SPATIOTEMPORAL OCCUPANCY IN BUILDING SETTINGS

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SPATIOTEMPORAL OCCUPANCY IN BUILDING SETTINGS

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To my family

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LIST OF SYMBOLS AND ABBREVIATIONS

CSV	Comma Separated Value
BIM	Building Information Modeling
CAD	Computer Aided Design
HVAC	Heating, Ventilation, and Air Conditioning System
AFD	Adjacency Frame Difference
WiFi	Wireless Fidelity
GPS	Global Positioning System
GMS	Global Mobile System
RGB	Red, Green, and Blue data
BLE	Bloothoth Low Energy
RF /RFID	Radio Frequency
UWB	Ultra Wideband
RSS	Received Signal Strenght
RGBD	Red, Green, Blue and Depth data
LowRes	Low Resolution
FPS	Frames Per Second
ID	Identification
EBD	Evidence-based Design
VGA	Visibility Graph Analysis
ICU	Intensive Care Unit
VMS	Video Management Software

TB	Terabytes
GB	Gigabytes
PZQ	Image Format
PIC	Image Format
IRB	Institutional Review Regulations
JPEG	Image Format. Stands for Join Photograpich Expert Goup
AVI	Video Format. Stands for Audio Video Interleaved
MKV	Video Format. Stands for Matroska Multimedia Container
C, C++	Programing Languages
Python	Programing Language
GPU	Graphical Processing Unit
I/O	Input/Output
HOG	Histogram of Oriented Gradients
RANSAC	Random Sample Consensus
ROI	Region of Interest
Bbox	Bounding Box
ANOVA	Analysis of Variance
GUI	Graphic User Interface
ACC	Accuracy
TPR	True Positive Rate
SPC	Specificity
FNR	False Negative Rate
FPR	False Positive Rate

2D	Two Dimensional
3D	Tridimensional
OCG	Occupancy Grid
OCC	Occupancy
AOI	Area of Interest
OOI	Object of Interest
SPOT	Spatial Positioning Tool
MATLAB	It stands for Matrix Laboratory. Multi-paradigm Numerical Computing Environment and Programming Language.
Isovist	Field of View From a Vantage Point

CHAPTER 1

INTRODUCTION

The built environments concept encompasses several aspects beyond the traditional three spatial dimensions. It acknowledges its social logic, incorporating the complexity of spatial configuration as well as its embedded social purposes (Hillier 2007). Unfolding the definition, built environment includes spatial aspects, such as the layout dimensions and the geometrical configuration, as well as non-spatial aspects, such as building program, organizational activity programming, and human behavior over time, considering human behavior not as actions that merely occur but as an attribute of the built environment. Activities such as walking, congregating, dispersing, communicating, and interacting create patterns of people distribution in space, influenced by spatial and non-spatial built environment's dimensions, which in turn are altered by those patterns. "Spaces are qualified by actions just as actions are qualified by spaces." (Tschumi, 1996, p.130). This dissertation is situated in the interplay of the aforementioned spatial and non-spatial dimensions of a building setting, and proposes a set of techniques to capture and analyze one aspect of human behavior: occupancy, with the purpose of demonstrating the value of behavioral related metrics.

The long-term goal of this research is to capturing and analyzing spatiotemporal occupancy patterns of high-resolution, with the purpose of determining specific occupancy-related metrics. To approach this goal, this dissertation proposes a four-steps methodology: 1) Capturing positioning data using scene analysis; 2) Processing positioning data to obtain location information in space; 3) Analyzing such data to improve accuracy and precision; 4) Developing new metrics (see figure 1.1). Specifically along these steps, this research emphases on four challenges: 1) Defining the appropriate behavioral mapping method that can help capture behavioral patterns at the right level of spatial and temporal resolution; 2) Determining location data resolution and accuracy for data processing, helping us understand the parameters and the scene conditions that affect them; 3) Understanding occupancy patterns to explain their distribution in certain scenarios, which are defined considering the spatial and non-spatial attributes of the built environment over a specific period of time, under certain conditions; and 4) Defining a new occupancy-related metric: the Isovist-minute, which attempt to capture both patterns of occupancy and their effect on specific behavioral outcomes, which in turn are tailored depending on the architectural program.

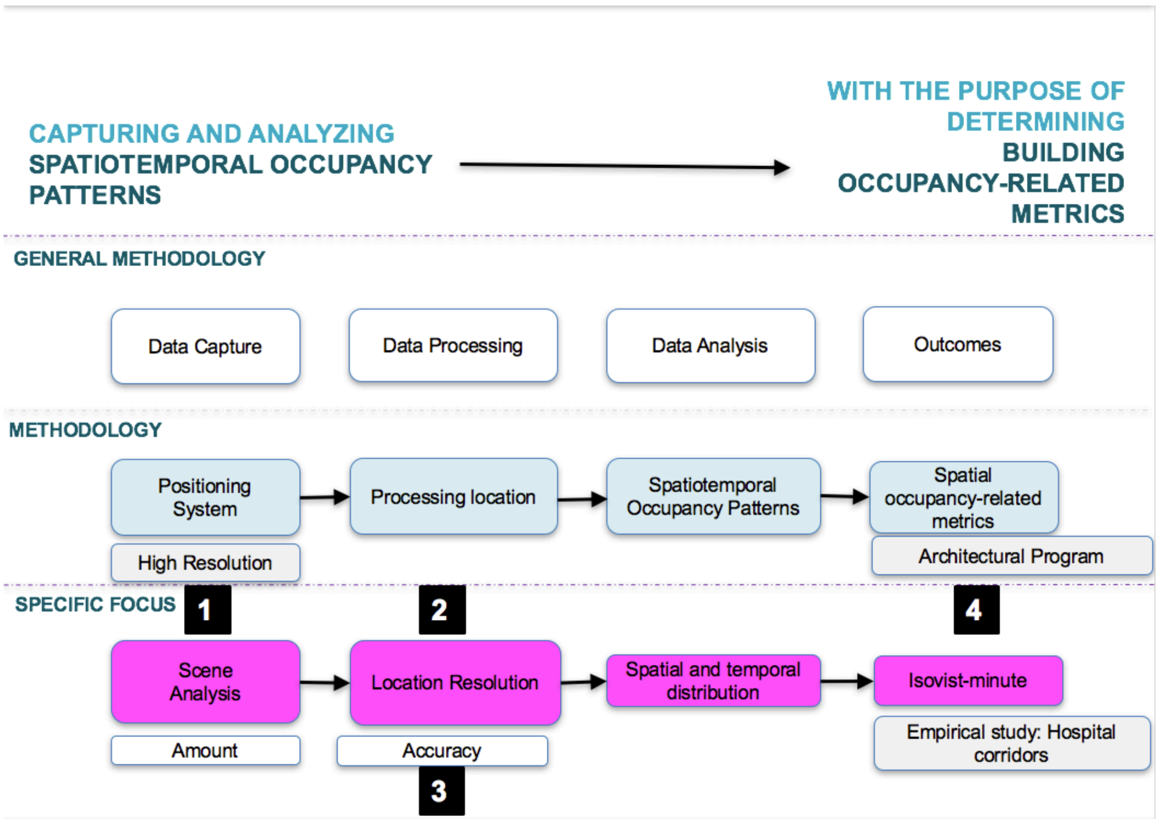

Figure 1-1. Research structure that represents the general methodology, the methodology, and the specific focus of this research, indicating the four specific challenges: 1) the selection of the location system; 2) the positioning techniques for collecting spatiotemporal occupancy; 3) the accuracy and precision of occupancy data; and 4) the value of a new metric.

1.1 The Problem of Capturing and Analyzing Spatiotemporal Occupancy

The importance of obtaining a high spatial-and-temporal resolution occupancy data lays on allowing the study of building occupancy dynamics. “Occupancy and movement data are crucial to deepen the understanding of the build environment performance” (Tome and Heitor, 2015). The high data resolution allows to broaden the range of research questions to be answered (see figure 1.2), from questions that require low occupancy data resolution, such as "the role of spatial layout in shaping the ways in which visitors explore, engage, and understand museums and museum exhibitions" (Peponis, 2010), to questions related to the length of stay of a patient in exam room by minute (Real-time Location System Extraction Sample by HDR research) (see figure 1.2).

