Interaction dynamics for crowdsourced obstacle data

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Introduction

Rapid changes in dynamic urban environments are difficult to map and track with traditional data collection methods and can pose difficulty for navigation and wayfinding. This research looks at an extension of a long-term research effort in assistive geotechnology, whose aim has been to help individuals with reduced vision, blindness, and mobility impairment, gain access to real-time geographic information, including obstacles to navigation. A real-time obstacle notification system deployed through smart phones is presented, along with positional accuracy metrics and field testing with moving end-users and obstacle notifications. This research provides a view of dynamic engagement and interaction with crowdsourced obstacle data and offers insights into how such a system can function in the context of accuracy and uncertainty.

Data collection and quality assessment in a geocrowdsourcing testbed

For the past fifteen years, crowdsourcing has developed from an idea of geographically distributed information sharing communities (Goodchild et al. 2005) to a modern, bedrock data contribution mechanism used by individuals, businesses, non-profits and government agencies. Data collection by the public with location-aware mobile devices is now a common. While geocrowdsourced data collection is no longer a novel, the accuracy, reliability, and fitness-for-use of crowdsourced data remain critical issues. This research aims to expand the knowledge of how accuracy can be used to guide dynamic engagement with geocrowdsourced data.

Along with research on general trends and applications (e.g., Sui et al. 2013), important work has been done on accuracy assessment, data limitations, and quality assessment protocols for crowdsourced data. Haklay (2010) and Girres and Touya (2010 compare OpenStreetMap is compared to authoritative data sources, noting positional error characteristics and other accuracy metrics. While Haklay (2010) focuses primarily on positional accuracy and issues of completeness and coverage, Girres and Touya perform a more comprehensive assessment of data quality, using metrics such as positional accuracy, attribute accuracy, logical consistency, completeness, semantic accuracy, temporal accuracy, and lineage. This set of metrics was identified and developed earlier during the nascent GIS era by Goodchild and Gopal (1989), Guptill and Morrison

(1995), Veregin and Hunter (1998), and Veregin (1999). Other notable work on attribute accuracy is presented by Camponovo and Freundschuh (2014), who analyse message data from the 2010 Haitian Earthquake, finding that 50% of messages were miscommunicated by volunteers, underscoring the importance of analysing attribute data in circumstances where crowdsourcing is used in disaster response.

Another important work is Goodchild and Li (2012), who discuss methods of geocrowdsourced quality assessment. They describe three general approaches for quality: a crowdsourced quality assessment approach based on Linus's Law, where errors are identified and corrected by the crowd; a social approach, where moderator intervention corrects errors; and a geographic approach, which uses rules and relationships that identify problematic data contributions. The list of quality assessment metrics in Girres and Touya (2010), and the approaches for quality assessment in Goodchild and Li (2012) form the basis of quality assessment used in this research. These quality assessment metrics and approaches are summarized comprehensively by Qin et al. (2016) and updated by Rice et al. (2018).

The George Mason University Geocrowdsourcing Testbed

The GMU geocrowdsourcing testbed was initially developed between 2012 and 2015 to explore the data contribution dynamics, training protocols, moderation mechanisms, and dynamic uses of geocrowdsourced data (Rice et al. 2014, 2015). A period of testing and refinement continued through 2016-2018, including field work summarized in student research theses by Rice (2015) and Williams (2018). The primary purpose of the testbed was to crowdsource transitory navigation obstacles, reported by local data contributors, and experiment with quality assessment metrics derived from the data. The transitory navigation obstacles reported through this system (Figure 1) pose a difficulty for individuals with vision and mobility impairments, due to their reliance on a small number of tested and learned safe navigation corridors. While sighted and mobile individuals simply find a new route around the obstacle, this process is much more challenging for individuals who are blind, visually-impaired, and mobility-impaired.

Figure 1. Transitory navigation obstacle

The community of users that contribute to the GMU geocrowdsourcing testbed submit obstacle reports through desktop applications (Figure 1), as well as various mobile applications. These contribution mechanisms allow positioning of obstacle reports through both asserted and derived methods, and allow the submission of a variety of attribute descriptions and images. This allows for a wide variety of quality assessment metrics to be used, based on User-ID (lineage and history), user-asserted positional accuracy and GPS-derived positional accuracy, attributes (location description text, obstacle description text) temporal consistency (asserted observation date and time, submission date and time), measures of asserted duration and urgency, image submissions, and free text responses, which are geoparsed and used for position validation (Aburizaiza et al. 2016).

