Assessing the accuracy of GPS for measuring physical activity in urban areas

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Background

Obesity and overweight are thought to be caused in part by low levels of physical activity.

Current methods of measuring physical activity for epidemiologic studies lack precision and reliability, but tracking position with Global Positioning Systems (GPS) has been suggested as a method of measuring active transport (walking, running and cycling) with greater accuracy and reliability than questionnaires, surveys, and time diaries.[1,2,3,4,5]

In recent years, GPS units have become commonplace in cellphones, and these devices are of particular interest in measuring active transport. Providing subjects with cell phones is thought to increase study compliance when subjects can use the devices to make calls and send text messages, and researchers can use the devices to track and contact subjects in real time.[6]

A number of services exist to track location and physical activity using cellphone GPS: AccuTracking.com markets a system which tracks the location of registered phones, with position data uploaded to servers in real time; several applications exist for the iPhone which log GPS data to the device for later export to other services, including mapping software.

Extant data suggest that GPS devices' accuracy is hampered in complex urban environments, where tall buildings can block or bounce satellite signal. However, little data exists on how and to what extent their performance measuring active transport is affected by such environments.[1,4]

Hypothesis

Cell phone GPS measurements of pedestrian trips taken in areas with high building densities will overestimate distance walked.

Methods

- Using Geographic Information Systems (GIS), a measure of "building bulk density" was created by joining NYC Department of Information Technology & Telecommunications Elevation Data to Building Footprints, Roadbeds, Transportation Structures and US Census Blocks, using elevation data to estimate building volume, and dividing building volume by city block area.
- Twenty walks of approximately 1200 ft were visually identified in the top and bottom quartiles of building bulk density across New York City ("high density" and "low density" respectively).
- Walks were conducted in linear trajectory on the sidewalk, and were recorded using two GPS-enabled cellphones and commercially available software: the Motorola i296 on Boost Mobile using AccuTracking.com's GPS tracking service, and the iPhone 4S using Kinetic GPS tracking software.
- Three distance measures were created for each walk:
  - street network, as measured by GIS (reference);
  - estimates from each device, created by summing the distance between serial GPS coordinate readings that occurred between the start and end of the walk.
- Using SAS, paired t-tests were used to evaluate whether GPS-measured distance differed significantly from GIS-measured distance, and two-sample t-tests were used to evaluate whether GPS error differed significantly between high and low building density areas. Average error of each device, directional and absolute, was calculated for low and high density walks.

Results

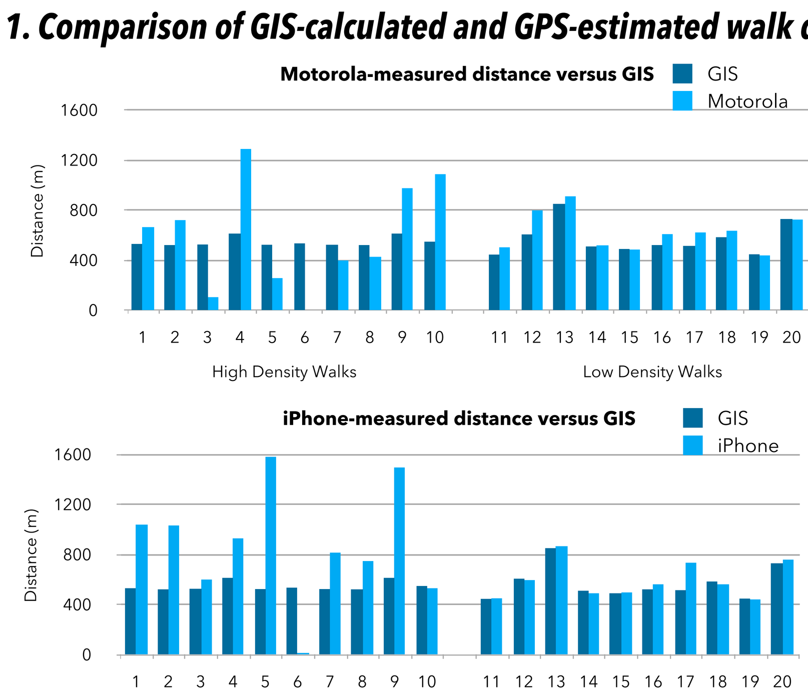
Table 1. GIS-calculated and GPS-estimated walk distances

