstacle from the GMU-GcT.

Dynamic Obstacle Engagement in the GMU Geocrowdsourcing Testbed

Having reviewed the uncertainty in obstacle positioning (Chapter 3) and the positioning capabilities of GPS devices (this chapter) and the associated estimates for interaction distances with obstacles (Table 5) the final consideration in dynamic obstacle engagement is the influence that movement of the end-user or moderator will have in obstacle engagement. The end-users of the GMU-GcT will be various, but likely students, faculty, and staff that are mobility or visually-impaired, or alternatively, their care givers who are accompanying them through an unfamiliar environment. These end-users need to be alerted to the presence of an obstacle ahead of their current path, so that they can avoid it. They may choose, depending on the nature of the obstacle, to return and reroute themselves along a different pathway. Mobile routing tools, which will be discussed at the next

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[77] Girres and Touya, “Quality Assessment of the French OpenStreetMap Dataset.”

[78] Anne-Marthe Ruitton-Allinieu, “Crowdsourcing of Geoinformation: Data Quality and Possible Applications” (Master of Science, Aalto University, 2011), http://maa.aalto.fi/fi/geoinformatiikan_tutkimusryhma-gma/geoinformatiikka_ja_kartografia/2011_ruitton-allinieu_a.pdf.

[79] Rice et al., “Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility.”

[80] Rice et al., “Position Validation in Crowdsourced Accessibility Mapping.”

[81] Rice, “Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study.”

chapter, allow for obstacle-avoidance routing. Because the end-users of our system are moving through space, the distance required to alert them of an obstacle ahead of them increases as their own speed increases. This dynamic suggests that we need to increase the obstacle engagement distances required for dynamic engagement (Table 5). While conducting field tests in July, and August, we experimented with various interaction distances based on known GPS characteristics and based on the information in Table 5 During testing in early August, we established 100 feet (30.48 meters) as an acceptable reflection of the uncertainties reflected in Table 5, as well as the impact that a moving end-user would have on the necessary obstacle alert distance.

A preliminary study by Eric Ong (Figure 58) for the pedestrian network on the George Mason University campus (our area of most significant activity) indicated an average segment length of 87.59 meters, with a majority of segments under 20 meters. An interaction distance of 100 feet (30.48 meters) would in some cases, result in an end-user needing to backtrack, but during testing the distance seemed to be a good compromise for all known factors and practical usability issues.

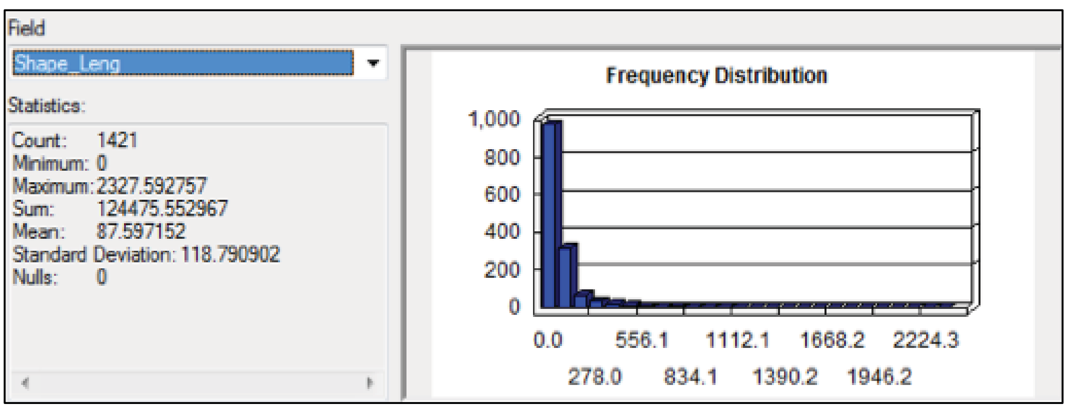


Figure 58 Segment lengths in meters for the George Mason University campus

The only unknown factor, after accepting general interaction distances based on multiple sources of uncertainty, was the latency and responsiveness of the computer data networks, server, and mobile software. These issues will be discussed in the context of our field work. The next section of this chapter discusses two applications for mobile obstacle engagement developed as a part of this work, and a set of field tests to measure, visualize, and analyze patterns in mobile obstacle engagement.

Mobile applications for obstacle engagement

The GMU-GcT end users can access our GMU-GcT obstacle information online through our web portal[82], but also through a new native mobile application developed by project researcher Samuel Ober (Figure 59). This native mobile application was developed from earlier incarnations coded with Sencha Touch, but has been updated using Swift, an open-source coding tool for iOS. Swift has a concise syntax that generates faster code for mobile devices with low-power processers. The current version is of the GMU-GcT Mobile App has been tested by moderators and will be released through Apple's App Store pending final approval. This native mobile application can take advantage of the wide range of functions in iOS, and has a benefit of running continuously, whether or not it is open and maximized on screen. An alternative mobile web application, developed by project researcher Ahmad Aburizaiza, uses Mapbox, Turf, and MongoDB, along with existing functionality from the desktop version of the GMU-GcT (Figure 60). This mobile web application has an advantage of being able to utilize the large library of spatial functions from Turf. The use of a NoSQL database (MongoDB) has significant performance benefits relative to the relational database used in the GMU-GcT and during preliminary testing had quick, rapid performance.

[82] http://geo.gmu.edu/vgi/ [accessed November 19, 2015]

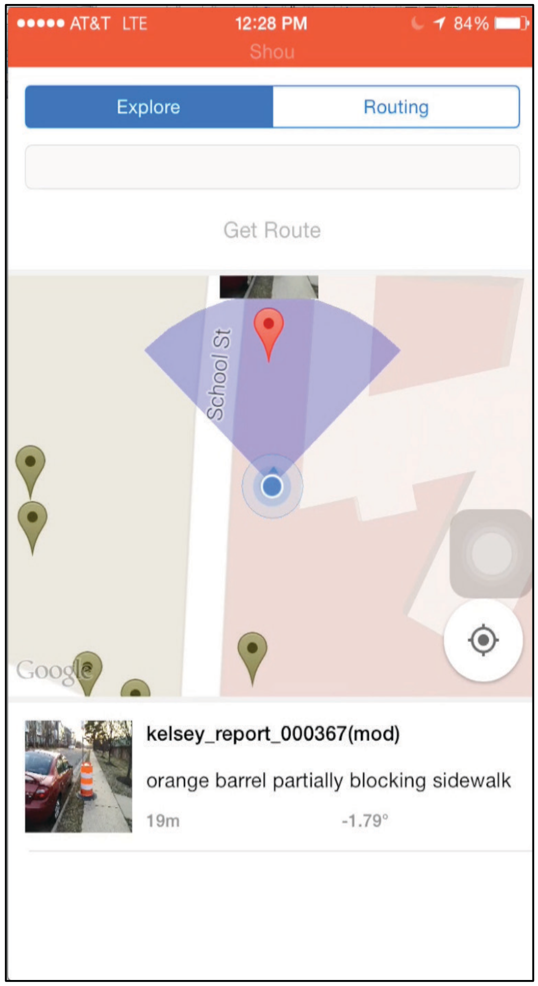


Figure 59. Native mobile application for obstacle engagement, developed with Swift for iOS

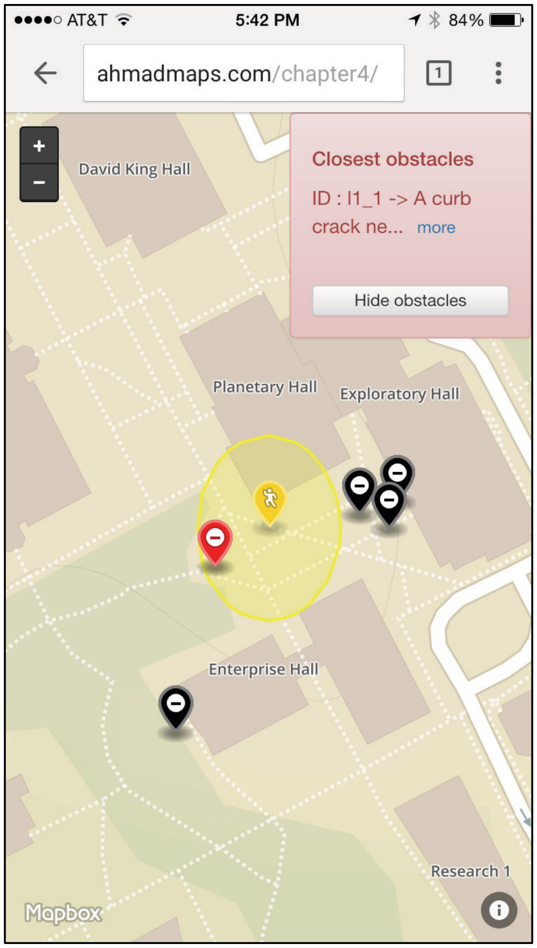


Figure 60. Web Application for mobile obstacle interaction, developed with Turf/Mapbox and MongoDB

Field studies of obstacle engagement

Between July 1 and present, the two different GMU-GcT mobile applications, referred to hereafter as the MobileApp (for Samuel Ober's Swift-based iOS native app, Figure 59), and WebApp (for Ahmad Aburizaiza's Turf/Mapbox web application, Figure 60) were tested extensively, to gauge the ability of a mobile user to receive alerts from each of the applications to notify him or her about the presence of an obstacle. A study location close to the GMU campus provided access to a dynamic, construction-filled environment with several obstacles that had been reported to the GMU-GcT repeatedly. Two obstacles were chosen and selected for a series of tests in which the end-user would move toward the obstacle from different directions. Research assistants would mark the exact location where an obstacle alert was delivered to the end-user's mobile device, and would then measure the distance between this alert position and the obstacle. In order to address variables such as canopy cover and building heights, one obstacle was chosen in close proximity to a 3.5-story row of townhouses with an approximate height of 48 feet and covered with a tree canopy. Another obstacle was chosen on a walkway adjacent to a single-story medical facility, with trees nearby in an area characterized as Partial Canopy.

Based on user needs assessments conducted for this project and discussed in Rice et al. (2014), we anticipate that end-users and moderators will need to be alerted to obstacles while moving through daily activities at the rates of speed similar to walking. Moderators, who may be riding a bicycle or moving at a faster speed, will have engagement distances with an even greater required alert distance. To explore the delivery of obstacle alerts to a moving end-user, a mobile data collection platform was constructed from a bicycle with camera and mobile device mounts. This allows an end-user to interact with a mobile application while riding, and film the interaction with a forward looking GoPro camera. A compact screen-capturing program running on the rear-facing mobile device records mobile alerts and user interaction with the mobile applications. Figure 61 shows this platform, which has an additional USB solar charging capacity for mobile devices and a small Bluetooth speaker for auditory cues (not pictured).

Figure 61. GMU-GcT Mobile Data Collection Platform, with LTE-enabled mobile device and forward facing video capture capability

Obstacle engagement dynamics with the GMU-GcT mobile WebApp

The mobile web application, or WebApp (Figure 60), was coded using Mapbox/Turf. It uses data and functionality from the GMU-GcT and uses the PostgreSQL database, but copied to a MongoDB NoSQL database to increase dynamic performance. The WebApp is responsive and performed well in preliminary testing. Because communication between the WebApp and the server is more verbose and frequent, we anticipated that there would be performance during dynamic field testing. For all dynamic field testing, we used four different mobile devices: an iPhone 5, and iPhone 6, an iPhone 6+, and an iPad2. All devices were capable of Long-Term

Evolution (LTE) data speeds and all devices used the same mobile service provider (AT&T). The two obstacles used in field testing are shown along with data summaries in Figure 62 and Figure 63. The field testing protocol involved the following steps:

1. The obstacle is verified in the GMU-GcT. Any discrepancies or errors are corrected before field testing begins.

2. The obstacle's ground center point is marked with tape.

3. The WebApp (or MobileApp) is loaded, and screen capture is initiated.

4. The forward facing camera is enabled and started for video capture.

5. The obstacle is approached at walking speed (2-3 mph), along one of eight pre-defined and marked directional trajectories (see Figures 58 and 59).

6. The exact ground point where an obstacle alert is received on the mobile device is marked with tape along the trajectory.

7. The dynamic alert distance is measured and recorded.

8. The process (steps 1-6) is repeated for each of the four mobile devices, along each of the eight pre-defined trajectories.

9. The process (steps 1-7) is repeated, but at a higher rate of speed (7-8 mph) using the GMU-GcT mobile data collection platform (Figure 57).