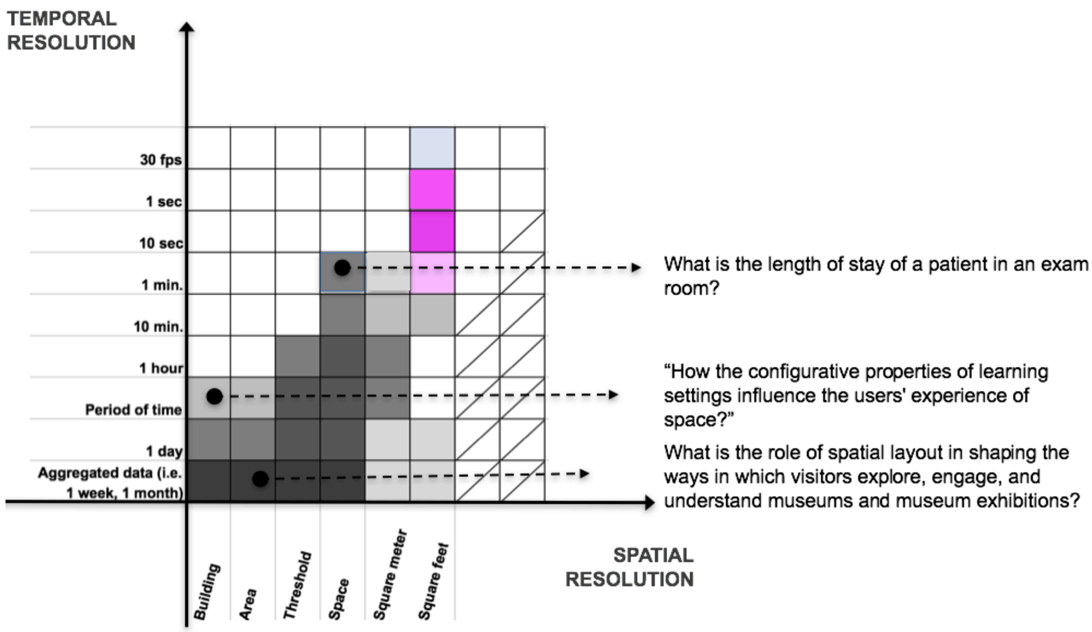

Figure 1-2. Intensity of research distribution regarding spatial and temporal resolution. Dark gray indicates more research, light gray indicates less research, and color indicates this research targeted position within the existing research context.

Numerous studies on human behavior in buildings have focused on exploring movements, occupancy and specific events –such as interactions– as outcomes of the influence of space. These approaches to capturing global patterns of human behavior as an explanatory variable of space have led to obtain aggregated results, involving totals or averages of such behaviors, due to the data collection methods and systems, which either do not provide high spatial and temporal resolution, or focus on particular events, i.e. visits to rooms. These research approaches, therefore, are subject to the following difficulties in data capture and data analyses: (1) limitations in using traditionally accessible methods for behavioral mapping, such as observation and manual mapping, which rely on human abilities that bring their own limits to collect occupancy data of high temporal-and-spatial resolution (i.e. one square feet per second), and (2) the resulting analyses limitations due to the dataset resolution obtained using such traditional methods. However, within the context of existing technologies, a remarkable opportunity for collecting data of high spatial and temporal resolution arises, allowing enhanced methods of behavioral data collection and data processing to promote new research analyses, such as the influence of organizational activities –both scheduled and unscheduled in time– on occupancy patterns.

Each of these systems provides occupancy data of different characteristics in terms of accuracy, precision, temporal scale, perceived privacy among others, stablishing an interdependency between a specific architectural research question and the positioning technology that provides the appropriate data to answer such a question. Hence, the problem becomes a multi-dependent problem, presenting a platform that, based on the review of positioning technologies, helps to technically select the appropriate methodology for high-resolution spatiotemporal occupancy data collection and analyses. It also supports the co-evaluative process of the research question formulation in correlation with both the positioning tools and the dimensions of the built environment possible to capture. This platform indicates the influence of one research variable over the next one, in a chain, providing a matrix of research possibilities (Figure 1.3).

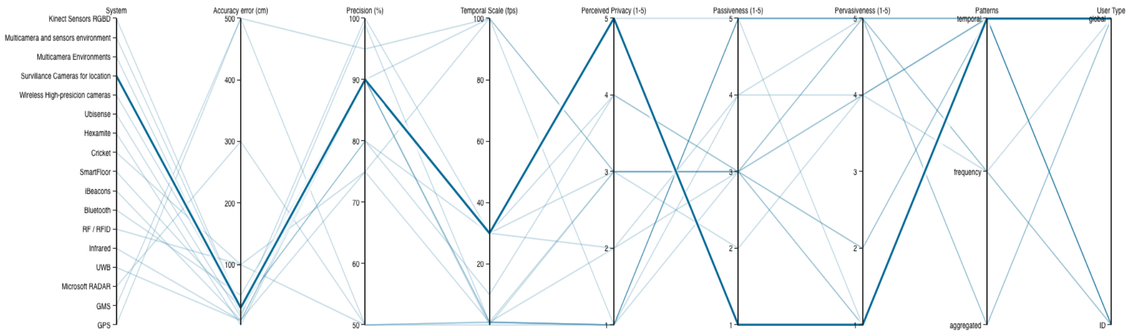

Figure 1-3. A Parallel Coordinates Plot that represents the links of a multi-dependent problem, indicating the relation of the positioning system selection (left) with the potential research question to be answered (right). Highlighted is the Scene Analyses selected method, emphasizing its technical and social aspects. This content is presented here as an introduction, and further detail is presented in Chapter 2. This Parallel Coordinates plot was created using '<u>Sprout Space Parallel Coordinates Plot</u>' developed by Perkins and Will Research Group.

Once one system is selected, the potential research question is narrowed down to a specific building program, social context, scenarios and data resolution and accuracy. In this particular proof-of-concept study, a hospital in Chile was selected, the scenarios were determined by the organizational schedule, and the data resolution was one square feet per second or higher. To achieve such resolution, Scene Analyses using Computer Vision was the selected method for positioning information. Specifically, the first challenge is to define the required data characteristics, consequently, the appropriate system that would allow capturing such data to answer the specific question of interest that belongs to the specific scenario. Additionally, a list of parameters that describe the diverse environmental conditions for determining accuracy in the automatic detection is proposed, shifting the focus to answering research questions that are sensible to the scenario's significance, and at the same time providing insights for meaningful detections in context to the computer vision area. This decision impacted the behavioral data type collected and its resolution and accuracy, which is calculated using a statistical model, intending to determine what are the scene parameters that determine such accuracy, estimating the probability of occupancy detection.

1.2 Description of the study

The aim of the study was to investigate practical and methodological issues involved in using scene analysis to collect occupancy data at high spatial and temporal resolutions, and to demonstrate how new measures of occupancy rates can be developed in order to understand the relationship between spatial configuration and behavior.

This dissertation addresses this task as a proof of concept study, by processing one week of surveillance videos over twelve corridors of a hospital in Chile; the resulting occupancy was captured at a spatiotemporal resolution of one feet per second using Scene Analyses methods based on Computer Vision. Scene Analysis, allows for the collection of high spatial-and-temporal occupancy data using 1-week of existing surveillance recordings from a hospital, avoiding interference with the social aspects of pervasiveness of technology into daily routines, which directly compromises the legitimacy of the data collection. Afterwards, computational methods adapted from Computer Vision rely on adapting pre-built algorithms for automatically recognizing occupancy. These algorithms can be trained and have a certain accuracy range influenced by environmental as well as occupancy parameters, which can be represented by a multiple regression model. Once the occupancy data are discerned, the goal is to measure the relationship between space and behavior in a specific scenario, delineating and developing a new key occupancy metric: Isovist-minute, which is defined as the relationship between real and probable occupancy and their temporal visual fields towards a target. All the methods proposed along this research are general enough to be applied to any specific built environment; However, this research focuses on occupancy of individuals in hospitals corridors, as they are a weak-program spaces into a strong building program. The corridors are characterized by its layout complexity, high spatial segregation, strong control over spatial divisions, strong control over the use of spaces and activities assigned to spaces, and strong control over inhabitants' routines and visitors' schedules (Koch and Steen, 2012).

The core content of this research is presented in five chapters. Chapter 2 reviews the traditional methods of behavioral mapping utilized in architecture research, and the contemporary indoor positioning systems developed in the area of Computer Science and Technology. The role of this stage of the research is to construct the argument for selecting the Scene Analysis computational method for automatic occupancy detection, based on Computer Vision. Chapter 3 defines the important aspects involved in selecting the proof-of-concept scenario: the building program type, the activity programming, and the specific areas of interest for mapping occupancy. The selection of a strong program building type – a hospital – restricted the building program variables and the activity program flexibility. The corridors of the hospital have no specific program or activity assigned to them other than their role as connectors of spaces. The upshot of this is that the activity in a corridor is somewhat unpredictable; part of it depends on the activity assigned to the rooms off the corridor, but part of it depends upon the place of the corridor within the network of corridors of the entire building. For this study, a set of corridors was selected such that all the corridors were matched in their shape, size, and their location vis-à-vis the entire corridor network. The differences in the activities, therefore, could be mostly assumed to be due to the differences of programming. The first two chapters present the framework for the contributions of Scene Analysis for occupancy detection in a restricted spatial and program context, assigning part of the responsibility for the outcomes to activities scheduling over time.

