Smartphone-Based Light Detection and Ranging: A Case Study of Measuring Homeless Encampments in Downtown San Diego, California

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Abstract

The United Nations Sustainable Development Goals (UN SDGs) wireframed an outline to reach global peace and prosperity through the achievement of the seventeen goals (UN, 2015). The Leave No One Behind (LNOB) motto is a commitment to assure the 2030 SDGs benefit all persons, especially marginalized groups. However, disadvantaged populations, such as homeless groups, are still getting left behind and not advocated globally. Global advocates such as the UN General Assembly did not pass a resolution for homelessness until late December 2021. By this time, homelessness in America remains a consistent problem with no visible solutions. California averaged 1 homeless person per square mile. Researchers at the Metabolism of Cities Living Lab (MOC-LLAB) under the Center for Human Dynamics in the Mobile Age at San Diego State University are tracking and visualizing homelessness using monitoring technologies at a local level to address the lack of attention the SDGs have applied to this issue in San Diego County, California. In this paper we use LiDAR, a surveying technique that utilizes laser light pulses to collect 3-D point clouds, as an alternative and open-source way to measure and visualize homelessness efficiently. Homelessness tends to be concentrated in urban neighborhoods near economically disadvantaged communities with limited resources, making them more prone to health disparities and further leaving them behind. The current study suggests that the densest homeless populations in San Diego County are three times more than the state average.

Introduction

The state of California has long been a hotspot for homelessness due to its mild Mediterranean-like climate and the long list of socio-economic challenges that accompany it. California has the largest population of homeless people, with one-fifth of the total homeless population in the United States (MaGee, 2022). More recently, the Covid-19 pandemic and related shutdowns accompanied by rising housing costs and inflation have further worsened the issue (Grinstein-Weiss, 2022). As of January 2020, there were about 161,548 individuals experiencing homelessness on any given day in California (California's Housing Crisis YEAR ; CalCAPA, 2021). Over the years, various government policies and actions have failed to solve the issue, which appears to be worsening.

The United Nations (UN) has outlined 17 Sustainable Development Goals (SDGs) to be achieved by 2030 for a better world with no poverty, hunger, and disease (UN, 2015).

Furthermore, the Leave No One Behind (LNOB) initiative represents the commitment of all UN member states to eradicate discrimination and exclusion, and reduce the inequalities and vulnerabilities and ensure that those furthest behind are not left behind. However, homelessness remains a pressing issue with not much being done to help or advocate for this vulnerable population globally. People experiencing homelessness remain victims of stereotypes that make the general public see the homeless less as a victim and more as a consequence of personal choice and poor decision making. All these factors have contributed to leaving the homeless population behind. Calls for change are usually impulsive and only heard when the problem becomes more visible and starts impacting the residents in a community. Thus, attention to the subject tends to be cyclical, and most solutions tend to focus on dealing with the impact of homelessness on the community rather than the actual problem itself.

A number of illnesses and diseases have arisen with the stigma associated with homelessness. For example, the County of San Diego declared a local health emergency on September 1, 2017, due to a Hepatitis A outbreak, a viral infection of the liver transmitted in unsanitary conditions which can cause nausea, abdominal pain, and fever. Additionally, in October 2021, the *San Diego Union-Tribune* announced an outbreak of shigellosis in San Diego, a contagious infection caused by shigella bacteria that can cause fever, stomach cramps, and diarrhea. Homeless communities were mainly infected through contaminated surfaces (i.e., food, water, or person to person). Outbreaks such as these build great concern around homeless encampments due to their lack of sanitation, the number of encampments, and proximity. Homeless encampments in San Diego equate to tents often placed side by side and stretching down streets, covering entire blocks. With encampments being so close to one another, diseases can quickly spread from block to block. It could be to San Diego's benefit to predict projected infection spreads to minimize and control disease outbreaks by being able to measure the distance of these encampments.

