Using Lidar to Examine Human Occupancy and Collisions within a Shared Indoor Environment

Addison Harris Flack

Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Science
In
Geography

Thomas Pingel. Co-Chair
Timothy Baird. Co-Chair
Nicole Abaid

08 May 2024
Blacksburg, Virginia

Keywords: indoor geography, lidar, remote sensing, placemaking, interaction

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ABSTRACT

Indoor spaces, where we spend the majority of our lives, greatly impact our work, social interactions, and well-being. In recognition of the central role that buildings play in our lives, architects and designers have increasingly focused on creating spaces that intentionally promote interaction and collaboration between building occupants. One challenge arising from this trend is evaluating the efficacy of new designs. This study used object tracking data for the Fall 2023 semester from a collection of lidar sensors installed in a portion of a mixed-use academic building on a university campus to algorithmically detect occupancy and serendipitous *collisions* between people - patterns of simultaneous movement and pause that indicate that two or more individuals have stopped and had a meaningful interaction. The algorithm detected over 14,000 collisions throughout the semester with high spatial and temporal precision. Occupancy and collisions were highly related over several scales of temporal and spatial analysis. Furthermore, several interesting patterns emerged, including (a) collisions peaked early in the semester, then declined before leveling off, (b) occupancy peaked in mid-afternoon, while collisions peaked in the late afternoon and early evening, (c) collisions peaked later in the week than did occupancy, and (d) specific hotspots were apparent at important nodes such as the bottom of stairs and near elevators. The patterns found in this study can provide insight as to how interactions can be measured using remote sensing data, and can aid designers in attempting to increase collaboration in shared indoor environments.

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GENERAL AUDIENCE ABSTRACT

We spend lots of our times in buildings, and they are very important for our well-being. Designers have recently been focusing on promoting collaboration and interaction between people within building spaces. Despite their importance, these interactions within buildings have been challenging to categorize and analyze. This study used object-tracking data for the Fall 2023 semester from a collection of lidar sensors, which were intermittently placed in the ground-floor public spaces of a new hybrid residential-academic university building on Virginia Tech's Blacksburg campus. A computer program was written to parse through this data, and detect unplanned *collisions* between people; patterns of movement and pause that indicate that two or more people have stopped and had a meaningful interaction (for example, running into a friend while walking down the hallway). This study was able to detect collisions relatively well using a computer algorithm. The patterns and distributions of these collisions were then analyzed in time and space. The number of collisions and the number of people present in the space were highly related on all scales of time and space. In terms of time itself, collisions happened the most at the beginning of the semester, where they then dropped off. Collisions happened more frequently both later in the day (in afternoon, evening, and night hours) and later in the week (on Thursday, Friday, and Saturday). In terms of space, these collisions happened most frequently in the areas around the elevator, at the base of the stairs, and in the building's main lobby area. They happened less in hallways and near some seating areas. The patterns revealed from this study can help us better understand how to detect interactions between people within buildings, and can help designers increase the amount of these interactions.

Acknowledgements

I would like to graciously thank Dr. Thomas Pingel and Dr. Timothy Baird for their continuous support and investment not only in this scholarship, but in my growth and development as a person and scientist. Through your guidance, I have learned more than I imagined was possible. I would also like to thank my final committee member, Dr. Nicole Abaid, for her valuable insight and feedback.

Finally, I would like to acknowledge and appreciate the support of my family and friends during the past two years. This project and time has come with difficulties, and the reinforcement, compassion, and the willingness to listen and discuss is something for which I will be forever grateful.

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1. Introduction

Indoor spaces play a key role in the lives of humans, and are becoming an increasingly important focus area for study in geography, geographic information science, and remote sensing (Zlatanova et al., 2013). New techniques for mapping include photogrammetry and lidar-based simultaneous localization and mapping (SLAM) (Durrant-Whyte & Bailey, 2006; Chen, 2019) and Indoor Positioning Systems (IPS) (Otero et al., 2020; Al-Ammar et al., 2014; Gutmann et al., 2013) that provide guidance for navigation inside buildings just as GPS is a navigation aid outdoors. These techniques have been found to be particularly useful within large, shared indoor environments such as shopping malls, hospitals, airports, and university common spaces (Karam et al., 2020).

First-year university students often undergo a challenging transition period when they move to campus, which can play a defining role in their lives (Temple, 2009). New social relationships, and sense of community and culture within their new residence halls can aid a transition from unfamiliar *spaces* to highly valued *places*, where a deeper sense of meaning and emotion can be associated with a location (Cassidy & Trew, 2004; Chow & Healey, 2008; Tuan, 1975). Rubin et al. (2011) found that serendipitous interactions could be a driving force in positive adjustment for many students. Correspondingly, by adjusting the design of indoor spaces, designers can intentionally encourage these positive interactions to occur, nudging students towards interaction, and ultimately meaningful relationships (Björneborn, 2017; Temple, 2009).

Scholarship by Otsuka and Mukawa (2004), Teixeira et al. (2010), and He (2020) has highlighted the use of object tracking to study human behavior indoors. Additionally, many survey-based studies have been conducted to better understand place-making and the transition to university for many students (Cassidy & Trew, 2004; Chow & Healey, 2008). However, research gaps exist in an operationalization of technical indoor geography (remote sensing and object tracking) to quantify the transition from *space* to *place* that many students undergo. This study seeks to address this gap by creating a method of quantification using terrestrial remote sensing and object tracking to examine the serendipitous interactions that can support a sense of community, culture, and feeling of home for many students.

Accordingly, a network of fixed-mounted lidar sensors was placed in the first-floor public area of the Creativity and Innovation District Living-Learning Community Building (CID) on Virginia Tech’s Blacksburg campus, called the Community Assembly, in order to capture the movement patterns of building occupants while protecting individuals’ anonymity (Teixeira et al., 2010), and preserving an atmosphere of comfort and safety where people work, learn, and live.

Serendipitous interactions (i.e., collisions) were detected using a Python algorithm applied to the entire 2023 fall academic semester, allowing us to see how the spatial and temporal distributions of collisions changed over the course of the semester as part of a larger project to better understand how space becomes place in indoor environments. Specifically, this study aimed to address two primary research questions, and three hypotheses, as outlined below:

1.1 Research Questions

1. How can we detect collisions, serendipitous interactions between people in physical space, within a shared indoor environment using lidar data?
2. How are collisions distributed in space and time, and what attributes are associated with those patterns?

1.2 Hypotheses

H1: Collisions are proportional to overall traffic of an indoor environment.

H2: Frequency of collisions over time is linear and increasing over the course of an academic year.

H3: Collisions are associated with the edges between zones of movement and pause in the study area. These might be areas where a conduit of movement occurs next to an area of often-used seating.

2. Background

2.1 - Indoor Geography

Although geography has traditionally been concerned with the outside world, geographers have recently begun to explore indoor environments and indoor mapping as areas of interest. One of the main factors supporting these interests has been the growing appreciation for the importance of buildings in daily life. Klepeis et al. (2001) found that Americans spend 87% of their time within indoor spaces. While the term ‘indoors’ has many different definitions in academic and geographic contexts, Chen and Clarke (2019) conclude that nearly all of the definitions of the term include a notion of full enclosure and finite size, often with greater levels of fine-scale intricacy.

To map indoor spaces, many different indoor mapping techniques exist - these include 3D modeling, floor plans, indoor positioning, and lidar. Karam et al. (2020) studied how indoor mapping techniques have been implemented and applied in indoor spaces, and found that they are particularly useful within large shared environments, such as hospitals, shopping malls, airports, and universities. Some of the major cartographic representations of indoor spaces include CAD drawings, building information models (BIMs), point clouds, and textured mesh (Chen & Clarke, 2019; Figure 1). Because of the increase in the prevalence of these technologies, many businesses and universities are beginning to appreciate the importance of indoor mapping (Zlatanova et al., 2013).

Figure 1: Different representations of indoor spaces including (a) Computer-Aided Drawing (CAD), (b) Building-Information Models (BIM), (c) Point-cloud, and (d) textured mesh. From Chen and Clarke (2019).

Zlatanova and Sithole (2016) differentiate between *position, location, place,* and *area* with respect to indoor mapping. Position is the absolute geographic position of an object within a space, and is often represented by coordinates. Location refers to the smallest physically-defined space within a building, and generally refers to rooms, hallways, staircases and more. Place is much more subjective, and is based on a person's experience within the indoor environment, and area is a generalized concept which encompasses multiple locations.

The field of indoor geography and indoor mapping has grown in recent years, partially driven by the commercial potential of mobile phones and their capabilities within indoor environments, as well as developments in mobile-terrestrial surveying technologies (Zlatanova & Sithole, 2016;

Otero et al., 2020). These developments have greatly improved the efficiency of building surveying and mapping, which has traditionally been time consuming and costly. Some of the major technologies which contribute to commercial indoor mapping systems include lidar, indoor positioning, and simultaneous localization and mapping (SLAM) (Otero et al., 2020).

Accurate indoor positioning systems (IPSs), which continuously determine the location of an object within an indoor environment in real-time, have been gaining popularity, as GPS can not be used reliably indoors (Otero et al., 2020, Al-Ammar et al., 2014). These systems often function through active beacons, in which multiple beacons at known locations use triangulation to capture the location of an object as it travels through space (Gutmann et al., 2013). IPSs capitalize on the advantageous characteristics of indoor environments which facilitate localization and positioning, such as smaller coverage areas with low levels of movement. Main target applications for IPS include shopping malls, museums, hospitals, and locations accessed frequently by first responders (Al-Ammar et al., 2014).

Developments in simultaneous localization and mapping systems are driven primarily by research on navigation systems for autonomous vehicles (Chen et al., 2019). SLAM techniques are used for mobile robotics systems, as they permit mobile robots, placed in an unknown location with unknown surroundings, to slowly navigate the environment while simultaneously building a three-dimensional model of the environment (Durrant-Whyte & Bailey, 2006). With indoor-SLAM, a robot or person with RGB camera or lidar sensors moves throughout an indoor environment and captures real-time data of local surroundings (Zou et al., 2022). From here, high resolution models of the space are built, and can be used for navigation. Through the integration of Inertial Measurement Units (IMUs), the spatial configuration can be added to the scans (Chen et al., 2019, Durrant-Whyte & Bailey, 2006). Promising innovations here include the use of lidar sensors for SLAM, which can achieve better precision, accuracy, and denser information of the environment under any lighting conditions (Chen et al., 2019).

Lidar is a form of active remote sensing in which a sensor emits a pulse of light, which strikes an object and then returns back to the sensor (Beraldin et al., 2010). By measuring the time this process takes, lidar sensors can accurately map a given area (Meng et al., 2010). Airborne lidar is used to capture large-extent outdoor areas (e.g., cities and counties) as a 3D *point cloud*, each point of which is then typically classified into a category, which can include vegetation, buildings, bare-earth and other types using algorithms and human-guided techniques (Meng et al., 2009; Beraldin et al., 2010). Individual people are not typically well-captured in such large-extent point clouds as the resolution is too low (e.g., 5-15 points per square meter).

2.2 - Human and Object Tracking Indoor Environments

Teixeira et al. (2010) outline an approach for detecting people within higher resolution point clouds, including metrics (increasing in complexity) of presence, count, location, track, and identity (Figure 2). Presence is the ability to detect if people currently occupy a space, while count involves the total number of people within the space at any given time. Location is concerned with the geometric positioning of humans within the space, tracking is a process in which previous locations are extracted and stored, and identity involves associating each unique person/object within a space with a globally unique ID.

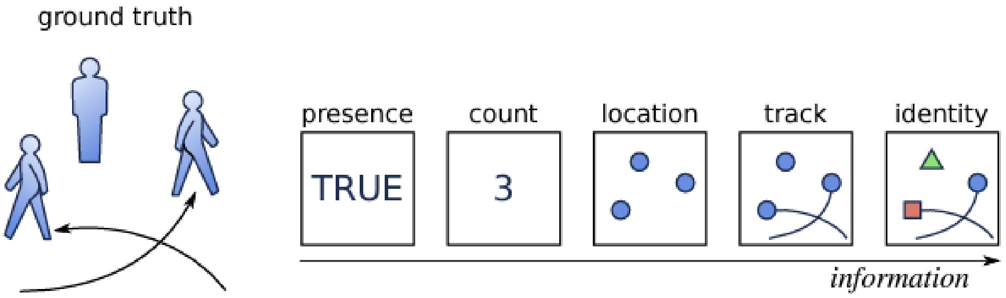

Figure 2: The five spatiotemporal properties of human sensing. From Teixeira et al. (2010).