While the above chapters construct the argument from a technical as well as theoretical perspective, Chapter 4 approaches the argument from an empirical perspective, introducing specific methods of Scene Analysis based on Computer Vision, including Video Acquisition and Video Processing, presenting in detail the Computer Vision detection algorithms as well as the practical and technical challenges faced in obtaining the required high-resolution occupancy data results. This chapter ends by presenting the linking connection between a specific research question of interest –what is the patient’s surveillance distribution per hour, for example– and the data type that the system allows to collect –square foot occupancy per second. Chapter 5 develops methods to determine the accuracy and precision of the occupancy detection algorithm. A two-step statistical technique is presented to model the systematic errors caused by the geometrical, environmental and occupancy factors: first, a logistic regression model is developed to examine the extent to which different factors can influence whether the system is able to detect the presence of an occupant; and then, a multiple regression technique is used to model the effect of these factors on the accuracy of the location computed. These models are then used to compute the probability that a cell will have occupancy within a given time, even when none is recorded, and so to predict actual occupancy rates. Finally, Chapter 6 demonstrates two applications of the proposed methodology, Scene Analysis of spatiotemporal occupancy. First, models developed in the previous chapter are used to compute the actual occupancy rates during a specific time period in each of the selected corridors. The results demonstrate that there are significant differences in the occupancy rates of corridors, thus confirming that, even though the space configuration remain the same, the programmed activities in the corridor create measurable difference in occupancy. Second, a new measure called Isovist-minute is proposed. It is designed to study the correlation among four aspects of the scene: spatial configuration, programming of activities, actual scheduled and unscheduled activities, and occupancy. Isovist-minute specifically measures the amount and the frequency of casual visual surveillance from the corridors over patients' beds.

CHAPTER 2

SURVEY AND REVIEW OF BUILDING OCCUPANCY DATA COLLECTION METHODS

Overview

This chapter provides a platform for selecting the methodology for high-resolution spatiotemporal occupancy data collection and analyses by constructing a comprehensive review of the location methods utilized in architecture research and the positioning systems developed in computer science with the same purpose. The first section reviews traditional behavioral data collection methods, focusing on their limitations in collecting high-resolution spatiotemporal data in real scenarios. The second section extends the survey to semi-automated methods. The third section presents a survey of location systems developed in computer science, identifying 10 technical and social criteria for comparison. The chapter concludes by introducing Scene Analysis, the system selected that meets this study's objective of adopting and adapting systems of low pervasiveness for determining people's location, exhaustively reviewing its 36 technical and social aspects, which offer new opportunities for research in architecture.

2.1 Behavioral Data Collection Methods Utilized in Architecture Research

For more than three decades, the influence of spatial configurations on human behavior in built environments has been an important focus of architecture research. An understanding of these correlations required the collection of behavioral data and the development of new methods. Contemporarily, several systems for tracking individuals and the location of objects have been developed in the area of computer science. This section presents a review and a survey of the traditional behavioral data collection methods utilized in architectural research.

One of the most important models for spatial description, developed in the 1980s by Hillier and Hanson (1984), is space syntax theory, which "investigates the relationship between human societies and space, from the perspective of a general building theroy of structure on inhabited space in all diverse forms: buildings, cities, or even landscapes." (Bafna, 2003). The major contributions of space syntax include not only the conecpt of configuration –or relations among discrete spatial units– but also the description of space through more abstract attributes –such as spatial depth, integration, and visual connectivity, and their correlation to social behavior. At building scale, researchers have focused on the effect of layout configuration of different building programs upon a specific behavior, with emphasis on occupancy, social interaction, and movements. These studies help to address a variety of issues such as the interplay of spatial configuration and face-to-face interactions, visual encounters, wayfinding, and navigation. Space syntax research has studied numerous building types, such as commercial, educational, residential and healthcare buildings, including buildings that support weak and strong programs, such as museums and office environments and healthcare environments. A strongly programmed building is defined as a program with minimum flexibility since the activities assigned to the space are exclusive and hardly interchangeable, e.g., courts, prisons, hospitals, and airports. A weakly programmed building, on the other hand, is defined as a program with spatial flexibility regarding activities and users, e.g., offices, museums, and galleries (Hillier, Hanson and Peponis, 1984; Hillier and Penn, 1991). In museums, space syntax research has found strong correlations between the spatial structure of building layout, particularly visibility, and visitors' circulations and movements, specifically with regard to accessibility, the patterns of exploration of art, art encounters, co-awareness, and encounters between visitors (Choi, 1999). Peponis and Stravroulaki (2003), for example, focused on the effects of spatial arrangements and visual perception – accessibility and visibility – on visitors' paths and their engagement with art. They also stated that "[t]he symbolic function of the museum bears on three aspects of spatial arrangement: building layout, the positioning of displays within the layout, and the structure of 'occupiable' space," which are primarily based on the visibility structure of space. Kaynar (2009) insisted that a crucial influence on visitors' behavior, such as path choice and art-element engagement in open plan museums, is visibility, the implicit boundaries of which are stronger than physical partitions. Other studies have suggested that the length of an encounter with art, or 'stop time' (Peponis, 2003), predicted a visitor's engagement with it, and, therefore, the process of learning (Falk, 1982; Serrel, 1995; Sandifer, 1997).

In mid-level weak programs, such as working environments, studies have focused on demonstrating the influences of spatial configurations on social interactions. The importance of these interactions relates to their impact on the organization, collaboration, and the transfer of knowledge. Some critical research questions addressed in this area include the influence of layouts on patterns of communication, occupancy and movements (Penn et al, 1997), as well as interconnectivity as a main factor for interaction and travels-for-interactions (Hillier and Grajewski, 1987; Grajewski, 1992). Layouts can either reinforce the segregation of organizational areas or diminish them (Hillier and Penn, 1991; 1992). At a local scale, within a building, the frequency of interactions among co-workers and their patterns of movement do not necessarily correlate to different layout types (Steen, 2001). At a global scale, however, spatial integration does correlate to human movement patterns. In support of this conclusion, Steen and Markede (2010) reported that visibility is an important factor for social behavior; however, across organizational borders, the spatial influence on spontaneous interactions is weak and their existence could be associated with programmed and scheduled activities (Steen and Markhede, 2010). Research in strong program buildings, such as hospitals, have focused on occupancy and movement – specifically visibility and accessibility – as important design criteria and the highest priorities for monitoring hospital patients. Previous studies have proven that visibility impacts patient observation as well as nurse responses, consequently decreasing nurses' travel time and patients' falls (Hendrich, Fay and Sorrels, 2002). These factors significantly increase nurse-patient caregiving and decrease the mortality rate of severely ill patients (Leaf, Home, and Factor, 2010). Visibility also impacts communication among staff and patients, improving patient satisfaction (Trites et al, 1970; Ulrich et al, 2004). Lu and Zimring (2011) explained the importance of visibility patterns for architects, planners and the healthcare organization by calculating patients' targeted visibility in a health care setting from the head of each patient's bed (Lu, 2009). In all the above studies, researchers utilized a series of manual methods to collect behavioral data. Those methods range from self-report to direct observation and mapping, either from a fixed vantage point or from shadowing individuals. Self-report refers to data collected through surveys or interviews of individuals about the events and activities occurring in a specific space and time setting (Weisman, 1981; Moeser, 1988). This method uses fewer resources since participants report their recollection of events, but it is also less accurate due to the fragility of memory to recall those events with precision. An example of a self-report method is the one utilized by the Steen and Markhede research (2010), in which researchers "asked every office worker on the three floor plans (in total 250 persons) to map all their interaction during (the) two (past) days." (Steen and Markhede, 2010).

Observation and mapping is one of the most popular method for behavioral data collection. It requires the constant presence of observers to annotate, code, and classify people's behavior, by mapping them on a layout or a space (Cosco, Moore, & Islam, 2009). Two factors influence the resulting data sets: the observers' location and the mapping researcher's criteria of a location in a conceptual space type. The mapping criteria is the association of the coded behavioral information to different conceptual spaces such as: (a) a specific location in a layout, (b) a convex space, (c) an axial line, or (d) another area defined by the radio of influence, such as the voronoi area of influence of a painting in a museum, which was defined for a specific research question for Choi's research (1999). These spatial mapping categories affect the data spatial resolution since it depends on the conceptual space selected for the research. The observers' location influences the data collection process since the observers' positions could be from (a) a fixed vantage point, (b) by shadowing an individual, or (c) by doing surveillance rounds. Factors such as reaction time, influence of the observer's presence, and lack of precision in spatial mapping, which depends on the observers' estimation accuracy, may result in errors that cannot be controlled in a research design. The time variable is aggregated since the annotations occur with low frequency (i.e. 10 minutes), or by event.

