Planning Research

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Journal of Planning Education and Research
2022, Vol. 42(2) 206–217

DOI: 10.1177/0739456X18805154
journals.sagepub.com/home/jpe
SAGE

The Usability of Unmanned Aerial Vehicles (UAVs) for Pedestrian Observation

Keunhyun Park[1] and Reid Ewing[2]

Abstract

The monitoring of pedestrian activity is challenging, primarily because its traffic levels are typically lower and more variable than those of motorized vehicles. Compared with other on-the-ground observation tools, unmanned aerial vehicles (UAVs) could be suitable for counting and mapping pedestrians in a reliable and efficient way. Thus, this study establishes and tests a new method of pedestrian observation using UAVs. The results show that UAV observations demonstrate high levels of interrater reliability (intraclass correlation coefficient = 0.99) and equivalence reliability (Cronbach's α = .97 with on-the-ground counts and .73 with Google Street View). Practical implications of the new tool are discussed.

Keywords

direct observation, pedestrian counting, pedestrian monitoring, unmanned aircraft systems, UAS

Introduction

In the fields of urban planning and design, observation is one of the classic, essential methods of studying the interaction between people and places. Jane Jacobs (1961, xiii) urges urban researchers to "look closely at real cities . . . and think about what we see." From observing urban residents and their interactions on sidewalks, she found the critical conditions of built environments for a vital urban life (Jacobs 1961), which are still considered valid in twenty-first–century cities (Sung, Lee, and Cheon 2015). As with William H. Whyte's (1980) case, systematic direct observation fosters researchers' understanding of the substance of urban public life in an objective and measurable way. In a direct observation, a researcher observes the activities of humans rather than intervening in their behavior and then documents, analyzes, and interprets user behaviors to determine how they use space (Gehl & Svarre 2013). This translates directly into measures of livability, physical activity, and vehicle trip reduction in cities (Ewing and Clemente 2013; Mehta 2013).

As a method to assess physical activity and its contexts, systematic observation is advantageous in that it is an objective method and allows for the simultaneous data collection of both behavioral and environmental information (McKenzie and van der Mars 2015). This is important because physical activity is "place-dependent," occurring in specific locations (Sallis 2009). Thus, several systematic observation tools for assessing physical activity have been developed in various contexts such as parks (McKenzie et al. 2006), schools (McKenzie et al. 2000), playgrounds (Ridgers, Stratton, and McKenzie 2010), and natural areas (Sasidharan and McKenzie 2014). The observation data then contribute to the better understanding of how environmental interventions impact physical activity (for review papers of this subject, see Davison and Lawson 2006; Evenson et al. 2016; Ferreira et al. 2007).

Monitoring pedestrian volume and activities is an essential task in transportation planning and design. Pedestrian traffic data can be applied to assess the safety and capacity of existing streets, provide input to traffic forecast models, measure the impact of changes before and after a street design intervention, and ultimately determine the efficient allocation of resources (Diogenes et al. 2007).

Two main approaches of direct observation in streets are manual observation and automatic counts, both of which have pros and cons. Although manual counts are labor-intensive and error-prone, which results from subjective observations by individuals collecting the data, manual observation captures not just the number of people but also their behaviors or attributes (Diogenes et al. 2007; US Federal Highway Association [FHWA] 2013). The other approach, automatic

Initial submission, January 2018; revised submission, June 2018; final acceptance, September 2018

[1]Utah State University, Logan, UT, USA
[2]University of Utah, Salt Lake City, UT, USA

Corresponding Author:
Keunhyun Park, Department of Landscape Architecture and Environmental Planning, Utah State University, 4005 Old Main Hill, Logan, UT 84322-4005, USA.
Email: keunhyun.park@usu.edu

count technologies, make use of devices installed in set locations, so it is a practical and less costly method of collecting ongoing and consistent data (Southern California Association of Governments [SCAG] 2013; US FHWA 2013). However, it often results in the collection of inaccurate, limited information (e.g., counts, not activities; Greene-Roesel et al. 2008; Schneider, Arnold, and Ragland 2009). A more accurate and thorough observation method is the use of video cameras, which allow subsequent verification (Diogenes et al. 2007; Figliozzi et al. 2014; Greene-Roesel et al. 2008). However, cameras are costly and subject to theft, vandalism, and occasional malfunctions (Ryus et al. 2014; SCAG 2013; US FHWA 2013). Another challenge is that the aforementioned methods take place within a limited number of locations that may not represent the entire area of interest.

To fill in the gap of existing tools, this study tests a new method of pedestrian observation: the use of unmanned aerial vehicles (UAVs), also known as drones. UAVs carrying a video camera combine the advantages of human observation and video recording (Park and Ewing 2017). As UAVs cover a greater area in a shorter amount of time than other methods, they are expected to save time and money required for data collection. UAV-recorded video files allow for post-observation data processing and validation (Lenhart et al. 2008). In addition, as they capture not only the number of pedestrians but also their activities, attributes, and spatial patterns in a more accurate way, they are also more informational.