To detect people within an indoor environment, Tiozzo-Fasiolo et al. (2022) propose combining RGB camera and a convolutional neural network (CNN) developed for object detection to create a bounding-box around an ‘object’ within a space: Multi-Camera Multi-Camera tracking involves using, although challenges have been noted with seamless and continuous tracking from camera to camera (He et al., 2020). The use of multiple sensors for object tracking aims to resolve issues with background clutter and object occlusion, which often occur with only one viewpoint from a single sensor (Otsuka & Mukawa, 2004).

Rather than using traditional camera-based sensing for indoor spaces and object tracking, the use of lidar has been growing in recent years (Günter, 2020; Obanawa et al., 2020; Zhou et al., 2020). Teixeira et al. (2010) outline major advantages of lidar sensing methods compared to alternatives, including camera-based sensing. Due to potential lower resolution and lack of color produced by lidar, the anonymity of persons within a sensing area is preserved (Teixeira et al., 2010). Lidar sensors also do not rely on ambient light - meaning they function properly under dynamic lighting conditions, including at night (Günter, 2020). Furthermore, data coming from lidar sensors are generally more dense, and tend to be less noisy than the data from camera based systems (Obanawa et al., 2020; Zhou et al., 2021). Because lidar processing is much easier over a large area, photogrammetric sensing/data processing, by comparison, can be expensive in both terms of cost and time (Meng et al., 2009). Additional advantages and disadvantages of lidar and camera based systems can be seen in Figure 3.

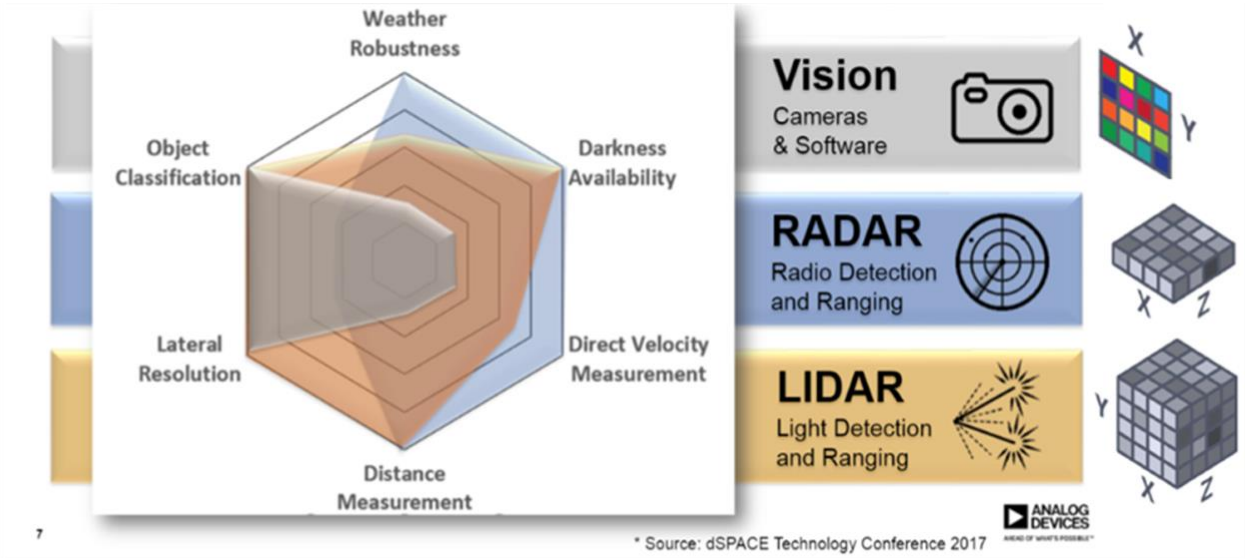

Figure 3: Advantages and disadvantages of camera, radar, and lidar. From Analog Devices | dSPACE Technology Conference, 2017

Finally, the active sensing ability of lidar measures position and allows for shape/geometry to be produced by the sensor itself, compared to cameras, which do not actively contain geometric/positional information (Teixeira et al., 2010). This provides lidar with advantages in geospatial analysis, as positional recording can easily allow for locations of objects to be translated into x-y coordinates within a cartesian system. Lidar can accurately measure a scene and create a point cloud, a three-dimensional representation of a space (Dassot et al., 2011). Terrestrial lidar has specifically become commonly used in other disciplines, including forest science, in which the technology has been more frequently used for fine-scale measurements and analyses (Dassot et al., 2011).

2.3 - Behavioral Geography and Human Ecology as models for Human Interaction

Behavioral geography is the study of how individuals perceive, think about, and act in their spatial surroundings (Golledge & Stimson, 1997). It involves studying the psychology associated with space, place, and the environment, and justifies mental explanations for observable behaviors within environments (Montello, 2018). This includes the study of cognitive and mental maps, navigation and wayfinding, accessibility in the built environment, orientation and distance estimation, and spatial abilities (Montello, 2013). Space-time models and GIS play a major role in modern behavioral geography. For instance, Miller (1991) used space-time prisms to model the movement of individuals in relation to transportation networks (Figure 5).

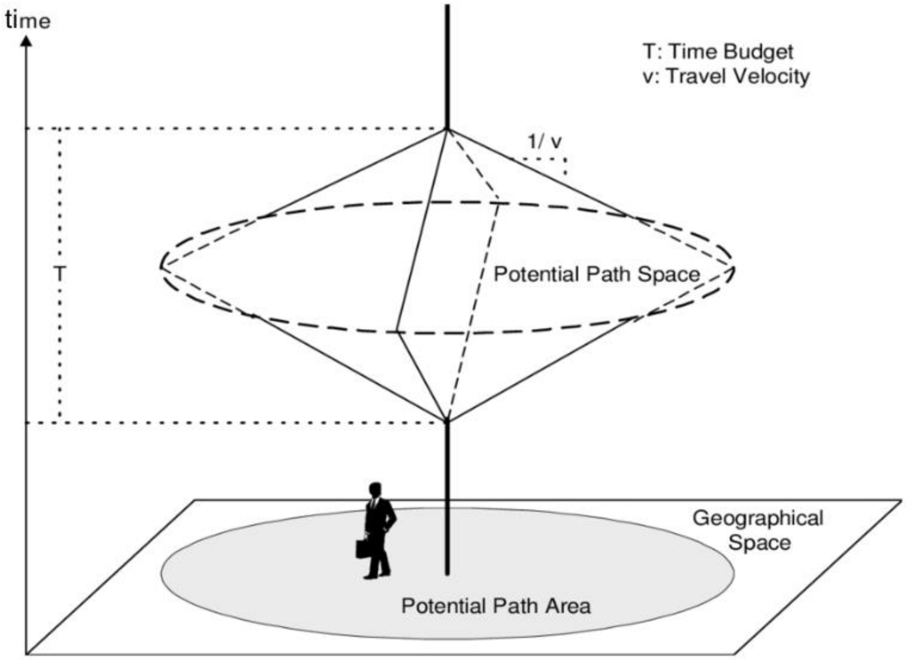

Figure 4: Space Time Prism showing potential movement of a person in space. From Wu and Miller (2001; Adapted from Miller, 1991).

De Vos (2022) has also argued that interlinking relationships exist between travel attitudes, behavior, and the local built environment. These relationships, he claims, additionally affect personal decisions such as travel choices and residential location choices (see Figure 5).

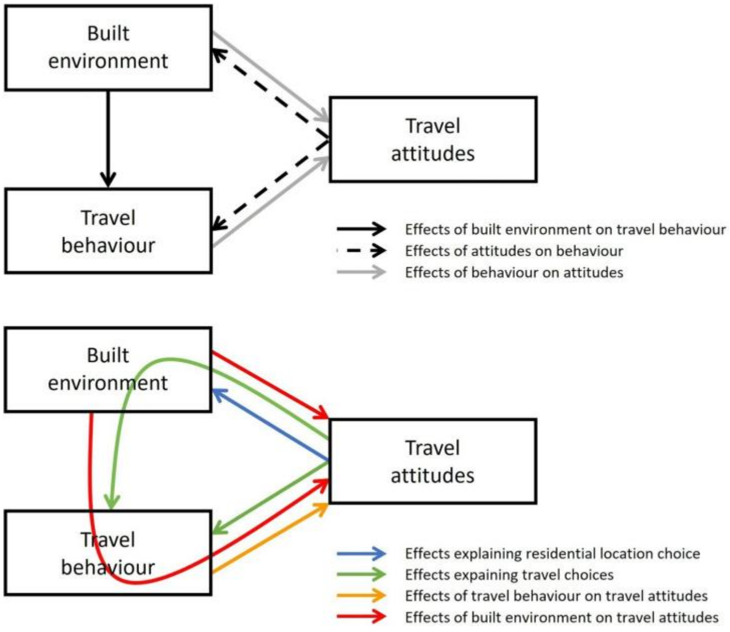

Figure 5: The interlinking relationships between the built environment, travel attitudes, and travel behavior, and how they affect travel choices. From De Vos (2022).

Policies and constraints placed on people influence their behavior in spaces and places, especially in locations where routine-living occurs (Golledge & Stimson, 1997). Human mobility in urban settings is often influenced by personal attitudes and beliefs, space design, and governance (Chaudhry et al., 2023).

Behavioral geography proposes additional theories of how people may move within shared environments, the first being the *least-angle strategy*, a common wayfinding method in which an individual's path, taken from a starting point to an ending point, is based on their ability and tendency to travel along a path that is the most well-aligned with the straight-line direction (Hochmair & Frank, 2000). Specifically regarding intra-building navigation, Hölscher et al.

(2006) found that as familiarity increases within a building, inhabitants were less likely to get lost, and were also more likely to adhere to the least-angle strategy, cover a shorter distance from point A to B, and move more quickly on their route. Another approach, the *least risk path algorithm*, which is a method of wayfinding that minimizes the risk of getting lost, also has been found to apply to indoor settings, especially within complex, multi-story indoor spaces (Vanclooster et al., 2014). Indoor wayfinding can also be broken down from the perspective of *space syntax*, a way of providing formal descriptions of built environments (Li & Kippel, 2010, Montello, 2007). Through space syntax, the importance of the environment on wayfinding can be categorized into three aspects: (1) the degree of differentiation - the visual variation of an environment; (2) the visual access - the parts of the environment visible from vantage points; (3) and the complexity of the spatial layout - which can be deconstructed into the areal size, number of route choices, and the angles present between route intersections (Li & Kippel, 2010).

While Behavioral Geography tends to be more concerned with the spatial characteristics of environments, wayfinding, and human mobility, the sub-field of Human Ecology is more broadly focused on groups' resource extraction and use, traditionally in natural environments, and the social and cultural practices and structures that evolve from this largely economic endeavor. Over many years, Human Ecology has been home to several different viewpoints and definitions related to human-environment interactions (Barrows, 1923; Rambo, 1983). Rather than defining Human Ecology as being concerned with the environment's influence on human behavior, Barrows (1923) established a geographical approach concerned with human's adjustments to different environments. Emphasis within Human Ecology is often placed on humans being both biological organisms and social beings - influencing how we interact with our surroundings (Bubolz & Sontag, 1993). Interactions with the physical environment and others, combined with the resources available within these environments can influence human-to-human interaction patterns.

2.4 - Spatiotemporal Analysis in Geography

Mei-Po Kwan has contributed to geographic information science in a number of key areas in the past several decades, especially in the development of space-time analytics (Kwan et al., 2014). Her early work focused on using network analysis to study individual and gender-based accessibility within urban settings (Kwan, 1998; Kwan, 1999). She has also studied how space-time analytics can highlight how issues of segregation and environmental justice impact travel mobility (Kwan, 2013).

One area of research of particular application to this study is the development of space-time path analysis. Space-time paths are continuous trajectory paths which visualize x- and y-coordinate movements in space conventionally, but plot time as the z-coordinate (Kwan, 2004; Figure 6). Color can be used to represent an additional variable, such as feeling towards one’s environment at a specific place and time (Figure 6). Space-time paths and space-time analysis are often utilized in the larger-scale analyses of urban, mobility, and transportation geography, where they are primarily useful for better understanding activity-travel patterns (Kwan, 1999, Kwan, 2004, Kwan, 2000), however, these techniques could also be used to visualize the tracking data produced by the lidar system used in this study.