10. The entire process (steps 1-8) is repeated using the MobileApp in place of the WebApp.

With this protocol in place, field testing was begun. Figure 62 shows engagement with a sidewalk obstruction consisting of an orange barrel, which in later phases was switched by the construction workers to an orange cone. This barrel and cone were being used as a marker for modifications to the curb and roadway for the nearby Eleven Oaks development. Underneath the obstacle picture and summary in Figure 62 and Figure 63, obstacle interaction distances and diagrams for a bicycling end-user (top), and for a walking end-user (bottom) are shown. The eight trajectories for each travel mode are numbered and marked in black, with color-coded markers showing the obstacle alert location and lines connected the color-coded points to allow for interpretation of shape and general device-based interaction dynamics. We also record the average interaction distance for each device and for each mode of travel, along with a standard deviation. The interaction distances consist of two measurements. First, we measure the distance between the end-user and the obstacle, which is summarized as 'average distance to obstacle'. Second, we record the distance between the 100-foot buffer (shown as a grey arc on the diagrams) and the user, which is summarized as 'average distance from buffer'. These distances sum to 100 feet, which is the total distance between the obstacle and the 100 foot buffer.

For both obstacles for all devices, (Figure 62 and Figure 63) the obstacle alert distances for a walking end-user are greater than for a biking end-user, which was an expected result related to the nature of dynamic interaction and the speed with which the WebApp would be able to detect and notify the end user. The alternative view of the interaction dynamics are that the walking end-user generally receives an obstacle alert closer to the intended 100 foot buffer than the bicycling end user. The 100 foot buffer and a summary of both interaction distances are contained in all obstacle interaction figures.

For Figure 62 and Figure 63, the obstacle alert distances increase as the trajectory moves away from the buildings on the north side (Figure 62) and south sides of the road (Figure 63). The fan shape in Figure 63 is prominent, with trajectories 4 and 5 having larger interaction distances than other trajectories, which is likely related to the decrease in multipath error and reflection for positions farther from the buildings. There is no apparent ordinal effect related to devices, which all delivered alerts in close proximity to one another, with a few exceptions (iPhone 6, biking trajectories 2 and 5 in Figure 62, and the iPad 2 trajectory 5 in Figure 63). The iPhone 4, used in earlier mobile GPS studies, was not used during our mobile obstacle interaction study. The iPhone 6+ was not tested earlier with Frechet distances, but was used, along with the iPad 2, in our mobile obstacle interaction study. Our goal was to test and experiment with a variety of mobile devices, and to explore their limitations under a variety of use scenarios and environmental conditions. The testing protocols presented in this chapter and in Chapter 2 will be continued with a variety of devices as they become available, and will help us augment our knowledge of mobile GPS capabilities and how these capabilities influence mobile geocrowdsourcing.

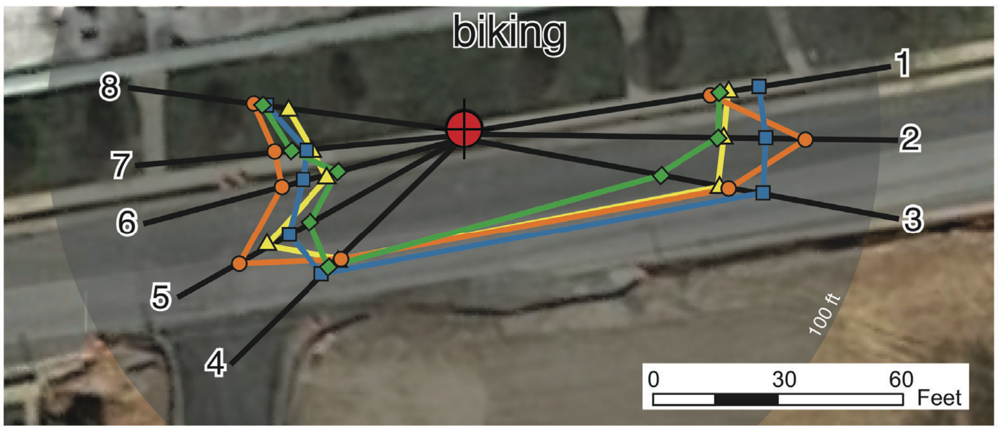
For the obstacle engagements studies presented here, we used an interaction distance of 100 feet (shown in following figures with a darkened gray circle). None of the alert distances for the WebApp are close to that distance, with the largest alert distance being 79.3 feet (iPhone 6+, Figure 63). The total range of alert distances for the WebApp was 48.1 to 79.3 feet. Figure 64 and Figure 65 show the same obstacle alert distances, but broken down by device. Side by side comparisons of the average distance ellipses and obstacle alert distances clearly show a decrease between walking and biking.

Obstacle Details

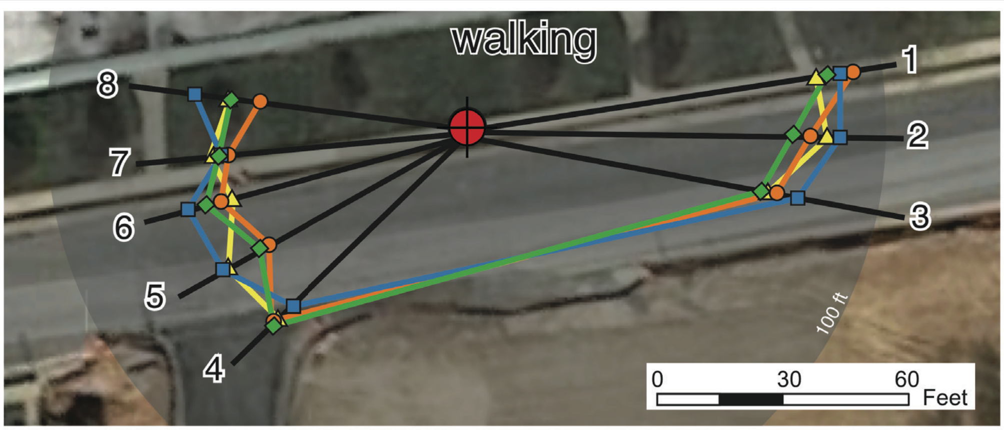
Type: Sidewalk Obstruction

Location: School St. sidewalk near one of the entrances to Inova Care Center, west of George Mason Blvd.

Description: Orange barrel partially blocking sidewalk



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	50.2	58.3	55.1	48.1
Average Distance from Buffer (ft):	49.8	41.7	44.9	51.9
Standard Deviation (ft):	11.9	11.5	14.6	9.4



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	69.1	67.4	72.7	67.8
Average Distance from Buffer (ft):	30.9	32.6	27.3	32.2
Standard Deviation (ft):	10.8	14.6	12.6	10.3

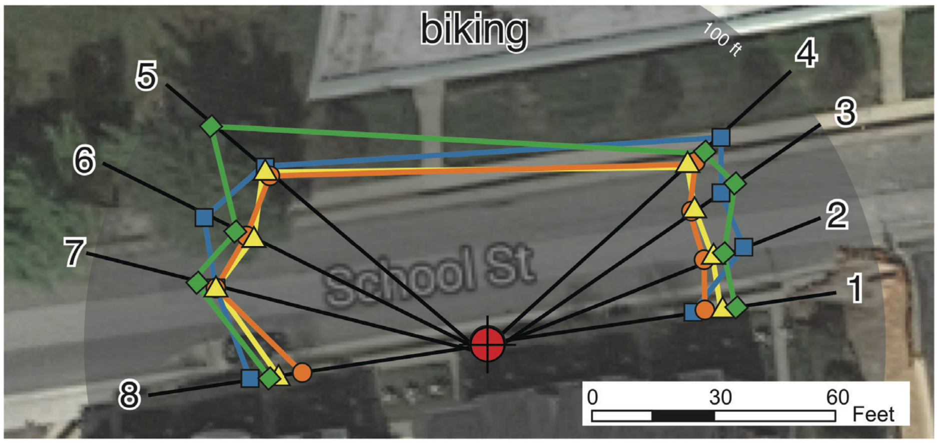
Figure 62. Dynamic obstacle engagement with WebApp, obstacle 367 summary

Obstacle Details

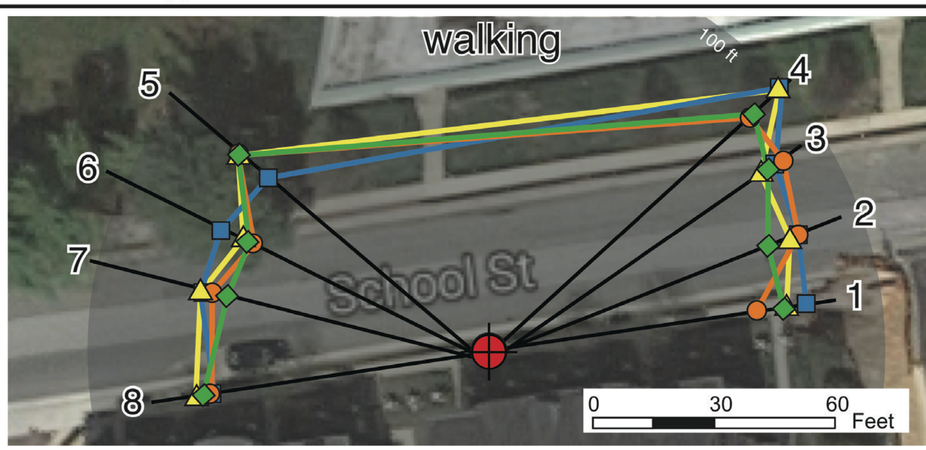
Type: Sidewalk Obstruction
Construction Detour

Location: On School St. on the sidewalk across from the Commonwealth Care Center

Description: Sidewalk excavation. Closed Sidewalk.



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	63.1	61.8	67.8	69.4
Average Distance from Buffer (ft):	36.9	38.2	32.2	30.6
Standard Deviation (ft):	5.5	7.5	7.7	10.2



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	79.1	76.4	79.3	76.6
Average Distance from Buffer (ft):	20.9	23.6	20.7	23.4
Standard Deviation (ft):	8.4	8.4	8.9	7.7

Figure 63. Dynamic obstacle engagement with the WebApp, obstacle 11 summary

Figure 64. Dynamic obstacle engagement with WebApp, obstacle 367 by device

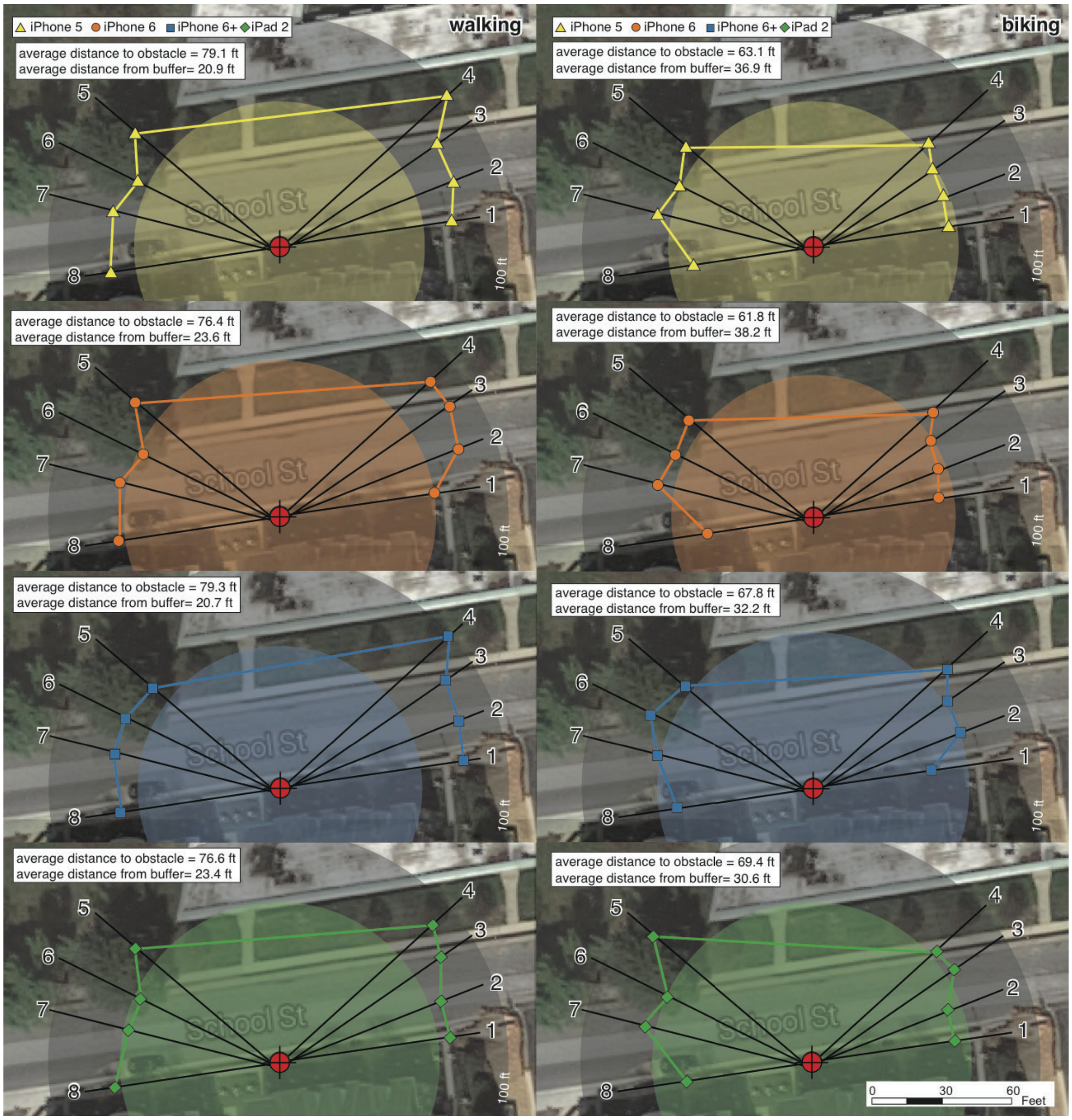


Figure 65. Dynamic obstacle engagement with WebApp, obstacle 11 by device

Obstacle engagement dynamics with the GMU-GcT MobileApp

The same field testing protocol discussed above was employed to test the functionality and obstacle alert distance for the native MobileApp, which we anticipated to be more responsive due to the less verbose communication required, and an assumption that for the same iOS devices, latency would be lower for similar tasks. Jobe (2013) compared native mobile and mobile web applications for map-based athletic tracking applications in Kenya, finding that “mobile web applications that require hardware interaction such as using the GPS, GPU, or camera are not yet viable alternatives for native applications.” He suggests that simpler mobile web applications “that only require a native interface and content consumption are suitable substitutes for native applications.” Clearly, our WebApp does need access to the device GPS and is much more than a simple reduction of a desktop application to a native interface, and based on this, we did expect to see differences. Our purpose in this study, however, is not to compare the GMU-GcT WebApp with the GMU-GcT MobileApp, but rather to look at what is possible with the two, recognizing the strengths of each and assessing what benefits each might provide to for an end-user.