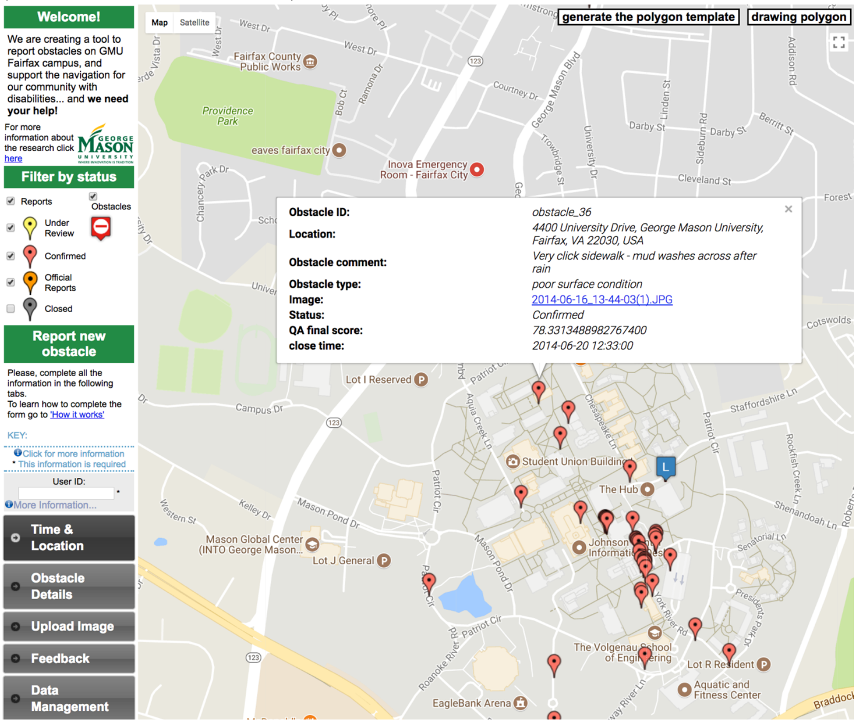


Figure 2.The GMU Geocrowdsourcing Testbed (2015).

Among these many quality assessment metrics derived and used in the GMU Geocrowdsourcing Testbed, this paper looks at closely at three specific aspects of quality and uncertainty: The positional uncertainty of unmoderated, raw data contributions, the positional uncertainty moderated data contributions, and the dynamic interaction of end-users with mobile devices whose positions are uncertain. Each of these aspects of uncertainty will be reviewed, followed by field testing results based on the uncertainties.

Positional uncertainty of data contributions and limitations of the moderation process

An early analysis of positional accuracy of raw submitted data was conducted in 2014 showing wide variation in horizontal positional accuracy of 55 contributed reports, with a mean of 18.36 meters, and a range spanning just above 0 meters to nearly 450 meters (Figure 3). This was discussed in Rice et al. (2014) as being primarily due to mistakes in asserted positioning near similarly-shaped buildings. The map-based asserted positioning routine (done through a desktop map interface) resulted in large errors that needed correction.

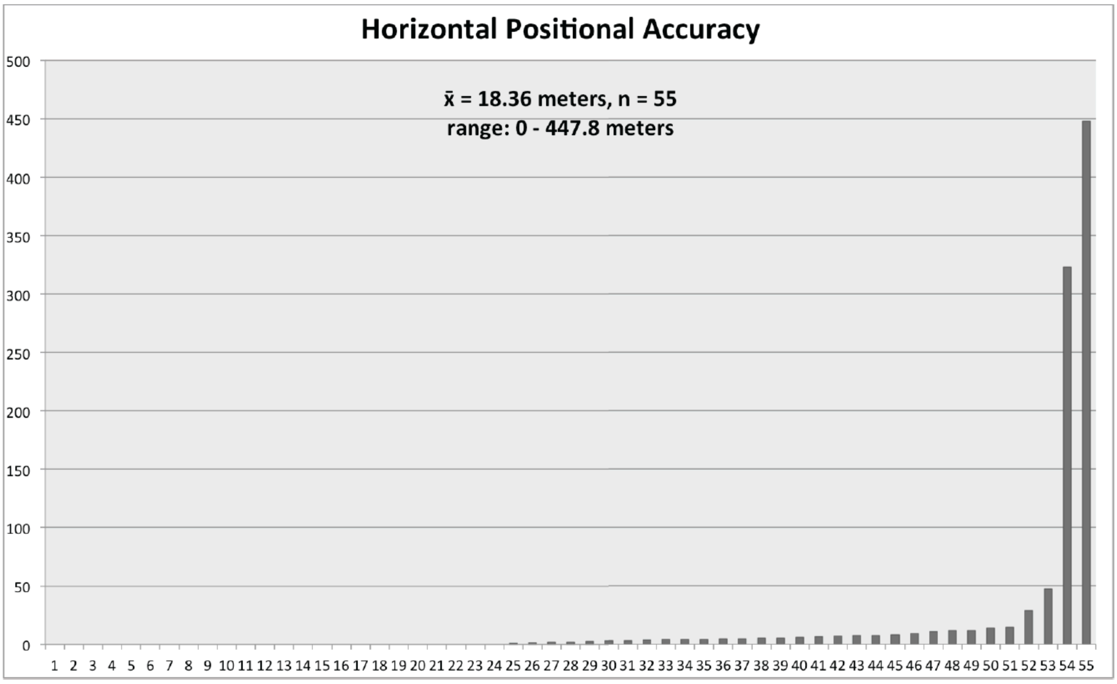


Figure 3. Positional accuracy of crowdsourced obstacle data.