This study tests the reliability of UAV observation on pedestrian counts and explores practical implications of the new tool in pedestrian studies. The use of UAVs has become popular in environmental studies such as geology (Vasuki et al. 2014), forestry (Getzin, Wiegand, and Schoning 2012; Lin et al. 2015), agriculture (Torres-Sanchez et al. 2014), and construction engineering (Siebert and Teizer 2014), but to date, only a few studies have tested UAVs in pedestrian observation. A more efficient and reliable observation tool could lead to savings in both time and money for urban planners and designers.

Literature Review

Over the years, methods of collecting useful traffic data have evolved with advancements in technology, including induction loops, overhead radar sensors, and fixed video camera systems (Coifman et al. 2006; Papageorgiou et al. 2003; Ryus et al. 2014). Use of these traditional devices for traffic surveillance and monitoring, however, has raised concerns about their limited extent of coverage, the high cost of installation and maintenance, inflexibility of response to unexpected events, and other issues (Barmpounakis, Vlahogianni, and Golias 2017; Coifman et al. 2006). Recently, researchers have examined the applicability of UAVs to traffic and roadway incident monitoring because of their low cost, easy deployment, high mobility, and large view scope (Kanistras et al. 2014; Lee et al. 2015). Although UAVs were first introduced for military missions, their use has been recently expanded to civil applications, supported by the UAV industry, which has steadily produced smaller and lower-cost aircraft (Mahadevan 2010). Civil applications have primarily involved the use of UAVs in aerial photography, especially with the latest advances in sensor technologies (Budiyono 2008; Cheng 2015), and the transportation engineering field has applied UAVs as a novel and cost-effective method of collecting massive trajectory data from road arterials and replacing old approaches on fixed spots (e.g., stationary cameras; Barmpounakis, Vlahogianni, and Golias 2017).

Earlier UAV research aimed at identifying their potential for monitoring vehicle traffic (Moranduzzo and Melgani 2014; Wang, Chen, and Yin 2016). Ro, Oh, and Dong (2007) tested the applicability of UAVs to highway traffic monitoring and concluded that UAVs could play a significant role in the ITS (Intelligent Transportation Systems) infrastructure. Coifman et al. (2006) used a UAV to conduct several empirical tasks in urban streets such as determining the level of service (LOS), estimating average annual daily travel (AADT), measuring intersection operating conditions, and creating origin-destination flows. Recent studies have focused on the post-processing of aerial videos using advanced modeling and machine learning for extracting traffic information (Lenhart et al. 2008; Li 2008). Although detecting and tracking vehicles by UAV videos have been the focus of increasing investigation by transportation scholars, the detection accuracy of existing technology usually is lower than 90 percent, so obtaining more comprehensive information, such as detailed trajectory data on drivers, is virtually impossible (Wang, Chen, and Yin 2016).

Recently, several researchers have explored the potential of using UAVs for pedestrian detection and tracking (Gaszczak, Breckon, and Han 2011; Ma et al. 2016; Portmann et al. 2014). However, pedestrian detection from images obtained from UAVs poses some challenges resulting from the small size of objects, motion of the UAV, and low quality of images (Ma et al. 2016). As a result, automatic object detection has become a challenging task. As an alternative, several researchers employed thermal imagery (Gaszczak, Breckon, and Han 2011), but it was still problematic because of the variability of human thermal signatures (Ma et al. 2016). Thus, as the current technology of automatic pedestrian detection and tracking remains too limited to be applied in common practice (US FHWA 2013), this study relies on the manual observation of UAV-recorded video files of pedestrian movements while reaping the benefits of high-altitude, high-quality video observation.

Pedestrian volume has been mainly measured through direct observation and related to the characteristics of nearby built environments. As pointed out by the US FHWA (2013), the methods of pedestrian counting have been inconsistent in applications. In the urban design field, the authors of several studies counted pedestrians passing a specific point or a line where someone was observing (Ameli et al. 2015; Hajrasouliha

Figure 1. Study site (left) and street views.
Source (basemap/image): Esri (left), Google Street View (right).

and Yin 2015; Rodríguez, Brisson, and Estupiñán 2009), while other studies recorded pedestrians that passed the observer from the following direction, as the observer walked down a sidewalk (Alasadi 2016; Ernawati, Adhitama, and Sudarmo 2016; Ewing et al. 2016; Maxwell 2016; Ozbil, Peponis, and Stone 2011; Yin 2017).

To identify urban design measures and streetscape variables that explain pedestrian traffic volumes, Reid Ewing and his colleagues (Ewing and Clemente 2013; Ewing et al. 2016) measured pedestrian volume as the average number of people encountered on four passes up and down a given block face. An observer walked the length of the segment one time for each count and included every pedestrian he or she encountered during that exercise. Then they established the reliability of manual counts against Web-based street images. This study utilizes their methodology of pedestrian counting. Their protocol has been applied in subsequent studies throughout the world (Alasadi 2016; Ernawati, Adhitama, and Sudarmo 2016; Ewing et al. 2016; Hamidi and Moazzeni 2018; Maxwell 2016; Yin 2017).