With this in mind, Figure 66 and Figure 67 (similar to Figure 62 and Figure 63) contain summaries of the obstacle alert distances for user-engagement with the same 4 mobile devices, the same 2 obstacles, and the same 8 pre-defined trajectories. Figure 68 and Figure 69 contain the same side-by-side device and travel mode comparisons. An inspection of the figures and the 100 foot gray interaction distance quickly leads to the conclusion that the native app is much better at delivering obstacle alerts closer to the intended 100 foot interaction distance.

For reasons that we are not able to yet explain, there are some directional asymmetries in the obstacle alert distances, where for Obstacle 367 (Figure 66) all four devices delivered alerts quicker on the west side (eastbound trajectories) than on the eastside (westbound trajectories). Similarly, in Figure 67 (biking mode) the MobileApp delivered obstacle alerts more quickly on the east side than on the west side. In summary, all obstacle alert distances were relatively close to the 100 foot interaction distance, with the walking trials being nearly identical for many devices. This is clearly seen in Figure 68 and Figure 69, where the colored average obstacle alert distance circles entirely (or nearly entirely) overlap the gray 100 foot interaction distance circle.

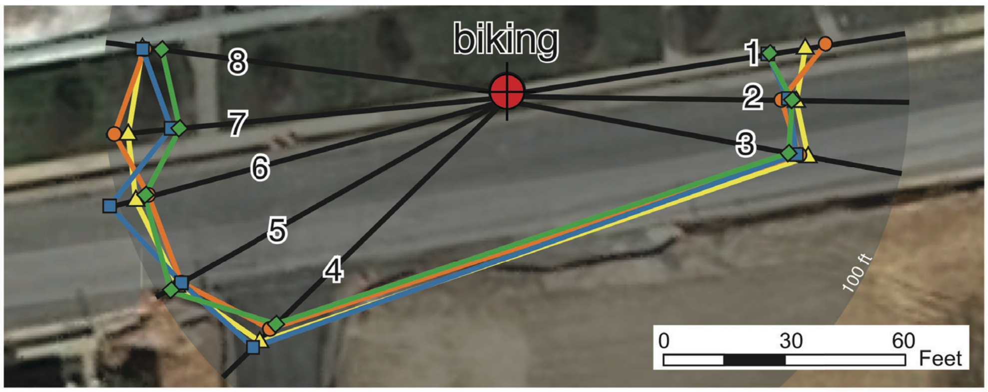
For walking end-users who approach obstacles slowly, this suggests that there will be no significant difference depending on the device they use, and that alerts should be delivered relatively close to the 100 foot interaction distance. For bicycling end-users, obstacle alerts are delivered further away from the intended 100 foot distance, and again, there is no statistically significant difference for which device they may be using to receive alerts, at least among the four that we tested.

Obstacle Details

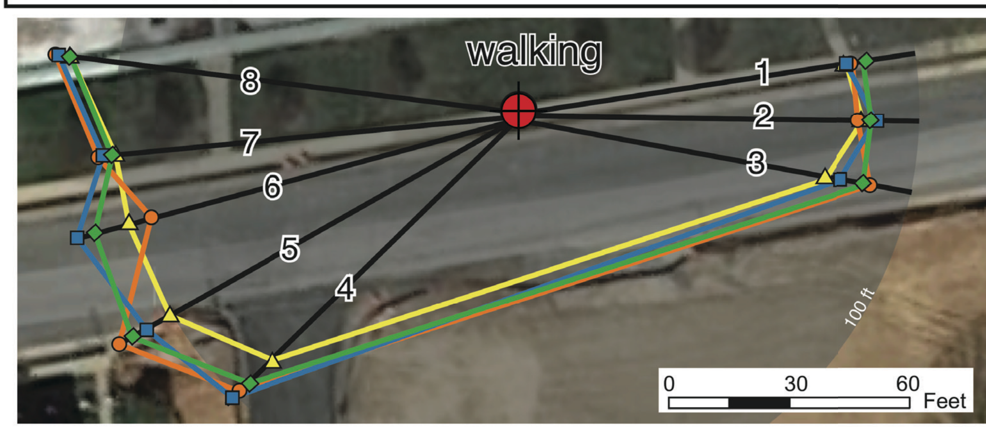
Type: Sidewalk Obstruction

Location: School St. sidewalk near one of the entrances to Inova Care Center, west of George Mason Blvd.

Description: Orange barrel partially blocking sidewalk



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	85.7	85.1	84.0	80.8
Average Distance from Buffer (ft):	14.3	14.9	16.0	19.2
Standard Deviation (ft):	6.6	6.5	6.5	6.2



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	93.5	98.6	99.8	99.6
Average Distance from Buffer (ft):	6.5	1.4	0.2	0.4
Standard Deviation (ft):	12.0	13.0	13.0	11.0

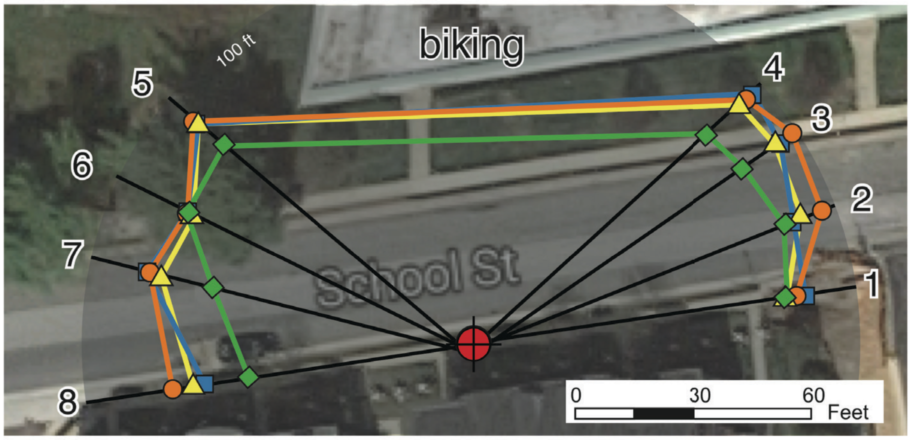
Figure 66. Dynamic obstacle engagement with MobileApp, obstacle 367 summary

Obstacle Details

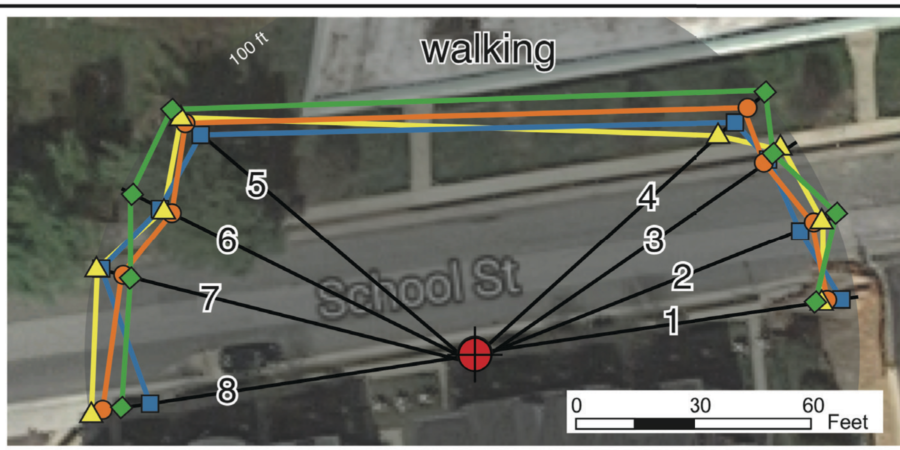
Type: Sidewalk Obstruction
Construction Detour

Location: On School St. on the sidewalk across from the Commonwealth Care Center

Description: Sidewalk excavation. Closed Sidewalk.



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	85.4	88.3	86.6	78.5
Average Distance from Buffer (ft):	14.6	11.7	13.4	21.5
Standard Deviation (ft):	7.2	7.4	5.8	6.1



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance to Obstacle (ft):	93.6	92.6	91.6	95.3
Average Distance from Buffer (ft):	6.4	7.4	8.4	4.7
Standard Deviation (ft):	7.3	7.2	7.1	7.4