Subsequent developments in data positioning via mobile device GPS allowed a much broader and more comprehensive set of position validation methods.

A quality assessment protocol based on Goodchild and Li's (2012) social approach for VGI data quality was developed, adopted, and tested. This approach involves data contribution correction and update by a trained moderator, who field checks submitted obstacle reports and moves reports to correct locations with the help of high-resolution imagery, base data, and a moderator dashboard. This approach, however, still has accuracy limits. In a research thesis, Rice (2015) explored the limitations of this moderated data quality approach by having three trained moderators independently field-check and correct a series of 31 obstacle reports contributed to the system. Rice subsequently analyzed the general positional and attribute accuracy of the 93 moderated reports. The moderator positioning of three of these reports is shown in Figure 4. Contrasting the earlier reported findings of positional error (Figure 3), Rice found the average positional error of moderated reports to be 2.12 meters for small features (contributed to the system as points) and 5.55 meters for large features (contributed to the system as areas). These findings generally concurred with other geocrowdsourcing accuracy studies (e.g., Haklay 2010, Girres and Touya 2010, and others) who report positional accuracies of well-defined crowdsourced points as being between 5 and 10 meters. A 6-meter threshold value (6.65 for Girres and Touya 2010, 5.83 for Haklay 2010) became an accepted rubric for positional quality in our study and was colloquially referred to as the "Haklay distance", noting his citation of this metric in his own influential 2010 paper.

Figure 4. Moderator positioning of reported obstacles (from Rice, 2015).

Positional uncertainty of GPS-based mobile devices

Concurrent with the moderated quality assessment study discussed above, research was conducted to verify mobile device GPS accuracy, in order to understand the limitations of the geocrowdsourcing testbed alert functions, which depend on end-user location relative to obstacles. Three mobile devices in use during our most extensive field research period (2015-2016) were tested over three tracks that included combinations of heavy tree canopy, no canopy, partial canopy, and urban building cover. Ground truth was gathered by a high-precision, differentially-corrected GPS device. The Fréchet distance (1906), computed as the offset between two curves, was recorded for all devices over the testing tracks and elapsed time. Figures 5 and 6 show these tracks, and Table 1 summarizes the positional accuracy for the devices under a variety of conditions and canopy types. The best device has an Fréchet distance of 5.92m, and the worst device had an average Fréchet distance of 10.51 meters. While newer devices have not yet been tested on the same tracks, this is a planned step for the near future.

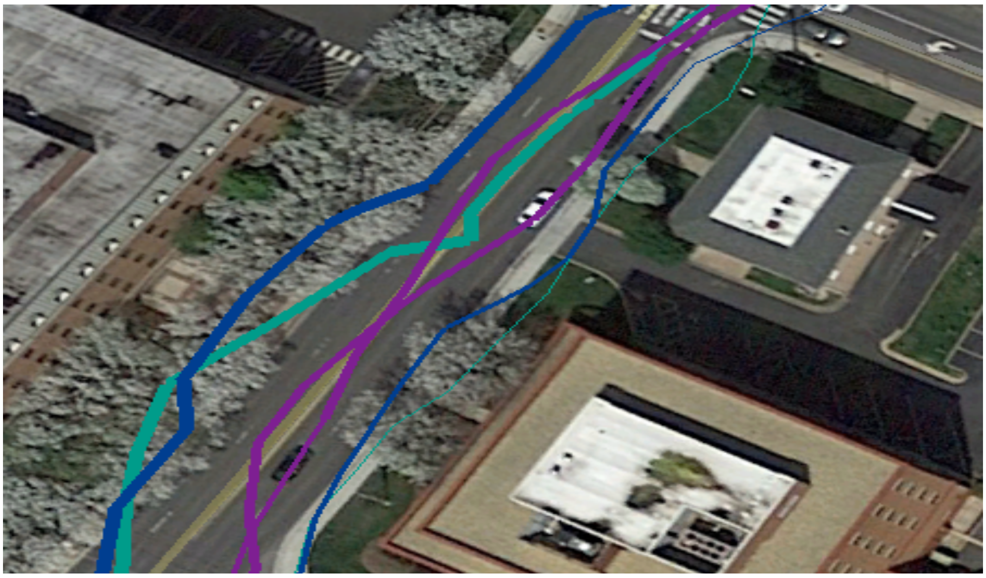


Figure 5. Overhead view of mobile device GPS tracks, Fairfax Virginia.