Walk ID	GIS	Motorola	iPhone
	High Density		
1	532.6	666.8	1040.7
2	524.3	723.6	1034.2
3	528.8	108.3	603.1
4	615.5	1292.2	932.7
5	525.8	259.1	1583.4
6	537.1	0.0	17.1
7	527.2	402.1	816.7
8	523.7	429.6	750.2
9	615.7	978.6	1497.5
10	550.1	1091.6	533.3
Mean:	**548.1**	**595.2**	**880.9**
	Low Density		
11	448.7	505.8	452.0
12	609.7	800.9	597.6
13	853.9	914.7	869.1
14	513.4	521.3	493.8
15	493.2	489.0	500.5
16	524.3	612.6	565.4
17	517.3	625.8	737.6
18	587.5	639.5	563.7
19	450.4	440.6	443.7
20	733.2	727.8	761.0
Mean:	**573.2**	**627.8**	**598.4**

Table 2. Mean GIS-calculated and GPS-estimated walk distances

	GIS		Motorola			iPhone		
	Mean	SD	Mean	SD	P-Value	Mean	SD	P-Value
Overall	560.6	93.8	611.5	314.4	0.4304	739.7	361.1	0.0341
High Density	548.1	36.4	595.2	430.7	0.7218	880.9	458.3	0.0439
Low Density	573.2	130.0	627.8	150.3	0.0233	598.4	144.3	0.2926

Figure 1. Comparison of GIS-calculated and GPS-estimated walk distances

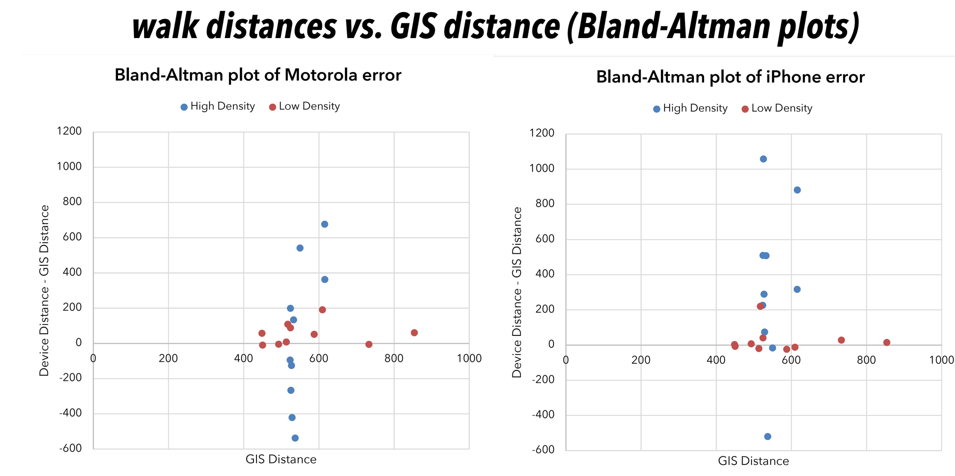


- Overall and in high density areas, walk distance estimates from the Motorola device were not significantly different from those measured by street network analyses via GIS. Walk distance estimates in low density areas were significantly longer than GIS-calculated distances (Table 2).
  - In high density areas, Motorola estimates both overestimated and underestimated walk distance frequently, reflected in its high standard deviation and absolute error for this category. The standard deviation (Table 2) and absolute error of estimates (Table 3) for low density walks was lower than for high density walks.