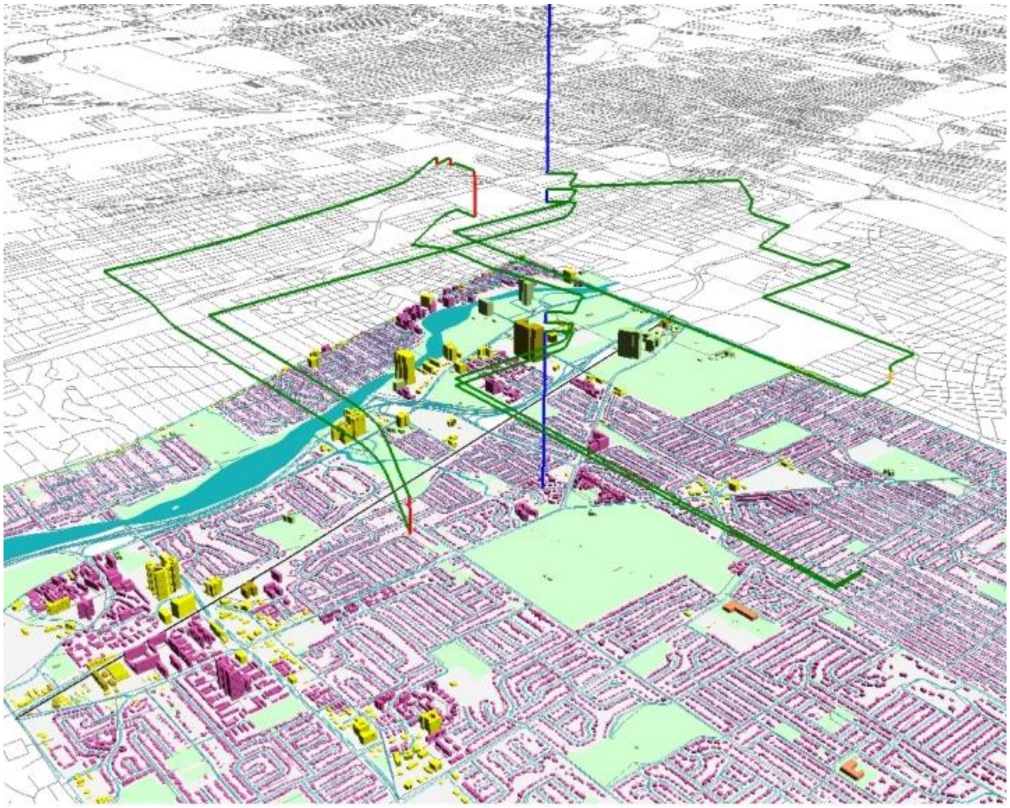

Figure 6. A space-time path showing a woman's travel pattern in Columbus, Ohio. Color is representative of her feeling towards the urban environment. From Kwan (Mei-Po Kwan's 3D GIS work - space-time paths)

A second area of research in particular application to this study is the concept of the Uncertain Geographic Context Problem (UGCoP; Chen & Kwan, 2015; Kwan, 2012; Liu et al., 2023; Zhao et al., 2018), which she and colleagues contrasted with the related and more well-known Modifiable Areal Unit Problem (MAUP; Openshaw, 1983). MAUP describes how the "enumeration units" of spatial analysis - census tracts, counties, zip codes, etc. - have a strong impact on subsequent analyses. For example, correlations observed with one unit of analysis may not be present or even reverse with other units of analysis. Much work over the past few decades has improved the understanding of MAUP and suggested mitigation strategies (Dark & Bram, 2007; Fotheringham & Wong, 1991; Viegas et al., 2009). In contrast, the UGCoP observes that individuals often operate in many enumeration units rather than solely the unit in which they are primarily considered to be bound to for the purpose of spatial analysis. For example, they may live in one census tract, but work in another. The unit in which someone lives their life is not normally bound by a census tract - each individual has their own activity pattern through their own experiences, and environmental influences in any of the units they travel through may affect their activity pattern (Zhao et al., 2018). To address the UGCoP, the best practice is to define and categorize an area unit which experiences the most “true causally relevant” geographic context, rather than just choose an arbitrary pre-existing enumeration unit (Kwan, 2012).

The Modifiable Temporal Unit Problem (MTUP) has been identified and studied in recent years as a temporal parallel of the MAUP (Coltekin et al., 2011). The grouping and aggregating of areas into units of analysis additionally occurs with time, where different temporal bins of aggregation are proposed to cause different results during analysis (Coltekin et al., 2011). With temporal data also often occurring on a cyclical scale (with analyses such as day-of-week, or hour-of-day), additional considerations are often necessary to account for the cyclical nature (Mahajan et al., 2021). Additionally, the framework provided by Mahajan et al., (2021) denotes the importance of adjusting for the concept that time itself can impact both the dependent and explanatory variables with a study frame.

2.5 - Physical Environments on Performance and Collaboration

Physical environments affect human’s work performance, social interactions, and well-being (Ali et al. 2015, Cleveland & Fisher, 2014). Specifically, in university spaces, positive relationships have been found between comfort within a physical environment and academic performance (Ali et al., 2015). In one study, respondents who studied and tested in low-comfort environments had difficulty concentrating, and performed worse when compared to respondents who studied and tested in environments in which they felt more comfortable (Ali et al., 2015).

The effects of indoor environments on work performance can be affected by the presence and quality of material resources within the environment (Whiteside et al., 2010; Cleveland & Fisher, 2014). In shared spaces, these material resources may include furniture, electricity/outlets, lighting, flat surfaces (for writing), and other resources which may impact the quality of the indoor shared environment. In many academic environments, these resources can support educational performance (Whiteside et al., 2010). Furthermore, material resource clusters (areas that have multiple resources available locally) increase the value of each resource within the cluster, and clustering of resources tends to facilitate activity and interaction within a space (Feldman & Florida, 1994). Clusters of material resources can be used as meeting points - facilitating the occurrence of collisions within these spaces.

Recently, architects and designers have focused on increasing serendipity in indoor environments - especially strategies to promote collisions between individuals/groups (Björneborn, 2017). Within university settings this remains true, where recent design trends have focused on managing interactions, maximizing positive collaboration, and making spaces feel comfortable and accessible for occupants (Temple, 2009) Specific and intentional designs of the local environment can impact how interactions between people can occur: Diverse and inconsistent environments with resource variation can facilitate serendipity and unplanned interactions (Björneborn, 2017). The potential for interactions and collisions also increases as the more traversable and accessible an indoor environment is from different routes and origin points (Björneborn, 2008; Björneborn, 2017)

Specifically, interactions between people on university campuses can support innovation (Jansz et al., 2022). Within academic settings, many factors can increase the potential for positive collisions to occur on campuses. These can include geographic proximity, building scale, presence and frequency of transitional spaces, comfort within a space, previous experiences within a space, shared facilities, and events (Jansz et al., 2020). Ultimately, these factors can be connected to the design principles and space design, which may intentionally promote productive collisions within an indoor environment.

2.6 - Space-Place Dynamics in University Settings

The physical environment itself has the ability to influence how its culture and sense of community is created; and that the creation of culture and community is how a university space can become place for many occupants (Temple, 2009). Additionally, serendipitous interactions (or positive collisions), despite being brief, can play a major role in place-making and bringing happiness daily life (Rubin et al., 2011).

The work of Yi-Fu Tuan has greatly contributed to our understanding of space and place dynamics, and how people associate locations with meaning (Tuan, 1975, Tuan, 1979). People form emotional connections with their homes, neighborhoods, and other locations they frequently visit. Over time these connections are forged into a “sense of place”, which affects people’s actions in a location and heightens their sense of freedom (Tuan, 2001).

The concept of place is pluralistic in geography, with several scholars offering descriptions. Shamai (1991) argues that place is dimensionless. Lewis (1979) used the term to describe emotional attachment towards a location. While place has a number of uses within geography, Tuan (1975) argues that the term place has both history and meaning behind it - and that place is a reality which must be understood from the perspectives of the people who experience it. While “space” is primarily concerned with surroundings and location, “place” delves into a true cultural understanding of a location, and often influences people’s feelings and actions (Tuan, 1979, Tuan, 2001).

Shamai and Ilatov (2005) proposed different methodological classifications to measure a “sense of place,” arguing that different social groups have different experiences of the same place. Gillespie et al. (2022) demonstrated that the concepts of a “sense of place” and “place attachment” contribute to population retention of a location - and that moving to a new location can disrupt one’s mental well-being (Ahmed, 1999).

Building on this distinction between space and place within geography, Tuan (1979) related these concepts to the concepts of movement and pause. Space, he argued, is a location that facilitates the movement of people. Conversely, place is made when people take time to pause in space - these pauses help people to cultivate a sense of place within a location, where meaning becomes associated, and where culture and community develop.

As the course of an academic year progresses, space may become place for many residents of a university campus/building. Place attachment itself is also connected to social well-being (Rollero and De Piccoli, 2010). The transition to university can be a very important period for new university students, especially in the development in their own sense of self-identity (Cassidy & Trew, 2004). This transition is heavily impacted by social relationships, place significance, place attachment, and how these factors change over the course of an academic year (Chow & Healey, 2008). Chow and Healey (2008) denoted that this transition changed students’ place identity, also finding that interaction and social relationships were the driving forces for a new sense of place for many students. Higher levels of a sense of community and greater levels of social interaction led to a decreased loneliness among first-year students, denoting the importance for social interaction and collaboration in public spaces (Thomas et al., 2020).

3. Methods

3.1 Study Aims

This study used a fixed-mounted multi-sensor lidar network to detect movement and interaction between occupants within the shared academic space of a hybrid academic and residential building on a university campus. Object-tracking software was applied to the lidar stream to produce tracks of anonymized individuals as they moved through the building. The resulting tracks were used to algorithmically detect serendipitous collisions between people, where two or more individuals have encountered each other in space and had a spatial interaction (RQ1). The spatio-temporal patterns of these collisions and their association with environmental factors were then analyzed (RQ2).

3.2 Study Area and Period

To address my research questions and hypotheses, a large shared space in the Creativity and Innovation District Living-Learning Community building (CID) on Virginia Tech's campus in Blacksburg, Virginia is being used for data collection. Virginia Tech is a large land-grant university with a growing tradition of supporting students' success through living-learning programs, which blend curricular and extracurricular activities, especially in residence halls. CID, which opened in August 2021, is a mixed-use academic and residential building, that contains various classrooms and serves as a residence hall for nearly 600 undergraduate students (Virginia Tech, 2023). Additionally, CID was designed to facilitate collaboration among its users and includes a variety of spaces: a makerspace, a rehearsal and performance hall, studio classrooms, a seminar room, a multipurpose conference room, an outdoor classroom, many study lounges, and a Community Assembly space that will be the focus of this research. The

Community Assembly space on the ground floor of the building is accessible from multiple exits and entrances. A gallery space in the east hallway of the Community Assembly showcases student artwork. Furthermore, the Community Assembly also houses many points of potential intersection for occupants (such as the elevator, staircase, and hallways), which can facilitate the occurrence of positive collisions between building users. Because of the design and accessibility of CID's Community Assembly, it is an ideal location to analyze occupants' movement patterns, and detect productive collisions which may occur. Figure 7 highlights the study area within the CID ground floor. Within this space, 11 Blickfeld lidar sensors (see Materials section) were placed in order to detect people as they move and interact with the assembly space. The study period lasted from 21 August (first day of classes) to December 13 (last day of final examinations), in 2023.

Figure 7: The ground-floor of the Community Assembly space of the CID at Virginia Tech. The extent of lidar data collection is outlined in red.

3.3 Lidar and Object Tracking in CID

Eleven Blickfeld Cube 1 forward-facing lidar sensors were mounted in the ceiling of the CID Community Assembly. These sensors allow for adjustable field of view and an adaptable scanning pattern to customize data collection (Blickfeld, 2021). An Ethernet port is used to send data and receive parameter changes with the user interface (web or Python API). Each scanner has a forward-facing application range of 1.5 - 75 meters, scans in a 70° x 30° field-of-view, and can capture an image at between 1.5 and 50 Hz, depending on scan resolution. Each sensor is accessed via a local-network hosted user interface, which allows for scanning parameters (such as scan patterns, noise reduction parameters, and object permanence parameters) to be changed and updated, as well as enabling data recording and storage, and adjusting time synchronization which allows for multiple Cubes to communicate consistently. This data collection began in August 2022, and Figure 8 shows the combined point cloud from all 11 sensors. During the study period from August 21 until December 13, there were four sensor outages in which the software was unable to record data: 09/21 18:00 to 09/22 11:00 (17 hour outage), 09/29 22:00 (less than one hour), 10/10 21:00 to 10/11 14:00 (17 hour outage), and 11/06 16:00 to 11/07 12:00 (20 hour outage).