Figure 6. Mobile GPS tracks and average Fréchet distances for iPhone4, iPhone5, and iPhone 6, Fairfax VA

Average Frechet Distances

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

Table 1. Fréchet distances of three mobile devices tested over three tracks.

Mobile application alerts and dynamic obstacle engagement

Two mobile applications were developed for testing the alert functionality of the GMU Geocrowdsourcing Testbed. Each application was required to track an end-users trajectory, and then query the GMU Geocrowdsourcing Testbed for nearby obstacles. Each mobile application was required to then deliver an auditory and information alert about reported obstacles ahead of the user. Figure 7 shows the native mobile application, developed with Swift for iOS and referred to generically below as “MobileApp”. Figure 8 shows the web application, for use with any mobile device, and referred to hereafter as “WebApp”. Each application was programmed to deliver an alert to the end-user when he or she approached within 30.48 meters (100 feet) of an obstacle. This alert threshold was set based on earlier knowledge about the average positional accuracy of reports (18.23 meters for raw reports, 2.2-5.5 meters for moderated reports) and mobile device GPS errors between 5.9m and 10.5m. In the case computed with the highest average errors (raw unmoderated reports and an older mobile devices) the additive positional error of the reports and the mobile device would be 28.73m (18.23m + 10.5m). A warning distance of 30.48 meters, reflecting this highest average error case, was thought to be sufficient, knowing that the majority of obstacle reports would be moderated and have positional error rates in a much lower range (2.2-5.5 meters).

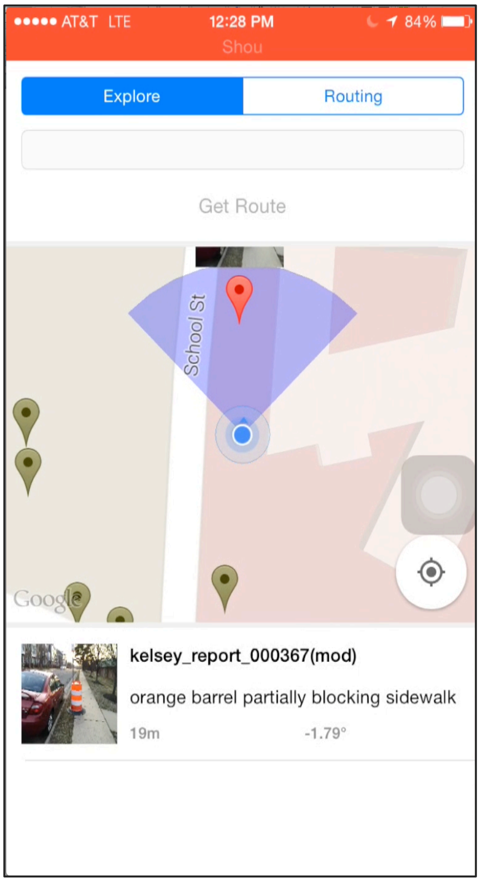


Figure 7. Native mobile application (“MobileApp”) for obstacle engagement, developed with Swift for iOS

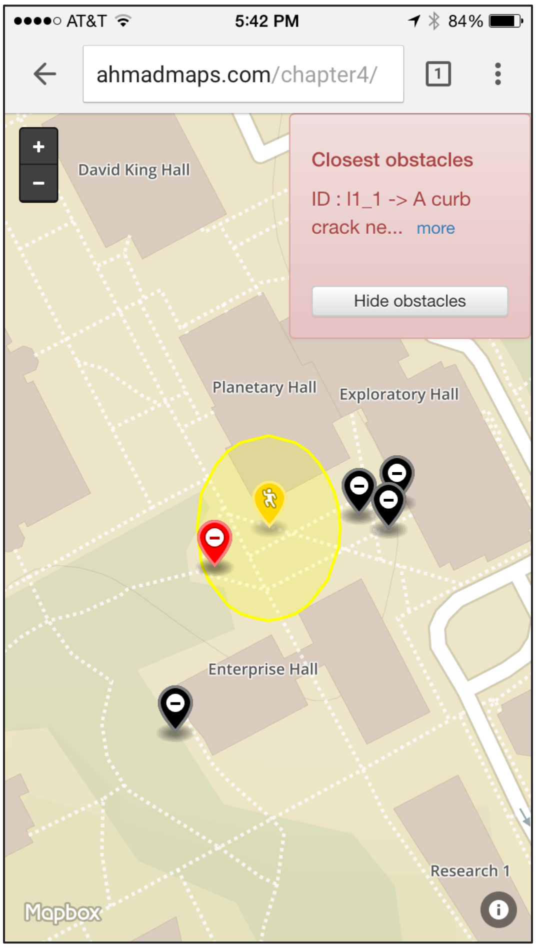


Figure 8. Web Application for mobile obstacle interaction ("WebApp"), developed with Turf/Mapbox and MongoDB