One cost effective method of measuring distance and developing homeless awareness in San Diego employed by this study is called LiDAR, or Light Detection and Ranging. LiDAR is a surveying technique that utilizes laser light pulses to collect 3D point clouds (Kuras et al., 2021). Together, a 3D model of the environment is scanned: vehicles, security systems, and iPhones use LiDAR technology. With the combination of the desire to assist homeless populations and utilize LiDAR technology, a research question is formed, *How can LiDAR technology be used to measure the volume of homeless communities in downtown San Diego?* This research aims to fill a much-needed gap of quantifying the distribution of homeless encampments. Few studies address the disadvantages that homeless communities face. This case study intends to fill this gap by leveraging LiDAR technology to measure the distance of homeless encampments with the hopes of mediating the spread of future diseases while also encouraging government officials and city planners to tend to the spatial needs of homeless individuals. Research such as this strives to make lasting change with an innovative approach for researchers, decision-makers, and practitioners.

Literature Review

The objective of this review is to view prior research on applying LiDAR data to measure the volume of homeless communities. Kuras et al. (2021) defines LiDAR data as a 3D point cloud (X, Y, Z) that provides information regarding elevation, multiple- returns, the reflected intensity, texture, and wave-form-derived feature spaces from items hit by a laser pulse. Due to a scarcity of literature regarding this topic, this review emphasizes scholarly sources that are dedicated to LiDAR technology and how it is used to model vegetation (Brock et al., 2011; Chen, 2014; Genc et al., 2004; Jimenes-Berni et al., 2018; Kelly et al., 2015; Peterson, 2005; Streutker et al.; Venier et al., 2019; Walker et al., 2019) and integrates with machine learning algorithms (Li et al., 2015; Kowalczuk et al., 2019; Kuras et al. 2021). The lack of results may indicate a gap in the literature in regards to homeless encampments and the use of LiDAR technology. Eliminating this gap allows scholars to further assist homeless communities through an innovative approach. The purpose of these twelves sources was to view literature similar to attribute knowledge to LiDAR technology. First, discussing the literature regarding mapping vegetation.

Based on the amount of literature, one might conclude that mapping vegetation is a common application that has been around for decades. Cartographers transitioned from aerial photography to digital remote sensing in the 1980s (Kelly et al., 2015). Genc et al. (2004) comments on the offerings LiDAR remote sensing provides as a possible alternative to field surveying and photogrammetric techniques for collecting elevation data. Past research demonstrates the capability to accurately estimate significant vegetation of structural characteristics such as forest canopy height (Genc et al., 2004). LiDAR has been noted to have exceptional accuracy in measuring the height of vegetation structures (Chen, 2014). Jimenes-Berni et al. (2018) remark on an advantage LiDAR technology has over RGB images, the color model of the primary colors red, green and blue: “LiDAR-derived images can avoid some of the limitations of RGB images… changes in ambient light conditions and shadows can result in over or under exposure, thereby reducing image quality and data reliability.” Authors such as Corona et al. (2010) and Streutker et al. integrate remotely sensed data and mapping of an entire region to produce maps of the attributes, improving the precision of specific estimates.

As technology rapidly advances, the variety of algorithms employed in datasets has advanced too. Within the sources collected, algorithm advancements are demonstrated through the classification of objects with LiDAR point clouds via Deep Neural Networks (Kowalczuk et al., 2019), machine learning and neural-network-based classification (Kuras et al., 2021), and pixel-based analysis (PBA) and object-based image analysis (OBIA) (Li et al., 2015). Although Kowalczuk et al. (2019) pursued a methodology that contrasts with the current research, the authors provide insight on how to pre-process LiDAR data effectively. Kuras et al. (2021) present foundational concepts and features for imaging, LiDAR, and the integration of the two through machine learning and deep learning classification algorithms. The authors recognized that manually derived features may not accurately represent the profoundly complex and unique urban environment (Kuras et al., 2021). Limitations mentioned by Kuras et al. (2021) provide the current research with practical expectations. Li et al. (2015) provide an alternative approach; instead of scanning urban environments, the authors applied analytical approaches to images. Using image analysis, the authors highlight the importance of suitable input layers and automated scale parameter selection approaches by applying LiDAR technology. The sources listed within this paragraph assisted with the understanding of LiDAR data and its limitations.

All of these studies have devoted themselves to the application of LiDAR technology. The lack of research exemplifies a gap in the literature in regards to homeless encampments and the use of LiDAR technology. Eradicating the gap provides scholars who study the health of homeless communities the opportunity to reflect on the potential LiDAR technology can contribute to this underserved group. More research could be dedicated to applying LiDAR data to measure the volume of homeless communities to further assist homelessness through an innovative approach.

