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RESEARCH ARTICLE

Assessing the influence of indoor mapping sources for indoor spatial analysis of physical distancing

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Abstract: GIScience and spatial information contributions to indoor mapping and navigation are many, but there remain significant challenges. Indoor environments are where people spend most of their time, socializing, working, learning, exercising, etc. During times of emergencies, disease outbreaks, and crises, indoor management and planning must be prepared to handle such events, yet doing so is often hindered by a lack of supporting spatial information and appropriate analytics. This paper focuses on COVID-19 mitigation measures to reduce disease transmission through physical distancing in indoor spaces, such as classrooms, offices, dining commons, restaurants, and entertainment venues. Geographical data to support indoor environments is discussed, particularly issues of acquisition, spatial data uncertainty, and implications for spatial analytics. Planning for classroom physical distancing on a university campus highlights capabilities, issues, and challenges, with a comparison made between previous studies relying on architectural data and more precise information obtained using LiDAR.

Keywords: spatial optimization, indoor GIS, uncertainty

1 Introduction

Indoor mapping and navigation are of critical importance. Not only do people largely inhabit and dwell inside of building structures the majority of each day, but supporting individuals with disabilities and mobility needs (as well as adhering to government-mandated requirements such as the Americans with Disabilities Act, see [29]), facilities management, efficient routing, evacuation, demand for location-based service, etc. necessitate methods and associated spatial data to make indoor mapping and navigation a practical reality.

While advances over the past two decades have been remarkable, it is generally the case that needed indoor base data indicating walls, doorways, windows, restrooms, elevators, stairwells, and other permanent features is generally lacking for various reasons. This is in part why indoor mapping and navigation are seen as major growth areas in the coming years, with approaches for generating and improving indoor data among the significant challenges to be addressed [4, 23, 29].

There are a number of recent efforts and examples on the indoor mapping front that highlight potential and advances to date. In recent years, significant investments have been made in indoor mapping and navigation, marking a notable shift from the traditional focus of online mapping and navigation services that primarily concentrate on outdoor elements, such as roads, buildings and transportation. As an example, Apple Indoor Maps and Positioning has been behind building interior data creation and tracking capabilities for a wide array of commercial endeavors [18]. One area is associated with airports across the United States and abroad. San Francisco International Airport and London Heathrow are representative examples. Shopping malls and stores too have undergone much investment in data creation and tracking, particularly those owned by the Westfield Group, Home Depot, etc. The Westfield San Francisco Centre is a good example of this. Esri has also invested in indoor positioning systems and indoor tracking services. The Indoor GIS by Esri service helps to capture the consumer experience in 3-D, providing accurate indoor location tracking and supporting geodatabases of interaction. The features provided have enhanced business analysis, space planning, and product display. What makes indoor mapping and navigation challenging? GPS and remote sensing technology, including Global Navigation Satellite Systems (GNSS), have made outdoor data collection relatively easy. GPS receivers are available through cellular phones, watches, automobiles, etc., enabling the creation of spatial information and movement tracking of objects. Precise geographic location can be established and collected using total stations, GPS, imagery, LiDAR, etc., in outdoor spaces [3, 14, 18, 30]. Unfortunately, this is not the case inside building structures, as GPS signals cannot generally be acquired, hindering the precise measurement and tracking of geographic location. Concerns revolve around the need for additional effort and the utilization of new technologies to acquire indoor data. Currently, a considerable amount of indoor data exists as architectural drawings that lack accurate spatial scale or location information, posing a challenge in seamlessly integrating this data into mapping and navigation systems.

The COVID-19 pandemic has also heightened the need for indoor mapping capabilities. As is well known at this stage, COVID-19 is a respiratory illness that spreads by way of person-to-person contact, via droplets and aerosols, with indoor environments being particularly susceptible to disease spread due to people in close proximity to each other, an inability to avoid indirect contact, poor ventilation, and other reasons. Analysis, tracking, and planning in most indoor environments to support pandemic response, however, was hindered by a lack of indoor spatial data as well as supporting spatial analytic capabilities. It is well established that various mitigation strategies are effective in reducing the spread of this airborne disease, including masking and washing hands, but also reducing close contact with others. In particular, physical distancing is critical in places where individuals are forced to congregate, such as classrooms, offices, dining commons, restaurants, entertainment venues, etc. Like many business, education, and service providers, the longer-term strategy and response at the University of California at Santa Barbara sought ways to continue operations under conditions where physical distancing could limit the spread of the disease. The plan included evaluation, assessment, and design of classroom seating arrangements where physical distancing would be ensured. However, the planning process had to contend with limited indoor data, largely in the form of architectural drawings, and manual approaches for seating assignment.

This paper discusses spatial information implications of indoor planning efforts to support COVID-19 physical distancing in classrooms. The next section offers background to the various aspects of indoor mapping, geographical data acquisition, spatial data uncertainty, and spatial analytics. The planning needs for classroom physical distancing are then detailed. In particular, the use of architectural drawings in previous research for underlying data is considered along with more precise spatial information derived using LiDAR. Methods to support physical distancing evaluation are then reviewed along with approaches to assess geographic uncertainty. Assessment involving classroom planning at the University of California at Santa Barbara is then offered, including comparison of findings derived using architectural drawings and more precise spatial information. The paper ends with discussion and concluding comments.