Methods

Study sites

The study sites include twenty-six block faces in Salt Lake City, Utah. The study area consists of typical car-oriented streets in the western United States, which is generalizable to average places such as medium-sized cities of average density (Figure 1). The specific addresses are State Street from 400 S to Williams Avenue and Main Street from 400 S to Fremont Avenue in Salt Lake City, Utah. This section is a part of the "Life on State" project, a collaborative corridor improvement project among regional partners, including Salt Lake City, Utah Department of Transportation (UDOT), Utah Transit Authority (UTA), Wasatch Front Regional Council (WFRC), and Salt Lake County.

A block face, the frontage on one side of a block, is the unit of observation. If a block is too long, it is divided into about 700-foot subsections so that an observer can conduct an on-the-ground observation concurrently with the UAV flight.

Observation process

The observations entail the use of a UAV, DJI Phantom 4 Professional, which carries a fully stabilized 4K video camera. Each observation of a street segment involved three steps (Figure 2): (1) An operator planned a flight path on the centerline of a roadway that accounts for boundaries and obstacles (e.g., powerlines) and collected contextual information such as weather (e.g., temperature) and specific events (e.g., a car accident, construction work); (2) after flying the UAV up to an appropriate height (50–70 ft.), the operator set flight waypoints—usually a start and an end point—on the preplanned path; and (3) the UAV automatically flew through the waypoints twice (i.e., two passes up and down a given block face) and recorded the area at a flight speed of about 4 mph (1.8 m/s), similar to walking speed. The flight height, 50 to 70 ft. (15-20 m), was chosen to allow identification of the gender, age group, and travel mode of pedestrians, making a tradeoff between data accuracy and flight safety.

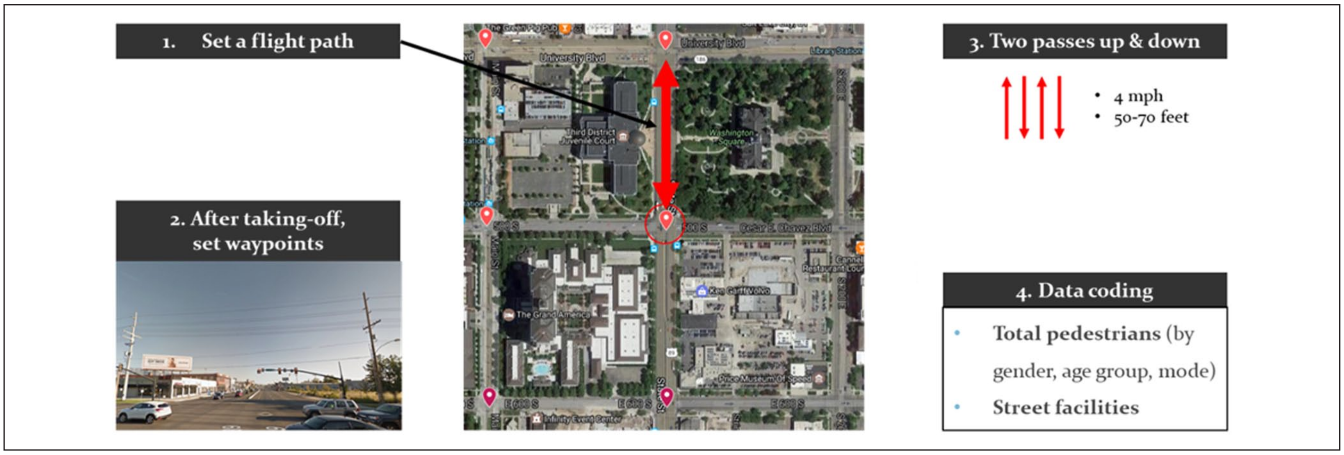

Figure 2. An unmanned aerial vehicle observation process.
Source (basemap): Google Maps.

Figure 3. Comparison between unmanned aerial vehicle view (left) and human-eye-view (right).
Source: Author (left), Google Street View (right).

After the on-site flights, an observer collected pedestrian information and street facilities by watching the recorded videos. Each pedestrian is coded with estimated information regarding gender (male or female), age group (senior, adult, or child), and mode of transportation (unassisted pedestrian, assisted pedestrian, or bicyclists). Then, the information was aggregated by block face to provide summary counts. Street facilities include bus stops, food vendors, bike racks, trash cans, benches, planters, and so on. To test interrater reliability of pedestrian counts from UAV observation, an additional observer watched the same video and collected pedestrian data.

Each UAV operation followed safety regulations established by the US Federal Aviation Administration (2016). The researchers obtained approval from the Institutional Review Board at the University of Utah (approved March 14, 2017). Also, the Utah Department of Transportation approved this study using drones in its right of way. In addition, upon a request by the UDOT, the author obtained an encroachment permit. Similar to previous pedestrian observation studies (Ewing and Clemente 2013; Ewing et al. 2016), this study conducted all field observations between 10 a.m. and 4 p.m. on weekdays in April 2017. The field work took place only on days in which no rain or strong winds occurred.

To test the appropriateness and effectiveness of UAV as a tool for collecting pedestrian volume data, this study compares results of the UAV data collection approach with those of on-the-ground observations, the present gold standard for this kind of research (Figure 3). On-the-ground observations were conducted concurrently with the UAV flights, meaning that a human observer walked the length of the block face twice at the same speed as the UAV and counted every pedestrian she encountered during that exercise. The resulting data were the average pedestrian counts of two passes, namely, total counts divided by two. Both observations collected the same set of data: pedestrian counts by gender, age group, and mode of transportation.