Figure 67. Dynamic obstacle engagement with MobileApp, obstacle 11 summary

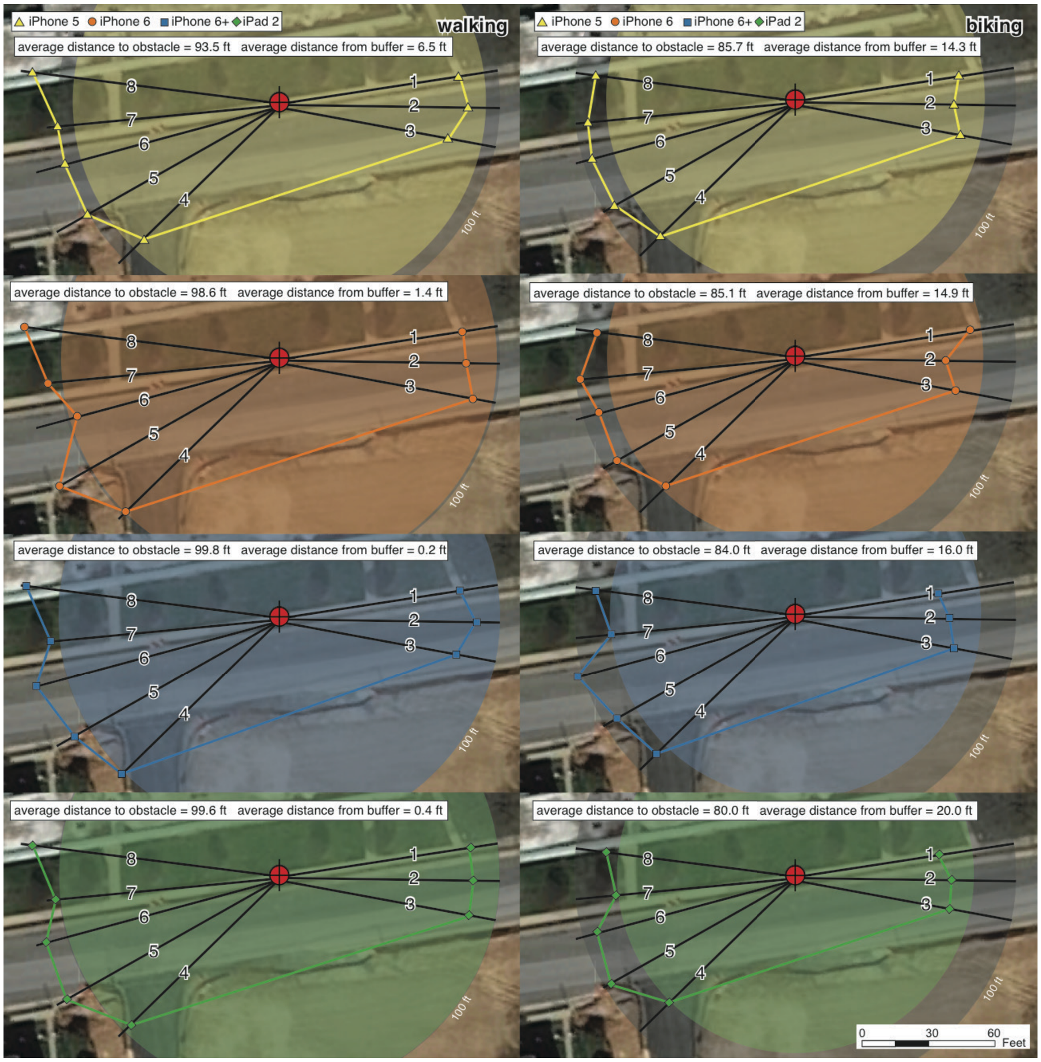


Figure 68. Dynamic obstacle engagement with MobileApp, obstacle 367 by device

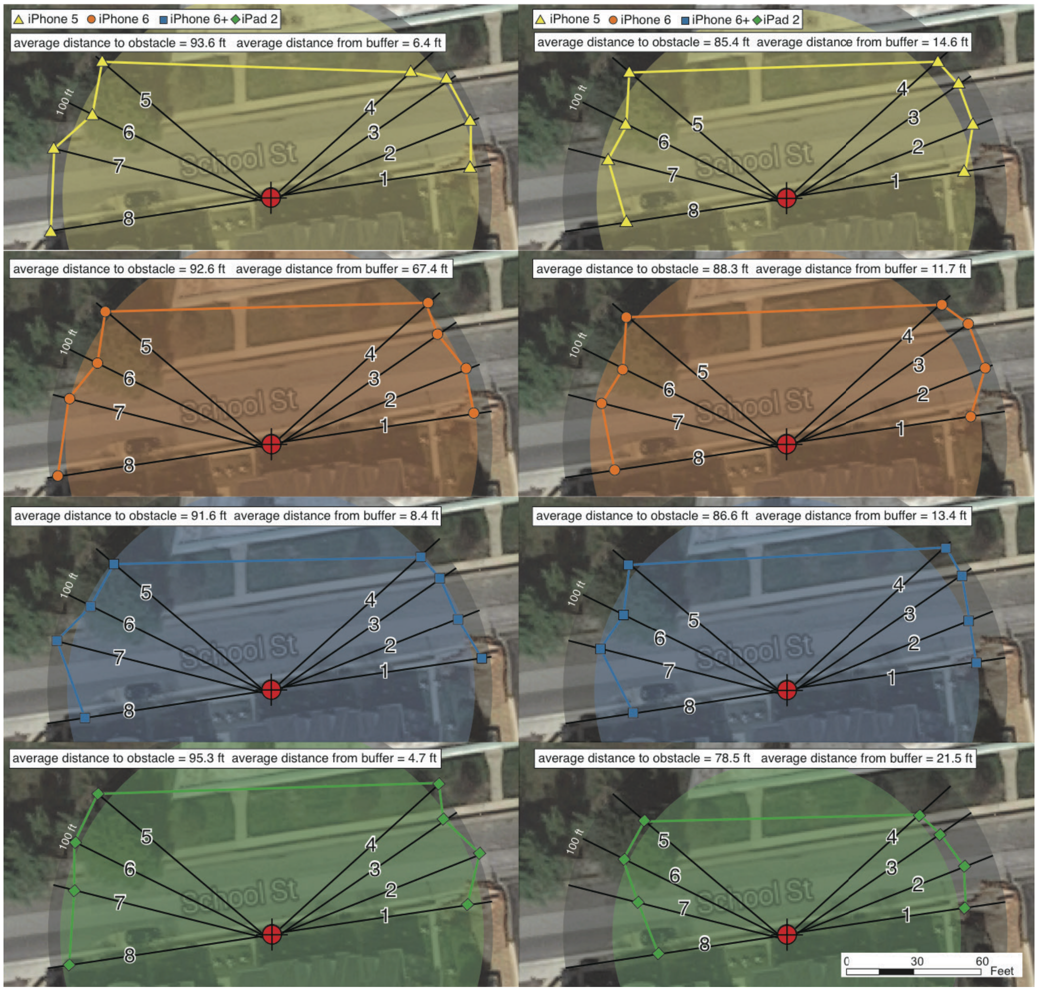


Figure 69. Dynamic obstacle engagement with MobileApp, obstacle 11 by device

Statistical Summaries for Mobile Obstacle Engagement

Engagement with the WebApp

Statistical analysis of the variables and factors in the WebApp portion of the field study indicate that the influence of device (iPhone 5, iPhone 6, iPhone plus, iPad 2) was not significant when using the WebApp (Figure 60). The associated analysis of variance (ANOVA) for device resulted in an F-statistics of 0.43361 with p-value = 0.7293, at 3 and 124 degrees of freedom (Table 10). Although small variations existed between devices during the study, no systematic, significant differences existed. The graphics presented on the preceding pages do seem to show a difference in the obstacle engagement distances for walking and biking, with the distance between the end-user and obstacle being smaller when bicycling. This is associated with a larger distance between the intended 100-foot warning buffer (shown in gray in Figure 62, Figure 63, Figure 64, Figure 65) and the point where an obstacle alert was delivered by the WebApp.

Table 10. Analysis of Variance for Mobile Device using WebApp

Analysis of Variance for Mobile Device (One-Way)

Summary

Groups	Sample size	Sum	Mean	Variance
iPhone 5	32	2,091.75	65.36719	194.58551
iPhone 6	32	2,110.41667	65.95052	154.86239
iPhone 6plus	32	2,199.41667	68.73177	195.73465
iPad2	32	2,095.66667	65.48958	196.13026

ANOVA

Source of Variation	SS	df	MS	F	p-level	F crit
Between Groups	241.08219	3	80.36073	0.43361	72.9309%	2.6777
Within Groups	22,980.69727	124	185.3282			
Total	23,221.77946	127				

After a preliminary test for the presence of homogeneity or heteroskedasticity in the sample variances (Table 11), a T-test for equality of means was conducted, resulting in a large, statistically significant t-value of 7.037 with p-value = 0.00 and t-critical value of 1.97 (Table 12). This suggests that the difference between the bicycling engagement distance and the walking engagement distances for the WebApp is statistically significant. End-users moving at a walking pace (2-3 mph) and using the WebApp receive obstacle warnings much closer to the 100-foot interaction buffer than end-users who are moving at a faster rate on a bicycle (7-8 mph).

Table 11. F-test for Homogeneity of Variances, Walking and Biking

F-Test Two-Sample for Variances: Walking and Biking

Descriptive Statistics

VAR	Walking	Biking
Sample size	64	64
Mean	73.54219	59.23047
Variance	119.01365	145.65978
Standard Deviation	10.90934	12.06896
Mean Standard Error	1.36367	1.50862

Summary

F	1.22389	F Critical value (5%)	1.51833
p-level 1-tailed	0.21245	p-level 2-tailed	0.4249
H0 (5%)?	accepted		

Table 12. T-test for Equality of Means, Walking and Biking

T-test for Equality of Means, Walking and Biking				
Descriptive Statistics				
VAR	*Sample size*	*Mean*	*Standard Deviation*	*Variance*
Walking	64	73.54219	10.90934	119.01365
Biking	64	59.23047	12.06896	145.65978
t-test assuming equal variances (homoscedastic)				
Degrees of Freedom	126			
Hypothesized Mean Difference	0.			
Pooled Variance	132.33671			
Test Statistics	7.03763			
Two-tailed distribution				
p-level	1.11397E-10	*Critical Value (5%)*	1.97897	
One-tailed distribution				
p-level	5.56983E-11	*Critical Value (5%)*	1.65704	

Finally, a test for the two obstacles shown in this field study indicates that the interaction distances for Obstacle 11 (Figure 63, Figure 65, Figure 67, Figure 69) are significantly larger (with an observed average of 71.7 meters) than for Obstacle 367 (Figure 62, Figure 64, Figure 66, Figure 68), where an average value of 61.1 was observed. The statistical analysis for this difference is shown in Table 13 and Table 14. The reasons for this difference are uncertain, and no clear contributing factors have been identified.

Future work on mobile device-based obstacle engagement with the WebApp or similar technology would test obstacles in a wide variety of settings under a number of different conditions and engagement dynamics. The latency associated with the WebApp, discussed earlier, may present itself as a temporally-significant covariate, where network conditions vary significantly throughout the testing period, impacting the ability of the WebApp and leading to temporally-significant dynamics. Because absolute time was not recorded as a factor, we cannot test for this possible source of variation, but it would be a part of future work.

Table 13: F-test for Homogeneity of Variances: Obstacle 367 and Obstacle 11

F-Test Two-Sample for Variances (Obstacle 367 & 0411)			
Descriptive Statistics			
VAR	**Obstacle 0411**	**Obstacle 367**	
Sample size	64	64	
Mean	71.6849	61.08464	
Variance	103.32352	208.20161	
Standard Deviation	10.16482	14.42919	
Mean Standard Error	1.2706	1.80365	
Summary			
F	2.01505	*F Critical value (5%)*	1.51833
p-level 1-tailed	0.00305	*p-level 2-tailed*	0.0061
H0 (5%)?	*rejected*		

Table 14. Test for Equality of Means, Obstacle 367 and Obstacle 11

Students T-test for Equality of Means, Obstacle 367 and Obstacle 0411				
Descriptive Statistics				
VAR	*Sample size*	*Mean*	*Standard Deviation*	*Variance*
Obstacle 367	64	61.08464	14.42919	208.20161
Obstacle 0411	64	71.6849	10.16482	103.32352
t-test assuming unequal variances (heteroscedastic)				
Degrees of Freedom	113			
Hypothesized Mean Difference	0.			
Pooled Variance	155.76256			
Test Statistics	4.80463			
Two-tailed distribution				
p-level	4.80359E-6	*Critical Value (5%)*	1.98118	

Engagement with the MobileApp

Statistical analysis of the field testing and obstacle interactions using the MobileApp (Figure 59) yielded results that were similar in some ways and different in other ways from the results of the field testing for the WebApp. As noted previously, the MobileApp has a more responsive design, and because it is deeply integrated with the mobile operating system, it can take advantage of interactions, cues, and alert functions from the operating system. These same features are not possible with the WebApp. Although these advantages do not always lead to more responsive performance, field testing with the native MobileApp quickly led to a hypothesis that interaction times would be quicker.

As a first step in our statistical analysis, an ANOVA for device type resulted in a conclusion of no significant differences (Table 15). The F-value for this test was 0.354 with a p-value of 0.7862 and an associated F-critical value of 2.6777, with 3 and 124 degrees of freedom. In summary, none of the mobile devices resulted in interaction distances that were significantly different. Small differences in interaction times were observed and are presented in Figure 62, Figure 63, Figure 64, and Figure 65, but these differences are not statistically significant. In this particular aspect, both the WebApp and MobileApp had the same statistical result of no significant mobile device differences.

Table 15. Analysis of Variance for Mobile Device using MobileApp

Analysis of Variance (One-Way)

Summary

Groups	Sample size	Sum	Mean	Variance
iPhone 5	32	2,865.25	89.53906	92.63888
iPhone 6	32	2,916.75	91.14844	104.17551
iPhone 6plus	32	2,896.41667	90.51302	126.17881
iPad2	32	2,832.83333	88.52604	152.67806

ANOVA

Source of Variation	SS	df	MS	F	p-level	F crit
Between Groups	126.34956	3	42.11652	0.35416	78.62019%	2.6777
Within Groups	14,745.80924	124	118.91782			
Total	14,872.1588	127				

Next, after a preliminary test for homogeneity of sample variances (Table 16), a T-test for equality of means was conducted, resulting in large, statistically significant T-value of 6.894, with p-value 0.000 and an associated T critical value of 1.97 (Table 17). This suggests that the difference between the bicycling engagement distance and the walking engagement distances for the MobileApp is statistically significant, similar to the WebApp. End-users moving at a walking page receive obstacle notifications much closer to the 100-foot interaction buffer.

Table 16. F-test for Homogeneity of Variances, Walking and Biking

F-Test Two-Sample for Variance: Walking and Biking

Descriptive Statistics

VAR	Biking	Walking
Sample size	64	64
Mean	84.29036	95.57292
Variance	85.24912	86.15862
Standard Deviation	9.23304	9.28217
Mean Standard Error	1.15413	1.16027

Summary

F	1.01067	*F Critical value (5%)*	1.51833
p-level 1-tailed	0.48327	*p-level 2-tailed*	0.96654
H0 (5%)?	*accepted*		

Table 17. T-test for Equality of Means, Walking and Biking

T-test for Equality of Means, Walking and Biking				
Descriptive Statistics				
VAR	*Sample size*	*Mean*	*Standard Deviation*	*Variance*
Walking	64	95.57292	9.28217	86.15862
Biking	64	84.29036	9.23304	85.24912
t-test assuming equal variances (homoscedastic)				
Degrees of Freedom	126			
Hypothesized Mean Difference	0.			
Pooled Variance	85.70387			
Test Statistics	6.89417			
Two-tailed distribution				
p-level	2.3245E-10	*Critical Value (5%)*	1.97897	
One-tailed distribution				
p-level	1.16225E-10	*Critical Value (5%)*	1.65704	

Finally, a test for differences in the interaction times for obstacles was performed. After an initial test for homogeneity (Table 18) of sample variances, a T-test was performed, resulting in no significant difference (Figure 19). In this regard, the MobileApp is different from the WebApp. The MobileApp performed similarly for both obstacles, while the WebApp did not. Conjecture about this dynamic is broad, but focuses on the possibility of temporal variations in cell phone and local network performance, which is a critical factor for the WebApp but not as influential for the MobileApp, which communicates less frequently with our project servers, and does not require server-based calculations or feedback.