2 Background

The literature of particular relevance to this research includes work in indoor mapping, geographical data acquisition, spatial data uncertainty, and spatial analytics. Indoor mapping, as well as indoor navigation, has been adopted here to convey the essence of understanding and movement within indoor spaces. Various naming conventions can be observed, including indoor GIS and building information modeling, among others (see [3,22,31]). A recent overview of work in this area can be found in Teixeira et al. [24], highlighting categories of management, geospatial analysis, positioning, data acquisition, and spatial data models for indoor environments. Chen and Chen [4] explain that within buildings there are many complications for spatial location technology, including the reflection, refraction and/or scattering of radio waves and disruption of signal propagation due to obstacles, walls and construction materials, somewhat in contrast to outdoors where GPS based technologies make precision location positioning possible. Further, frequent object location changes and constant pedestrian movements also make indoor environments challenging. A wide range of technology can and has been used to support indoor positioning, including WLAN / WiFi, Bluetooth, RFID tags, and other sensors, particularly cameras and CCTV (see [2,4,20]). Chen and Chen [4] focus on smartphone technologies given the range of sensors they contain. However, general positioning does assume that underlying base information does exist, for which relative movement and position within a building can be established. Where does this base geographic indoor information come from? As is the case for GIS in outdoor environments (see [3,14]), one can rely on a range of methods for indoor data creation, including surveying, LiDAR, and conversion of maps, photographs, and other sources through some digitization process (see [2,4,9,18,19]). However, this is complicated for indoor environments due to the inability to establish accurate relative geographic position within a building. As a result, there is generally minimal, if any, existing data sources to carry out mapping and/or analysis in indoor environments.

Given a lack of base data sources for indoor environments or accessible methods for data creation, relied upon information may be inaccurate or incomplete in many ways. Geographic data uncertainty results from a host of issues, including sampling bias and/or omission, abstraction, attribute measurement error, locational imprecision, etc. These issues and others have long been recognized as challenges for achieving high levels of data quality, with Goodchild and Gopal [8] offering an early overview. A fairly comprehensive discussion of uncertainty can be found in Longley et al. [14]. A case study in positional accuracy is carried out by Lawford [12]. Recent reflections are offered on uncertainty in spatial data by Li et al. [13] and GIScience by Goodchild [7], but more generally the International Organization for Standardization (ISO) defines aspects of data quality, how to register data quality, and procedures for evaluating geographic data through ISO 19157:2013 (geographic information – data quality) [10]. For indoor mapping and navigation, there is much contributing to potential uncertainty, yet perhaps less margin for acceptable errors, depending on intended usage and context.

Spatial analytics are particularly critical for indoor mapping and navigation, especially in the context of pandemic response and the support of physical distancing mitigation efforts. The COVID-19 years have seen much interest in spatial analytics that specifically address physical distancing planning. Murray [15] and Kudela [11] were among the first to recognize that spatial optimization could aid planning along these lines, assuming that underlying indoor data was available. A number of related spatial modeling efforts have followed (see [1, 5, 6, 17, 21, 28]). In the context of pandemic mitigation, an important area of spatial analytics work recognizes that many modeling approaches are sensitive to geographic scale, unit definition and data uncertainty [16, 25]. The significance of this is that data and methods must undergo systematic evaluation to understand the extent to which potential sensitivities may impact analytical insights, as well as the management, planning, and policy implications. Thus, an open research question is whether methods supporting physical distancing evaluation are sufficiently reliable, particularly given the reliance on architectural drawings to support indoor planning efforts.

3 Spatial separation

Pandemic oriented physical distancing planning for classrooms at the University of California, Santa Barbara was undertaken by the Instructional and Study Space Workgroup convened by the Executive Vice Chancellor [27] in the early stages of COVID-19 lockdowns. Accounting for only two dimensions, detailed seating configurations were derived for each classroom in anticipation of in person learning, with assumed minimum physical distancing requirements of 2.62 meters (or 8.58 feet) between the center of seated individuals. This represents the recommended distancing of 1.83 meters (or 6 feet) by health agencies plus 0.79 meters (or 2.58 feet) to account for the size and seat occupancy of an individual.

The physical distancing evaluation and analysis of indoor classroom environments relied on paper / digital images that are effectively architectural drawings. Detailed geographic information exists for building footprints on campus, as do AutoCAD files of building footprints, walls, doorways, etc. for interior spaces. Unfortunately, no digital information exists on fixed seating locations in classrooms. Thus, the analysis and planning relied on architectural drawings, such as the one shown in Figure 1, which is only 2-dimensional and necessary ignores seat elevation, if any.

A member(s) of the Workgroup undertook trial-and-error analysis based upon assumed scale and derived distance to estimate maximal seat occupancy for each classroom on campus. This served as classroom capacities for individual course enrollment. Of course, the above discussion of geographic data quality along with the trial-and-error process to estimate room capacity suggest the potential for a number of sources of uncertainty. At the top of the list is that architectural drawings, like maps, are artistic in nature and may lack geographic precision compared to actual seating size, positioning, and arrangement. The supporting base data for indoor mapping and navigation in this case is much like the early decades of GIS that relied heavily on the digitization of maps, which necessitates close scrutiny of data quality and assessment of associated spatial analytical findings.