Analyses

This study uses two tests of reliability of pedestrian counts to determine the reliability of the UAV measures. Both the UAV

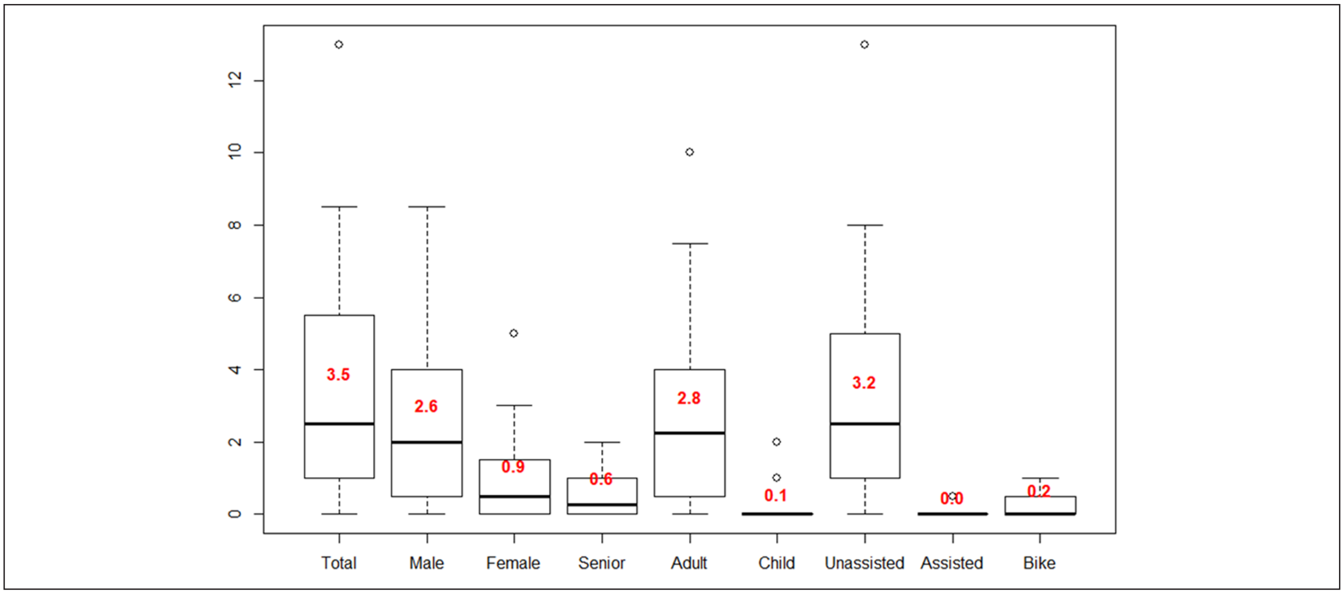

Figure 4. Box plot of unmanned aerial vehicle observation.
Note: Red texts are average values for each category.

and on-the-ground counts are the average of the two passes up and down a block face.

The first test of reliability determines equivalence, the extent to which variables measure the same underlying construct, which in this case is pedestrian activity. Equivalence reliability is determined by relating the values of the variables to highlight the degree of their relationship or association (Ewing and Clemente 2013). This study compares pedestrian counts by the UAV to on-the-ground observation and counts on two street view websites: Google Street View (mostly photographed in May 2016) and Bing StreetSide (mostly shot in August 2014), both of which offer a reliable alternative to pedestrian counts (Campanella 2017; Ewing and Clemente 2013; Yin et al. 2015).

Equivalence reliability is judged with Cronbach's alpha, widely used in social science to determine if items measure the same thing consistently. If independent counts—one based on UAV observation, one on on-the-ground observation, and two on street imagery—agree, one can assume that the UAV counts are reliable measures of pedestrian activity. Some professionals require reliability of 0.70 or higher before they will use an instrument (Ewing and Clemente 2013).

The other test is a test of interrater reliability for the counts from two observers watching the same UAV-recorded video files. To check for the interrater reliability, this study uses intraclass correlation coefficients (ICCs) as a measure of agreement. Using ICCs, researchers analyze the consistency, or conformity, of measurements taken by multiple observers measuring the same quantity (Gwet 2014; Shrout and Fleiss 1979). In particular, this study used the one-way analysis of variance (ANOVA) as a form of the ICC, representing the ratio of between-group variance to total variance of counts (Shrout and Fleiss 1979). The ICC was computed not only for the total number of pedestrians but also for the numbers by gender, age group (senior, adult, child), and mode of transportation (unassisted pedestrian, assisted pedestrian, and bicyclists).

Results

Summary of UAV observations

For the 26 block faces, 90 pedestrians (average 3.5 per block face) were counted from the UAV observations (Figure 4). The number of users per block ranged from 0 to 13 with a standard deviation of 3.1. The UAV observations recorded more males (2.6 on average) than females (0.9). The primary age group was adults (2.8 persons), followed by seniors (0.4) and children (0.1). The most common mode of transportation was unassisted walking (3.2 persons), followed by bike (0.2). There were almost no assisted pedestrians (e.g., skaters, wheelchairs, or strollers; 0.02 on average).