Table 18. F-test for Homogeneity of Variances: Obstacle 367 & Obstacle 0411

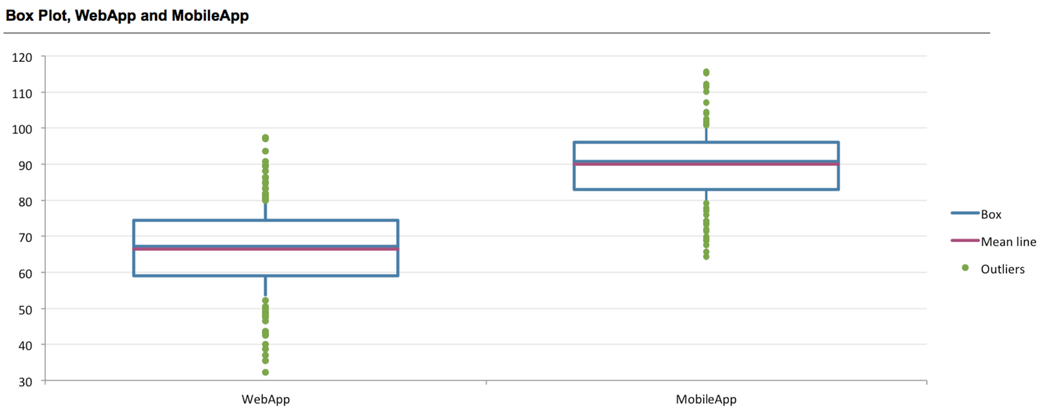
F-Test Two-Sample for Variances			
Descriptive Statistics			
VAR	**Obstacle 0411**	**Obstacle 367**	
Sample size	64	64	
Mean	88.97786	90.88542	
Variance	56.69582	177.52194	
Standard Deviation	7.52966	13.32374	
Mean Standard Error	0.94121	1.66547	
Summary			
F	3.13113	*F Critical value (5%)*	1.51833
p-level 1-tailed	5.4611E-6	*p-level 2-tailed*	0.00001
H0 (5%)?	*rejected*		

Table 19. T-test for Equality of Means, Obstacle 367 and Obstacle 11

T-test for Equality of Means, Obstacle 367 and Obstacle 0411				
Descriptive Statistics				
VAR	*Sample size*	*Mean*	*Standard Deviation*	*Variance*
Obstacle 367	64	90.88542	13.32374	177.52194
Obstacle 0411	64	88.97786	7.52966	56.69582
t-test assuming unequal variances (heteroscedastic)				
Degrees of Freedom	100			
Hypothesized Mean Difference	0.			
Pooled Variance	117.10888			
Test Statistics	0.99714			
Two-tailed distribution				
p-level	0.3211	*Critical Value (5%)*	1.98397	
One-tailed distribution				
p-level	0.16055	*Critical Value (5%)*	1.66023	

Statistical Comparisons of the WebApp and MobileApp

A view of the distribution of interactions times provided by the Box Plots (Figure 70) leads to a preliminary hypothesis that there is a significant difference between the mean distances at which an end-user receives an obstacle alert notification. As noted previously, the MobileApp, due to its design, is more responsive. A statistical validation of this hypothesis is seen inTable 20 and Table 21, where a mildly significant F-value (1.56) leads to a T-test with accommodations for heteroskedasticity. This T-test (Table 21) results in a t-test statistic of 15.38, which is far enough into the distributional tail that the p-value is not displayed, other than noted to be 0. The critical value for this test is 1.969. Clearly, the obstacle notification times for the MobileApp are delivered much closer to the 100-foot interaction buffer than for the WebApp.



Variable	Count	Mean	Minimum	Lower whisker	Q1	Median	Q3	Upper whisker	Maximum
WebApp	128	66.38477	32.33333	52.86261	58.97917	67.20833	74.33333	79.90692	97.41667
MobileApp	128	89.93164	64.25	79.11021	82.8975	90.67	96.105	100.75307	115.67

Figure 70. Box Plots for Obstacle Interaction Distances, WebApp (left) and MobileApp (right)

Table 20. F-test for Homogeneity of Variances, MobileApp and WebApp

F-Test Two-Sample for Variances

Descriptive Statistics

VAR	**MobileApp**	**WebApp**
Sample size	128	128
Mean	89.93164	66.38477
Variance	117.10343	182.84866
Standard Deviation	10.82143	13.52215
Mean Standard Error	0.95649	1.1952

Summary

F	1.56143	*F Critical value (5%)*	1.34046
p-level 1-tailed	0.00629	*p-level 2-tailed*	0.01257
H0 (5%)?	*rejected*		

Table 21. T-test for Equality of Means, WebApp and MobileApp

T-test for Equality of Means, WebApp and MobileApp

Descriptive Statistics				
VAR	*Sample size*	*Mean*	*Standard Deviation*	*Variance*
WebApp	128	66.38477	13.52215	182.84866
MobileApp	128	89.93164	10.82143	117.10343
t-test assuming unequal variances (heteroscedastic)				
Degrees of Freedom	242			
Hypothesized Mean Difference	0.			
Pooled Variance	149.97604			
Test Statistics	15.38198			
Two-tailed distribution				
p-level	0.	*Critical Value (5%)*	1.96982	
One-tailed distribution				
p-level	0.	*Critical Value (5%)*	1.65117	

Dynamic Obstacle Interaction: Video and Demonstration

Statistical and graphical summaries of the GMU-GcT dynamic obstacle engagement study are useful. They indicate a more responsive delivery of alerts with the MobileApp, which is due to many of the same issues noted by Jobe (2013). The WebApp, with some innate latency, was slower in delivering obstacle alerts, which resulted in alert distances between 50% and 80% of the intended 100 foot distance. Useful accompaniments to this analysis are the following videos (Table 22), which demonstrate the alert functionality of the WebApp and MobileApp. The videos contain side-by-side views of the forward-looking GoPro, and the respective screens of the WebApp and the MobileApp, and basic functionality of these software packages can be seen. The applications are not commercial software, but were coded to provide a proof-of-concept, to provide dynamic extensions to the GMU-GcT, and to test the limits of current mobile software development environments for geospatial applications.

Table 22. Obstacle Interaction Videos

	Web Application	Mobile Application
Obstacle 367 (westbound)	http://geo.gmu.edu/videos/webapp_1.mp4	http://geo.gmu.edu/videos/mobileapp_1.mp4
Obstacle 367 (eastbound)	http://geo.gmu.edu/videos/webapp_2.mp4	http://geo.gmu.edu/videos/mobileapp_2.mp4
Obstacle 011 (westbound)	http://geo.gmu.edu/videos/webapp_3.mp4	http://geo.gmu.edu/videos/mobileapp_3.mp4
Full videos	http://geo.gmu.edu/videos/webapp_full.mp4	http://geo.gmu.edu/videos/mobileapp_full.mp4

Mobile Routing in the GMU-GcT

General routing functionality in the GMU-GcT was reviewed by Rice et al. (2014)[83] and Qin et al. (2015a)[84]. Recent work has focused on the development of mobile routing routines in the GMU-GcT with two purposes. First, moderators have an interest in using the MobileApp to explore the region, or to purposefully navigate toward and engage with obstacles needing moderation. In either case, they are not attempting to avoid engagement with obstacles. This exploration functionality in the MobileApp allows the moderators to report obstacles using device GPS location, attach photographs, and perform quality assessments. Second, some end-users have an interest in defining routes that avoid obstacles, stairs, and steep paths, recognizing that this mode frequently results in longer shortest cost paths (as presented in the next chapter). The GMU-GcT uses a default mode titled 'Explore' where routes are not defined. With a simple finger tap on the route button at the top of the MobileApp (Figure 59, Figure 60), end-users can select between a standard shortest cost path route, and an obstacle-avoiding route. In this mode, obstacles will not be directly engaged because pedestrian network segments containing obstacles will not be used. Our general analysis of routing is contained in the next chapter (Chapter 5), and views of the 'Explore' and 'Route' functionality are shown in Figure 71 and Figure 72, respectively. These examples of GMU-GcT were generated with the MobileApp running on an iPad.

[83] Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed," 201.

[84] Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

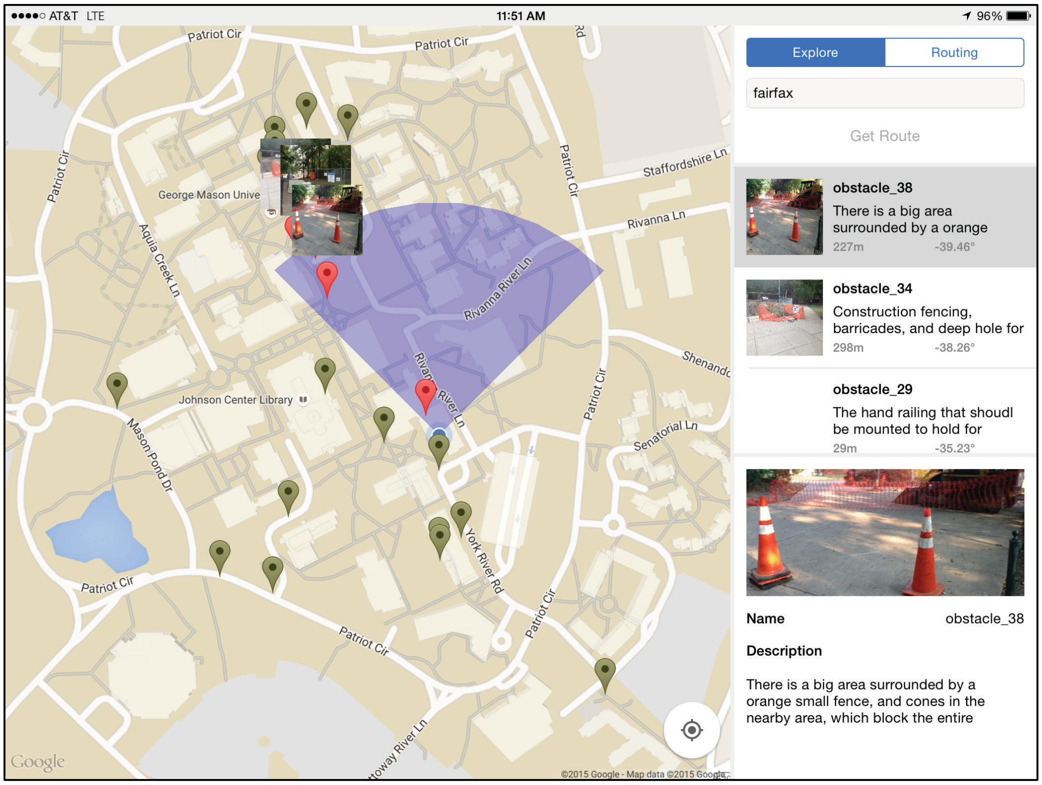


Figure 71. Dynamic Obstacle Engagement in GMU-GcT MobileApp, in "Explore" mode (iPad)