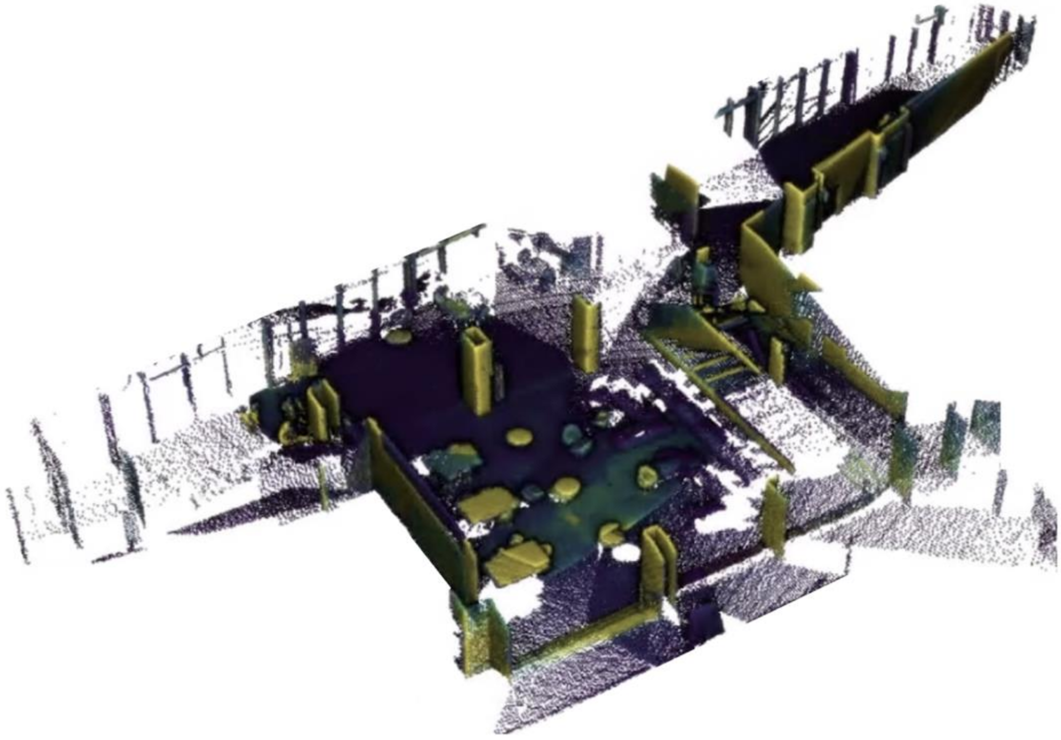

Figure 8. Combined point cloud from 11 lidar sensors for study area in CID.

The Cube sensors output data that can be manipulated and accessed in two ways: 1) using the Python API to retrieve frames and log them using custom software written for this project (Pingel, 2022) and/or 2) Blickfeld's own lidar object-tracking software, *Percept*. While ongoing work investigates tracking using Deep Learning and OpenCV-based approaches using method 1 data (Karki, 2024), the work presented here was done using only data from the Percept system.

Percept is a real-time object tracking software which uses movement-based detection to identify objects in the combined point cloud from the 11 sensors. It records timestamped position (x,y), volume, velocity, and other object parameters (Blickfeld, 2021). Each object in the observation area is assigned a random unique ID and is seamlessly tracked through the project space. If a person leaves and re-enters the frame, they are not assigned their previous unique ID, thus preserving anonymity. A visualization of sample track data from Percept over a one-hour period is shown in Figure 9.

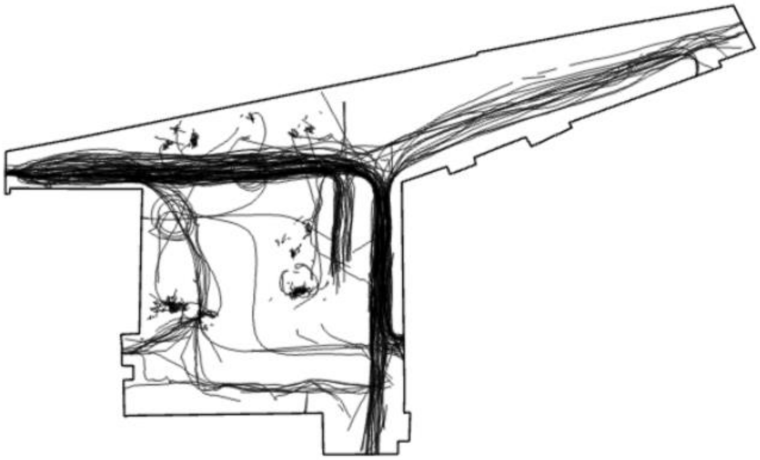

Figure 9: One hour of Percept tracks in the CID.

Percept includes several tuning parameters, such as object decay parameters, minimum weight thresholds for object detection, and nearest neighbor radii thresholds. These parameters are designed to achieve optimal data collection through noise reduction and fine tuning of object size and object permanence. For this project, parameters were set after an extended period of testing to ensure as high of a detection rate as possible while minimizing false positives. Table 1 presents the final parameter settings.

Parameter	**Setting**
Dynamic Background	Mixture of Gaussians (background subtraction)
Initialization Frames	10
Exponential Decay	0.005
Minimum Weight Threshold	0.17
Minimum # of Neighbor Points	3
Neighbor Radius	0.5 m
Point Clustering Method	Mean Shift
Minimum Points for a Cluster	30
Average Radius of Objects	0.33 m

Table 1. Parameters for Percept object tracking software.

Percept logs are recorded as JSON files (see Figure 10), but Percept can also record in Google's binary *protobuf* format, and information can be transmitted via MQTT. Logs are read using the Python package Pandas, and can be converted to more traditional geospatial formats (e.g., shapefiles) via GeoPandas. Track data can then be analyzed directly in Python or in GIS software such as ArcGIS. The file sizes depend on the amount of activity in the space; a typical day was on the order of 800-1,000 MB of plaintext JSON files.

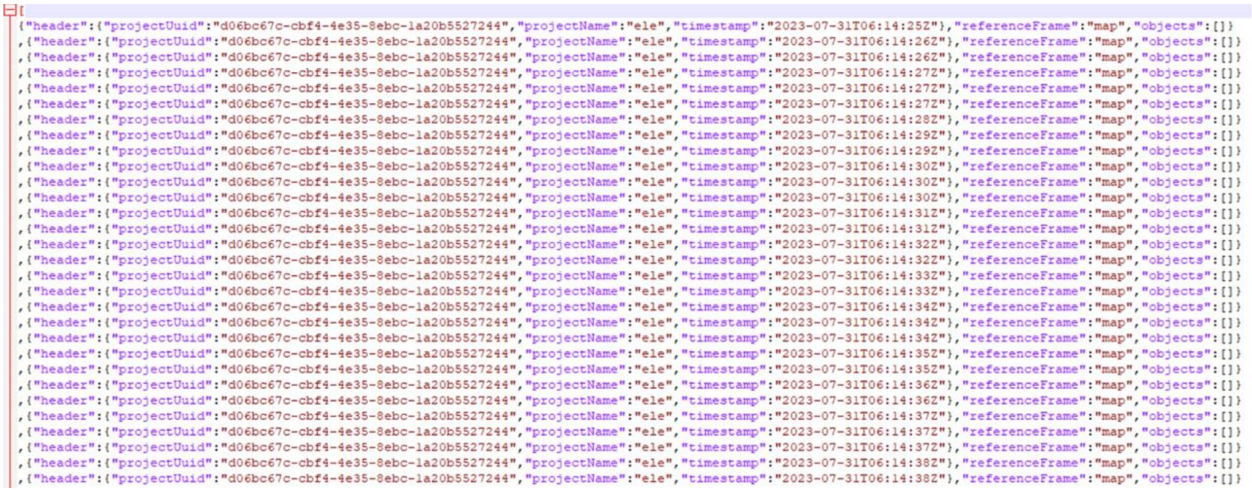

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Figure 10: Screengrab from one Percept JSON log denoting each unique object's timestamped position and velocity.

In order to examine relationships between algorithmically-detected collisions and overall occupancy/activity of the CID study area, an explicit operationalization of occupancy is needed. I defined occupancy as the total number of seconds within an area (raster grid cell) occupied by a person (person-seconds) across a specified period of time. The person-seconds framework idealizes the collision potential within the space over a period of time: The number of unique IDs (i.e., a person count) in a space over a period of time is a potential alternative, but would be a less reliable metric for collision potential, as someone briefly passing through the space would be weighted equally to someone spending an extended period of time within the spice.

3.4 Detecting Collisions

Patterns of movement in the Percept software logs were used to spatially detect collisions – unplanned, serendipitous interactions between people. The algorithm focused exclusively on the spatiotemporal qualities of collisions, but did not examine any sound data (an auditory component is usually a part of these interactions). An example of a collision might be a person traveling through the space when they run into another person and stop to talk. Three types of collisions were considered in the development of the detection algorithm:

- **Two-way collision** - Two people traveling in different directions stop and interact, then continue on separately.
- **Stationary collision** - A person traveling through the space stops to interact with someone who is stationary, and then continues on their way.
- **Conjoining collision** - Two people traveling in different directions stop and interact, then continue on together.

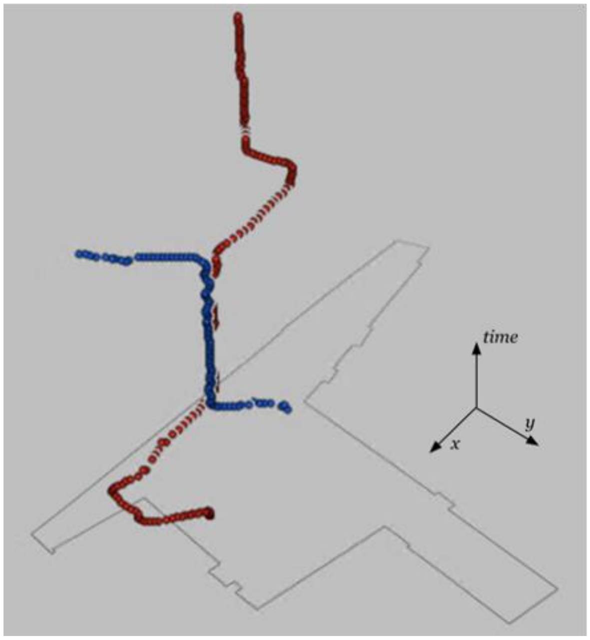

Figure 11: A Space-time path depicting a two-way collision in the CID space. One person's points are shown in blue, and the other's in red.

I chose primarily to focus on two-way and conjoining collisions due to their more straightforward operationalization and clearer spatio-temporal signature. Percept software identifies people moving in space by virtue of a mean-shift algorithm; when people remain stationary for a long period of time, they are often lost by the software, and when reacquired after they move again and are assigned a new unique object ID. This makes matching the pause of one person in transit difficult to accurately match to a stationary person using the Percept dataset.

A custom algorithm written in Python (Appendix A) was used to detect collisions in the Percept data. Because of the large file size of Percept's output for the entire Fall 2023 semester (18 GB as binary data), the data was broken into 20 equal-size subcomponents, and the algorithm was applied to each one individually and re-combined later to accelerate processing time. The algorithm focused on identifying moments where two individuals moved separately and then paused together. The first step of algorithm development involved careful observation by the author in the space to observe and note the kinds of collisions the algorithm was being developed to find. This involved direct observation in 12 one-hour sessions over a period of seven weeks during the semester, noting 35 separate collisions in the space. In addition, Dr. Tim Baird, a frequent occupant in the study area, would relay the date-times and locations of his own collisions during the same period. These ground-truth observations were used to design and tune the algorithm.

The collision detection algorithm used open-source Python packages including Numpy, Pandas, Geopandas, and Scipy to process a GeoDataFrame created from the Percept JSON data. Through the application of several spatiotemporal data filters, designed to isolate specific patterns within the data, which coincided with collision movement patterns, collisions were detected and then written out as GIS shapefiles for further inspection and processing. The processing time for 115 days worth of Percept data (broken into 20 equal-sized pieces) took approximately 5.5 hours total on a Dell Precision 5820 Tower X-Series with a Intel Core i9-10980 XE CPU @ 3.00GHz processor and 256 GB RAM.

A brief overview of the collision detection algorithm is provided below, before each individual step is explained more in-depth. To remove noise and prevent human-object interaction being classified as a collision, a displacement filter removes all tracks with a total displacement less than 4 meters. Next, a movement filter isolates tracks with movement and pause signatures like a collision, keeping only records which currently move less than 0.3 m/s and are decelerating. A spatiotemporal filter then keeps only records which are within 1.5 meters of another individual's records, attempting to match up two individuals. To ensure that individuals have different origins, a heading filter is used to ensure that individuals’ headings differ by at least 90 degrees, signifying they are coming from different directions. Lastly, to remove subsequent interactions between the same two individuals, to ensure that group interactions are not counted multiple times, a duplication filter is applied to remove all collisions within 2 m and 5 s of an initial collision. A flowchart depicting the general diagram steps can be found in Figure 12.