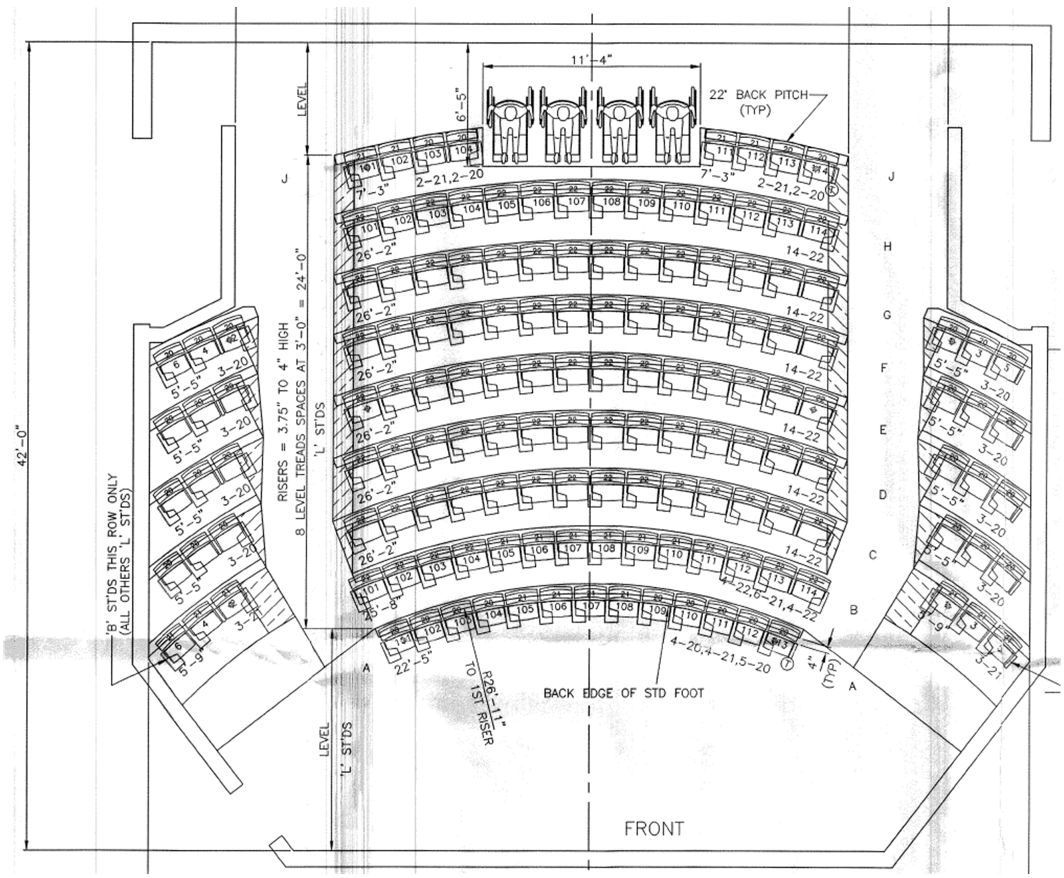


Figure 1: Buchanan Hall 1940.

4 Spatial analytics

A preliminary assessment of a major lecture hall (classroom) at the University of California, Santa Barbara with respect to physical distancing planning was reported in Murray [17], seating 867 people for large classes, concerts, and public events. Of note was that capacity assessment could actually be viewed as a spatial optimization problem, seeking the maximum number of seats that could be occupied without violating the physical distancing requirement of 2.62 meters. It was demonstrated that maximum seating capacities could be structured as an integer program and subsequently solved using a commercial optimization solver.

Consider the following notation:
j = index of potential seats (entire set J)
β_j = benefit for selecting seat j
S = required separation distance between selected seats
d_{ji} = distance between seat j and seat i
Ω_j = set of seats too close to seat j, $\{i \in J | d_{ji} \leq S\}$
$X_j = \begin{cases} 1 & \text{if seat } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

The notation indicates coefficients and parameters, all known or derived in advance, generally through the use and support of GIS. In addition, the decision variables, or unknowns, reflect the intention of the model to select seats to be occupied.

The spatial optimization model for determining maximum seating occupancy is as follows:

$$\text{Maximize} \sum_{j \in J} \beta_j X_j \tag{1}$$

$$\text{Subject to } |\Omega_j| X_j + \sum_{i \in \Omega_j} X_i \leq |\Omega_j| \qquad \forall j \in J \tag{2}$$

$$X_j \in \{0, 1\} \qquad \forall j \in J \tag{3}$$

Objective (1) indicates the intent to maximize the total benefit of selected seats. The use of β_j allows for quality characteristics to be taken into account for each seat j, such as better visibility, proximity to aisles and exits, etc. Constraints (2) impose the spatial restriction between selected seats. Binary conditions are imposed in constraints (3).

It is also possible to use spatial optimization for determining minimum seating capacity, where no additional seats could be occupied. A model to support this is as follows:

$$\text{Minimize} \sum_{j \in J} \beta_j X_j \tag{4}$$

$$\text{Subject to } |\Omega_j| X_j + \sum_{i \in \Omega_j} X_i \leq |\Omega_j| \qquad \forall j \in J \tag{5}$$

$$X_j + \sum_{i \in \Omega_j} X_i \geq 1 \qquad \forall j \in J \tag{6}$$

$$X_j \in \{0, 1\} \qquad \forall j \in J \tag{7}$$

Objective (4) indicates the intent to minimize the total benefit of selected seats. Constraints (5) impose the spatial restriction between selected seats. Constraints (6) require a seat to be selected if it is not restricted by other seat selections. Binary conditions are imposed in constraints (3).

The maximum and minimum capacities provide upper and lower bounds on seating possible under conditions of physical distancing. However, the models necessarily assume that underlying spatial information on fixed seating locations exists and is accurate and without error. If there is any data uncertainty, the associated spatial analysis using (1)-(3) or (4)-(7) may be problematic or misleading. Formal assessment of geographic data quality is clearly important, as is subsequent analysis if any error is suspected or detected.

A prominent source of indoor data in the early days of the COVID-19 pandemic, as noted above, relied on architectural drawings given the need for quick decision-making. Subsequent analysis conducted by Murray [15], as an example, georeferenced architectural drawings then digitized seat position from this data source (see also [17]). Assessment of data uncertainty is possible only with accurate and precise base data. Fortunately, accurate indoor seating position data can be derived through indoor 3-D scanning, among others, though it may be costly and time-consuming to acquire. Based on the scan results, the position of each seat can be digitized. Thus, points can be regarded as the truth, accurately representing the actual seat position. Methodologically, assessment of data quality requires that any two (or more) geographic data layers have a standard referencing system, so that object location is comparable. This may be achieved through the transformation of one data layer to sync with the coordinate referencing of the other layer.