Observation and mapping methods include counting the events occurring, independently of the frequency of occurrence. In studies of wayfinding, a fundamental technique for navigation studies, the focus is on the awareness of the environment by observation and the counting of the subjects that reach a destination (Peponis, Zimring, Choi, 1990). This method requires that an observer be located at a finish or crossing line, counting and annotating the number of individuals that reach that objective. In addition to standing at a fixed vantage point, an observer can also cover the space in movement by shadowing a specific individual or by doing rounds. In the first case, annotations are much more precise in time and location, but the presence of the observer following the individual could have a huge impact on daily activities. In the second case, annotations are less precise since the observer could miss some activities when he or she is not present or activities could be duplicated if the individuals observed are also in movement. An example is Choi's research (2010) exploring the question of "whether the spatial distribution of people can be explained in terms of configurational variables", which stated:

" By a common technique of observation, the location of each visitor was recorded on a building plan during ten rounds of observations at regular intervals. Though people moving and standing when they were observed were identified separately, the observation data provide a static description of the visitor group."

Observation and mapping methods have been adapted depending on the research needs and the data characteristics required to answer specific research questions. The set of classical methods presented above allowed research in architecture and spatial behavior to answer a certain range of research questions based on the data characteristics. Most of the studies have focused on the unidirectional influence of layout on human behavior, analyzing movements, flows, occupancy, and interaction among individuals in different layout configurations, as previously reviewed. These studies have answered questions such as how open-layouts influence patterns of exploration (Peponis, Conroy, Wineman, Dalton, 2004); how buildings become available as search structures (Peponis, Zimring, Choi, 1990); or how spatial layouts affect face-to-face interaction in offices (Rashid, Kampschroer, Wineman, Zimring, 2006), to name a few. Some findings reported that in complex layouts, such as museums, the spatial configuration restricts human movements and directs their flow and viewing patterns (Bafna, 2003). In re-configurable layouts, such as offices, "spatial configuration directs movements and influences the field of vision, directly affecting the co-presence of people and their face-to-face interaction." (Gomez et al. 2012; Choi, 1999). Such findings provide evidence that layouts, in fact, influence behavior and movements; however, most of the conclusions reached by these studies have been based on aggregated behavioral data correlated with geometrically derived attributes of space only. The range of such research questions has not broadened since data spatial and temporal resolution cannot increase as long as the data collection methods require human intervention and interpretation. Despite these observations, such traditional methods of data collection are very popular and accessible (See table 2-1).

Table 2-1. Sample of studies on behavioral data capturing used in Architecture research.

METHODS DATA CAPTURING	TITLE	AUTHOR	YEAR
SELF REPORT			
Self-report data	Evaluating Architectural Legibility Way-Finding in the Built Environment	Weisman	1981
SR instrument	Space Syntax as a determinant of spatial orientation perception	Ortega, Jimenes, Mercado, Estrada	2005
SR Mapping	Children's active free play in local neighborhoods: a behavioral mapping study	J. Veitch*, J. Salmon and K. Ball	2007
SR Mapping	Spatial and Social Configurations in Offices	Steen and Markhede	2010
OBSERVATION AND MAPPING			
Observation	Behavioral Mapping: The Ecology of Child Behavior in a Planned Residential Setting	Coates, Sanoff	1972
Shadow	Finding the building in Wayfinding. Environment and Behavior	Peponis, Zimring, Choi	1990
Shadow	Space, Time, and Family Interaction: Visitor Behavior at the Sc. Museum of Minnesota	Cone	1994
Rounds	The morphology of exploration and encounter in museum layouts	Choi	1999
Observation	Floorplate shape as generators of circulation	Shpuza	2001
Observation	Measuring the effects of layout upon visitors' spatial behaviors in open plan exhibition settings	Peponis, Conroy Dalton, Wineman, Dalton	2004
Observation	The effects of spatial behavior and layout attributes	Rashid	2005
Observation	A Study Of Variations Among Mies's Courtyard Houses By A Combined Set Of Visual And Environmental Properties	Ruchi, Heo, Bafna	2008
Observation	Constructing Spatial Meaning: Spatial Affordances in Museum Design	Wineman, Peponis	2009

Problems and Limitations

The characteristics of behavioral data collected through these classical methods lead the research questions toward general descriptions of behavioral data patterns, presenting three main issues that are central to this thesis. First, the data collection procedures include the investment of resources and the continuous presence of observers. Second, the variables collected usually refer to humans' position in space and their role, as well as to some particular event that it is possible to be captured within a human reaction timeframe, which is ussually in the range of minutes. And third, the spatial and temporal resolution of the data obtained is limited to human capacity to observe and annotate. Observation methods require considerable resources and effort to collect the data in situ, involving the continuous presence of observers and, in practice, limiting the area covered. The constant presence of observers may also influence normal routines. Moreover, human capacity to annotate manually the fundamental variables of the data is limited, usually as to the location and the role of an individual in fairly regular intervals of time. Also, the methods are only conceptually, but not exactly, replicable, impacting the consistency of annotations among observers or findings among studies. To overcome these limitations, the area of computer science has developed a series of positioning systems and algorithms. However, very little architecture research has incorporated them. The few existing cases are presented in the following section, and a survey and review of all location systems are presented in detail in Section 3 of this dissertation, with the purpose of selecting the most appropriate system for this research.

2.2 Semi-automated systems utilized in Architecture Research

Since 2009, very few studies in architecture have adopted new technology for collecting behavioral data (See Table 2-2). Some attempts included the use of radio-frequency identification (RFID) proximity-tracking sensors (Choudhary, Bafna, Heo, Hendrich, and Chow, 2009; and Heo et atl., 2009), followed by scene analysis systems based on video capture (Gomez, Romero, and Do, 2012; Tomé and Heitor, 2012, 2013 and 2015 a and b), and proximity and triangulation sensors (Erickson, Lin, Kamthe, Brahme, Surana, Cerpa, Sohn, and Narayanan, 2009; Hormazábal, 2013).

The research motivation for each of these studies was completely different, ranging from health-care related, shapes of activity patterns, movements in education layouts, to individual energy consumption in houses. An example is RFID tracking, used in two studies in health-care environments where the goal was to “identify opportunities to increase direct care time through improvements in work process, technology, and unit layout” (Choundhary et al., 2009; Hendrich et al., 2009), demonstrated that higher spatial integration could lead to a higher frequency of visits to patient rooms and nurse stations. In both studies, technical and social issues appeared during the system review. Technically, RFID sensors allow the recognition of an individual’s area of location, but the sensors cannot specify in which convex space the individual is located. For example, individuals could be located in either of two adjacent rooms. Socially, the participants’ use of tags had both negative and positive implications. On the one hand, the participants had concerns about privacy, but on the other hand, the data set included participant’s roles such as doctors or nurses.

Other examples of the use of technology in collecting behavioral data for architectural research purposes can be found in the scene analysis systems employed in two different studies, Activity Shapes (Gomez, Romero and Do, 2012) and the Informal Learning Spaces (Tome me and Heitor, 2012). In both studies, the two technical issues of data amount and occlusion of the target were overcome by top-down orientation of the cameras. The Activity Shapes study was set in a multi-camera environment laboratory, where three of the cameras were strategically located on the ceiling, simultaneously recording three top-down videos to cover the entire area and facilitating floor layout mapping. Videos were stored on a server next door. For this study, the information was assigned to a spatial grid of 21 x 13 cells, of one square foot each, weighting each cell’s occupancy to understand the topology of the occupancy. This work had a similar basis to Bechtel’s work, the “*Hodometer* floor use study”, on topology of movements (Bechtel, 1967). The Informal Learning Spaces study analyzed movements using a single camera that was located in the ceiling of an atrium, recording top-view videos of a larger public atrium and using computer vision to capture movements. Socially, in both cases, the systems did not interfere with the scenarios' routines. In the first case, three scenarios, each with a different activity set-up, were designed to study the differences of the occupancy patterns produced by the activities in a particular space. In the second case, the focus was on the effect of daily movements on a real scenario. Two major differences between these two studies were the focus on occupancy versus movements and the time aggregation range, with the first study having a time resolution of one second and the second having a time resolution of one hour.