Next, the time needed for two observation methods are compared in Table 1. On-the-ground observations required 194 min in total for 26 block faces. This includes an average of 2 min of pre- and post-setting time. On the average block face with a length of 820 ft. (250 m), on-the-ground observation took 7.46 min. On the other hand, the UAV observations required 26 min for pre/post-flight setting such as setting waypoints, taking off, and landing; 71 min for actual flights; and 142 min for video counts by an observer, meaning 239 min in total for 13 street segments, or 26 block faces because a single flight could observe both sides of a street. Video counts took approximately twice of the flight time because

Table 1. Comparison of Total Time Spent for 26 Block Faces (13 Segments) between Two Observation Methods.

On-the-Ground Observation	Time Spent (min.)	Unmanned Aerial Vehicle Observation	Time Spent (min.)
Observation 1 (one side): pre/post setting	26	Pre/post setting (e.g., waypoints, taking off, landing)	26
Observation 1 (one side): actual observation	71	Flights (recording both sides)	71
Observation 2 (other side): pre/post setting	26	Video observations	142
Observation 2 (other side): actual observation	71		
Total time (min.)	194	Total time (min.)	239
Average min. per block face (250 m; 820 ft)	7.46	Average min. per block face (250 m; 820 ft)	9.19

Table 2. Equivalence Reliability: Cronbach's Alpha Values for Unmanned Aerial Vehicle (UAV) Counts Versus on-the-Ground Counts and Web Counts.

Category	UAV Counts Versus On-the-Ground Counts [CI] (n = 26)	UAV Counts Versus Google Counts [CI] (n = 25)	UAV Counts Versus Bing Counts [CI] (n = 24)
Cronbach's alpha	0.97 [0.95, 0.99]	0.73 [0.53, 0.94]	0.46 [0.04, 0.89]

Note: [CI] = 95 percent confidence interval.

the observer had to observe both sides and occasionally pause and rewind the video. This equals to 9.19 min per block face. This result shows that a UAV observation needs an additional 1.73 min, or extra 23 percent of the time, per block face area under the current research protocol.

However, as explored in the introduction and discussion sections, a UAV can cover larger areas in one observation than a human observer. If a flight area and speed are doubled (1,500 ft. and 8 mph), both of which are realistic assumptions, the required time will become half—4.6 minutes per block face, meaning 2.9 min (or 38 percent) of time saved compared to on-the-ground observations. In terms of money spent on both methods, apart from the labor costs (which are basically proportional to the time spent), the UAV observation required the purchase of a UAV and necessary accessories (approximately \$2,000) and a test fee for a remote pilot certificate (\$150), a commercial license required by the U.S. Federal Aviation Administration.

Reliability of the UAV observations

To check the equivalence reliability of the UAV observation method, this study calculated the Cronbach's alpha of the results for the UAV compared to those of three other observation methods—on-the-ground observation and two street view websites. Table 2 shows that the alpha values are high for UAV versus on-the-ground counts comparison (0.97) and UAV versus Google counts comparison (0.73). The lower level of reliability with Bing counts (0.46) was similarly reported in a previous study (Ewing and Clemente 2013) and might be attributed to the time and seasonal difference—April 2017 (UAV observation) versus August 2014 (Bing StreetSide).

To check the interrater reliability of the UAV observation method, this study calculated the ICCs between data from a primary observer and an additional observer watching the same video files taken by the UAV. Table 3 shows that the two observers saw a similar average number of pedestrians per target area (3.46 persons and 3.56 persons). The UAV counts between two observers demonstrate a high level of interrater reliability (ICC $>$ 0.8) for all categories except the child group. Reliability measures for assisted pedestrians and bicycle riders were not calculated due to too small counts.

Discussion

Comparison of Different Pedestrian Observation Methods

In this study, observations by the UAV yielded reliable results. From the results of the analysis, field notes, and literature, we compare and discuss four main tools of pedestrian observation—human eyes, video camera, automatic counter, and UAV (Table 4).

A manual observation by human eyes has been a traditional and easy-to-implement approach in counting pedestrians and studying their activities. Jan Gehl and his team counted and mapped pedestrian activities in an intersection and found that many pedestrians occupied places not designed for them (Transport for London & Central London Partnership 2004), which later became a key motivation to redesign the Oxford Circus in London. Manual counting is not only portable but also capable of gathering detailed information about pedestrians (e.g., gender, age group, race/ethnicity, activity type). On the other hand, it is labor-intensive and prone to subjective data collection (Diogenes et al. 2007).

A more accurate and thorough way of counting manually is by using video cameras or time-lapse photography for they

Table 3. Interrater Reliability: Intraclass Correlation Coefficients between Two Observers Watching Unmanned Aerial Vehicle Video Files (n = 26).