Given a desired coordinate referencing system (u, v), the existing (or created) data layer in another coordinate referencing system (ϕ, λ) must be converted, or transformed. Thus, one seeks functions $u = f(\phi, \lambda)$ and $v = g(\phi, \lambda)$ to accomplish this process. The 2-D affine transformation is [14, 26]:

$$u = \alpha_0 + \alpha_1\phi + \alpha_2\lambda \tag{8}$$

$$v = \alpha_3 + \alpha_4\phi + \alpha_5\lambda \tag{9}$$

where α_0, α_1, α_2, α_3, α_4 and α_5 are transformation parameters that must be known or estimated to best match coincident points in the two referencing systems. With known or estimated parameters, one can then derive the location in (u, v) for any point (ϕ_j, λ_j) using (8) and (9).

The modeling and assessment framework is given in Figure 2 focused on data uncertainty and implications for maximum and minimum seating capacities under physical distancing. The first major component in Figure 2 is to acquire indoor data. In this research, there are two sources, or layers. One is the georeferenced architectural drawings, and the other is a 3-D scan (LiDAR) projected to 2-D and viewed as the truth. The second major component in Figure 2 is to digitize seat position for each data source. The third major component in Figure 2 is coordinate system synchronization, where the 2-D georeferenced architectural drawing undergoes transformation to be consistent with the actual seat location layer. Figure 2 then examines data uncertainty, comparing the seat location extracted from the architectural drawing, $\left(u'_j, v'_j\right)$, to the actual location $\left(u^*_j, v^*_j\right)$. Total resulting error in terms of distance can be summarized as:

$$\sum_{j \in J} \sqrt{\left(u^*_j - u'_j\right)^2 + \left(v^*_j - v'_j\right)^2} \tag{10}$$

Average error distance is therefore:

$$\frac{1}{|J|} \sum_{j \in J} \sqrt{\left(u^*_j - u'_j\right)^2 + \left(v^*_j - v'_j\right)^2} \tag{11}$$

If the error is unacceptable, then adjustments to the input data source could be considered, if this is possible. The final major component in Figure 2 is assessment of maximum and minimum seating capacities using (1)-(3) and (4)-(7).

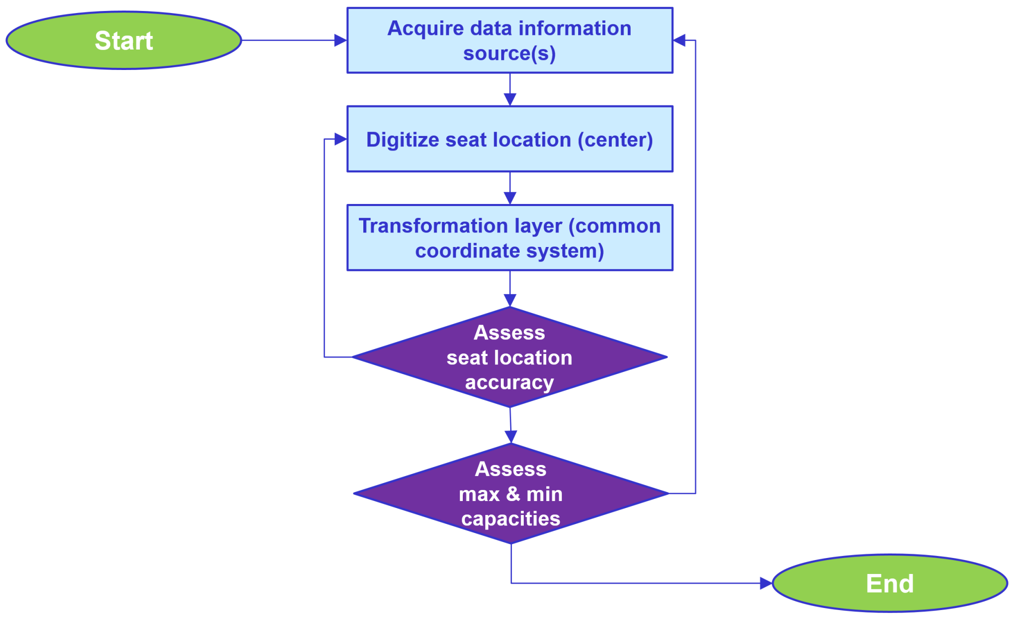


Figure 2: Framework for pandemic response physical distancing evaluation and planning.

5 Application results

In order to demonstrate the challenges of indoor mapping and navigation as well as support physical distancing planning efforts, a classroom on the University of California at Santa Barbara campus, 1940 Buchanan Hall (149 seats), is considered. Seating capacity analyses are carried out on a Windows 10 AMD Ryzen CPU 3600 with 64 GB RAM desktop computer. The estimated seat locations are acquired from the architectural drawing shown in Figure 1. In order to achieve precise scale matching and ensure the highest level of locational accuracy possible, the AutoCAD file containing indoor walls and doors shown in Figure 3 was used. The AutoCAD file was georeferenced using the building footprint represented by a red-dotted line as a reference, with the architectural drawing georectified based on the shared wall structures between the two layers. The seat locations derived from the architectural drawing are based on the state plane coordinate system (2-D), as they were georeferenced in accordance with the building footprint. Again, this is based on the process undertaken by University of California at Santa Barbara [27]. The actual seat locations are derived using a RIEGL terrestrial laser scanner, LMS-Z420i. The scanner has a measuring range of 2 to 1000 meters and a geographic accuracy of 1 centimeter. The scan results are converted into LiDAR point clouds, and are shown in Figure 4. 1,997,924 3-D points were retrieved from the classroom space with a floor area of 155.47 square meters, ranging in height (high of 3.15 m and low of 1.5 m). From the point cloud data, the center position of the upper back of each chair was digitized. Again, these points are regarded as the actual seat location.