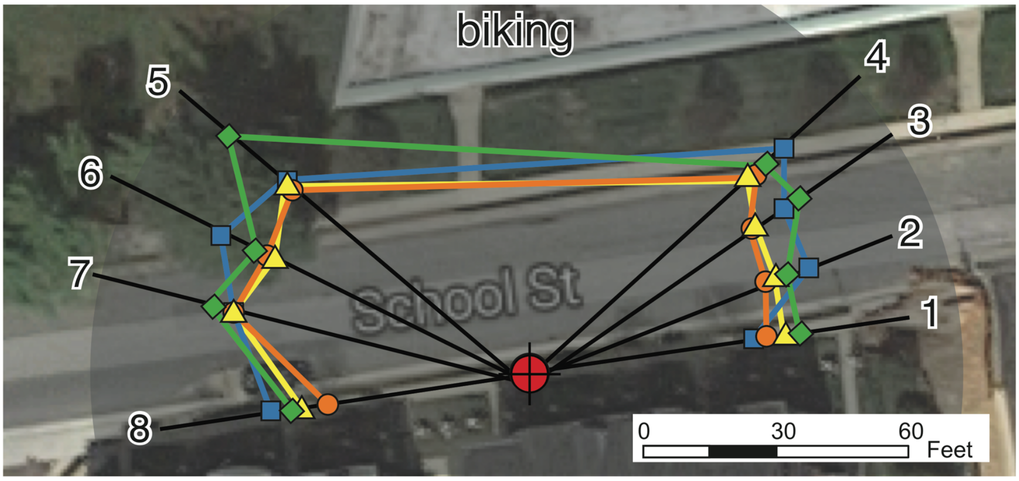
The field-testing protocol required an end-user to move toward a specific reported obstacle from eight different directions in consecutive trials, in order to remove any systematic error due to overhead canopy or multipath GPS error from nearby buildings. During the first set of trials, the end-user also travelled toward obstacles at a walking pace (3 miles per hour / 4.8 km per hour) followed by a second set of trials traveling at a bicycling pace (10 miles per hour / 16.1 km per hour). The end user engaged with both obstacles in consecutive sets of trials. The obstacles used in this field study are referred to in our geocrowdsourcing tested and figures below as Obstacle 11 and Obstacle 367. The position and the distance at which an alert was received by the moving end-user was recorded for each device, for each application, and for each obstacle. These results are shown below in Figures 9, 10, 11, and 12.

Obstacle Details

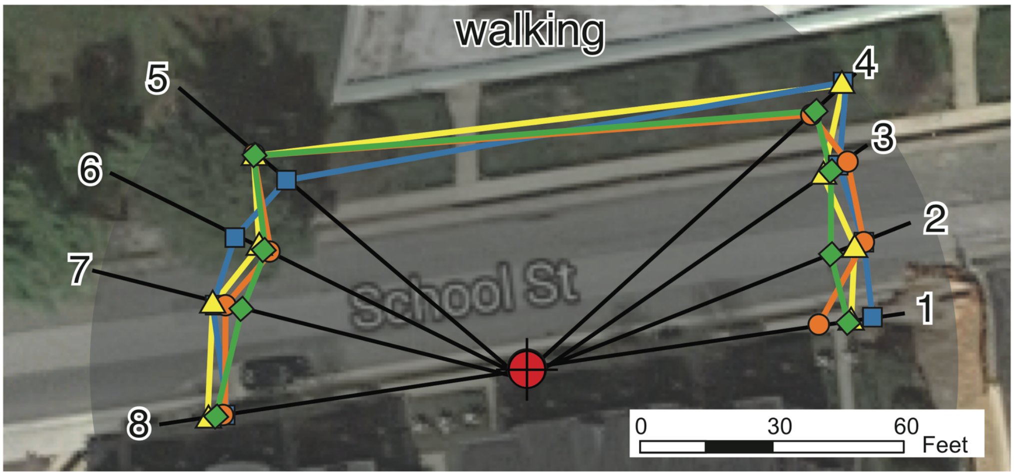
Type: Sidewalk Obstruction
Construction Detour