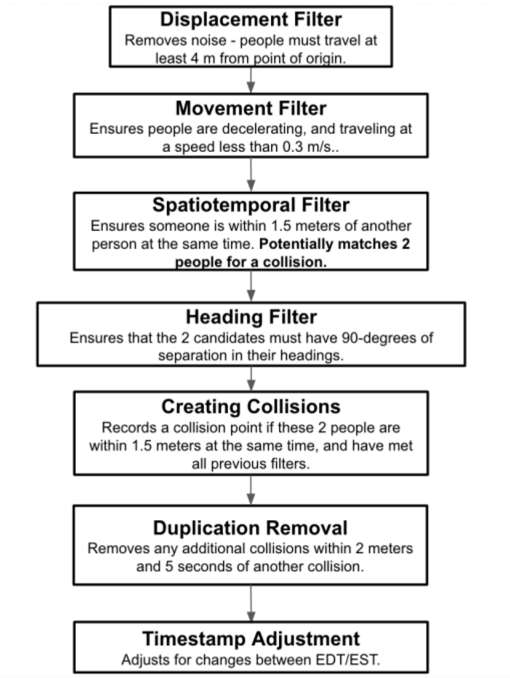

Figure 12: Flowchart depicting the order of steps and general process of the collision detection algorithm.

3.4.1 Displacement Filter

Because the detection algorithm is designed to detect only two-way and conjoining collision types, the movement of both parties in the Community Assembly space is an important detection criterion. Additionally, while Percept parameters have been fine-tuned to reduce noise and ensure high data quality and precision in the study space, the displacement filter also works to remove small instances of noise within the data, and prevent human-object interaction from being classified as a collision. An example of this could be a student moving a chair before sitting down. If the chair is only briefly assigned its own universally unique identifier (UUID), even momentarily, it may meet all of the other parameters/filters, and the student and chair may be algorithmically classified as having had a collision.

The displacement filter works by first grouping all Percept points by UUID. Then, it uses the tabular geometry data provided by Percept (which provides the meter-coordinates for the distance away from the CID's geographic origin) the first instance the UUID's geometry is noted. In order for a person to be considered for a collision, they must travel at least four meters from the point where they were initially recorded at any point during their UUID's lifetime. As people enter and walk through the space, they easily travel more than 4 meters to reach any destination. Correspondingly, it is assumed that only Percept-based noise and non-human objects will deviate less than 4 meters from a spatial origin. If objects do not meet this displacement filter, their UUID record is removed from the dataset ensuring that only people with significant movements are recorded.

3.4.2 Movement Filter

One of the most important considerations for detecting collisions within the CID is the ability to detect movement and pause. Velocity and acceleration information enables the tracking of these by highlighting areas in space and time in which multiple people are simultaneously slowing down. This filter retains only the data points which are traveling under 0.3 meters per second, and are actively slowing down. The average person under 30 years old walks at an average pace of 1.34 m/s (Alves et al., 2020; Schimpl et al., 2011), meaning a collision is only possible at significantly lower speeds. The value of 0.3 m/s was chosen to find a balance between genuine detection and consistency: a velocity threshold that is not low enough can exclude some collisions - especially those that occur "in passing," in which only a brief interaction occurs and neither party comes to a full stop. A threshold that's too high can include too many false positives in the output, as it was occasionally including the "collision" of two people passing one another, especially during times/locations of greater congestion, where velocity patterns are generally slower.

First, the linear velocity, which measures the instantaneous velocity regardless of direction of travel (always positive), is calculated based on the X-direction and Y-direction linear velocity which Percept records. The acceleration is then calculated based on the instantaneous change in velocity. Using the velocity and acceleration for a person's UUID, a filter is applied to then remove all data points with velocities and accelerations greater than the threshold - this preserves only data points which are moving less than 0.3 meters per second, and are actively slowing down to have an interaction.

3.4.3 Spatiotemporal Filter

This filter is designed to emphasize and isolate instances in which two or more people are within 1.5 meters of one another - fundamentally, this is the basis of collisions. Like the movement filter, the spatial thresholds were iteratively modified to determine an ideal value. At a threshold greater than 1.5 meters, the false-positive rate was significantly higher due to the inclusion of simultaneous pause without an apparent interaction. Thresholds less than 1.5 meters tended to not include any collisions without any significant physical contact (handshaking, hug, etc), which must also be included.

The spatiotemporal data filter uses the geometry information provided by Percept within the point-based dataset (i.e., recording the person's location in meters based on a local x/y coordinate system), and distance calculations in Python to measure the distance between two people. If a person's UUID is within 1.5 meters of another's at the same recorded timestamp, these points are kept - all points that do not meet this threshold are removed. After this filter is applied, the criteria for a collision are met: people with the required movement patterns, who are decelerating at an already slow speed, within close proximity to another person.

3.4.4 Heading Filter

The heading filter is designed to reduce the false positive rate by capturing only genuine two way collisions, in which two or more people are traveling from different directions initially. The difference in their heading of travel must be greater than 90 degrees apart in order to be considered. If two people enter the space together, walk to a table and stop at the table to sit down together, they are technically experiencing the aforementioned requirements for a collision, as described above: a prevalent movement pattern, a simultaneous slowdown, and they are in close proximity with one another. But this is a planned interaction and shouldn't be counted as a collision. Similar patterns of movement and pause can occur immediately outside of classrooms, the elevator, or any other spatial chokepoints in the study space in which movement is slowed as people funnel into a smaller space. The purpose of the heading filter is to ensure that spontaneity is captured, by requiring that all eligible people for a collision must also be traveling in semi-opposite directions. This step greatly reduces false-positives by removing potential "collisions" which would only be detected due to chokepoints and natural impediments in general movement patterns. During algorithm development, multiple different angle thresholds were tested, and the choice of 90 degrees appeared to best minimize false positives and correspond to the orientation of major traffic corridors.

This filter requires that two eligible parties are considered with one another - so this step is applied along with the "Creating Collisions" step (below) in the algorithm in order to properly match and determine if a collision has taken place. First, the rolling average of a person's heading/direction of travel (in degrees) is calculated over three seconds. This was done using the circular statistics function from Python’s Scipy package. After two people are potentially matched up for a collision using criteria already outlined, their headings are compared. Again using circular statistics (so that a heading of 30-degrees is treated as being within 90-degrees of a heading of 330-degrees), the headings of travel for both people are checked - and if they are within 90 degrees of the other person’s heading, this collision pair is removed as we can assume they are traveling together. Only collision-pairs with heading differences greater than 90 degrees are kept in this step.

3.4.5 Creating Collisions

Using the above input of filtered points, which are still eligible to be recorded as collisions, the next step in the algorithm is to define the instance and location a collision occurs. This step is done simultaneously with the heading filter, as the angles of both parties must be checked at the same time matching is done. .

This filter groups all data points by UUID, and again checks for other UUIDs within the spatial threshold of 1.5 m at the same timestamp. After the angular filter is applied, once two UUIDs are matched, and after the event passes this final filter, it is recorded as a collision. Following this, no additional collisions, between this UUID pair can be considered.

At the beginning of this step, a blank geodataframe is created to store all initially-detected collisions. For each collision detected, one row of data is appended to this dataframe, which includes the UUIDs for both parties, the exact timestamp of the collision, and the combined geometry, which is a spatial average of the geometry of both people. All potential collisions are then passed through the “Duplication Removal” filter.

3.4.6 Duplication Removal Filter

A final consideration for collision detection is the presence of two confounding issues within the CID space: special events, and “group” collisions. The Community Assembly space hosts many special events throughout the semester, ranging from smaller weekly events to larger single-instance events. At these planned events, people typically mingle for at least a portion of the time. These interactions, which arguably are not truly spontaneous, get recorded by the collision algorithm all-the-same. Correspondingly collision frequency is much higher during events compared to other times.

Similarly, “group” collisions can artificially inflate the number of collisions. For example, if three people enter the study space together and collide with another group of three, their interaction could produce nine unique recorded collisions, disregarding intra-group collisions due to the heading filter. For this study, I treat this as one collision - a single, spontaneous interaction even though it involves more than two people.

This filter takes the collision dataframe as input, goes through each collision record, and removes all other collisions within five seconds. Then, the distances between the initial and subsequent collisions are calculated. For each distance under the threshold of two meters, the collision record is removed from the dataset.

3.4.7 Timestamp adjustment

After the collision dataset was gathered, a small timestamp adjustment was required to attain temporal consistency. Because Percept records all of its information in UTC, the conversion difference between the Percept Logs and local Eastern Time (EDT/EST) was altered from 4 hours to 5 hours at the end of Daylight Savings Time on 5 November 2023 at 02:00:00. To adjust for this, all Percept data was analyzed with a 4 hour offset for collisions, and then the timestamps for all collisions which occurred after this time change were adjusted by one hour to account for this temporal offset.

3.5 Analysis

3.5.1 Evaluation of Algorithm Performance

To evaluate the performance of the collision detection algorithm, I plotted detections over a render of the raw lidar data, which helps to highlight both false positives and false negatives. Data from each of the 11 sensors was fused and rasterized as an orthographic maximum elevation surface (i.e., Digital Surface Model). Using code written in Python and using ffmpeg open-source video processing software, the algorithmically-detected collisions were overlaid on the raw lidar frames, resulting in an animation. Playback and review of these animations was used both during the development of the algorithm and for a formal post-hoc performance assessment, and a 10-minute example of the overlaid animations (showing one hour of high-density data) can be found at the following link: https://youtu.be/Ixklw3qsCIA. A true-positive example showing an algorithmically detected collision overlaid on two people interacting in the CID space can be seen in Figure 13 below.

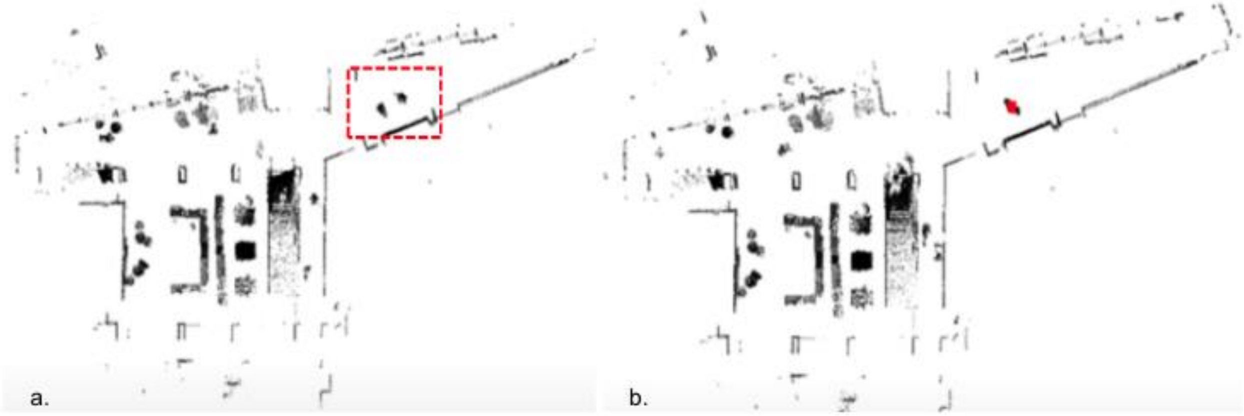

Figure 13: Two orthographic lidar frames overlaid with the collision algorithm. In frame a, two people are approaching one another (dashed box). In frame b, they stop and interact - the algorithm successfully detected this collision, denoted by the red point symbol.

For the post-hoc performance analysis, these orthographic animations overlaid with algorithmically-detected collisions were used to count: (1) true positives, (2) false positives, and (3) situations where it was unclear whether a collision occurred. This method was used for three hour-long periods of data, in which 127 collisions were detected by the algorithm**.** One hour was a low-occupancy time period, one was during a medium-occupancy period, and the final hour was during a high-occupancy period. As true negatives occur in an algorithmically inconsistent pattern, providing validation for non-collisions is not feasible. A similar concern exists with false negatives; some false negative collisions are visually much more clear than others, meaning that a true rate of false negatives cannot be unambiguously determined via animations.

3.5.2 Temporal Analysis

For this study, temporal analysis aimed to describe how collisions relate to overall occupancy/traffic in the study area [H1], and how the frequency of collisions is distributed throughout the fall semester [H2]. To test temporal relationships between collisions and occupancy, both datasets were grouped by week of the semester [H1, H2], day of the week [H1], and hour of the day [H1]. For each of these intervals, figures were generated showing overall trends**.** To statistically interpret the temporal patterns, a standard multivariate Ordinary Least Squares regression was performed with *Week of semester grouping with collisions* as the dependent variable and *Occupancy* and *Week of the semester* as independent variables.