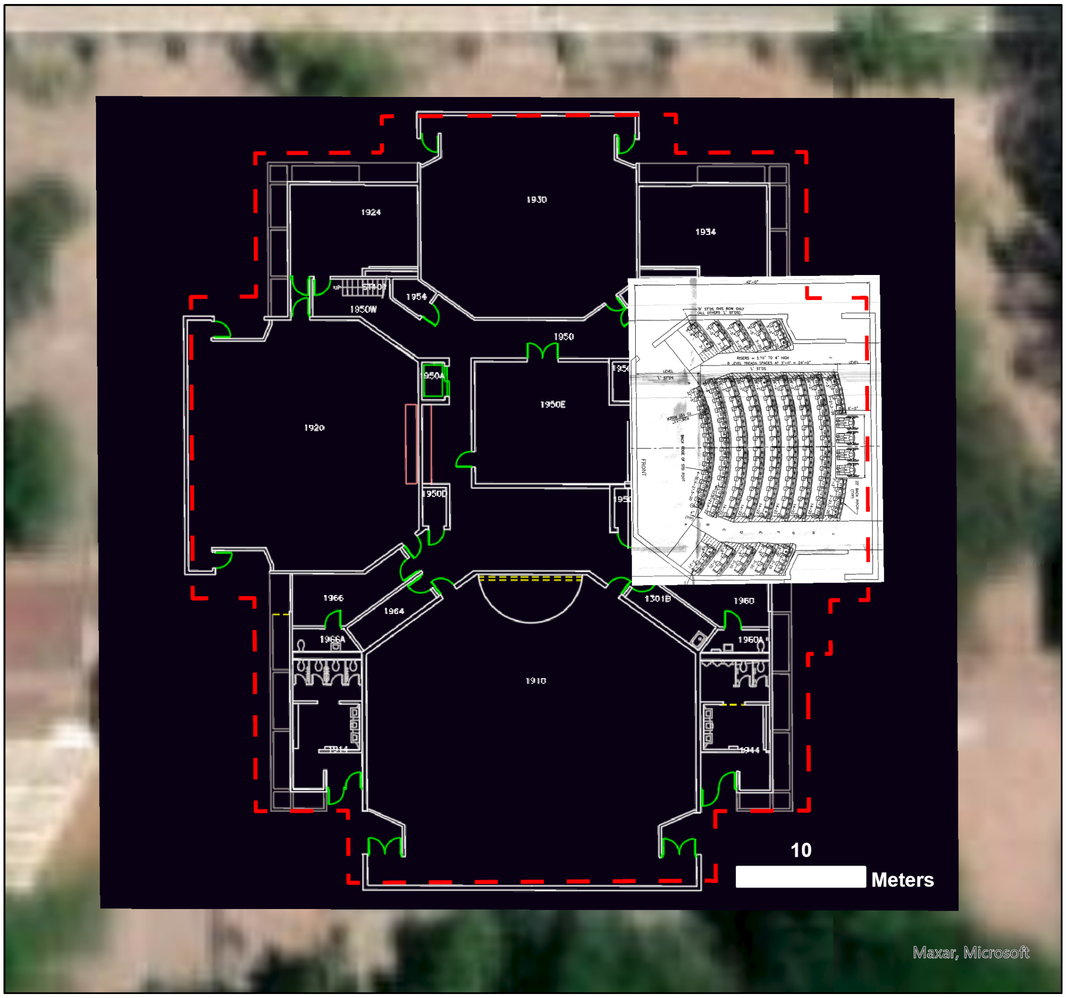


Figure 3: Georeferenced AutoCAD file and architectural drawing.

Following transformation, the two indoor data sources can be compared, as shown in Figure 5. The overlay illustrates that the architectural drawing does not represent the actual location of seats particularly well. The difference in seat position sums to 96.5 meters. Given that there are 149 seats, the architectural drawing has an average positional error of 0.65 meters per seat with an observed maximum of 1.19 meters.

An important question is whether such error impacts subsequent spatial analysis if the architectural drawing data layer is relied upon. To assess this in the context of planning

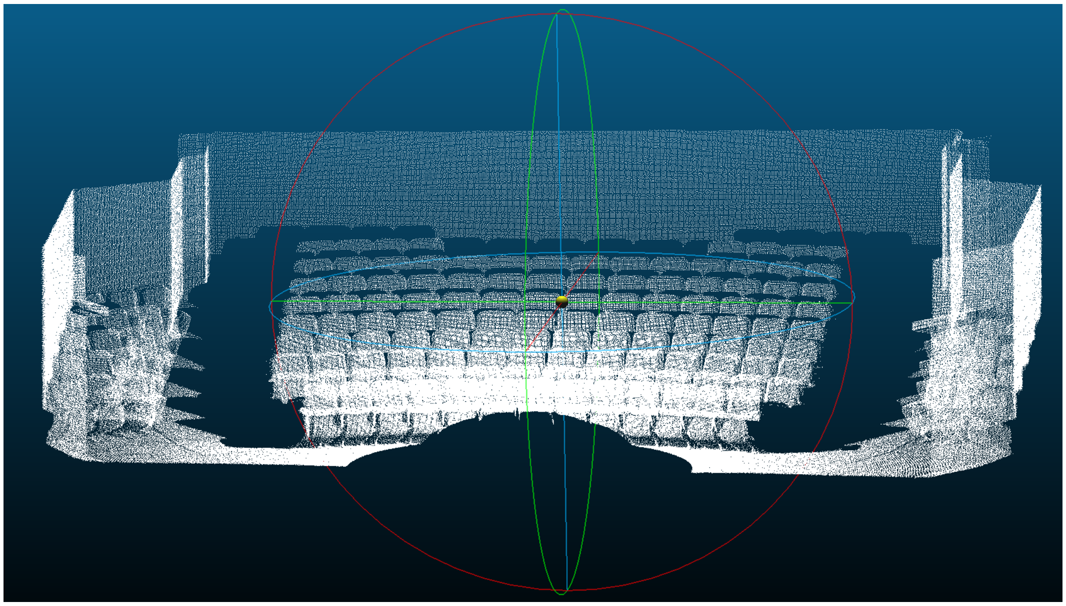


Figure 4: Point cloud from the 3-D scan of 1940 Buchanan Hall.

for physical distancing, the maximum, (1)-(3), and minimum, (4)-(7), room capacity spatial optimization models were implemented in a Jupiter Notebook (Python) and solved using GUROBI (version 9.5). All seats were treated as having equal benefit, though the model could readily accommodate heterogeneous benefit values as well. Time to set up and solve each model was less than 1 second.