Table 2-2. Summary of semi-automated methods of behavioral data collection utilized in architectural research

METHODSDATA CAPTURING	***TITLE***	***AUTHOR***	***YEAR***
SEMI-AUTOMATED			
Tracking RFID	A Modeling Approach for Estimating the Impact of Spatial Configuration on Nurses' Movement	Heo, Choudhary, Bafna, Hendrich, Chow	2009
Tracking RFID	Unit-related factors that affect nursing time with patients: spatial analysis of the time and motion study.	Hendrich, Chow, Bafna, Choudhary, Heo, Skierczynski.	2009
Tracking RFID	A predictive model for computing the influence of space layouts on nurses' movement in hospital units	Choudhary, Bafna, Heo, Hendrich, Chow	2010
Wireless camera sensor network	Energy efficient building environment control strategies using real-time occupancy measurements	Erickson, Lin, Kamthe, Brahme, Surana, Cerpa, Sohn, and Narayanan	2009
Camera / Video Observation	Activity Shapes: Analysis methods of video-recorded human activity in a co-visible space	Gomez, Romero, Do	2012
Camera / Computer Vision	Computer Vision Of Mobility In Informal Learning Spaces	Tomé and Heitor	2012, 2013, 2015
Ubisense Sensors	Post Occupancy Evaluation Of Homes In The United Kingdom To Develop An Affordable P.O. Methodology For Homes In Chile	Hormazábal	2013

Cameras and sensors were used to analyze building energy efficiency in two studies, the “Energy efficient building environment control strategies using real-time occupancy measurements” study by Erickson et al. (Erickson, Lin, Kamthe, Brahme, Surana, Cerpa, Sohn, and Narayanan, 2009) and the “Post Occupancy Evaluation Of Homes In The United Kingdom To Develop An Affordable P.O. Methodology For Homes In Chile” study by Hormazábal (2013). While Erickson et al. (2009) used the SCOPES system (Kamthe, Jiang, Dudys, and Cerpa, 2009), a wireless smart camera sensor network installed on the ceiling of real environments, to collect mobility patterns in a building’s floorplan, Hormazábal used the Ubisense system (ubisense.net) for the same purpose. Both studies focused on energy consumption in relation to individuals, but the first one predicted occupancy for the use of HVAC systems and the second one concerned the real use of appliances and systems.

Erickson et al. (2009) utilized SCOPES to capture the corridors of the science and *engineering* buildings at the University of California. Technical challenges, such as the cameras’ and sensor nodes’ location, were designed to catch movements at transition points. Other computational limitations were solved by using object detection algorithms after processing the data. However, social challenges are not mentioned in this study. Hormazábal’s research was conducted in a BASF house, a home-lab setting, where all technical challenges were previously designed and solved (www.basf.com). Participants agreed to use wearable sensors during the entire period of research, resulting in a high accuracy of positions and identification of roles. Social challenges, however, arose from the requirement that participants consent to live in a BASF house for at least one month, using the wearable sensors, which highly impacted pervasiveness, or effect on normal routines. Privacy was also an important issue, being poorly evaluated by 75% of participants (Hormazábal, 2013).

Three architectural-related computer science studies with a focus on technology development are also crucial to this research, i.e., “Vis-A-Viz” (Romero, 2008), “The History of Living Spaces” (Ivanov, 2007), and (WeWorkBIM, 2015). All the studies utilized information visualization techniques, including time as a variable for human occupancy and movement analysis. Vis-A-Viz provides a tool for visualizing human activity through computer vision (Romero et al., 2008), which automatically records and after-processes human movements from overhead videos, allowing a close one-to-one mapping of individuals' positions over the architectural layout. It computes motion by adjacency frame difference (AFD); therefore, static presence is not taken into account. Vis-A-Viz constructs an activity map by aggregating images of people's movements from a top view, and it displays an interactive activity cube, which a three-dimensional visualization displayed on "SketchUp" (www.sketchup.com). From the perspective of this thesis, the most important technical challenges of Vis-A-Vis involved assigning a specific movement type to a particular person or role and discriminating static occupancy from lack of presence. The most important social challenge is to extrapolate the system installation and settings from a lab environment to a real and large-scale environment.

Another visualization tool for building occupancy is the History of Living Spaces (Ivanov et al., 2007), a mixed application composed of a small number of video cameras and a large number of motion sensors, making the monitoring of large-scale buildings possible. Technically, the system was designed to capture individuals' positions, covering 3,000-square-feet of office space during one year; however, the spatial and temporal resolution of the data collected is low. Another important technical factor is the resources needed to replicate the study since it requires the reinstallation of the system using the same design criteria. Moreover, while cameras in buildings help to improve security levels, they also raise privacy issues due to the resolution of the information captured. However, motion sensors do not provide the same security level or enough information to extract positions in space with high precision as video cameras do. WeWorkBIM's research (2015) by Davis and Payne, incorporated iBeacons, a protocol developed and introduced by Apple in 2013 (www.ibeacon.com), that uses Bluetooth low energy proximity sensors that transmit a unique identifier for the development of an application for indoor individuals' tracking in real-time. Their goal was "to explore the potential of indoor positioning technology" since they believe that "[it] has the potential to transform the design and use of buildings, the same way we have seen GPS transform the design and use of cities." (WeWorkBIM, 2015).

After reviewing the few architecture-related studies that have incorporated a location system, this paper next presents a survey and review of all location systems developed in the computer science area, with the purpose of selecting the most appropriate one for this research taking into account technical solutions, the social implications in the use of the systems in real environments, and an adequate spatiotemporal resolution of occupancy data.

2.3 Location Systems

As mentioned in the previous section, developments in location systems have been focused on the automation, precision and resolution of tracking, and positioning information of people and objects. Tracking and positioning systems differ by the privacy level involved. While tracking systems allow for following objects or individuals, positioning systems use the environment to calculate an object's position (Cook and Das, 2004). The development of these systems was intended to address several specific needs, including Geo location; the location and tracking of objects stored in a warehouse; the location detection of medical personnel or equipment in a hospital; the location of firemen in a building; and behavior surveillance, monitoring, security, and sensing in smart environments (Liu, Darabi, Banerjee, and Liu, 2007; Lui, 2014).

Each aforementioned system was developed to solve a slightly different problem, differentiating themselves on the following six technical parameters, as Hightower and Borriello proposed (2001): (1) Location physical phenomena, (2) portable elements versus infrastructure, (3) form factor of sensing devices, (4) power requirements, (5) portable elements versus infrastructure, and (6) resolution in time and space. These technical parameters have a direct impact on social parameters. Physical phenomena impact privacy, allowing or hindering identity and the associated information.

Table 2-3. List of systems, technologies, techniques, years of development, and years that technology was adopted by architectural research or Computer Science research related to indoor spaces [(1)].

System	Technology	Technique	Computer Science Development	Architecture Research Related (1)
GPS	Global Positioning System	Triangulation	1973	
GMS	Global Mobile System	Triangulation	1991	
Microsoft RADAR	WLAN, Received Signal Strength (RSS)	Triangulation	2000	
UWB	Radio Ultra-Wideband >500MHz	Triangulation	2002	2010
Infrared	Infrared waves	Proximity	1992	
RF / RFID	Low Radio frequency RF	Proximity	2004	2009
Bluetooth	Low Radio frequency RF	Proximity	1994	
iBeacons	Bluetooth Low Energy (BLE)	Proximity	2013	2015
Wi-Fi signals	Cellphones and Wi-Fi signals (avg acc-2mt)	(50%acc within 10m) Trilateration, fingerprints	2002	2015
Smart Floor	Pressure Sensors	Proximity*, physical contact	1997	
Cricket	Ultrasonic Pulses +RF	Proximity, Triangulation	2000	
Hexamite	Ultrasonic ID + RFID	Proximity, Triangulation	2002	
Ubisense	UWB+RF	Proximity Triangulation	2005	2013
Wireless High-precision cameras	High-precision video cameras	Scene Analysis	2000	2012
Surveillance Cameras for location	Low resolution cameras network	Scene Analysis	1980's	
Multicamera Environments	High-resolution cameras network	Scene Analysis	2005	2008*/2012
Accuware Wearabouts	Wi-Fi, GMS, GPS, Camera Visual Features			2015
Multicamera and sensors environment	LowRes cameras, Sensors network	Scene Analysis, Proximity and Triangulation	2007	2009*
Kinect Sensors RGBD	Depth sensor, RGB camera	Scene Analysis, Proximity and Triangulation	2011	

Infrastructure or portability, form factor, and power requirements may impact the level of the systems' intrusion on the scenario and the systems' effect on normal routines, or pervasiveness. Power supply also has an impact on the duration and continuity of data recording. Additionally, resolution in time and space of collected data has an impact on research questions. The most influential technical parameter for determining the approach that best suits a specific study, interfering the least with the social parameters, is physical phenomenon that refers to the system's automatic location sensing techniques, i.e., triangulation, proximity, and scene analysis. Triangulation uses lateration or distance measurements from three non-collinear points, as well as angulation or angle measurements to compute object location, which impacts on passiveness since it requires at least three vantage points. Proximity determines when the target is within range of the source by monitoring wireless cellular access points and by tracking automatic ID systems or by pressure, which increases the effect on normal routines. And scene analysis compares a sequence of observed sight, from a fixed vantage point, detecting the features in the observation. Although scene analysis does not require geometric information, motion, or emission of signals, it requires storing changes on the environment that alter the scene, usually visual images, compromising privacy (Hightower and Borridello, 2001).