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 (ft):	63.1	61.8	67.8	69.4
Standard Deviation (ft):	5.5	7.5	7.7	10.2



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance (ft):	79.1	76.4	79.3	76.6
Standard Deviation (ft):	8.4	8.4	8.9	7.7

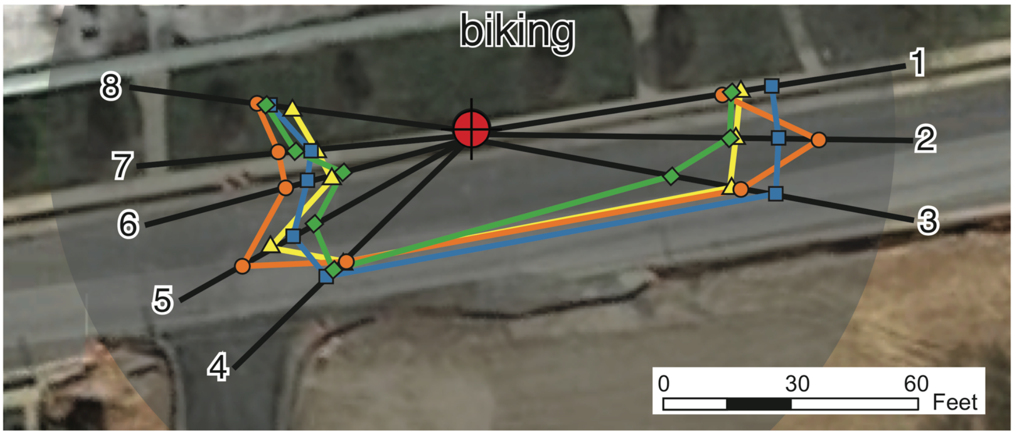
Figure 9. Dynamic obstacle engagement and alert distances with WebApp, Obstacle 11 summary

Obstacle Details

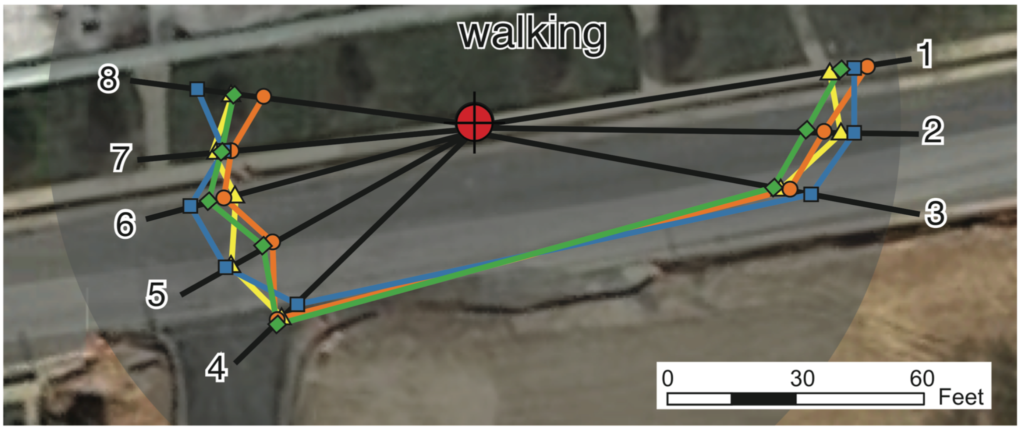
Type: Sidewalk Obstruction

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 (ft):	50.2	58.3	55.1	48.1
Standard Deviation (ft):	11.9	11.5	14.6	9.4



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance (ft):	69.1	67.4	72.7	67.8
Standard Deviation (ft):	10.8	14.6	12.6	10.3

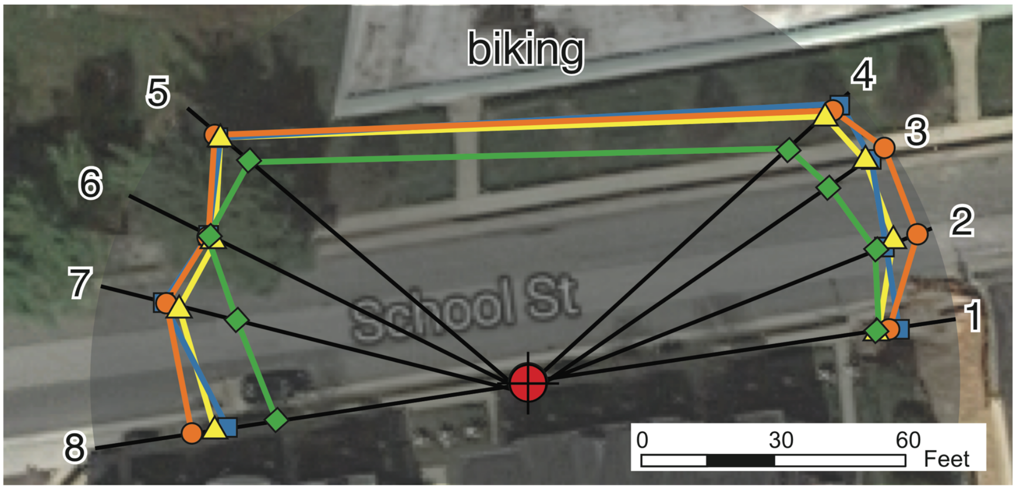
Figure 50. Dynamic obstacle engagement and alert distances with WebApp, Obstacle 367 summary