Figure 6 shows the seating configurations for achieving the maximum room capacity in Buchanan 1940 under the given physical distancing constraints using the two different indoor data sources. Figure 6a demonstrates the configuration using the architectural drawing seat locations, while Figure 6b shows the configuration for the actual seat positions. Since the physical distancing standard is 2.62 meters, a buffer of 1.31 meters is drawn around each selected seat. An overlap of the buffers would signify that the seats are violating distancing standards. Evident in Figure 6 is that the maximum configurations for both indoor data sources are feasible with respect to their underlying data. For the architectural drawing, the maximum seating capacity is suggested to be 20 seats, while the actual maximum capacity under physical distancing constraints is 15 seats for this classroom. Thus, the error in seat location does impact the derived maximum seating capacity under physical distancing. To visualize this more explicitly, Figure 7 shows what would happen using the architectural drawing to derive maximum capacity seating, where the selected seat locations would actually violate the physical distancing requirement in the classroom in practice. As noted above, this is evident when there are overlapping 1.31 buffers, reflecting that the two or more selected seats are actually separated by less than the required physical distancing standard of 2.62 m. Four pairs of seats would violate this constraint, making the proposed configuration using architectural drawing data infeasible

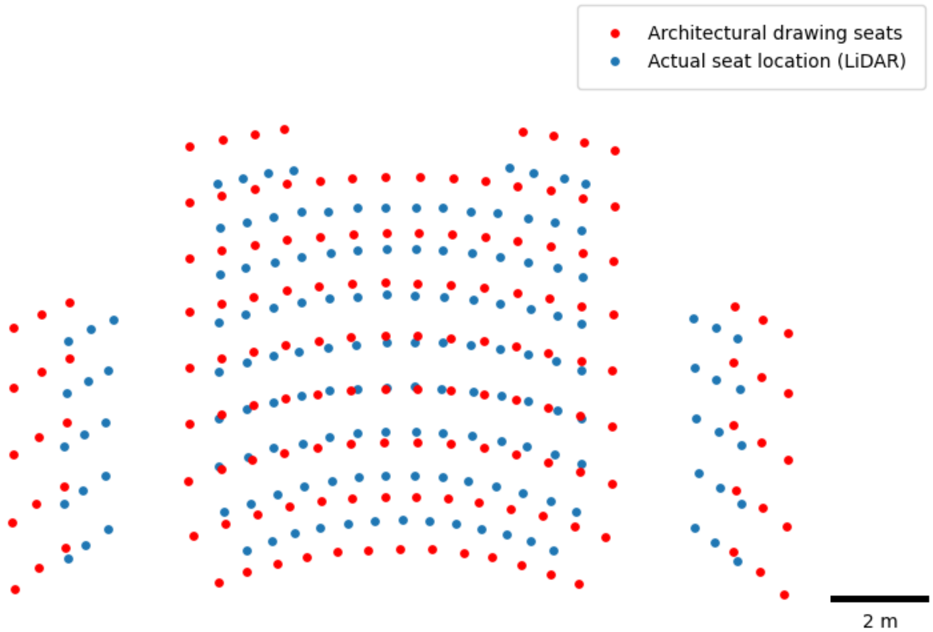
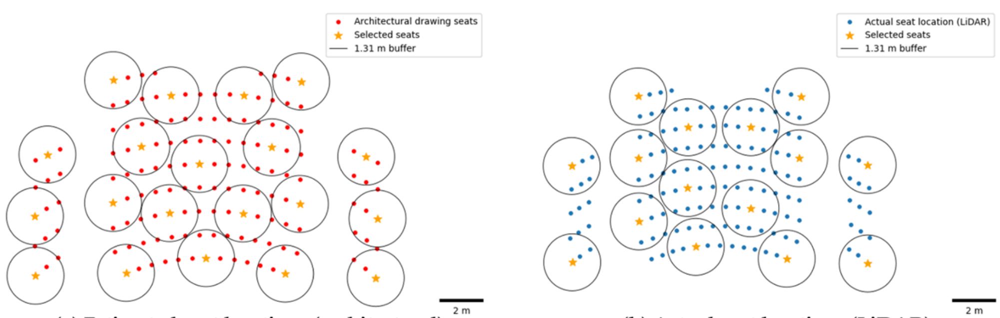


Figure 5: Comparing seat location data sources.

in practice. The true maximum capacity is 15, as shown in Figure 6b, so 20 is simply not possible without violating the physical distancing standard.



(a) Estimated seat locations (architectural) **(b) Actual seat locations (LiDAR)**

Figure 6: Maximum seating capacity possible under physical distancing.