Methodology

A team of three researchers identified densely occupied homeless encampments along streets in the zip code of 92101 City of San Diego, California. This was done by mapping data points collected by the San Diego Regional Task Force on Homeless, providing a raw count of homeless populations receiving services, as well as, poverty data from CalEnviro (2021) in an interactive dashboard. Following the dashboard, the population density by zip code was calculated.

Both video and LiDAR data was collected on July 22, 2022 using three handheld smartphones (iPhone 12 Pro) and three different apps (vGIS, Scaniverse, Polycam from the iPhone App store) which utilized the three-dimensional (3D) feature capabilities on Commercial and 17th Street. Step one, scans and footage were captured by walking along the streets with 3 handheld devices to capture encampments established on the sidewalks. Step two, scans were expanded by driving at a speed of 5 mph along encampments to efficiently capture a larger area. Streets were active with tents, makeshift tarps and shaded easy ups used as shelter, while occupants were found in and along encampments. To evaluate the suitability of each application, multiple runs were taken to collect LiDAR point cloud data, still imagery and motion picture. This initial survey lasted approximately 1.5 hours and a total of 250MB imagery stored for later spatial analysis.

Results & Discussion

Understanding the distribution of homelessness in San Diego County is an important initial step to draw connections and utilize resources effectively. An Interactive dashboard was developed to visualize the homelessness in the city as well as various socio-economic factors that contribute to it. It was hypothesized that homelessness tends to be more concentrated in poorer and disadvantaged neighborhoods in major urban centers. Figure 1 shows the number of individuals receiving services per service center zip code. Poverty percentile per zip code was also added as a layer on the map. The map below supports the above hypothesis, with a drastically higher number of homeless individuals found near San Diego City Center compared to other areas across the county, and what appears to be a positive correlation between poverty and homelessness. The map reflects that homeless individuals tend to be found in disadvantaged neighborhoods located in major urban developments. Since the data was based on zip codes of service centers across the county, it can be predicted that the lack of services is not the reason for this distribution. Possibly, other underlying factors can be contributing to this, such as accessibility and enforcement.