Table 3. Mean error of GPS-estimated walks (difference between measured & reference)

	Error			
	Directional		Absolute	
	Distance (m)	Relative (% GIS)	Distance (m)	Relative (% GIS)
	Motorola			
Overall	50.9	7.7%	197.2	35.3%
High Density	47.1	5.9%	335.8	60.3%
Low Desity	54.7	9.6%	58.5	10.3%
	iPhone			
Overall	179.1	32.4%	238.9	43.5%
High Density	332.8	60.1%	440.2	80.1%
Low Density	25.3	4.7%	37.7	7.0%

Figure 2. Difference between GPS-estimated and GIS-calculated walk distances vs. GIS distance (Bland-Altman plots)



- The iPhone exhibited a different pattern of error: overall, distance estimates were significantly longer than those calculated with GIS; with walk distance estimates in high density were significantly higher and those in low density areas were not.
  - Similarly to the Motorola device, the standard deviation and absolute error for high density walks were higher than for low density walks, indicating greater variation in estimated walk distance for the former category.
- For both devices, the average absolute error of measurement (the percentage that walk distance estimates from GPS devices differed from the GIS-calculated walk distance) differed significantly between walks conducted in high and low density areas (Motorola p = 0.0012; p = 0.0038).

Figure 3. Selection of walks in high density (top, left) and low density (bottom, right) areas, showing GIS-calculated and device-estimated routes

Discussion

The behavior initially hypothesized—that GPS error in high density areas would lead to consistent overestimates of distances walked—was exhibited by the iPhone but not the Motorola.

- The iPhone continued to record position estimates at regular intervals regardless of GPS signal. This, combined with the scattering of these estimates in high density areas due to GPS signal obstruction by tall buildings caused the phone to record a serpentine route, overestimating walk distances in all but one case.
- Conversely, the AccuTracking software on the Motorola device recorded coordinates less frequently in areas with poor GPS signal. On some walks, these data points closely aligned with the GIS-calculated walk route; on others, the device produced a serpentine path; and on yet others, the device failed to capture data near the start or the end of the walk, underestimating distance.

Thus, while both devices exhibited significantly greater absolute error in high density areas, each exhibited a different error profile: the Motorola's high density distance estimates were spread around the GIS-calculated distances, whereas the iPhones were on largely greater. These characteristics are illustrated in Figures 1–3.

Conclusion

- GPS-enabled cellphones can, in certain circumstances, provide accurate estimates of distances walked in urban environments.
  - Error is greater in areas of high building density, but whether error significantly biases estimates in a particular direction is dependent upon the interplay of hardware and software in a particular device.
- Future studies using GPS cell phones to measure active transport should perform similar tests to understand the error profiles of devices used. Furthermore, as decisions made in software design can greatly influence how GPS devices behave in low-signal conditions, researchers should endeavor to work with software developers to maximize accuracy.

References

1. Stopher P, FitzGerald C, Zhang J. Search for a global positioning system device to measure person travel. Transportation Research Part C: Emerging Technologies. 2008;16(3):350–369.
2. Cooper AR, Page AS, Wheeler BW, et al. Mapping the Walk to School Using Accelerometry Combined with a Global Positioning System. AMEPRE. 2010;38(2):178–183.
3. Duncan MJ, Badland HM, MUMMERY WK. Applying GPS to enhance understanding of transport-related physical activity. J Sci Med Sport. 2009;12(5):549–556.
4. Duncan MJ, Mummery KW, Ben J Dascombe. Utility of global positioning system to measure active transport in urban areas. Med Sci Sports Exerc. 2007;39(10): 1851–1857.
5. Michael Y, McGregor E, Allen J, Fickas S. Observing outdoor activity using Global Positioning System-enabled cell phones. Smart Homes and Health Telematics. 2008:177–184.
6. Wiehe SE, Carroll AE, Liu GC, et al. Using GPS-enabled cell phones to track the travel patterns of adolescents. Int J Health Geogr. 2008;7(1):22.