Assessment of minimum seating capacity is offered in Figure 8, where the worst-case configuration with no additional seating possible is derived. Figure 8a demonstrates the configuration for the architectural drawing data source, while Figure 8b shows the configuration for the actual seat locations. A 2.62 meter buffer is shown in this case for each

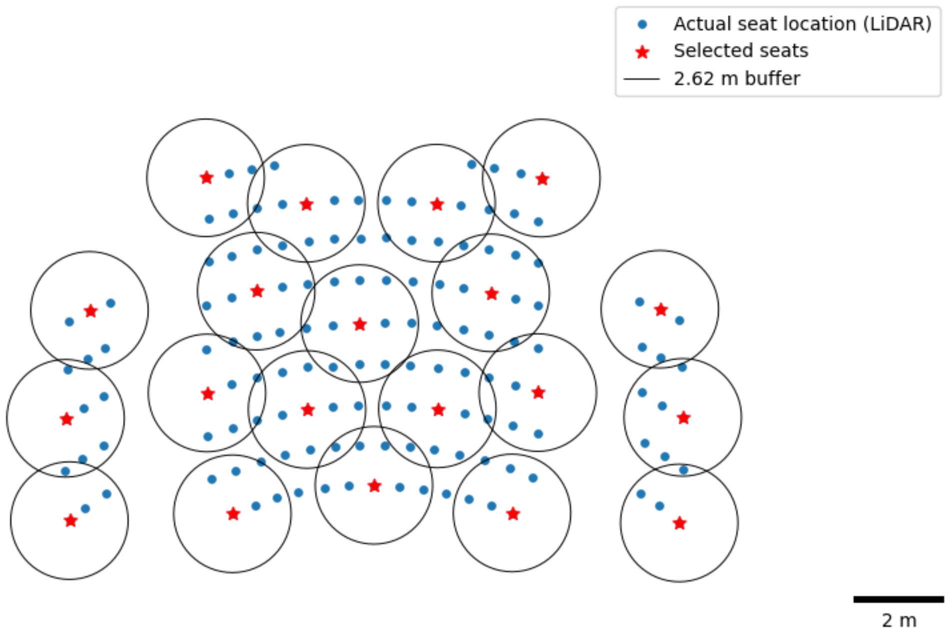
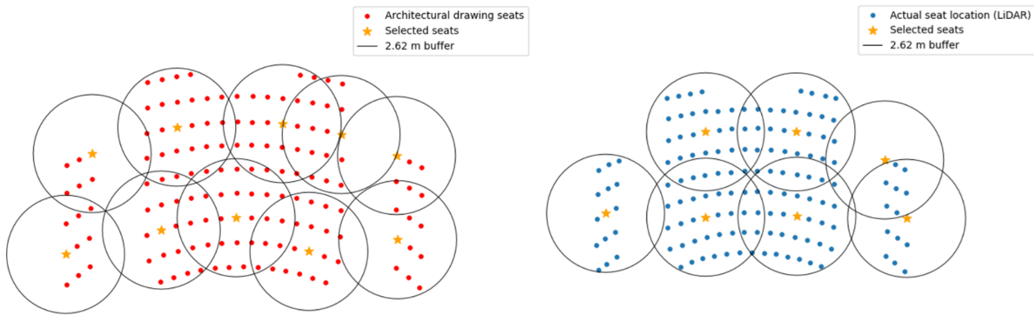


Figure 7: Actual seat location (LiDAR) that implements selected seats from architectural drawing.

selected seat, reflecting the physical distancing standard. A feasible solution is one where no available seat is outside of the buffers. Of concern is that the minimum seating configuration of 10 for the architectural drawing approximation is not actually the true minimum of 7 found using the LiDAR actual seat locations. Again, the error in seat location using the architectural drawing does impact the derived minimum seating capacity under physical distancing. Figure 9 shows the result of applying the minimum capacity seating configuration derived from actual seat location to the architectural drawing source data. A buffer of 2.62 meters is drawn from each selected seat to demonstrate the physical distancing standards. If an available seat is uncovered by buffers, then it violates constraints (6) requiring that all available seats be utilized. This would make the solution infeasible. Figure 9 shows there are eight seats uncovered by the buffers, so the lower bound on seating capacity is incorrect using the architectural drawing seat locations.

6 Discussion

The analysis reported in the previous section relied on a 2-D representation of space. This was assumed given the original analysis based on the use of 2-D architectural drawings to identify seat locations. The LiDAR scan generates a 3-D point cloud from which seat locations could be identified manually. If the analysis is carried out assuming a 3-D environment, this could have implications when the physical distancing standard is considered.



(a) Estimated seat locations (architectural) **(b) Actual seat locations (LiDAR)**

Figure 8: Minimum seating capacity possible under physical distancing.

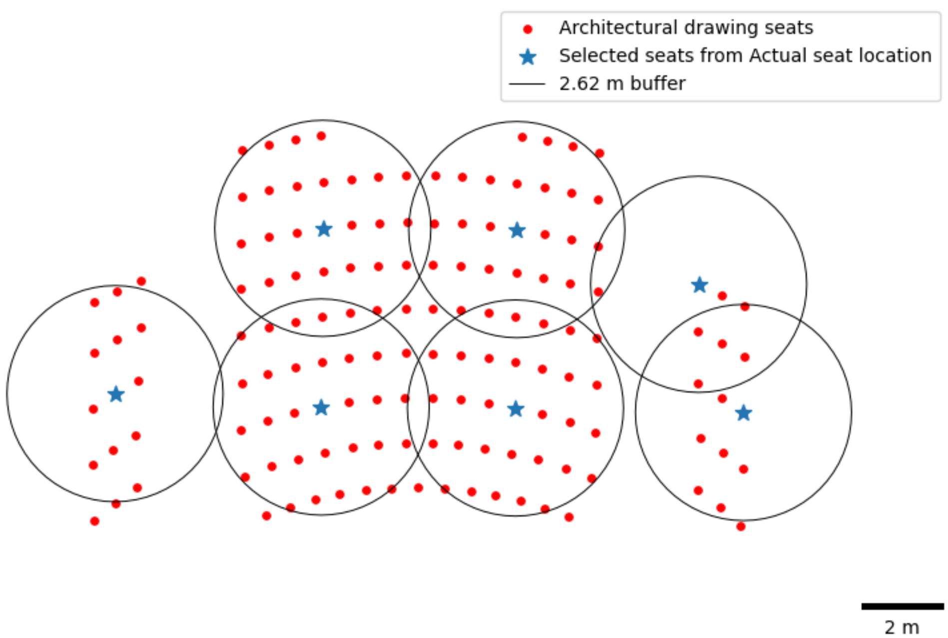


Figure 9: Architectural drawing seat locations depicting selected seats using actual seat locations.