Hour of the day is cyclical and cannot be considered as a categorical variable, as each time period is short in duration, and the transition from one hour to another does not correlate with a direct stop in the space-use pattern; therefore, neighboring hours cannot considered fully independent of one another. A multivariate regression was used in which the time variable was normalized from 0-1, then transformed first as a circular metric (2 * pi * t), then transformed to sine and cosine components as is commonly recommended for both time data (Mahajan et al., 2021) and spatial circular variables such as azimuths (Jones, 2006). Angles were adjusted to align the peak of the period with the cosine component and the before/after peak to the sine component.

3.5.3 Spatial Analysis

To examine the spatial traffic/occupancy and relate it to collision locations [H1], a generalized linear regression (GLR) model was run on the 1 m fishnet, with *Occupancy* as explanatory variable, and *Collisions* as the dependent variable. This focuses on the relationship between overall zonal occupancy and zonal collisions for the entire Fall 2023 academic semester. In addition to estimating the overall relationship (R^2) between occupancy and collisions, analysis of the residuals highlights the spaces in the study area where collisions are higher or lower than could be expected given the amount of traffic [H3]. A second geographically weighted regression (GWR) was also run on the 1 m fishnet to quantify the relationship between occupancy and collisions accounting for spatial autocorrelation [H1].

To determine the association between collisions and the edges between zones of movement and pause in the study area [H3], I focused on the western corridor of the study area, as shown in Figure 14. Several horizontal gridlines (0.10-meters wide) were created, with the focal point for each positioned in the center of the hallway, which was manually chosen using a kernel density of occupancy in the study, weighted by velocity. To examine how the relationship between collisions, seating locations, and intersections changes as we move outwards from the center of the hallway [H3], three variables were calculated within each gridline: (1) the sum of occupancy, (2) the average velocity of all occupancy, (3) and the sum of collisions. Figures were then generated relating the areas of high movement friction and the frequency of collisions in those areas.

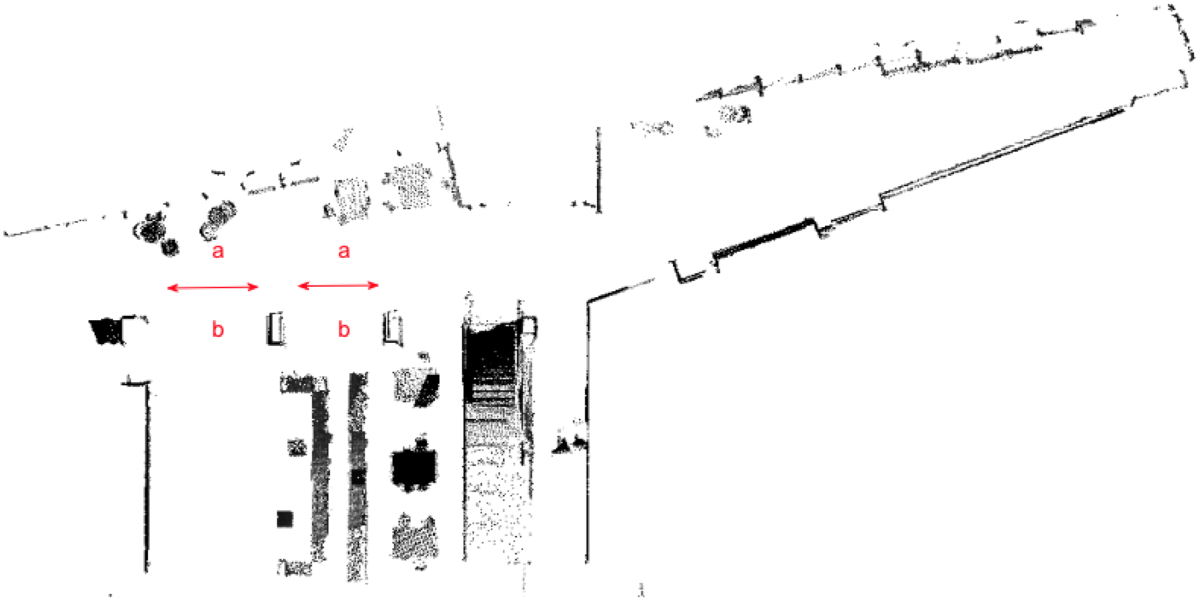

Figure 14: Collision frequency may differ at area "a" where seating is next to high traffic movement conduits (arrow) compared to area "b".

Figure 14 highlights the focus area for this sub-analysis. It was chosen because one side of the hallway (a) is next to an area of seating and the other side (b) is more open and more frequently used as a 'cut through.' By examining differences in collisions, velocity, and occupancy within the gridlines, we can better understand what spatial attributes are associated with collisions. For example, the distribution of collisions orthogonal to the direction of travel may be asymmetrical and/or bimodal (as people move out of the way of people walking through the corridor) potentially indicating a type of "friction" associated with the seating area.

4. Results

4.1 Algorithm Performance

During the study period, there were approximately 67 million person-seconds of Percept data collected over a period of 115 days, from which my algorithm detected a total of 14,022 collisions (averaging 121.9 per day; 5.1 per hour). To assess the false positive rate, the collision algorithm was manually validated against three hours of lidar data, each hour having a different occupancy scenario (low / middle / high use). Detected collisions were placed into three categories: “True Positives”, “Unclear”, and “False Positives”. Of the 127 total detected collisions, 68.5% were certain true positives and 11.0% were certain false positives, with the remaining 20.5% unclear. Assuming half of the “unclear” collisions are genuine, the algorithm had an estimated accuracy of 78.7%. During the 12 hours of in-person observation there were 11 two-way collisions and 6 conjoining collisions in the space. Six of the two-way collisions were detected by the algorithm for an estimated false negative rate of 46%. None of the 6 conjoining collisions were detected.

4.2 Temporal Analysis

Occupancy and collisions were both highest during the first few weeks of the semester, and generally declined as the semester progressed (Figure 15). Daily collisions were highest through mid-September, when they began to drop off (15a). Until September 18, no days contained fewer than 100 collisions - after this date, 45 days had fewer than 100 collisions. There was a notable increase in collisions between Thanksgiving and winter breaks. Major troughs correspond to breaks in the semester (Fall Break in Week 6, Thanksgiving Break in Week 13, and end of semester in Week 16 - 15b). On a weekly basis, occupancy was highest during weekdays, whereas collisions peaked towards the end of the week on Fridays and Saturdays (15c). A notable temporal lag between occupancy and collisions was evident in the hourly data (15d). Occupancy was highest during typical working hours for students (9:00 to 20:00) and peaked at 15:00. Collisions however, increased throughout the course of the day until a later-evening peak from 17:00 to 20:00.

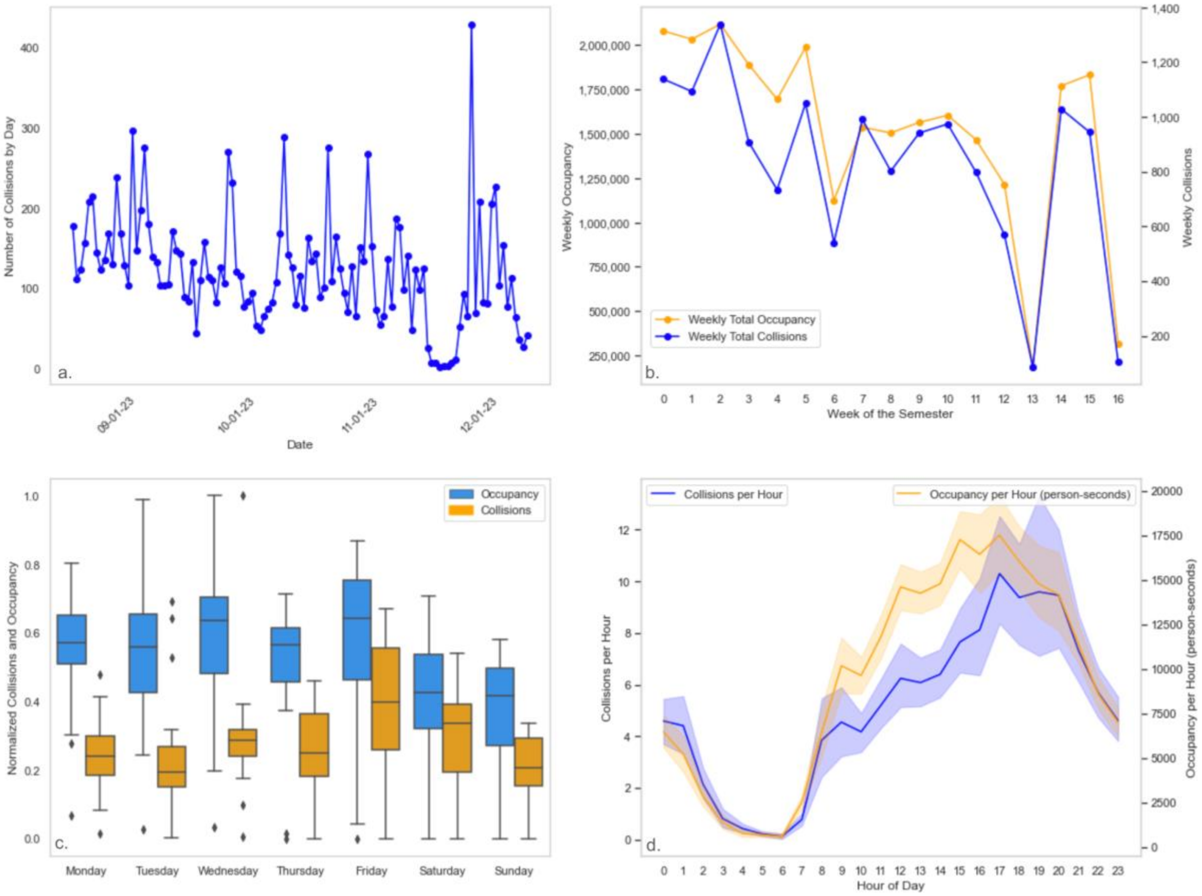

Figure 15. (a) Total collisions by day, (b) total collisions and occupancy by week of the semester, (c) normalized collisions and occupancy averaged by day of week, and (d) mean (line) and upper/lower quartiles (shaded region) of collisions and occupancy by hour of day.

When fit with a second-order polynomial, occupancy and collisions were strongly statistically related when aggregated by hour-of-semester ($R^2 = .76$, $F(2,2672) = 4128.97$, $p < 0.001$), day-of-semester ($R^2 = .74$, $F(2,112) = 161.97$, $p < 0.001$), and week-of-semester ($R^2 = .92$, $F(2,14) = 81.22$, $p < 0.001$) intervals. (Figure 16, Panels a, b, c respectively). A log-log transformation was additionally applied to the occupancy/collision relationship on all three temporal intervals shows a varying relationship on temporal scales, with daily (n = 1.17) and weekly (n = 1.15) intervals potentially suggesting a slightly super-linear relationship, and the hourly (n = 0.78) interval potentially suggesting a slight sub-linear trend.

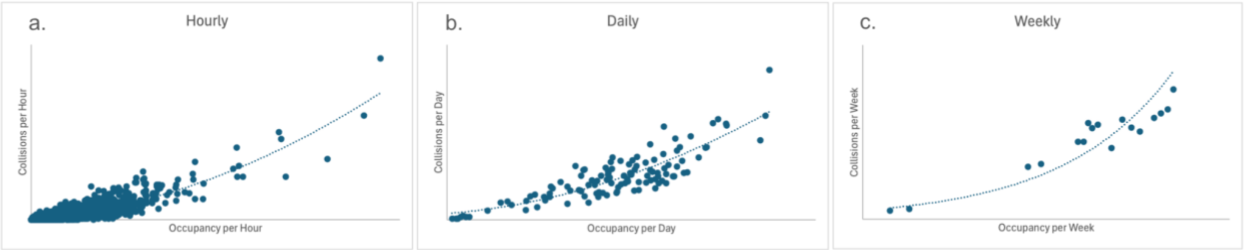

Figure 16. (a) Hourly, (b) daily, and (c) weekly relationships between occupancy and collisions, with an exponential trendline showing the relationship between the two variables.

Statistically examining time of day along with a collision/occupancy relationship, an Ordinary Least Squares Regression that included a sine/cosine peak-aligned time shows that time of day during peak space-use (cosine component) was not a significant predictor ($p = .22$), but before or after the 4 pm daily peak of space-use (sine component) was significant ($p < .001$).