Obstacle Details

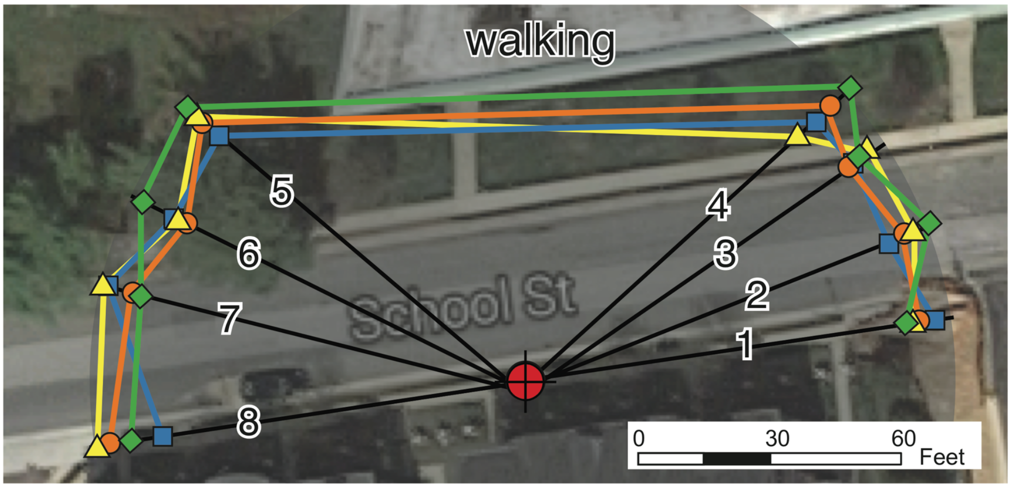
Type: Sidewalk Obstruction
Construction Detour

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 (ft):	85.4	88.3	86.6	78.5
Standard Deviation (ft):	7.2	7.4	5.8	6.1



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance (ft):	93.6	92.6	91.6	95.3
Standard Deviation (ft):	7.3	7.2	7.1	7.4

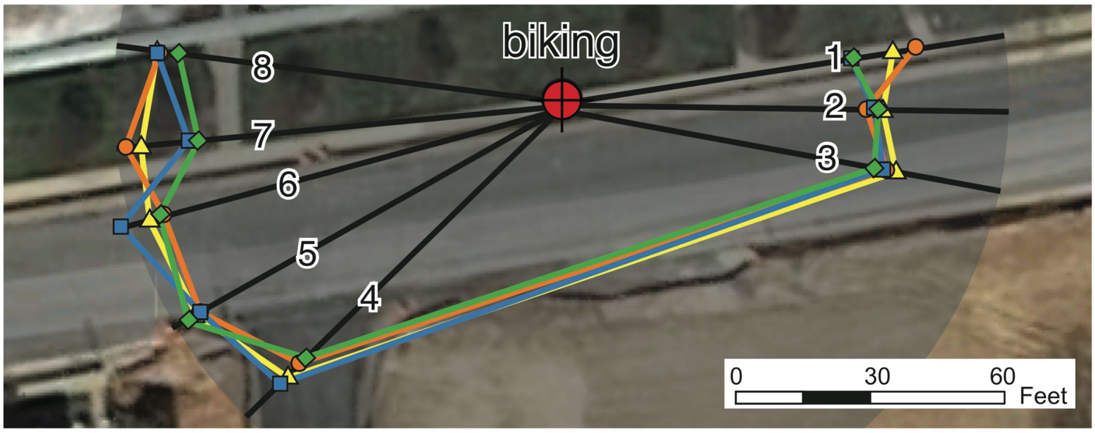
Figure 61. Dynamic obstacle engagement with MobileApp, obstacle 11 summary