Category		Average Number of People		ICC [CI][a]
		Primary Observer	Secondary Observer	
Total		3.46	3.56	0.99 [0.99, 1]
Gender	Male	2.58	2.65	0.99 [0.98, 1]
	Female	0.88	0.90	0.94 [0.88, 0.97]
Age group	Senior	0.56	0.60	0.82 [0.65, 0.92]
	Adult	2.79	2.83	0.99 [0.97, 0.99]
	Child	0.12	0.14	0.44 [0.08, 0.71]
Mode of transportation	Pedestrian (unassisted)	3.23	3.33	0.99 [0.99, 1]
	Pedestrian (assisted)	0.02	0.02	N/A[b]
	Bicycle	0.21	0.21	N/A[b]

[a][CI] = 95 percent confidence interval.
[b]N/A: The intraclass correlation coefficients was not calculated for too small counts.

Table 4. Comparison of Four Methods for Pedestrian Observation.

Method	Human Eyes	Video Camera	Automatic Counter	Unmanned Aerial Vehicle (UAV)
Examples	• Fixed spot (e.g., intersection) • Screen line • Walking observer	• Stationary camera • Dashboard camera • Online street view image	• Infrared sensor • Induction loop • Radar sensor • And so on	• UAV in motion to cover a larger area • UAV in a fixed location
Advantages	• Easy to implement • Portable • Comprehensive data	• Comprehensive data • Accurate • Image processing	• Affordable • Long-term data collection	• Portable/covering larger areas easily • Comprehensive data • Accurate • Image processing
Disadvantages	• Labor-intensive • Subjectivity issue	• Expensive • Limited view • Prone to theft and malfunctions	• Counting only • Undercounting issue	• Short duration • Subject to poor weather
Applications	• Quick survey • Observing larger areas (e.g., downtown) • Collecting both behavioral and environmental information	• Observing key spots for a long time and gathering detailed information	• Long-term monitoring of pedestrian traffic • Comparative survey across different areas	• Observing larger areas (e.g., downtown) • Collecting both behavioral and environmental information • Repetitive survey to see temporal variation (e.g., season, year)

allow subsequent verification. Since Whyte (1980) observed people in public plazas and streets in New York City and ascertained why some places were successful while others were not, video observation has been used in many pedestrian studies (Diogenes et al. 2007; Figliozzi et al. 2014; Greene-Roesel et al. 2008). Unfortunately, video cameras are not only costly but also subject to theft, vandalism, and occasional malfunctions. Instead of installing expensive fixed cameras, a dashboard camera or online street images (e.g., Google Street View) can be affordable tools and provide reliable data (Campanella 2017; Ewing and Clemente 2013; Ewing et al. 2016). However, such methods have a limited view and are easily blocked by cars parked on the street or street furniture.

It is important to note significant works on automated pedestrian detection and behavior analysis using stationary cameras (Ge, Collins, and Ruback 2012; Kilambi et al. 2008; Xia, Zhang, and Kruger 2015; Yan and Forsyth 2005). Using computerized algorithms, researchers have figured out ways to detect a frame-by-frame change in pixels in a video image to tell whether or not objects in the image are pedestrians. Yin et al. (2015) used Google Street View for automatic pedestrian detection and tested its reliability. US FHWA (2013) points out that advanced video image processing algorithms have not been incorporated into most commercial products yet, and thus, this method has the highest equipment costs.

The other approach, automatic count technologies, makes use of devices installed in a set location, so the automatic observation is a practical and less costly method of collecting ongoing and consistent data (SCAG 2013; US FHWA 2013). However, it often results in the collection of inaccurate, limited information (Greene-Roesel et al. 2008; Schneider, Arnold, and Ragland 2009). A common source of inaccuracy in automatic counters is occlusion, or undercounting (i.e., only counting one person when multiple users are walking next to each other; Ryus et al. 2014). This effect was observed for various automatic counting tools, including passive infrared, active infrared, and radio beam sensors, especially with higher pedestrian volumes (Arnberger, Haider, and Brandenburg 2005; Ozbay et al. 2010; Ryus et al. 2014; Schneider et al. 2012). Also, pedestrians are less confined to fixed paths of travel (e.g., taking shortcuts off the sidewalk or crossing streets at unmarked crossing locations), which decreases the accuracy of sensor equipment counts.

As shown in this study, UAV-based pedestrian observation can be efficient, accurate, and informative. For one, a UAV can cover a larger area during each observation period than a human observer. We found that a UAV could fly as far as a remote pilot can see the aircraft—about 1,500 to 2,000 ft. In addition, even in ten-lane streets, a camera on a UAV can capture both sides of the street, which reduces the observation time by half. These advantages would make the UAV useful for car-oriented and sprawling areas with wide roads and large blocks. After considering the additional time for video watching, this study found that UAV observation could save about 40 percent of the person-hours with an assumption that the observation area and speed could be twice (1,500 ft. and 8 mph) that of manual observation.

Second, in UAV observation, a researcher can collect more accurate user data with the support of recorded video. Post–data collection analysis has the potential to estimate attributes of pedestrians (e.g., age, gender, travel mode), while that is a limitation of automated counters. Compared with a walking observer or a moving camera installed in a car (e.g., Google Street View), a UAV can move at a constant speed without any interrupting traffic, which provides more consistent data. While automatic pedestrian detection has seldom been used in a UAV setting yet, future advancement in image processing technology would realize a more efficient pedestrian observation from UAV-recorded video data.