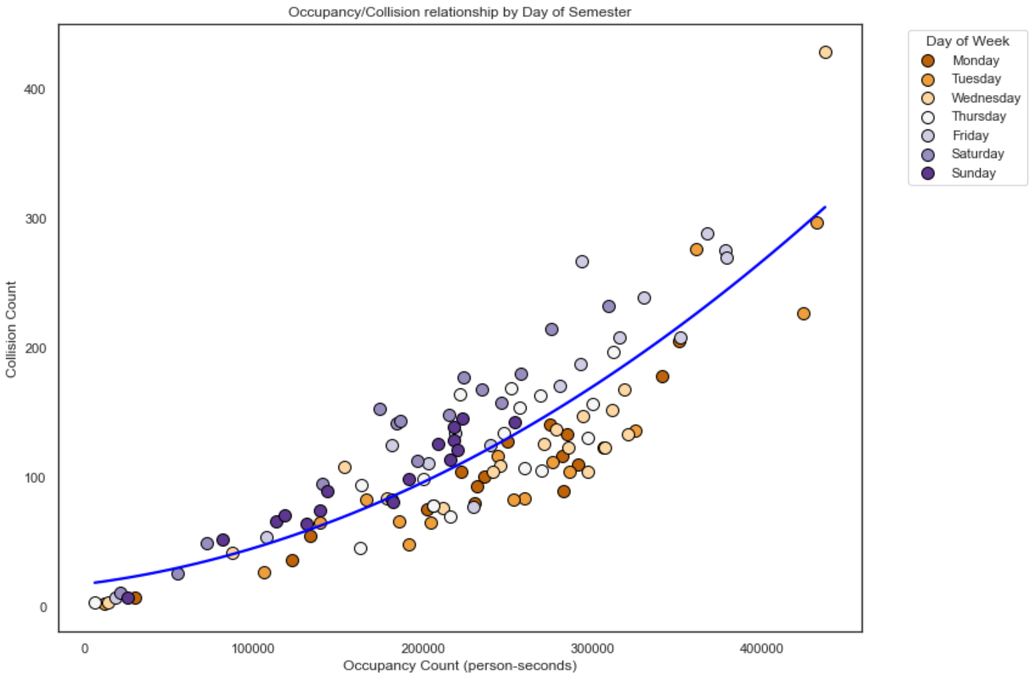

Figure 17. Collisions vs occupancy, differently symbolized by day of week, fitted with a quadratic trendline.

To examine the effect of time on collision frequency, a one-way analysis of variance (ANOVA) was performed on the relationship between *Day of Week* (explanatory) and *Collisions per thousand-Occupancy.* It showed that *Day the Week* statistically influences the number of collisions occurring throughout the study space ($p < .001$), even when normalized by occupancy. For example, in terms of the collisions per occupancy compared with the weekly average, Friday (24.53%) and Saturday (51.90%) experience much greater collision frequency than the weekly average, than Monday (-17.13%), Tuesday (-32.37%), and Wednesday (-12.07%). Plotting each individual day of the semester demonstrates how the day of the week consistently impacts collision-occupancy ratio (Figure 17).

4.3 Spatial Analysis

Figure 18 shows total collisions and occupancy for the Fall 2023 semester summarized into a 1 meter gridded-fishnet over the Community Assembly space. The occupancy pattern (panel a) shows that the corridors, base of stairs, seating areas, and the elevator were the most used areas in the study space. The left corridor, which exits towards Virginia Tech's campus, was used more than the right, which exits towards Blacksburg's downtown. The most popular seating area was in the center of the study space, where large tables and accessible floor-outlets can encourage occupants to stay for extended periods of time. Generally, transition areas between hallways and seating, and edge spaces closer to walls, were used least.

Collision counts (panel b) were high at the base of the stairs, around seating areas in the study space, and the area around the elevator, which contained over 2,000 of the semester's 14,000 collisions. Collision counts were lowest in corridors, edge spaces (e.g., near walls), and by exits (excluding the elevator).

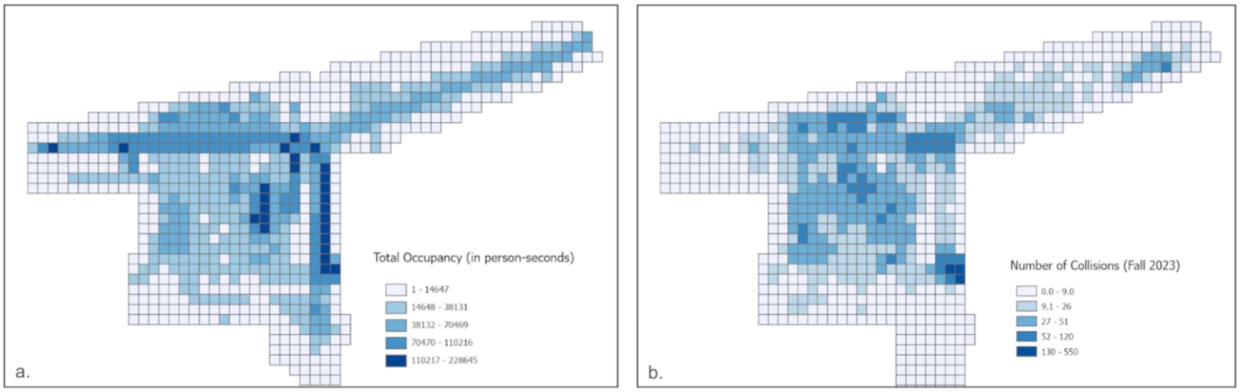

Figure 18: Occupancy (a) and collisions (b) within the CID over the course of the Fall 2023 academic semester.

To identify the locations that experienced more or fewer collisions compared to the traffic [H1], a generalized linear regression (GLR) was run on a 1-meter fishnet over the study space, where the resulting image maps the residuals (i.e., places where there are more or fewer collisions than one would expect given the occupancy (Figure 19)). This revealed a significant relationship between occupancy and collisions ($R^2 = .598$, $F(3,785) = 390.02$ $p < 0.001$).

While not accounting for spatial autocorrelation, the GLR can be used to highlight the residuals of the fit (i.e., the areas that experienced higher or lower collision rates than would be expected given occupancy). The left and center corridors and the stairs were sites of fewer collisions than expected, while the right hallway had about as many as were expected. Notably, the right hallway houses two classrooms and often exhibits student artwork, while the left hallway does not. Additionally, the study/seating areas with the highest occupancy had fewer collisions than expected. However, many other areas of seating experienced a higher number of collisions than expected when compared to occupancy. The base of the stairs, a major point of intersection, and the center of the Community Assembly space, often used during events, both experienced more collisions than expected. The most extreme collision-to-occupancy distribution occurred at the elevator, which causes people to wait in the space.

A geographically weighted regression that better accounts for local variation between collisions and occupancy, and therefore better estimates their relationship, had a moderately higher R^2 value ($R^2 = .84$).

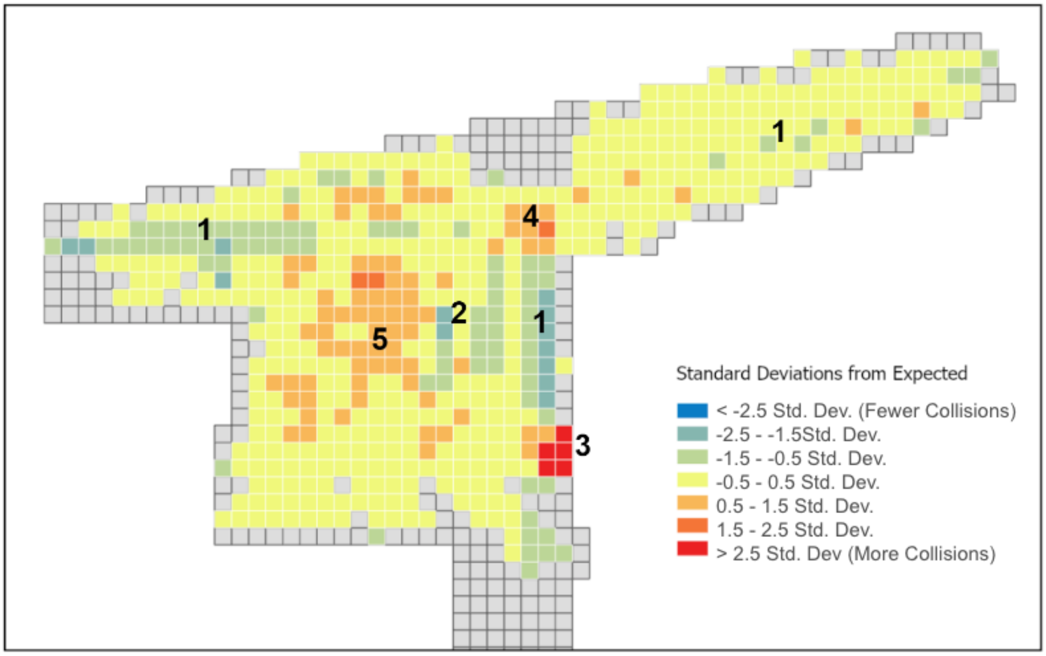

Figure 19: GLR Results showing that hallways (1) and some seating areas (2) experienced fewer collisions than expected given occupancy. The elevator (3), base of the stairs (4), and center of Community Assembly (5) all experienced more than expected.

To examine the relationships between movement friction and collisions [H3], I calculated the average velocity of all occupancy, the total occupancy, and the total collisions using 0.10-meter horizontal gridlines within the CID (Figure 20). Areas of high movement friction occurred where the rates of velocity changed rapidly. Collisions peaked towards the side of the hallway with seating. However, a peak can be found on each side of the hallway, indicating a bimodal distribution. Velocity and occupancy both peak at the hallway center, but the gradient of velocity decrease is much steeper on the side with seating, compared to the side without. Occupancy remains higher on the side with seating, and is lowest on the side without seating. Collisions have minima in the center of the hallway and on the very edge of the seating area.

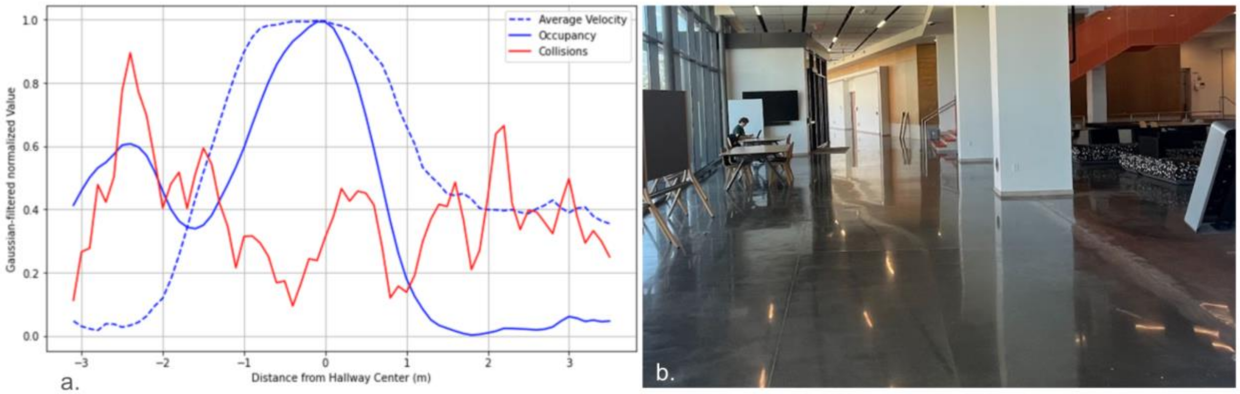

Figure 20: Normalized and smoothed average velocity, occupancy, and collisions in 0.1 meter gridlines on both sides of the hallway. The -x values in panel a correspond with the left side of the hallway in panel b.

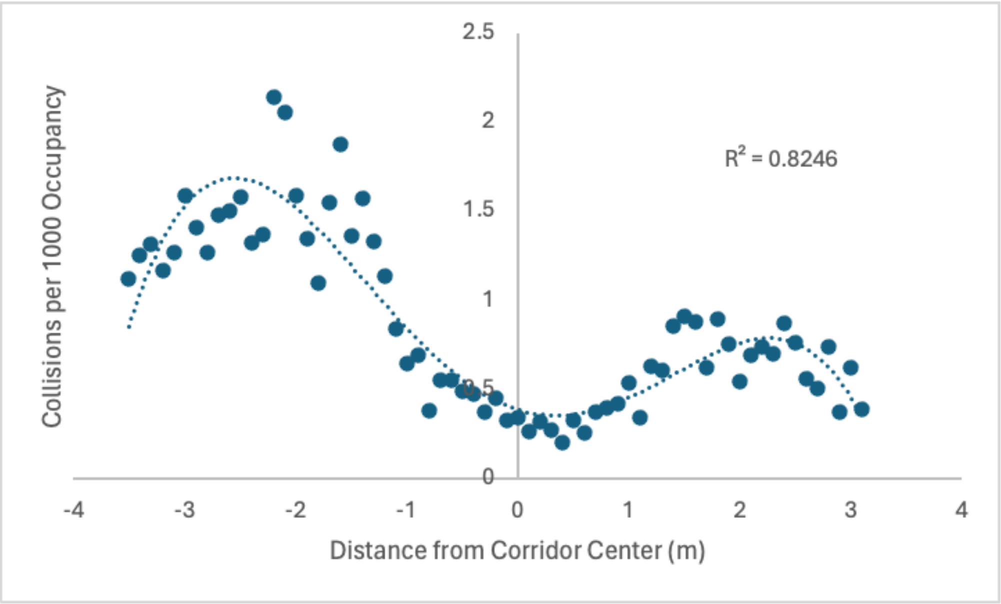

Figure 21: Collisions per 1000 Occupancy on both sides of the corridor, fitted with a fourth-order polynomial.