As background for this thesis, a detailed survey and comprehensive review of existing indoor location systems was condructed by adapting and extending the taxonomy developed by Hightower and Borridello (2001) and Lui et al. (2007). The objective of the survey was to make an informed system selection, considering all technical and social aspects that may have an impact on this research's objective of collecting high resolution physical and temporal location information for spatiotemporal analysis. The survey covers a subset of indoor location technologies that were developed over the last three decades, including: global positioning systems (GPS), global mobile systems (GMS), ultra-wideband sensors (UWB), infrared signals, fadio-frequency (RF) signals, RFID, Bluetooth, pressure sensors, and high-resolution cameras. Also, the survey includes a set of systems that represent a series of mixed technology, including RADAR, Cricket, Hexamite, Ubisense, multi-camera and sensor environments, and Kinect sensors.

To construct the survey, the systems were categorized under the three techniques they use for location: (1) triangulation; (2) proximity; and (3) scene analysis. GPS, GMS, RADAR, UWB, Infrared, and RF/RFID are some of the systems that use the triangulation technique. Proximity technique is used for Bluetooth applications, such as iBeacons. Also, pressure sensors under each tile, such as the ones used in a smart floor, could be considered a proximity technique. Wireless high-precision cameras, low-precision cameras, and multi-camera environments use scene analysis as the position calculation technique. Also, hybrid systems, which use two or three techniques for location calculation, are incorporated in the review. They include Cricket, Hexamite, Ubisense, multi-camera and sensor environments, and Kinect sensors. Each technology also implicates an object identification system or method, which could include the use of tags on triangulation and proximity or inferred location on scene analysis and pressure techniques.

For selecting the system to be utilized in this research, an exhaustive review of each system and technology was done based on previous research and the products' online reviews. This review included ten specific technical and social criteria: accuracy, precision, range, dimensions, temporal scale, robustness, cost, privacy, passiveness and pervasiveness (See Table 1-4). Accuracy, in this context, refers to the system's location error or the unit in which the data are collected (i.e. three seconds and two square feet), and precision refers to the system's consistency of measurement unit. These first two measurements arise in the context of the technology assessment, and, therefore, they will be renamed in this document system accuracy and system precision.[1]

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[1] Accuracy and Precision terms will be redefined later in Chapter 4, from the perspective of the statistical analysis.

Table 2-4. Summary of location systems survey organized by location techniques, and an exhaustive review of their technical and social aspects. (*) estimations that depend on the entire system set up.

	System	System Accuracy	System Precision (consistency)	Range (Coverage m.)	Dimensions (2D, 3D, 4D)	Temporal Scale (fps)	Robustness (1-5)	Cost (1-5 expensive)	Perceived Privacy (1-5)	Passiveness (1-5)	Pervasiveness (1-5)	power supply	Infrastructure vs. portable	identification system	Expedite size and location (number of Devices)	Recording Duration & continuity
Triangulation	GPS	1 - 15 m	95-99%	Outdoor	3D	40 nSec	5	5	3	2	4	battery	P	tag	1 tag/object	
Triangulation	GMS	50 m	*50%	100-150m	2D				3	3	4	battery	P	tag	1 tag/object	
Triangulation	Microsoft RADAR	3-4.3m	50%	1/floor	2D		4		2	4	4	battery	P	tag	1 tag/object	
Triangulation	UWB	9 cm	90-95%	10.5 m	1D, 2D		5	2	1	4	5	battery	P	tag		
Proximity	Infrared	9 cm	90-95%	< 5m	2D	10 sec	5	1	3	3	4	battery	P	tag	1 tag/object	
Proximity	RF / RFID	<1m	50%	10 m2	2D	10 sec	3	1	1	5	5	battery	I P	tag	tag/ object, Nodes placed densely	
Proximity	Bluetooth	0.5-1.5m	90-95%	<10m	3D	15-30 sec	3	3	3	3	5	battery	P	tag	every 2-15 m	
Proximity	iBeacons	Few cm.	75%-90%	70 mt./ 450 mt.	3D	1ms	3	4	1	3	5	battery	P	tag	1 tag/object	
Proximity	Smart Floor	grid cell	100%	0.5m / cell	2D	by event	3	5	3	5	1	net	I	inferred	1/cell (50cm)	
Proximity & Triangulation	Cricket	1-5m	75-91%	3m	3D		4	2	1	5	5	battery	P	tag	1 tag/object	
Proximity & Triangulation	Hexamite	2 cm	High	14 m	2D, 3D		4	2	1	5	5	battery net	P	tag	1 tag/object	
Proximity & Triangulation	Ubisense	15 cm	99%	1000m	2D, 3D	6 sec	1	4	1	5	5	battery net	I P	tag	1 tag/object	
Scene Analysis	Wireless High-precision cameras	30 cm	90%	27m 170°	4D	148 fps	4	4	3	3	1	battery net	P	inferred	1 / convex space	**2 hrs.**
Scene Analysis	Surveillance Cameras for location	30 cm	*80-90%	27m	2D, 4D	1-30 fps	4	1	4	1	1	net	I	inferred	1 / convex space	***1 week**
Scene Analysis	Multicamera Environments	20 cm	90%	27m	2D, 4D	6-30 fps	4	3	2	3	2	net	I	inferred	<1/9m	**4 hrs.**
Scene Analysis, proximity and Triangulation	Multicamera and sensors environment	*30 cm	*80-90%	*27 m	4D	by event	3	4	4	3	1	net	I	inferred	1 / 7m	*1 week
Scene Analysis, proximity and Triangulation	Kinect Sensors RGBD	*30 cm	*80-90%	0.7m–6m 57°	4D	15-30 fps	3	2	4	3	2	net	P	inferred	1 / 6m	10 min.*

Range refers to the area of coverage of a system or its radius of influence from the source that makes it possible to obtain accurate data. The term “dimensions” refers to the capacity of capturing 2D or 3D locations and details Temporal scale is the frequency of recording information (i.e. 24 fps, 60s, one hour, one month), and robustness refers to the normal functionality in exceptional cases. Cost includes the use of resources, such as money, number of sensors, time, space, human labor for installation, and maintenance. Privacy refers to whether the system allows individual recognition of or association to a person, and passiveness refers to the level of intrusion of the system in the use of tags or consent. Finally, pervasiveness relates to its effect on normal routines.

Regarding these technical aspects, nine of the seventeen reviewed systems provide a system accuracy of 30 cm or less; eight of them supply data with around 90% system precision, providing consistency between reality and the data obtained. Those systems include GPS, UWB, infrared, Bluetooth, Smartfloor, Ubisense, high precision video cameras, and multi-camera environments. Their individual coverages are as follows: UWB systems cover approximately 10 meters; seven systems including GPS, GMS (outdoor), RADAR and Ubisense cover areas up to 1000 meters; and scene analysis systems, such as high-precision cameras, surveillance cameras, and multi-camera environments, cover distances of approximately 27-36 meters (88-120 feet) in the direction of the scene. For this research, an accuracy of 30 cm (approximately 1 feet) and a range between 90-120 feet are the appropriate distances that provide enough resolution and cover a reasonable large area. Infrared technology is obstructed by physical objects like walls. Radio frequency and RFID, Smart Floor, Cricket, and Hexamite systems are based on UWB and RFID; therefore, they are obstructed by physical objects and have a radius shorter than 10 meters. Most of the scene analysis and triangulation systems capture 2D and 3D information, but only five really capture 4D information with a relatively high temporal resolution of six seconds or less, with some of them reaching 148 fps, like GoPro high-resolution cameras. Although the Kinect sensor belongs to the scene analysis and triangulation category, it is also based on infrared (IR) emitter and an IR depth sensor, therefore its coverage range is reduced to approximately 0.5 to 8 meters (1.6 to 26 feet). Some of the systems, such as Smart Floor and infrared, record data by event, and the data collection is not temporally continuous. Also, most of the systems ranked average in robustness, a variable that reflects users' positive technical reception and confidence in the system.