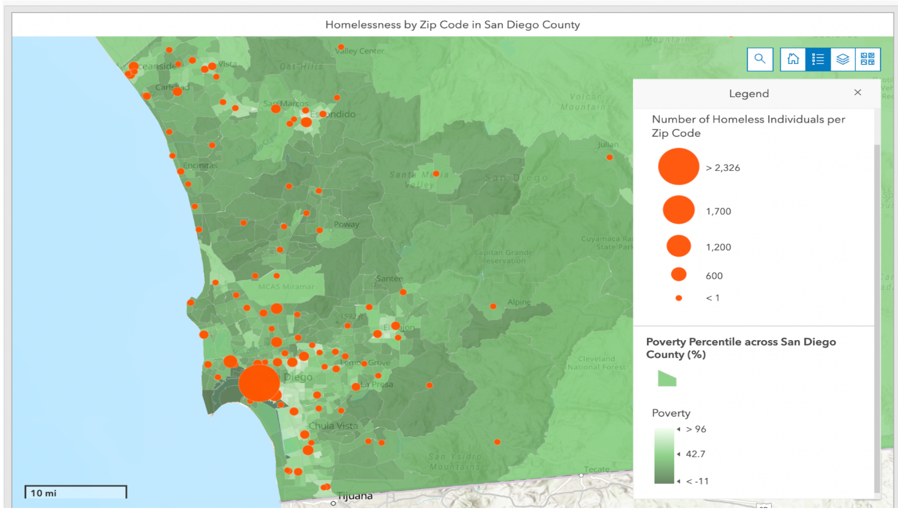


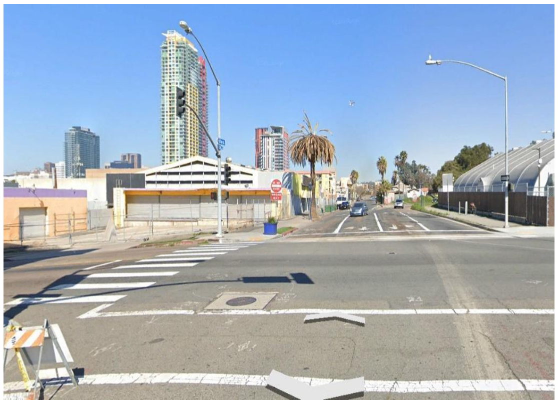
Figure 1. Homeless Individuals receiving service by Zip Code in San Diego County According to the Regional Task Force on Homelessness
The green choropleth map depicts the gradient change of poverty and the size of the red circles visualize the count of homeless persons.

Based on the results in Table 1, the zip code with the largest population density of homelessness in San Diego County is 92101. Further investigation of homeless encampments were obtained in the field using LiDAR technology and capturing videos within this zip code.

Table 1: Population Density of Homelessness by the Top 5 Populated Zip Codes

Zip Code	Homeless Population	Area	Population Density (person/acre)
92101	20,351	5851.557	3.477878
92108	8,163	3192.929	2.556586
92103	3,859	2324.103	1.660426
92110	4,118	3061.568	1.345062

From the data collected, researchers were able to observe living conditions, identify materials used for shelter, and capture the resources currently available for their use. From observation, it appears that this vulnerable population lacks access to basic sanitation, clean water and lives in unclean conditions. How long these homeless encampments have been established is unclear; however, a Google Street View from February 2020 indicates no encampments (Figure 2). Two years later (March 24, 2022) Figure 3 shows at least thirteen tents on 17th Street - where the survey was conducted for this study.



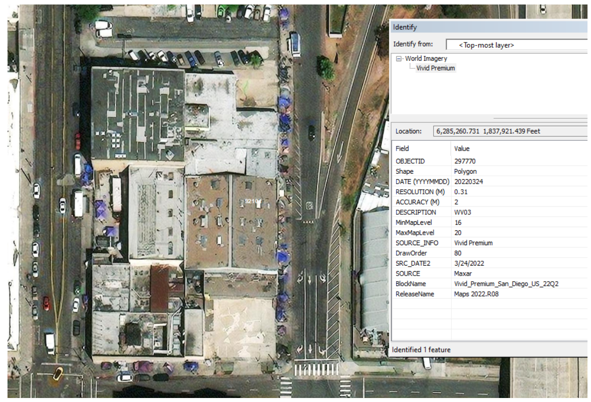


Figure 2: Google Street View from February 2020, 17th Street (On the left)
Figure 3: Aerial Image from ESRI Arcmap, March 24, 2022 (On the right)

Of the three apps used, Scaniverse collected the most LiDAR point cloud data, shown in Figure 4. Polycam and vGIS may be programmed differently and therefore were not able to collect data beyond its measurable distance (5m length), and tents taller than 6ft when moving approximately less than five miles/hr through the street.

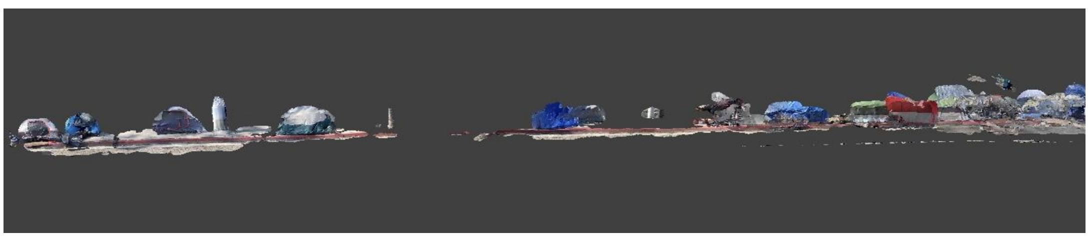


Figure 4: Homeless Encampments Scanned via Scaniverse, 17th and Commercial St.