Figure 21 presents results from an OLS regression run between the *distance from the hallway's center* and the *number of collisions per 1000 occupancy* taken globally. When both sides are examined independently, the side with seating ($R^2 = 0.76$, $p < 0.001$) and the side without seating

($R^2 = 0.62$, $p < 0.001$) were statistically significant, indicating there were more collisions per occupancy than would be expected. There were, however, more collisions per 1000 occupancy on the side of the hallway with seating. On both sides of the hallway, collisions per occupancy began to decline after 2.5 m away from the hallway center.

5. Discussion

5.1 General Discussion

The lidar-based algorithm to detect collisions – serendipitous interactions between people in an shared indoor environment – was developed using principles outlined by Otsuka and Mukawa (2004) and Teixeira et al. (2010) and successfully detected a large sample of those interactions over the course of an academic semester. The resulting dataset of 14,022 collisions was derived from 67 million total person-seconds of tabular lidar data, and featured an estimated true positive rate of 78.7%, and a true negative rate for two-way collisions of 47%, with very limited ability to detect stationary and conjoining types of collisions. Parameters for the lidar detection software, Percept, were chosen to minimize noise in the data, and algorithm parameters were chosen to reduce the false positive rate. As such, the recorded collisions are best viewed as a sample from which to derive insights about aggregate spatial behavior. Easing of algorithm parameters, for example, by increasing the spatial threshold for an interaction from 1.5 to 2.5 m, could increase the number of collisions and decrease false negatives, but would also increase the rate of false positives.

This study afforded an insight at these spatiotemporal interactions in the space. Collisions peaked during the first five weeks of the Fall 2023 semester before leveling off. The pattern was disrupted at the end of the semester when the period after Thanksgiving break was marked by a large rebound in collisions. However, these space-place dynamics outlined by Chow and Healey (2008) may not align fully with the frequency of collisions across an academic semester: results from this study indicate that the collision/occupancy rate does not significantly increase as the semester goes along, indicating that the assumption made in H2 was not supported. This may be because students may have a larger social circle and “cast a wider net” at the beginning of the semester. As the semester goes on, a subset of these relationships evolve to form stronger friendships. While these relationships play a major role in placemaking (Rubin et al., 2011), the number of people each person is willing to stop and talk to decreases as the semester goes on, despite knowing more people in total. Another potential explanation for this decrease is that as people become more connected with one another, their collisions may become more subtle and more efficient, meaning they may be more difficult to detect via an algorithm. Finally, as students become more familiar with one another, they may be more willing to meet in areas other than the Community Assembly in the CID, such as in dorm rooms or residential hallways, or at other CID amenities, suggesting that a decrease in collisions may only occur in open, public spaces.

Occupancy and collisions were strongly correlated, but with local spatio-temporal variations. A prominent temporal lag exists throughout the day, with occupancy peaking during working hours, and collisions peaking in the evening. A similar pattern exists with certain days of the week, with Saturday, for example, having nearly double the rate of collisions per occupancy compared to Tuesdays. These findings align with work by Harari et al. (2020), who found that conversation frequency among young adults is highest on Fridays and Saturdays, and lowest on Tuesdays, and that conversations are more likely in the afternoon and evening hours than at night or in the morning. Spatially, collisions occurred throughout the study area, but were particularly dense given occupancy near the elevator, bottom of the stairs, and seating areas. Statistical tests support the ideas provided in H1 that there is a strong relationship between traffic volume (occupancy) and collisions within these environments, but with some interesting spatial and temporal caveats.

The elevator serves as both a spatial and temporal bottleneck within the Community Assembly, as it forces people to wait together in the same location. The areas within and just outside the elevator were the sites more than 2,000 of the semester's total collisions (14.2%), and also featured the highest rate of collisions per occupancy (Figure 19). While it is possible that a localized false positive rate is higher around the elevator, as the pattern of waiting for an elevator is consistent with a collision's movement pattern, in-person observation corroborates that the elevator is an important collision space. Additionally, collisions per occupancy are lower in the middle of the corridors as people move to the side to have a collision. The side of the hallway with seating experienced a higher proportion and rate of collisions per occupancy than the side without seating – in effect, the higher "friction" of the tables (and those seated there) was associated with more collisions. These results support H3, indicating that collisions do occur more frequently on the boundaries between movement and pause zones, rather than in one specific zone themselves. A stronger velocity gradient also appeared to support a greater frequency of collisions. Ultimately, designers and others seeking to promote collisions may draw insight here.

This study also contributes to longstanding discussions in Geography regarding the importance of both spatial and temporal scale. Work by Gehlke and Biehl (1934) was extended by Openshaw (1984) to describe how spatial analyses conducted at one level of aggregation (e.g., state/county/tract/raster grid) may yield different findings than those conducted at a different level, now referred to as the Modifiable Areal Unit Problem (MAUP). Coltekin et al. (2011) extended this idea to the temporal domain describing the Modifiable Temporal Unit Problem. In this study, the relationship between occupancy and collisions weakened over increasing temporal resolution, although the relationship was consistently strong throughout. One meter and 10 cm scales were used for spatial analysis, but the selection of different spatial scales could slightly alter the relationships between collisions and occupancy, as suggested by the MAUP.

5.2 Limitations

The parameters in the algorithm were tuned to maximize detection while suppressing noise (i.e., false positives). However, not all collisions can be detected from lidar data. For instance, individuals may not pause when interacting, or may interact at a distance larger than the 1.5 m detection threshold, or have approached one another at an angle less than 90 degrees. Smaller collisions which occur from a distance, such as waving at someone you see from across the room, are still very meaningful - but were not captured by my methodological approach.

The Percept software, which was used to detect and track people, has limitations that affected the results. For example, people who stop moving for an extended period (~ 15 seconds) are dropped as tracked objects; when they move again they are tracked as new objects with new unique IDs, and are not connected to their previous locations/movements. This is done to allow the dynamic removal of stationary objects such as chairs or bags. Percept, like the collision detection algorithm, was tuned to maximize detection while suppressing noise. Karki (2024) developed alternatives to Percept using deep learning and OpenCV to track movement using lidar data. The output of these methods, or integration of these with Percept, could be used to detect collisions, potentially with more accurate results.

Layout changes to the space can also greatly affect corridors, movement patterns, and possibly collisions as a result. When furniture is moved, movement corridors change, creating opportunities to better test how boundary spaces and edge zones affect occupancy and collisions [H3]. Aside from some events which temporarily moved furniture, there were no major, permanent, layout changes to the seating locations during the Fall 2023 semester.

One of the other major challenges to collision detection was the quantification of collisions during various planned social events and other high density periods. In an empty space, a two-way collision is relatively easy to both quantify and validate using animation. However, during periods of high density the algorithm appeared to perform worse, and validation was much more difficult due to the frequent and brief interactions at these times. The event filter in the algorithm was designed to limit the effects of these events on the entire dataset, but by better classifying and categorizing collisions as occurring during events or not-during events, a more organic understanding of space-use classification could be derived.

5.3 Future Work

There are a multiple ways in which the collision detection algorithm can be improved. First, improving parallelization, optimization, and scalability of the algorithm would allow for better computational performance. Second, introducing new filters and/or reworking existing filters could improve the algorithm's true positive rate, especially during high-density settings where interactions may be less organic. Pacchierotti et al. (2005) define a 1.2 - 3.5m bound as the distance within which social interactions are likely to occur in public spaces. This suggests that additional adjustment of the distance threshold for the spatiotemporal filter in combination with other algorithm adjustments could aid in limiting false positive/false negative rate. In this study, tuning of the parameters was done to limit FP/FN rate, but a full optimization of parametric values was not done. A third strategy to improve the algorithm could involve adjusting the heading filter to use the origin points of people's UUIDs, rather than a 3-second rolling average of heading, to better ensure if they interact.

A foundational challenge of moving-object tracking is that if objects stop moving, tracking often fails. Work for this study found that Percept drops people if they are stationary for too long; and when they move again they are detected as a new object. Algorithmically connecting the new UUID to the old could prevent the double-counting of collisions between the same two people. Additional improvements to the detection algorithm could help identify stationary and conjoining collisions.

Future research could also seek to better classify types of collisions. As events played a large role in shaping the spatiotemporal patterns of collisions in the Community Assembly, collisions could be classified as being either during-event or not-during-event. By adjusting and/or syncing temporal and spatial analyses to examine patterns only during periods of low/medium occupancy, or incorporating data from an event schedule for a given space, researchers could exclude organized events to better examine more patterns of informal use. The use of an event-classification system could increase understanding of how use and collisions change as a function of density.

Another direction for future research would be to incorporate different types of data. Collisions can have more than spatial and temporal signatures. When a collision occurs, its participants are likely to verbally communicate, which acoustic sensors could detect. As with lidar data, which affords anonymity, acoustic data collection could be limited to volume and direction provided by a collection of spatial audio sensors in the study space, preserving occupants' privacy. A spatialization of the acoustic triangulation (i.e. placing the sound origin into the building's coordinates) can be implemented into the detection algorithm to serve as an additional way to verify that a collision has occurred.

Future work could build upon the relationships and patterns identified in this study by examining particular spatiotemporal cases within the study area more closely, specifically to determine if other types of patterns are evident in certain areas at certain times. For example, looking to see if the elevator is used more in the evening hours, when people may be more tired, or if early morning collisions occur in different locations than collisions in the evening. Relatedly, how does the university's class schedule impact collisions? Which exits/entrances to the space are more frequently used at which times? What other specific resources/locations in the study space are associated with a greater rate of collisions, and why might those spaces be associated in this way? All of these future research questions could lead to greater insight into how shared indoor environments are used, and suggest new design choices to increase collisions.

Vroman and Lagrange (2017) found that both visual and physical obstructions altered previously established movement patterns, and suggested that the placement of either visually-attractive or physically impeding objects within a space could be done intentionally to alter/slow movement patterns. Future work could build on this, using an experimental approach, by intentionally placing visual distractions (e.g., artwork, etc.), or by adjusting the layout of furniture and resources in a study space. This could also inform designers' approaches to large, open indoor spaces.

6. Conclusions

This study has provided an initial case study for the use of terrestrial lidar to detect, study, and analyze interaction patterns within a shared indoor environments at the scale of (anonymized) individual people and centimeter spatial precision over a continuous period of several months. A collision-detection algorithm was developed to parse through tabular-based object tracking data, which achieved mixed results with a low false positive rate (21.3%), but a higher-than-expected false negative rate (46%) for two-way collisions. Based on validation assessments, the number of algorithmically-detected collisions may be an underrepresentation of the true collision count, with conjoining collisions estimated to have a high (> 50%) false negative rate, and with stationary collisions not yet being reliably detected.

Examining the impact of time on collisions from a variety of temporal scales, several interesting patterns were observed in the data: Collision count was highest during the first weeks of the semester before dropping-off to a more constant rate, suggesting that the social circle of first-year students may decrease and tighten after the beginning of the semester, that collisions may become more nuanced, or that collisions move elsewhere in the building. Both the day of week and hour of day were found to statistically impact the rate at which collisions occurred. On a daily basis, collisions-per-occupancy generally increased throughout the week, with Friday and Saturday having the most collisions per occupancy. Similarly, on an hourly basis, occupancy peaked during the working hours, but collisions peaked later in the evening. Collisions tended to mirror hourly occupancy patterns, but with a 2-3 hour temporal lag.

Spatial patterns of collisions and occupancy were also analyzed, finding that occupancy and collisions are highly spatially related, but with many caveats. The base of the stairs and the main area of the Community Assembly space both had more collisions per occupancy than expected, with the areas around the elevator had the most collisions per occupancy within the study area. Corridors all tended to experience much less per occupancy than expected, aside from the area at the base of the stairs (in which multiple corridors intersect). A “friction effect” was observed in which the number of collisions was larger on the side of the movement corridor with seating than on the side without seating. However, collisions were bimodal about the throughway with with more collisions at the edges of the movement corridor than in its center.

Overall, this project demonstrated that lidar can be used to characterize use, movement, and activity broadly, and to detect collisions within a shared indoor environment. These data can be used to reveal interesting spatio-temporal patterns that exist in where and how people interact. By considering these patterns, designers can attempt to increase collision frequency and collaboration in university settings.

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