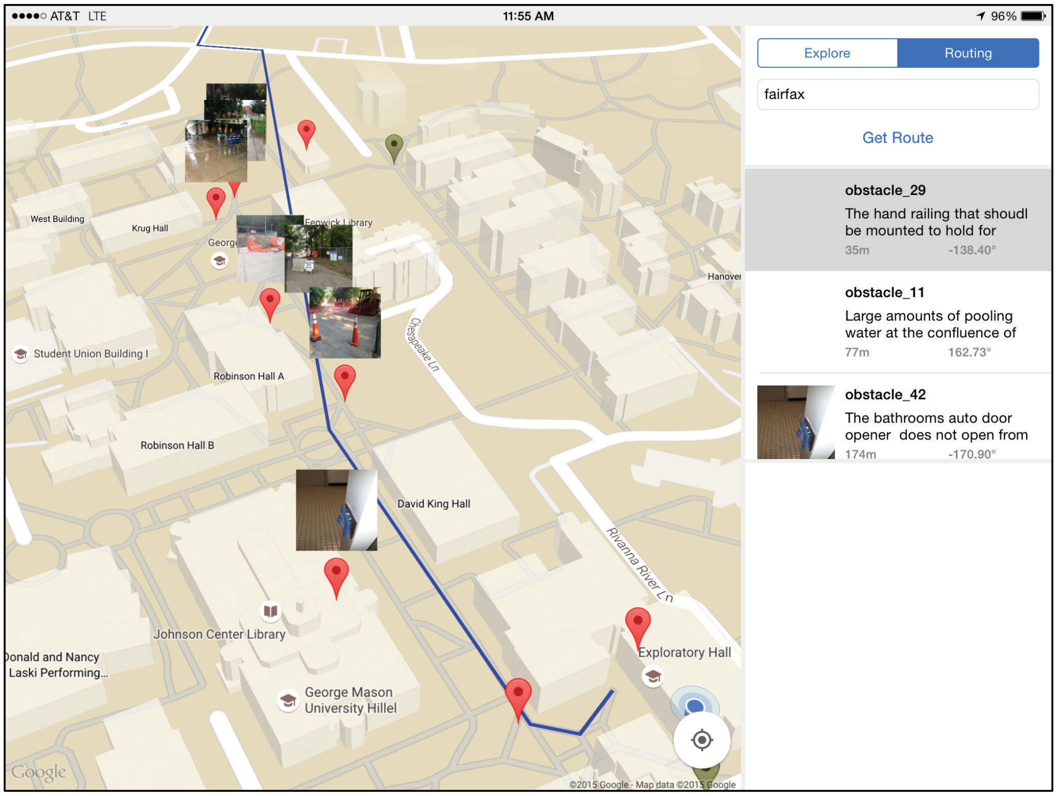


Figure 72. Dynamic obstacle engagement in GMU-GcT MobileApp, in regular "Route" mode (iPad)

The next chapter addresses an important extension of the GMU-GcT in the area of routing, which is premised on our past work (and work presented in this report) on quality assessment and social moderation. We discuss how the GMU-GcT provides an ability to analyze accessibility routing in the local area. This work builds on earlier work presented in Rice et al. (2012b, 2013b, 2014)[85,86,87] and Qin et al. (2015a).[88]

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[85] Rice et al., "Crowdsourced Geospatial Data: A Report on the Emerging Phenomena of Crowdsourced and User-Generated Geospatial Data."

[86] Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

[87] Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed."

[88] Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

5 Dynamic Use of the GMU Geocrowdsourcing Testbed: Routing Analysis

Obstacle Avoidance Routing in Pedestrian Networks

This chapter addresses an important dynamic use of the GMU-GcT: the ability to generate obstacle-avoidance routes across the local pedestrian network using geocrowdsourcing, quality assessment, and basic information about the accessibility of the pedestrian network. To articulate how this dynamic GMU-GcT functionality works, we present the generation of the current, underlying pedestrian network, the basic characteristics of this network, the geocrowdsourced obstacles, and their corresponding influence on routing results. As reviewed in Rice et al. (2013a, 2013b)[89,90] and Qin et al. (2015a)[91], capturing and documenting obstacle information on pedestrian pathways can be difficult and time consuming, depending on the design of the system and data model specifications. Formal approaches for modeling accessibility obstacles, such as those proposed by Laakso et al. (2013)[92] and Chen et al. (2015)[93] are thorough, but not well adapted for transient events. A crowdsourcing approach with a relatively less structured, flexible workflow for collecting transient obstacle and infrastructure data has shown to be effective in our local area (Paez 2014, Rice 2015)[94,95]. This approach presupposes an effective quality assessment implementation, where a team of moderators performs a quality check on crowdsourced data. The quality of this moderation approach has been addressed in Chapter 3 of this report.

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[89] Rice et al., "Crowdsourcing Techniques for Augmenting Traditional Accessibility Maps with Transitory Obstacle Information."

[90] Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

[91] Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

[92] Mari Laakso et al., "An Information Model for Pedestrian Routing and Navigation Databases Supporting Universal Accessibility," *Cartographica: The International Journal for Geographic Information and Geovisualization* 48, no. 2 (2013): 89–99.

[93] Min Chen et al., "An Object-Oriented Data Model Built for Blind Navigation in Outdoor Space," *Applied Geography* 60 (2015): 84–94.

[94] Paez, "Recruitment, Training, and Social Dynamics in Geo-Crowdsourcing for Accessibility."

[95] Rice, "Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study."

Two obstacle types are collected by the GMU-GcT: permanent obstacles and transient obstacles. Permanent obstacles include stairways or steps, paths with a steep slope, narrow sidewalks, crosswalks, curb cuts, pathway surface conditions (such as gravel, cobble stones, etc.), protrusions, and urban furniture (such as a trash cans, benchs, or tables blocking a pathway). Transient obstacles include vehicles, construction detours, construction barricades, temporary fencing and barriers related to crowds or special events. These transient obstacles are crowdsourced and checked by moderators.

Pedestrian Networks

Based on a review of pedestrian routing across several large online mapping websites (Qin et al. 2015a)[96] it is known that many routing services for pedestrians utilize roadways instead of sidewalks. Presumably, this is due to the difficulty of assembling the underlying data for an effective pedestrian network, which would -- at a minimum -- include sidewalk centerlines and crosswalks. Figure 73 shows a typical Google Maps example for routing between two proximate buildings on the GMU university campus, with routing on maps and written directions. For mobility and visually impaired users, the routing shown is not adequate. Sidewalk centerlines and crosswalks, if they exist and are used in the routing process, are not sufficient by themselves. Mobility and visually impaired users also require information about the presence of ramps, curb cuts, running and cross slope along the pedestrian network, sidewalk widths, and the accessibility of crossing transition points. These items are difficult to collect and are generally not included in standard pedestrian routes such as those shown in Figure 73.

[96] Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

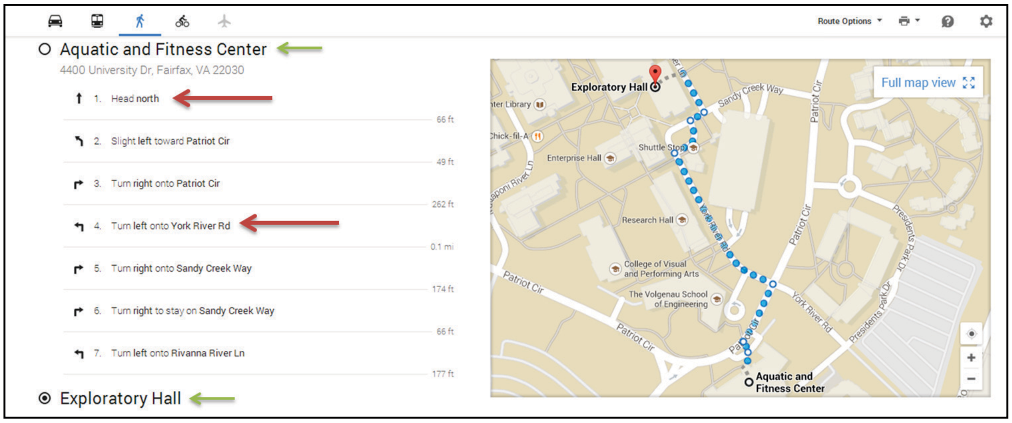

Figure 73. Google Maps pedestrian routing on the GMU Campus (September 2014)

An exemplar for accessible routing that includes some accessibility-related data is the Accessible Paths in Pinhel Web Portal, where information about sidewalk widths, surface conditions, and running slope are used to generate an accessible route.[97] For the local area, the only pedestrian infrastructure data that existed prior to this project was an incomplete ArcGIS dataset with selected sidewalk edges, digitized by the Fairfax County GIS Team using the Virginia Base Mapping Program (VBMP) Orthoimagery collected and provided by the Virginia Information Technologies Agency (VITA).[98] Using this preliminary dataset as a guide, along with some incomplete sidewalk data from the GMU campus, a detailed pedestrian network and supporting datasets were generated to support this research, as discussed in Rice et al. (2013b)[99].

The pedestrian network generated for this project (Figure 74) was digitized from the existing incomplete sidewalk datasets and VBMP orthoimagery, and incorporated into the GMU-GcT, as noted in Rice et al. (2013b)[100] and Qin et al. (2015a)[101]. The pedestrian network encompasses the GMU campus and adjacent portions of Fairfax County and the City of Fairfax. The selected study area was chosen in collaboration with City of Fairfax and GMU Campus planning and transportation agencies to represent common origin and destination points for commuters, including blind,

97 http://percursos.pinhel.proasolutions.pt/ [accessed August 23, 2015]

98 http://www.vita.virginia.gov/isp/default.aspx?id=8412 [accessed August 23, 2015]

99 Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

100 Ibid.

101 Qin et al., "Geocrowdsourcing and Accessibility for Dynamic Environments."

visually-impaired, and mobility-impaired users that walk, ride shuttles, or commute to campus.

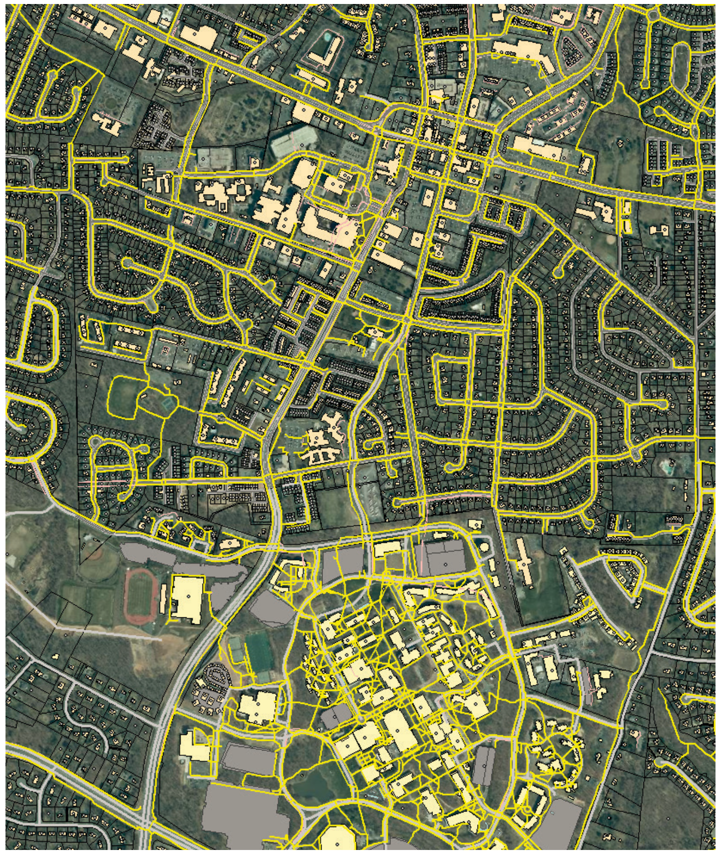

Figure 74. A section of the pedestrian network for the local area (in yellow).

The pedestrian network in the GMU-GcT includes sidewalk centerlines, stairs, steps, steep paths (with greater than 1:12 slope), crosswalks, and curb cuts. The embedded pedestrian network contains 3,489 network segments covering an area of 5.97 square miles, centered on the GMU Campus and the City of Fairfax.

Pedestrian Network Coverage

Figure 75 shows the roadways in the study areas without adjacent sidewalks, and Figure 76 shows an alternative representation with pedestrian-inaccessible areas of the region masked with polygons. The total length of roadways in the study area is 187.2 kilometers and the total length of the pedestrian network (Figure 74), with both sides of the roadways included, is 230.0 kilometers. The total length of the pedestrian-inaccessible roadways (Figure 75) is 58.8 kilometers, or 31.4% of the total roadway length. This number appears consistent with the observed conditions in the field study area.

Figure 75. Roads (in black) without adjacent sidewalks (at left, with all roads, and isolated, at right)

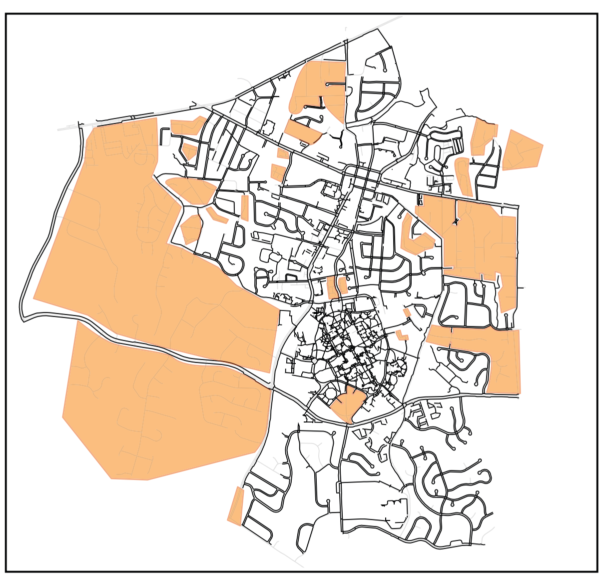

Figure 76. Pedestrian-inaccessible regions masked with polygons

Obstacles and their Influence on the Accessible Pedestrian Network

Figure 77 and Figure 78 show the distribution of stairs, steep paths, and crowdsourced obstacles in the GMU-GcT. For the density of buildings and terrain variability, the stairs and steep paths are more heavily concentrated on the GMU campus and at one notable section in downtown City of Fairfax.