Obstacle Details

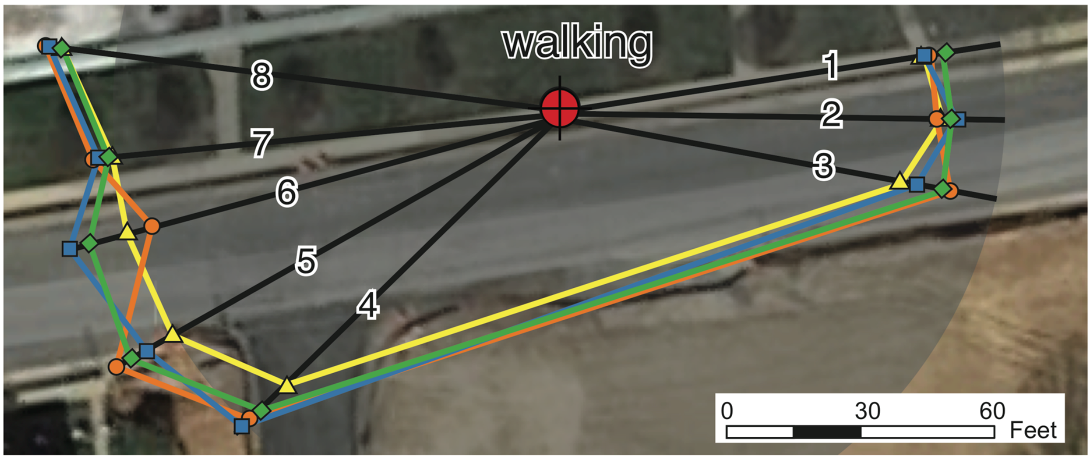
Type: Sidewalk Obstruction

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 (ft):	85.7	85.1	84.0	80.8
Standard Deviation (ft):	6.6	6.5	6.5	6.2



	△ iPhone 5	● iPhone 6	■ iPhone 6+	◆ iPad 2
Average Distance (ft):	93.5	98.6	99.8	99.6
Standard Deviation (ft):	12.0	13.0	13.0	11.0

Figure 72. Dynamic obstacle engagement and alert distances with MobileApp, obstacle 367 summary

In the figures above, the best performance is indicated with a curve the furthest out from the obstacle (red point), indicating the specific mobile device has triggered an alert the most quickly as the user moves toward the obstacle. During the elapsed time between the start of movement and the alert point, the application has calculated the movement direction and distance, and has queried the server for obstacles nearby. The application has then tracked distance, and provided an alert when the user reaches 100 feet (30.48 meters). In every case reported here, the alert distance is less than 100 feet (30.48 meters) as expected. There does not appear to be a systematic difference between any specific devices tested with regard to the alert distances, but there does appear to be significant differences between the WebApp and the native MobileApp, and between the modes of travel, both of which were anticipated. These results are summarized in Table 2 (below). The walking speed alert distances were higher in every case than the biking speed alert distances, and the MobileApp performed better than the WebApp in each case. As indicated above, the warning distance (100 ft. / 30.48m) was designed to cover the case of an unmoderated report (with an average error of 18.23m) and a device with a positional error of 10.5 meters, reflecting our own testing. This scenario was only matched by the MobileApp used at walking speed, where the alert was triggered 29.8 meters away. In each summary case below (Table 2) the observed alert distances did accommodate the usual or expected cases of moderated reports in the geocrowdsourcing testbed, with positional errors between 2.2m and 5.5m, and mobile devices with positional errors between 5.9 and 10.5 meters, for a composite distance of 8.1 to 16.0 meters.

Distances in ft (meters)	**Obstacle 11**		**Obstacle 367**	
	WebApp	**MobileApp**	**WebApp**	**MobileApp**
Walking	77.9 (23.7)	93.3 (28.4)	69.3 (21.1)	97.9 (29.8)
Biking	65.5 (20.0)	84.7 (25.5)	52.9 (16.1)	83.9 (25.6)

Table 2. Alert distances summarized by mode of travel and by application type

Summary and Conclusions

Geocrowdsourced data is an important input for GIS and cartographic processes, and research on applications, uses, dynamics, and social aspects has matured. Analysis of error and uncertainty is still important and remains a critical factor in the use of such data. An important domain for geocrowdsourcing is transitory obstacles, which are a major problem for individuals who depend on consistent routes between origin and destination, including those that are blind, visually-impaired, and mobility-impaired. The GMU geocrowdsourcing testbed was created to study the dynamics of geocrowdsourcing and to offer a potential solution for this problem. Accuracy assessment workflows based on best practices and innovative approaches have been developed, tested, and published. This research documents how knowledge about positional error can be used to design an obstacle alert system that works within the expected tolerances for positional error of reported obstacles, and for the expected errors in mobile device GPS. Future work will focus on the use of native mobile applications, due to better observed performance as seen in this work. We also intend to analyze redundant user reporting patterns, and image metadata to augment and validate other accuracy metrics.

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