Given this the analysis was repeated using the 3-D representation of seat locations, accounting for elevation in the evaluation of distance and proximity. The maximum capacity using the 3-D representation was 15 seats, and the minimum capacity was 7 seats, consistent with the 2-D analysis. The maximum seating configuration for the 3-D case is shown in Figure 10, also including the LiDAR point cloud scan showing seat locations. While it would not generally be the case, the 2-D and 3-D analysis are the same. This may be due to geographic scale as well as seat elevation changing very gradually within the classroom.

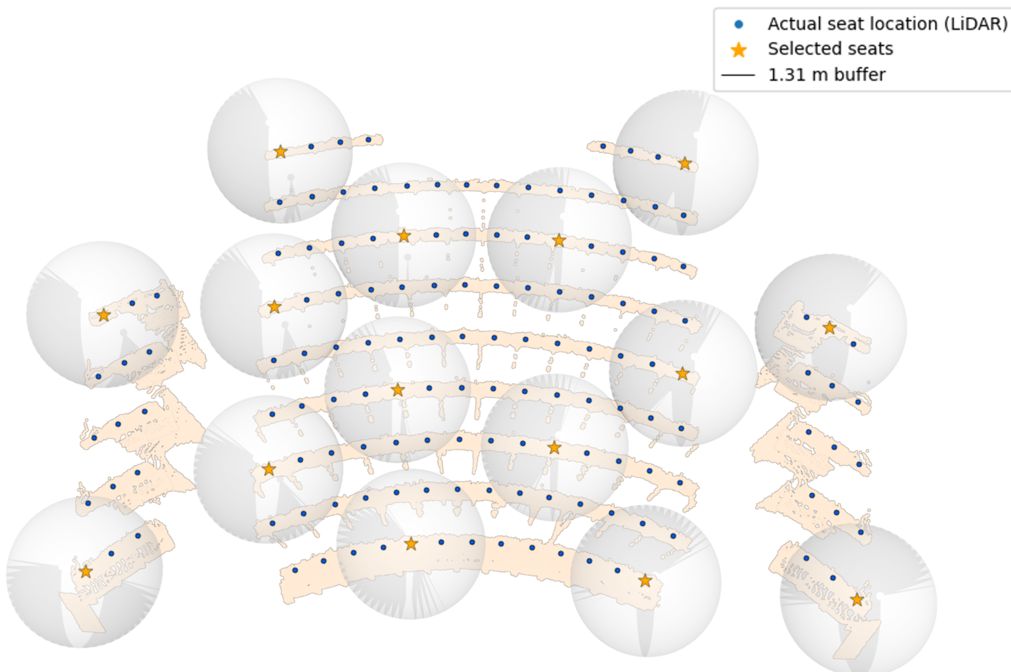


Figure 10: Optimal seat location taking into account 3-dimensions, showing both the LiDAR point cloud as well as the spatial separation standard.

Base data to support indoor mapping and navigation is challenging to obtain for a number of reasons. While accurate maps of building interiors are critical, finding precise indoor data is difficult, and methods to create such data are not generally accessible. Further, maintaining and keeping indoor mapping up to date is also challenging. Reliance on drawings, sketches and illustrations for indoor environments is likely to be problematic in various ways, with spatial precision and accuracy clearly evident in the analysis reported in this paper. Methods do exist for generating precise and accurate data for indoor environments, such as laser scanners [9] and WiFi [19]. 360-degree cameras too can be exploited to create a 3-D digital twin out of multiple 2-D panoramas, which has been explored in computer vision. Modern cellular phones even have the technology to approximate LiDAR sensing. Nevertheless, generating accurate indoor data that can be leveraged for further analysis is costly and time-consuming. A 3-D scan by itself is not sufficient for most indoor mapping and navigation contexts and often requires proper georeferencing, transformation, data merge, and/or digitization, along with object detection and representation.

The conducted indoor spatial data uncertainty analysis holds significant potential beyond COVID-19 mitigation, with applications in diverse areas such as wireless equipment deployment, facility service site selection, emergency response planning, indoor navigation, retail and marketing analysis, facilities management, augmented reality, energy efficiency optimization and security and surveillance systems. By addressing uncertainties in indoor data, these applications can benefit from improved accuracy, efficiency and decision-making, leading to enhanced user experiences, resource optimization and increased safety and security measures.

7 Conclusions

Indoor environments are fundamentally important to humans. Spatial information science has much to offer indoor mapping and navigation, with many notable contributions to date but many challenges remaining. Monitoring, analysis, planning and management of indoor environments are hindered by a lack of supporting spatial information and analytics. An often relied upon source of spatial information is maps and architectural drawings of indoor spaces. However, such information lacks precision and accuracy to support most monitoring, analysis, planning, and management contexts. As highlighted in this paper, data uncertainty leads to errors, and such errors impact spatial analyses, planning and management processes. Public health implications were considered in this paper, focusing on physical distancing mitigation in indoor spaces, such as classrooms, offices, dining commons, restaurants, and entertainment venues. There is a clear need for highly accurate indoor geospatial information, and there will no doubt be increasing needs for more broadly conceived indoor mapping and navigation contexts in the future.

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