Figure 77. Location of Stairs and Steep pathways (buffered for visibility), with pedestrian network (left) and isolated (right)

Figure 78. Location of Obstacles in the GMU Geocrowdsourcing Testbed, as of October 10, 2014

Figure 79 and Figure 80 show the segments of the pedestrian network that were impacted by the presence of stairs, steep paths, and transient obstacles, and include many lengthy segments in the central transportation axis from the downtown City of Fairfax through the center of the George Mason University campus. The total length of pedestrian network segments currently impacted by stairs and steep paths, and transient obstacles is 14.1 kilometers, or 6.1% of the total length of the pedestrian network. While this proportion seems rather small, the distribution of impacted segments can, and does, have a significant influence on the accessible routes, as seen in the next section.

Figure 79. Location of pedestrian network segments impacted by obstacles, with pedestrian network (left) and isolated (right)

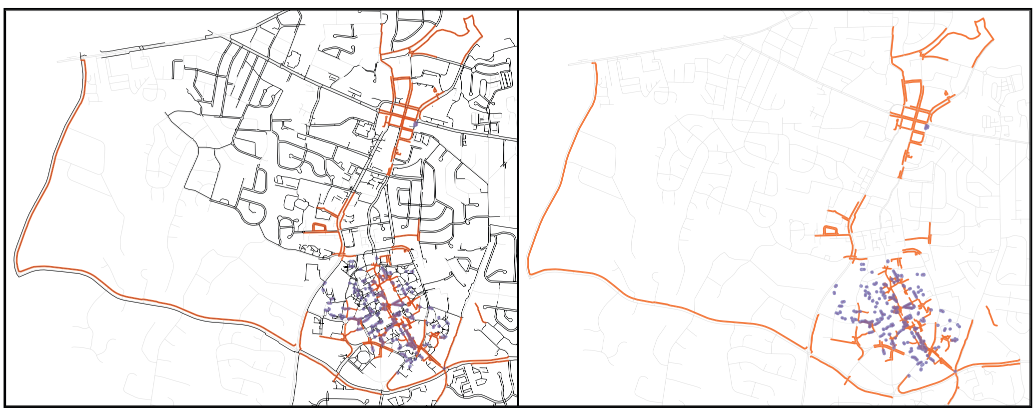

Figure 80. Location of pedestrian network segments impacted by Stairs and Steep Paths (purple), and Obstacles (red), with pedestrian network (left) and isolated (right)

Routing and Accessibility Dynamics

It is possible for a given route chosen by a pedestrian to begin and end anywhere within the pedestrian network. In order to capture this diversity of possible routes, this research employed all network junctions as potential start and end points of pedestrian trips. The underlying pedestrian network (Figure 74) contains 2,772 junctions, which generate 7,681,212 origin-destination pairs. The majority of these pairs produce routing results under normal conditions, while more than 1/8 origin-destination pairs failed to route, which is indicative of the normal topological disruptions of a real-world pedestrian network, where segments of the network are topologically stranded from larger sections.

In order to study the general accessibility characteristics of the study area, a routing analysis was constructed under three general conditions. The first condition is an initial unrestricted condition, using every possible pairwise combination of network junctions. This represents routing across the entire pedestrian network without any accessibility constraints imposed, and resulted in 6,683,094 successful routes and an average route length of 1,834.7 meters (Table 23). The second condition is one in which the network is restricted by stairs and steep paths. This condition represents the most common general accessibility routing approach not taking into account transient obstacles. This resulted in 4,381,686 successful routes and an average route length of 2,121.23 meters, or an increase of 15.62% from the unrestricted condition (Table 23). As the most restrictive condition, the third condition is one in which the network is restricted by stairs, steep paths, and transient obstacles. This condition is the closest to reality for many of the end-users interviewed for our research (Rice et al. 2013a, 2014). This resulted in 3,868,459 successful routes and an average route length of 2,215.5 meters, or an increase of 20.76% above the unrestricted condition (Table 23).

Table 23. Summary Results of Routing Analysis

	No restrictions	**Stairs & Steep Paths Restricted**	**Stairs, Steep Paths, & Obstacles Restricted**
Junctions	2772	2665	2758
Routes	6,683,094	4,381,686	3,868,459
Average route length (m)	1,834.70	2,121.23	2,215.50
Increase (%)	0%	15.62%	20.76%

Three routing result scenarios are presented in Figure 81, Figure 82, and Figure 83, on the following pages. They represent a range of characteristic results for the three scenarios in this study. They include routing with modest (Figure 81), substantial (Figure 82), and immense (Figure 83) increases in path length under the three conditions, with accessibility restriction increasing. Figure 81 shows an initial routing scenario from an origin to a destination 1,982 meters away. This route takes the user directly through the center of the GMU campus. When stairs and steep paths are restricted, the shortest cost path increases by 4.4% to 2,070 meters, which represents a small reroute or deviation from the shortest cost path. The more restrictive condition, where transient obstacles are used to eliminate additional network segments, increases the length of the path to 2,115 meters, a 6.7% increase over the least restrictive condition. This represents many routing scenarios encountered in our system, where routing around stairs, steep paths, and obstacles requires a modest increase in path length.

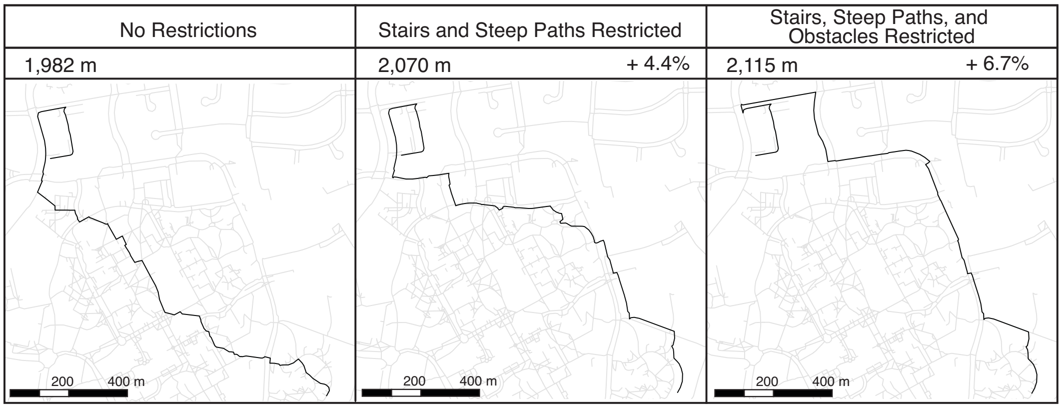

Figure 81. Routing scenario 1: modest route length increase

Figure 82 shows a route from the study with a substantial path increase under restrictive accessibility conditions. The first condition (no restrictions) results in a path length between origin and destination of 1,319 meters. Under the second condition (stairs and steep paths restricted), the path length changes modestly, increasing to 1,432 meters or 8.6%. Under the third condition (stairs, steep paths, and transient obstacles restricted) the path length increases substantially to 4,065 meters, for an increase of 208.2%. This increase is due to transient obstacles along a main road, resulting in a long route around an entire neighborhood, to arrive at a destination close to the south side of the study area. This substantial increase in the length of an accessible path happens when transient obstacles impact critical areas with poor sidewalk coverage.

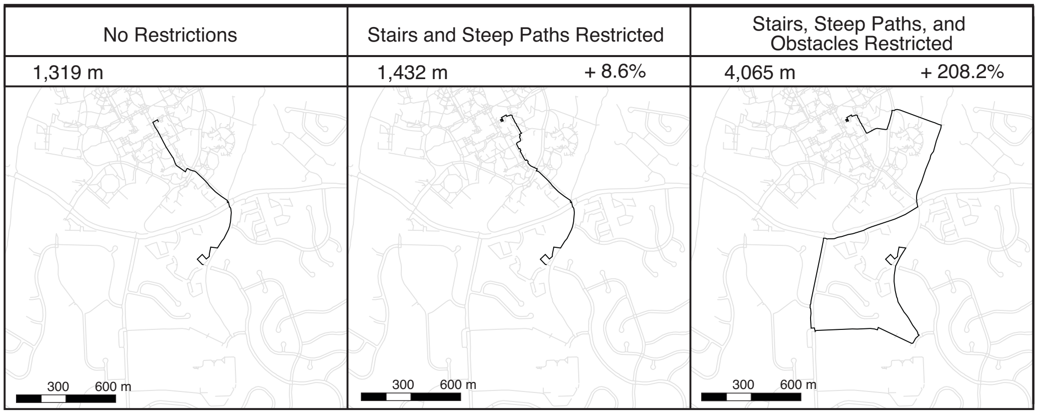

Figure 82. Routing scenario 2: substantial route length increase

Figure 83 shows the progression from normal conditions to restrictive accessibility conditions in one of the most unusual examples covered by this study. The figure shows a short route from an origin and destination 69 meters apart, under no restrictions. Imposing the second condition (stairs and steep paths restricted) yields an enormous increase in length, to 1,052 meters or an increase of 1421%. The route is increased even further by the imposition of the third condition (stairs, steep paths, and transient obstacles restricted), with a final route of 1,294 meters, or 1915% above the initial route length. Inspection of this scenario allows us to conclude that an unusual combination of stairs, steep paths, obstacles, and man-made features (buildings) causes a reroute of unusual length. This scenario is rare, and represents one of the worst cases of route length increase in the GMU study area under restrictive accessibility conditions.

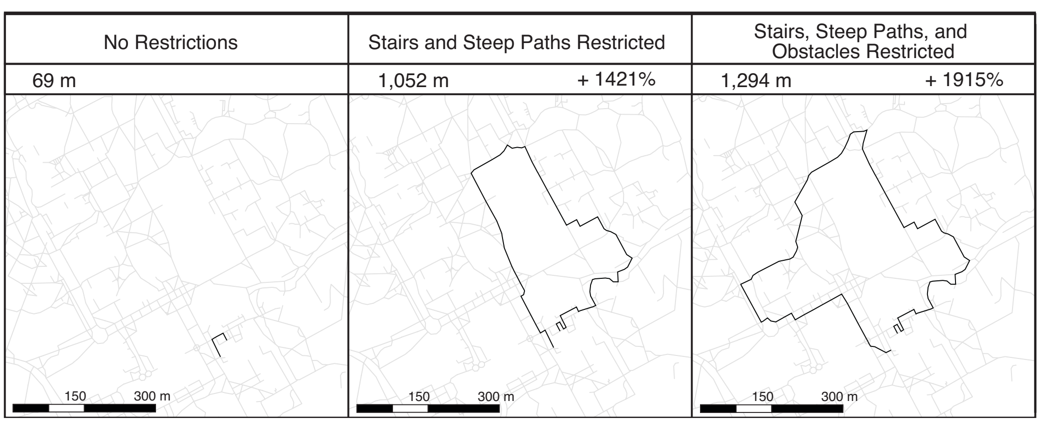

Figure 83. Routing Scenario 3: Immense route length increase

Discussion

Routing in the GMU campus region is difficult due to the overwhelming emphasis on vehicular transportation as the preferred mode of transit. While portions of the local area are urbanized and walkable (notably the City of Fairfax), other portions of the study area remain largely inaccessible due to the lack of sidewalks along roadways, lack of curb cuts and connecting crossing points, and the presence of transient obstacles. Figure 24 shows that large portions of the study area are inaccessible due to the lack of sidewalks and other infrastructure such as curb cuts and crosswalks. Figure 28 shows that large portions of the study region with sidewalks are in fact inaccessible for many individuals because of the presence of stairs, steep paths, and transient obstacles that block access to the pedestrian network. These transient obstacles have a very large impact on the accessibility of the local area. Figure 81, Figure 82, and Figure 83 demonstrate some of the characteristic results of imposing accessibility constraints on routing.

The routing analysis demonstrates that restricted routing (without using stairs and steep paths) substantially increases the route length. Under this restricted routing condition, the average path length increase for the study was 15.62% above normal (unrestricted) conditions. For the third condition (stairs, steep paths, and obstacles restricted) the average path length increased 20.76% above normal (unrestricted) conditions. This impact is felt directly by blind, visually-impaired, and mobility-impaired individuals who require accessible sidewalks, but it is also felt by senior citizens, families with strollers, and individuals with minor and temporary mobility impairments.