Cost, privacy, passiveness, and pervasiveness are considered social variables for the purposes of this study, since they originate in the social context of the research. These variables are not exactly replicable since they depend on the research financing agreement and on the cultural aspects of the society in which the research is carried out. The cost of installing the system, for example, varies depending on the area of interest to be covered by the research and on the sponsoring institution's investment in technology. Most of the systems are relatively expensive (above average), with the exception of infrastructure systems, which are conceived as part of the building infrastructure, such as infrared networks or surveillance camera networks. Some systems, such as Kinect sensors, are comparatively cheaper by unit, but since they cover a relatively small area, the amount of sensors needed to cover a building floor makes the total system's installation expensive. Therefore, the cost of the system installation is the ratio between the areas of interest of the research and the number of devices needed to cover them, which in turn defines the system scalability. Also, the cost of maintenance share the same area of interest and number of devices ratio, adding the durability of the system and the frequency of manual labor required. Privacy refers to the direct recognition and identification of individuals. Although some wearable technology does not link a person's identification (ID) with an ID tag, participants perceive that by wearing them they are being continuously tracked. Therefore, privacy in this survey refers to "perceived privacy" by the user, which does not necessarily relate to an actual ID recognition. A high perception of privacy is directly related to not wearing the devices. An example of high perceived privacy involves a surveillance camera system, which calculates the location of individuals through scene analysis. Although this system continuously records actions and activities that could be interpretable, it does not automatically identify a specific person, resulting in a highly evaluated perceived privacy. Also, the use of scene analysis technology usually does not require an individually signed consent, since a general consent is obtained when the users agree to enter the space covered by the surveillance cameras in a building. Alternatively, systems that require the use of wearable tags normally relate the individual to an identification code, although not to an actual name or ID. Despite these technology specifics, users perceive a high level of privacy invasion in the use of wearable tags because they provide continuous tracking and require individual consent.

Other aspects, such as infrastructure or portability requirements, size, location, coverage and distribution of technology, and necessary power supply are addressed as they impact passiveness and pervasiveness of the system. More than 75% of the reviewed systems scored an above average level of intrusion on the environment – or passiveness – due to their physical invasion of architectural and personal space. The size and location of technology, as well as the number of devices needed to cover an area and the type of their required power supply (i.e., battery or plug), are the four most influential variables for system scalability, including coverage, duration, continuity, and resolution of the data collected, which directly impact the passiveness level. The distribution of wearable tags among participants plus their signed consent are the two most influential aspects affecting the effect of the use of the technology on normal routines – or pervasiveness. Ultimately, pervasiveness and passiveness levels impact the validation of the data collected since it defines the partial or total number of participants.

Problems and Limitations

Most of the systems studied hold real promise to inform architectural research practices since they are more automatic and less time-consuming than the traditional methods of behavioral data collection reviewed in the first section of this chapter. Also, they provide higher spatial and temporal data resolution due to their system accuracy and precision and the duration and continuity of data recording, as supported by their power supply capacity. Additionally, from the perspective of research methodology, the implementation of these systems allows almost exact research replication compared to the observation and mapping methods. However, all of these systems and methods require more concrete resources than the traditional ones and have diverse social implications. Further, some systems, compared with others, have a higher level of perceived privacy invasion and of passiveness – requiring a considerable benefit-to-cost ratio for participants to provide consent (Lachello & Abowd, 2006) and therefore affecting the number of participants and compromising the data sample. Also, they promote a high level of pervasiveness – affecting normal routines, therefore having an influence on real scenarios and thus on the research findings. Because this research seeks to accomplish the certain social objectives, scene analysis was the system selected to support the maximum perceived privacy and the minimum pervasiveness and passiveness levels, allowing for the collection of a dataset that most closely represents a real scenario.

2.4 Toward Spatiotemporal Data Collection: Why Scene Analysis?

Following the exhaustive review of location systems presented in the previous section, further assessment determined that the system that best contributes to the purpose of this study is a scene analysis system, specifically, a video surveillance data acquisition process, followed by a computer vision video process and video analysis. As with any system, scene analysis involves technical and social implications. However, the negative implications become minimal in relation to the accomplishment of one of the primary objectives of this research, i.e., to automatically collect spatiotemporal data of high resolution in a real scenario. This section presents a more detailed review and comparison of all location techniques, supporting the choice of the scene analysis system. Afterwards, a more comprehensive technical and social description of this specific system is presented, followed by a discussion building the argument for its selection. This assessment was performed by the principal researcher to rationalize the selection of the methodology, contemplating the context of this research. The selected technique – scene analysis – acts as a version of the implementation of the framework.

First, the comparative evaluation of the three computational location techniques – triangulation, proximity, and scene analysis – is presented to support the selection of scene analysis as the most appropriate one for this research. The classic method of behavioral observation and mapping is included for comparison purposes. This evaluation weighs the contribution, neutrality, or negative impact of each aspect as it relates to the objective of collecting spatiotemporal data of high resolution in a real scenario, assigning them the values of one (1), zero (0), or negative one (-1) respectively. The techniques are reviewed under the ten technical and social criteria presented earlier in this chapter. Each criterion, however, was more accurately subdivided in a number of aspects that concern this research. This review starts with the technical criteria, followed by the social ones.

From the technical perspective, the first criterion is system accuracy, which is composed of three crucial aspects, location error, units of data collection, and occlusion of the target. Second is system precision, which is composed of consistency of measurement units, consistency of target location, and access to the original data to validate it. As highlighted in Table 2-4, the system accuracy score is high for the triangulation and proximity techniques (0.7), but it is low for scene analysis (0.3) due to the occlusion of the targets from a particular vantage point. Although occlusion of the target is one of the weakest aspects of scene analysis, its precision score is the highest (0.7) due to the access it allows to original data, avoiding manipulation errors. The combination of system precision and system accuracy define data authenticity, which is constant and averages among the three computational location techniques (0.5).

Table 2-5. The three location techniques: Triangulation, Proximity and Scene Analysis evaluated under the 10 technical and social criteria, and compared to the observation method.

CRITERIA	CRITERIA ASPECTS	LOCATION TECHNIQUES												
		TRIANGULATION				PROXIMITY			SCENE ANALYSIS			OBSERVATION		
		Aspects Score	Aspects Avg		Criteria avg	Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg
1 Accuracy	Location error	1				1			1			0		
	Unit in which the data is collected	1	0.7			1	0.7		1	0.3		-1	0	
	Occlusion of Target	0		0.5		0			-1			1		
2 Precision	Consistency of measurement unit	1				1			1			1		
	Consistency on target location	1	0.3			1	0.3		0	0.7		-1	-0.3	
	Access to original data (Avoid manipulation errors)	-1				-1			1			-1		
3 Range	Coverage area or radius of influence	1				0			1			0		
	Infrastructure versus portable elements	1	0.3			1	0		1	1		1	0.7	
	Scalability	-1				-1			1			1		
4 Dimensions	4D	1	1	0.8	0.47	1	1	0.35	1	1	0.71	-1	-1	0.00
5 Temporal Scale	Frequency of data recording	1				1			1			-1		
	Recording duration and continuity	1	1			0	0.7		1	1		0	-0.7	
	Spatiotemporal resolution	1				1			1			-1		
6 Roboustness	Normal functionality	1				1			1			1		
	Percieved confidence on the system	1	0	0		1	0		1	0.5		1	0.5	
	Level of implementation	-1				-1			-1			0		
	Scalability	-1				-1			1			0		
7 Cost	Money	-1				-1			1			-1		
	Human Resources	1				1			1			-1		
	Number of devices	-1	-0.2			-1	-0.2		1	0.4		1	-0.2	
	HH of Instalation	-1				-1			0			0		
	HH of implementation	1				1			-1			0		
8 Privacy (high+)	Percieved privacy	-1				-1			1			0		
	User identification	-1				-1			1			0		
	Use of tags	-1	-0.8		-0.56	-1	-0.8	-0.56	1	0.4	0.61	1	0	-0.22
	Individual consent	-1				-1			0			0		
	Register within context (Interpretable original actions)	0				0			-1			-1		
9 Low Passiveness	Level of intrusion of the system	-1				-1			1			-1		
	Identification system (use of tags)	-1				-1			1			1		
	Power supply disruption	0	-0.4			0	-0.4		0	0.8		1	0	
	Infrastructure disrruption	1				1			1			0		
	Portable elements disrruption	-1				-1			1			-1		
10 Low Pervasiveness	Effect in Normal Routines	-1				-1			1			-1		
	Extension to Natural environment	-1	-1			-1	-1		1	1		-1	-1	
	Expedite size, location and distribution of devices	-1				-1			1			-1		
Total Score		**-2**			**-0.04**	**-4**		**-0.10**	**23**		**0.66**	**-4**		**-0.11**

The third criterion is range, which refers to the area or range covered by the technology's influence, its infrastructure or portable aspect, and the scalability of the system to cover the area of interest. Proximity location technique has the shortest range (0), followed by triangulation (0.3). Scene analysis, however, has the highest range (1) not only because of the distance it covers, but also due to its scalability (1). The fourth criterion shows that the number of dimensions captured is 4D for all the techniques, except the classic observation method, as reviewed in the first section. Fifth, temporal scale is characterized by the frequency of the data recorded (i.e. fps), the duration and continuity of recording capacity, and the spatiotemporal resolution. Its scores are very high for the three techniques, with proximity the lowest among them (0.7). Sixth, robustness refers to the system's functionality in normal and extreme conditions, the perceived confidence in the system, the level of implementation, and its scalability to larger areas. Robustness is not the strongest characteristic of any of the techniques (0 - 0.5), mostly due to the current developmental stage and scalability of all systems, which is constantly improving.