Figure 4 provides a glimpse of the data collected with Scaniverse. As shown above, a fraction of the encampments were retrieved to generate a 3-D image. While Google Street View has been utilizing LiDAR technology since 2017 (Wikipedia, 2022), this study is the first of its kind to measure homeless encampments with point cloud data from handheld devices. When LiDAR scans are taken, the level of accuracy is to the centimeter, however using a desktop mapping service to measure the length along the streets, estimating height becomes a challenge and there remains the need for up-to-date ground truth. This is true for two reasons; many virtual reality displays transform the point cloud data to TIN (triangulated irregular network) to smooth the sharp edges and overlay RGB (red, green blue) imagery thus losing some of the data quality and detail. Two familiar data types used in GIS (geographic information systems) include vector and raster – both of which are two-dimensional, but both can have depth or elevation values added. X,Y and Z (length, width and elevation) coordinates are inherent to LiDAR thus giving its 3-D graphic display. While one downfall of this data type is its graphic memory size, its accuracy and precision are reduced when compared to raster cellular classification which is commonly at the 2-10 ft2 or 3m2 measurement.

According to our results, data suggests the density of encampments (also considered temporary housing units) per acre exceeds average prior year point in time count estimates. Just a single block along Commercial Street contained at least 22 encampments from the most recent video captured.

Figure 5: Still Image of Commercial St Leading to 17th St

The unsanitary conditions, close proximity, and encampment density observed suggest that these encampments are susceptible to the spread of diseases. Bringing new ideas and technology to the homeless problem can solve issues of how much space is needed to house individuals experiencing homelessness in urban San Diego areas as well as preventing the spread of infectious diseases.

Conclusion

To observe this survey area in great detail combining LiDAR and imagery into a 3-D integrated mesh provides an accurate virtual reality representation. Although this study collected a sample dataset of what exists, future studies may decide to encroach or invest in more advanced technology. Techniques to capture homeless encampment volumetrics are a challenge for multiple reasons. Safety and working in numbers help reduce anxiety although every attempt was taken to not disturb current occupants. This study aims to remain anonymous and respect personal space and their belongings, and being that it is in a public space, the dimensionality of a robust homeless examination would consider how long individual encampments have been established, number of transients entering and remaining long term and the resources available for consumption. As mentioned earlier, LiDAR can be converted to vector and/or raster data but information is lost with each transformation.

Aside from conventional methods, in this paper we attempted to present LiDAR as an alternative way to measure and create awareness of homeless encampments using open-source technologies. LiDAR is already employed by tech companies such as Google to create a point in time street view in maps. The technology is useful in providing insight on homeless encampments, changing distributions over time, as well as visual changes in neighborhoods that can indicate changes in the population overtime. Furthermore, LiDAR can be used to predict the space that homeless individuals are taking up in a certain area. This data would be particularly important for sanitation and disease management in those encampments as well as developing housing solutions. Using the LiDAR data, government officials can determine and rank the urgency of dealing with an encampment as well as monitoring progress on cleanup efforts. The LiDAR data will also provide a better representation on how homeless encampments are affecting the surrounding communities.

We utilized free applications to perform LiDAR scans through smartphones. Based on the data above, a hotspot zip code was chosen in downtown San Diego for an experimental scan. The attempted scans were unsuccessful due to various reasons;

however, this does not exclude LiDAR as a possible tool to visualize homelessness. Our experiment showed the limitations of applying the technology through limited resources. One of the main limitations was the lack of equipment and the use of an open-source app which did not allow full functionality. Furthermore, logistical challenges were presented in approaching and scanning tents as the detection range for the phone scan was very limited and required being within the personal space of the individuals in the street. Performing scans while driving was a challenge because tents were higher than the car's height. Also, the lack of any government credential or authority, while having to point a filming device at people for an extended period of time as the scans were processed made the situation very challenging for the crew. Finally, the limited access to the vGIS portal to process and visualize collected scans, and the lack of any free alternatives prevented further analyses.

Although limited results were obtained from the performed scans, a set of recommendations can be made for future attempts. A handheld LiDAR scanner is needed for a better range and faster scans. In addition, homeless encampment visits can be handled by a government agency or arranged with the police department in the area. Furthermore, companies like Google are already conducting large scale street scans regularly. A collaboration is possible to access this data and utilize it with respect to homelessness to develop policy and awareness using monitoring technologies. These measurements become useful for urban planning by translating the area occupied to allow architects, engineers, and city planners a tool and data to solve the homeless issue that is becoming ever more prevalent.

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