Church and Marston (2003)[102] note that route choice is highly individual, and that traditional accessibility measures do not take into account the significant physical and mobility differences of individuals. Their 2003 study demonstrated these individual differences in four individually-selected routing results between the same origin and destination with lengths varying from 198 meters to 610 meters. This 308% increase, due to individual preferences, was reported to represent common variation between individuals. Interviews with end-users of the GMU-GcT included anecdotal information confirming the large individual variation in routing

[102] Richard L. Church and James R. Marston, “Measuring Accessibility for People with a Disability,” *Geographical Analysis* 35, no. 1 (2003): 83–96.

preferences, due to conditions such as tree cover, sunlight, ambient temperature, and minor variations in cross slope (Rice et al. 2014, Figure 84). This individual variation in routing preference makes a single accessible routing portal difficult to implement, unless extensive routing customization is allowed for each user. Recent efforts have taken individual preferences into consideration in the routing process, such as the work of Karimi et al. (2014)[103] and the Pinhel Accessibility Platform (2014).

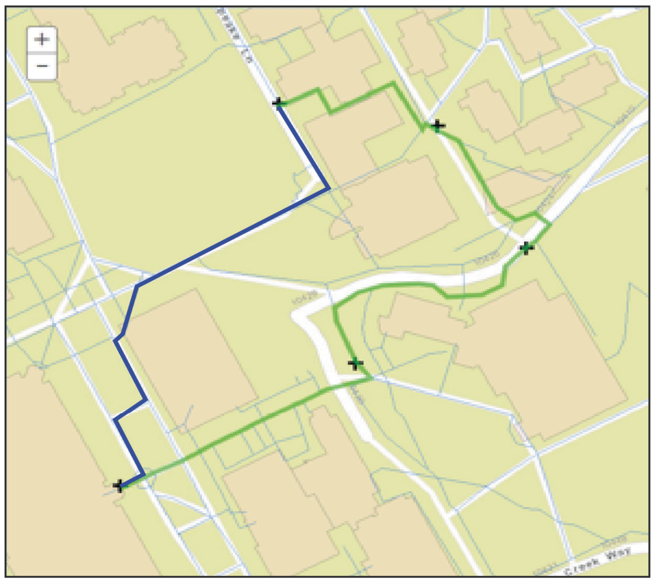

Figure 84. Individual route preference (green) and the shortest cost path (blue), from Rice et al. 2014.

Summary

New applications involving distributed services (such as Thatcher 2013)[104] are a developing theme in geocrowdsourcing, as are analysis performed with volunteered and ambient data. This chapter presents a detailed routing analysis performed with geocrowdsourced obstacle data and accessibility infrastructure data, but collected and integrated into the GMU-GcT. While the analysis here identified the individual routes influenced by barriers to pedestrian travel and summarized the impact on the network as a whole, it has treated each individual path as if it were

[103] Hassan A. Karimi, Lei Zhang, and Jessica G. Benner, "Personalized Accessibility Map (PAM): A Novel Assisted Wayfinding Approach for People with Disabilities," *Annals of GIS* 20, no. 2 (April 3, 2014): 99–108, doi:10.1080/19475683.2014.904438.

[104] Thatcher, "From Volunteered Geographic Information to Volunteered Geographic Services."

equally important from the perspective of pedestrian demand. Further research can be envisioned that will enumerate the actual, or likely, routes to be taken by the typical daily pedestrian population and as a special case, by the disabled population. Once routing dynamics are identified, a more robust measure of the magnitude of the problems caused by stationary and transient obstacles can be determined. Comparisons of shortest-cost routes with actual routes, and the specific differences between the two would yield important data about routing preference. Furthermore, knowing the demand for routes, and the set of obstacles causing variable interference on those routes would permit an investigation of which obstacles to remove under limited funding conditions. One can imagine an optimization problem that would direct the planning for network update and maintenance. The expanding and growing university and local urban area and concomitant interest in multimodal transportation patterns makes an expansion of this routing analysis a worthwhile future activity.

6 Conclusions and Future Prospects for Crowdsourced Geospatial Data

The purpose of this chapter is to reflect on the research contributions of this project, and the general developments in geocrowdsourcing. As noted in Sui et al. (2013)[105], rapid developments in technology, including smart phones, GPS, distributed sensor networks, and cloud computing, have radically transformed the way geographic data are collected, stored, analyzed, and used. The former definition of what could be considered geospatial data, based on traditional cartographic production processes has dramatically changed. Several authors have captured and articulated this dynamic. In addition to Sui et al. (2013) and many of the chapters in their book, we recommend Elwood (2010)[106] and Elwood et al. (2012)[107] for the way that the authors analyze and synthesize technological, cultural, and social aspects of geocrowdsourcing.

A major concern cited by Goodchild (2007)[108] is the quality and reliability of volunteered geographic information (VGI). To provide a context for discussing quality assessment in geocrowdsourced data, Rice et al. (2012b)[109] summarize the National Map Accuracy Standards (NMAS)[110] from 1947 and the more recent National Standard for Spatial Data Accuracy (NSSDA)[111] developed by the Federal Geographic Data Committee (FGDC) for addressing the quality assessment of digital geospatial data. These general standards, and approaches for quality

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105 Sui, Elwood, and Goodchild, *Crowdsourcing Geographic Knowledge Volunteered Geographic Information (VGI) in Theory and Practice.*

106 Sarah Elwood, "Geographic Information Science: Emerging Research on the Societal Implications of the Geospatial Web," *Progress in Human Geography* 34, no. 3 (2010): 349–57.

107 Sarah Elwood, Michael F. Goodchild, and Daniel Z. Sui, "Researching Volunteered Geographic Information: Spatial Data, Geographic Research, and New Social Practice," *Annals of the Association of American Geographers* 102, no. 3 (May 2012): 571–90, doi:10.1080/00045608.2011.595657.

108 Goodchild, "Citizens as Sensors: The World of Volunteered Geography."

109 Rice et al., "Crowdsourced Geospatial Data: A Report on the Emerging Phenomena of Crowdsourced and User-Generated Geospatial Data."

110 "United States National Map Accuracy Standards" (U.S. Bureau of the Budget, 1947), http://nationalmap.gov/standards/pdf/NMAS647.PDF.

111 U.S. Geological Survey, "Geospatial Positioning Accuracy Standards, Part 3: National Standard for Spatial Data Accuracy," *Federal Geographic Data Committee*, August 19, 2008.

assessment from the 1980s and 1990s, were used extensively during the era when quality assessment and accuracy of digital GIS data was a primary research theme. Notable publications from this era include Veregin and Hunter (1998)[112], Goodchild and Gopal (1989)[113], and Guptill and Morrison (1995)[114]. Many of the recent research papers in quality assessment for geocrowdsourced data (i.e., Haklay 2010, Girres and Touya 2010) refer back to these earlier traditional GIS-based quality assessment works.[115,116] We wonder how far the traditional approaches for quality assessment can be stretched to fit what is emerging in geocrowdsourcing and geosocial media.

While it is easy to see the influences and sensibility of NMAS, NSSDA, and GIS quality assessment approaches in Girres and Touya (2010)[117], these approaches begin to crumble when faced with unstructured geosocial media and aggregations of geocrowdsourced and linked data. Measurements related to horizontal positional accuracy begin to lose meaning when dealing with disparate collections of semi-structured geocrowdsourced data and unstructured geosocial media.

Accepting that quality assessment methods will need to expand to accommodate new sources of data and new combinations of existing data, seems to be a common theme of conversation at academic conferences and university hallways. One approach, discussed in Rice et al. (2012b) is to consider fitness-for-use and risk analysis criteria when using geocrowdsourced data or geosocial media. Is the new source of data or information useful? Can it address the geographic question or problem? If the new source of data is incorrect, what will the consequence be? Do the generally low costs of geocrowdsourced data merit consideration in some less critical roles, for instance, in validating, improving, or updating traditional geospatial data sources (e.g., McCartney et al. 2015)?[118] In

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[112] Howard Veregin and Gary Hunter, "Data Quality Measurement and Assessment," Educational resource, *The NCGIA Core Curriculum in GIScience*, (1998), http://www.ncgia.ucsb.edu/giscc/units/u100/u100_f.html.

[113] Michael F. Goodchild and Sucharita Gopal, *The Accuracy of Spatial Databases* (London; New York: Taylor & Francis, 1989).

[114] S.C. Guptill and Morrsion, J.L., *Elements of Spatial Data Quality*, vol. 202 (Elsevier Science Limited, 1995).

[115] Haklay, "How Good Is Volunteered Geographical Information?"

[116] Girres and Touya, "Quality Assessment of the French OpenStreetMap Dataset."

[117] Ibid.

[118] McCartney et al., "Crowdsourcing The National Map."

some applications and settings, such as in disaster response (Zook et al. 2010)[119], authoritative data may not exist, and there are no other reasonable options.

The quality assessment approach taken in this research (Rice 2013b, 2014)[120,121], is similar to Girres and Touya in that it adapts a GIS-centric quality assessment approach to semi-structured geocrowdsourced data. This approach is feasible, yet there are weaknesses. The social moderation approach presented by Goodchild and Li (2012)[122] and implemented in this research (Rice 2015)[123] relies on a team of well-trained moderators, whose judgment is accepted as a replacement for ground truth. A contribution of this report and a benefit of our research is the first large-scale study of positional accuracy for social moderation, conducted by Ms. Rebecca Rice as a part of an MS Thesis project (2015)[124]. As presented in summarized form in Chapter 2, the social moderation process implemented in the GMU-GcT results in positional accuracies between 2.12 and 5.55 meters, depending on whether the reported obstacle is more similar to a point, or polygon. Rice (2015) finds the positional accuracy for the social moderation in the GMU-GcT to be equivalent or better than similar positional assessments of geocrowdsourced data, as summarized in Chapter 3 of this report.

An important aspect of the success for a geocrowdsourcing project is whether or not the project is able to attract a committed user base. While applications such as Waze count end-users and contributors in the tens of millions, the GMU-GcT has a user contributor pool counted in the high double digits. Our area of interests, geographic scope, and goals are substantially different. Throughout the duration of this project, outside reviewers and collaborators have encouraged us to both radically simplify, and substantially 'gamify' the GMU-GcT in order to attract contributors.

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119 Matthew Zook et al., "Volunteered Geographic Information and Crowdsourcing Disaster Relief: A Case Study of the Haitian Earthquake," *World Medical & Health Policy* 2, no. 2 (July 21, 2010): 6–32, doi:10.2202/1948-4682.1069.

120 Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

121 Rice et al., "Quality Assessment and Accessibility Applications of Crowdsourced Geospatial Data: A Report on the Development and Extension of the George Mason University Geocrowdsourcing Testbed."

122 Goodchild and Li, "Assuring the Quality of Volunteered Geographic Information."

123 Rice, "Validating VGI Data Quality in Local Crowdsourced Accessibility Mapping Applications: A George Mason University Case Study."

124 Ibid.

They suggest that if the contribution process is quick, easy, and fun, the number of contributors will grow. Making a substantial change in the direction of the GMU-GcT was difficult, particularly with four years of scheduled research deliverables that could not otherwise have been met. One suggested incarnation of the GMU-GcT is as an Instagram-style application that focuses nearly exclusively on the image. We have determined and noted that the image is by far the most important aspect of a geocrowdsourced contribution to the GMU-GcT, as the image itself and the content of the image header contain a wealth of validation information. Preliminary work to extract information from submitted images is presented in Chapter 3, during discussion of multiposition validation. It would be feasible to completely redesign the GMU-GcT to focus on image contribution with a short twitter-length message. The most important triple of geographic information (location, time, attribute) could be derived automatically from the image, short message, and from the web submission or mobile submission process. Any extra information needed could be geocrowdsourced from the contributor community. While an extensive quality assessment procedure would be missing, a greater purpose might be served by radically increasing the volume and coverage of the GMU-GcT. The trade-offs might make this new direction worthwhile.

Another important conclusion of the research contributors to this project is a recognition of the extent to which mobile devices have become the near complete focus for geocrowdsourcing. Many of the elements built into our original GMU-GcT (reviewed in Rice et al. 2013b)[125] were focused on web-based contributions done with a desktop computer. The design of the contribution tools changed over time but preserved this desktop focus, as did the moderation tools, routing tools, and visualization tools. The recent switch to mobile development, and the exploration of the limitations and capabilities of mobile devices (discussed in Chapter 2) caused us to make fundamental changes to the GMU-GcT and the workflows for moderation and quality assessment. These changes have been positive, as they allow geocrowdsourcing, quality assessment, and moderation to be done from the field rather than from the office. Authors such as Muehlenhaus (2013)[126], recognize this fundamental shift toward mobile devices for web mapping and geocrowdsourcing. Chapter 2 of this report contains many

[125] Rice et al., "Crowdsourcing to Support Navigation for the Disabled: A Report on the Motivations, Design, Creation and Assessment of a Testbed Environment for Accessibility."

[126] Muehlenhaus, *Web Cartography: Map Design for Interactive and Mobile Devices.*

useful insights into the basic capabilities and limitations of GPS-enabled mobile devices, and how well they function in dynamic settings.

We welcome readers of this report to send feedback and communicate with us through the project Principal Investigator, Dr. Matt Rice.[127]

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