On the other hand, the utilization of UAVs has some limitations. UAV observation is more subject to survey area conditions such as weather, time, topography, or surrounding buildings. On a rainy or windy day, flying a UAV is not recommended for safety reasons. Even manual counts are typically done under good weather conditions, so this is not a major limitation. While a UAV can be equipped with a thermal camera to capture nighttime activities (Gaszczak, Breckon, and Han 2011; Ma et al. 2016), nighttime operation requires an operational waiver from most current UAV regulations, including US FAA Part 107. The flight time of maximum 30 minutes is another limitation, which makes the method only suitable for momentary observation. Lastly, bird's-eye–level observation complicates the identification of people behind obstacles (e.g., street trees or big trucks). In this case, the UAV might fly over the sidewalk, which requires greater care and may require property owner permission.

Practical and social implications of the UAV observation

When using a UAV to investigate pedestrian activities, researchers must consider practical implications and social complications of their method. For one, they must ensure that the remote pilot follows UAV operational rules governed by an aviation administration. For example, on June 21, 2016, the US Federal Aviation Administration (2016) announced a rule called "Operation and Certification of Small Unmanned Aircraft Systems (Part 107)" for small UAVs of less than 55 lbs. (25 kg). Part 107 requires that UAVs be registered, remain within the visual line-of-sight of the remote pilot, and not fly at night or above 400 ft. (122 m) above ground level. Also, a person operating a small UAV must hold (or be under the direct supervision of a person holding) a remote pilot certificate. One important rule of Part 107 regarding pedestrian observation is that a UAV must not fly directly above people. While an operator might be able to request a waiver from FAA, it is easier and safer to fly a UAV over the centerline of the road, as was done in this study, instead of the sidewalk.

Researchers must bear in mind that the deployment of UAVs in civil applications raises safety, ethical, and privacy issues (Finn and Wright 2012; Rapp 2009). When a UAV crashes on the street, it could seriously injure people or damage cars, facilities, and/or the ground. One legal review (Finn and Wright 2012) found that a UAV flight within or too close to a private property might lead to trespass or nuisance claims by homeowners. At the same time, however, they also found that privacy claims are limited to wherever "a UAV captures images that could have been obtained from civilian aircraft traveling in a legally authorized manner," that is, data already available to the public (Finn and Wright 2012, 642). As the use of UAVs becomes more popular with the public, a survey using a UAV on a public street may raise fewer concerns.

For both safety and reliability, researchers must ensure the provision of sufficient training to UAV pilots in advance and conduct a preliminary survey of study sites. If the observation process involves too much variation in data among different observers, observation data will not be reliable. Thus, researchers need to prepare an observation protocol, including the observation process, flight waypoints, speed, height, and camera shooting method. They could also set the flight

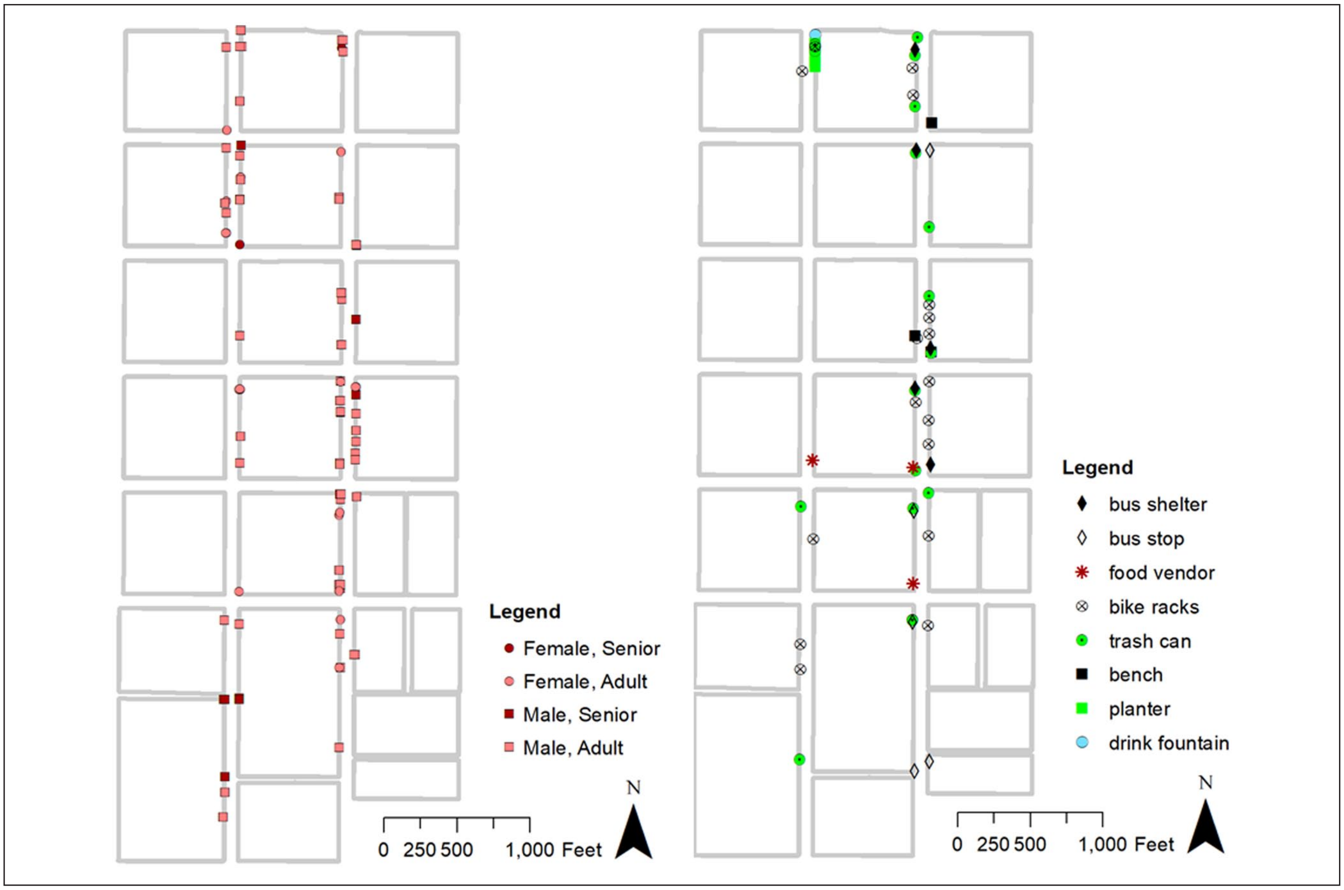

Figure 5. Examples of mapping from unmanned aerial vehicle observation processed in ESRI ArcGIS (left: pedestrians, right: street facilities).

height according to a survey purpose. For an accurate count of the number of users, a UAV could fly high (e.g., 100 ft.) with minimum movement. On the other hand, to collect detailed user information, it must fly lower and more slowly (e.g., 30~60 ft.) and observe pedestrians more carefully.

While the results of this study show that the UAV method is reliable in counting the number of users by gender, age group, and mode, the less reliable category—child group—might be attributed to a teenager looking like an adult when there is a great distance between a person and a UAV. Thus, greater interrater reliability requires a more accurate survey protocol, sufficient observer training, and validation studies.

As one of its future applications, we found that the UAV-recorded video enables the researcher to survey spatial patterns of pedestrians in street environments. Figure 5 shows two mapping examples from the UAV observation. Pedestrians with their attributes (gender and age group) are mapped on the left map, and the right map has the exact location of street furniture, including bus stops, food vendors, bike racks, trash cans, benches, and so on. Using those maps, an urban designer could conduct an exploratory analysis of street life and vitality (e.g., where senior people walk, women are populated, or the relationship between the presence of specific street furniture and pedestrian volume). For example, in Figure 5, a reader can see that senior people are hardly found in these streets and pedestrians are populated near bus stops or food vendors. The behavioral map could be drawn multiple times throughout the day or year for an analysis of changes in pedestrian activity patterns.

Limitations

As a study examining the usability of a new observational method, this research involves several limitations. One is the limited size of the observation area, which allowed for a direct comparison to the on-the-ground observation. However, as this study has found that a UAV could cover a larger area, a subsequent study could determine the practical use of UAVs in streets by examining larger observation areas (e.g., 1,500–2,000 ft.). In addition, the streets in this study might not have been a representative sample of the United States. The average number of pedestrians per block face was only 3.6, which is relatively low. To ensure better generalizability, further research could include diverse samples such as downtown areas in a large city.

Conclusions

While some instruments for monitoring nonmotorized traffic have been developed, no tool that ideally fits all situations is currently available. Compared to on-the-ground counting and online street imagery counting, this study demonstrates that UAV-based pedestrian counting is reliable, as previously verified in a setting of urban parks by the same authors (Park and Ewing 2017). Also, the interrater reliability between two observers watching the same UAV video files is high. A UAV is capable of collecting more information via recorded video files that capture various characteristics of nonmotorized traffic (e.g., attributes, behaviors, spatial patterns), and after it collects data, a technician can assess them. Given enough video data, computer vision and machine learning techniques could achieve an accurate autonomous analysis of pedestrian activities in the future. In addition, as the UAV can cover larger areas in a shorter time period, it is also more efficient. On the other hand, it may not be suitable for long-term monitoring or survey on under poor conditions (e.g., narrow streets, poor weather). Thus, depending on their purpose and context, planners and transportation engineers can select an appropriate counting method and use the acquired data to not only inform an analysis of existing street capacity and safety but also provide ideas for proper interventions on existing streets.

Acknowledgments

The authors appreciate Utah Department of Transportation for approving the unmanned aerial vehicle flights in its right of way and issuing an encroachment permit.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported by the Utah Agricultural Experiment Station, Utah State University, and approved as journal paper number 9132.

ORCID iD

Keunhyun Park https://orcid.org/0000-0001-5055-7833

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Author Biographies

Keunhyun Park is an assistant professor in Department of Landscape Architecture and Environmental Planning at Utah State University. His research interests include technology-driven behavioral research in public space and behavioral outcomes of smart growth.

Reid Ewing is a distinguished professor and distinguished chair for Resilient Places at the University of Utah and a columnist for *Planning* magazine. He is a coauthor of *Measuring Urban Design: Metrics for Livable Places*.