This assessment also reviews the social aspects of cost, privacy, passiveness, and pervasiveness. First, cost is considered a social criterion since it does not focus on budget as the principal aspect, but on the total resources of the research. Therefore, the social aspects of cost are monetary budget, human resources, number of devices to cover the necessary area, and the time invested on installation of devices and on implementation of the system or the time invested in mapping. The three techniques have similar scores on Cost (-0.2), with the exception of Scene analysis (0.4). The human resources needed scored high in the three computational techniques, excluding observation, making cost one of the crucial aspects for choosing computational methods over manual methods. However, differences in cost among the computational techniques appear in the hours of installation and implementation. Scene analysis is the only system that requires more hours for implementation than installation.

The eighth criteria, privacy, refers to the perceived privacy, which is the fundamental factor for users to agree to participate in the research. Scene analysis is the only technique that scores positively in this aspect. Potential participant identification, the use of tags, the individual consent requirement, and the capacity to interpret the original actions are the other aspects that impact privacy. Triangulation and proximity both scored similarly negative in privacy (-0.56), followed by the observation method. Scene analysis is the least invasive method in regard to privacy (0.61). Although the data format allows accessing the data captured and interpreting original actions, which allows for individual identification, the participants accept this aspect as part of the system. The ninth criteria, low passiveness, refers to the level of intrusion of the system, the use of tags, power supply, and infrastructure or portable elements disruption. Triangulation and proximity score negatively (-0.4) compared to observation methods (0), and scene analysis is the only one that scored positively in low passiveness (0.8). The last criteria, low pervasiveness, refers to the effect of technology on normal routines, the ease of extending the system to natural environments, and the expedited size, location and distribution of the devices. All these aspects scored negatively for all technologies, except for scene analysis. In conclusion, despite occlusion of the target, a fundamental negative aspect of scene analysis, the capture of real occupancy data from a real scenario, with no intrusion of the system and no effect on normal routines, proved the most crucial factor for selecting scene analysis over other technologies.

Scene Analysis Assessment

Scene analysis is organized in two components, hardware and software, and the following three stages: (1) video acquisition supported by a hardware system, (2) video processing and (3) video analysis, all supported by software systems. In this section, a comparison of hardware among all scene analysis methods is presented, supporting the selection of the most suitable one for this study –surveillance environment. Alone, the surveillance environment is not capable of obtaining people's location in space and time, since the data are stored in a video format. Therefore, it is crucial to implement video processing for occupancy detection based on computer vision, as well as video analysis, in the later stages. This section will review the scene analysis hardware component. The three stages will be presented in detail in Chapter 4, after introducing the proof-of-concept scenario for the specific characterization of the methods in Chapter 3.

This review addresses the total variety of scene analysis technologies under the same ten criteria presented in the previous section (see Table 2-6). First, it covers the technical aspects followed by the social ones, and then, it weighs the contribution (1), neutrality (0), or negative impact of each aspect toward the objective of collecting spatiotemporal data of high resolution in a real scenario, exactly like the previous review.

Table 2-6. Four Scene Analysis systems evaluated under the 10 technical and social criteria, and compared to Kinect hybrid system.

	CRITERIA	CRITERIA ASPECTS	SCENE ANALYSIS SYSTEMS														
			Surveillance Sys			Multicam Environ			Multicam-Sensor			HR Cameras (GoPro)			RGBD (Kinect)		
			Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg	Aspects Score	Aspects Avg	Criteria avg
1	Accuracy	Location error	1.0			1.0			1.0			1.0			1.0		
		Unit in which the data is collected	1.0	0.3		1.0	0.7		1.0	1.0		1.0	0.3		1.0	0.3	
		Occlusion of Target	-1.0			0.0			1.0			-1.0			-1.0		
2	Precision	Consistency of measurement unit	1.0			1.0			1.0			1.0			1.0		
		Consistency on target location	0.0	0.7		1.0	1.0		1.0	0.7		0.0	0.7		1.0	0.7	
		Access to original data (Avoid manipulation errors)	1.0			1.0			0.0			1.0			0.0		
3	Range	Coverage area or radius of influence	1.0			0.0			1.0			-1.0			-1.0		
		Infrastructure versus portable elements	1.0	1.0		0.0	-0.3		1.0	1.0		-1.0	-1.0		-1.0	-1.0	
		Scalability	1.0			-1.0			1.0			-1.0			-1.0		
4	Dimensions	4D	1.0	1.0	0.8	1.0	1.0	0.5	1.0	1.0	0.8	1.0	1.0	0.2	1.0	1.0	0.1
5	Temporal Scale	Frequency of data recording	1.0			1.0			1.0			1.0			1.0		
		Recording duration and continuity	1.0	1.0		0.0	0.7		1.0	1.0		-1.0	0.3		-1.0	0.3	
		Spatiotemporal resolution	1.0			1.0			1.0			1.0			1.0		
6	Robustness	Normal functionality	1.0			1.0			1.0			1.0			1.0		
		Perceived confidence on the system	1.0	1.0		1.0	0.3		1.0	0.5		1.0	0.3		0.0	-0.3	
		Level of implementation	1.0			-1.0			-1.0			0.0			-1.0		
		Scalability	1.0			0.0			1.0			-1.0			-1.0		
7	Cost	Cost of devices	1.0			0.0			0.0			-1.0			-1.0		
		Number of devices	1.0			-1.0			-1.0			-1.0			-1.0		
		HH of installation	1.0			-1.0			-1.0			0.0			-1.0		
		HH of implementation	1.0	0.9		0.0	-0.1		0.0	-0.4		-1.0	-0.6		0.0	-0.7	
		Human resources	1.0			1.0			1.0			1.0			0.0		
		Cost of maintenance	1.0			1.0			-1.0			-1.0			-1.0		
		HH of maintenance	0.0			-1.0			-1.0			-1.0			-1.0		
8	Privacy (high+)	Perceived privacy	1.0			-1.0			-1.0			1.0			1.0		
		User identification	1.0			1.0			1.0			1.0			1.0		
		Use of tags	1.0	0.8	0.9	1.0	-0.2	-0.1	1.0	0.4	0.2	1.0	0.2	-0.2	1.0	0.8	-0.2
		Individual consent	1.0			-1.0			1.0			-1.0			1.0		
		Register within context (Interpretable original action	0.0			-1.0			0.0			-1.0			0.0		
9	Low Passiveness	Level of intrusion of the system	1.0			-1.0			0.0			1.0			-1.0		
		Identification system (use of tags)	1.0			1.0			1.0			1.0			1.0		
		Power supply disruption	1.0	1.0		1.0	0.2		1.0	0.4		-1.0	0.2		-1.0	-0.4	
		Infrastructure disruption	1.0			-1.0			-1.0			1.0			0.0		
		Portable elements disruption	1.0			1.0			1.0			-1.0			-1.0		
10	Low Pervasiveness	Effect in Normal Routines	1.0			0.0			1.0			1.0			1.0		
		Extension to Natural environment	1.0	1.0		-1.0	0.0		1.0	0.7		-1.0	-0.3		-1.0	-0.3	
		Expedite size, location and distribution of devices	1.0			1.0			0.0			-1.0			-1.0		
	Total Score		32.0		0.9	7.0		0.2	##		0.5	0.0		0.0	-3.0		-0.1

From the technical perspective, the highest total average belongs to multi-camera sensor systems (0.82), which is obvious result since it utilizes the best aspects of two technologies, cameras and sensors. These systems are closely followed by surveillance systems (0.71). The multi-camera environment takes third place, and high-resolution cameras (GoPro) and RGBD sensors (Kinect) fall far below (0.18 and 0.06 respectively). Comparing multi-camera sensor environments and surveillance systems, they significantly differ on system accuracy and system precision. System accuracy has an average of 0.7 over 0.3, and system precision 1 over 0.7, respectively. This crucial difference may be explained by the occlusion of target and the consistency of target locations, both due to the same factor, the position of camera vantage points on surveillance cameras and multi-camera environments. This assumes that multi-camera environments distribute more cameras in different and more appropriate locations for the location task as compared to the distribution of surveillance cameras for the surveillance task. Multi-camera sensor environments and surveillance systems are equally evaluated in range (1), dimensions captured (1), temporal scale (1), and precision (0.7).

From the perspective of social criteria, most scene analysis systems score low, with the exception of the surveillance system. In terms of cost, most systems require a huge amount of resources since they are not pre-installed in the building infrastructure like existing surveillance systems. Money, human, technical, and time resources are indispensable to mounting the new systems; therefore, all systems scored below (-0.4), with the exception of surveillance systems, which scored 0.6. In terms of privacy, only surveillance systems score over the average (0.6), primarily because of perceived privacy by users and the absence of individual consent. As previously reviewed, the interpretation of original actions from videos in a surveillance system could negatively affect privacy, as in all scene analysis systems; however, perceived privacy increases over time with the acceptance of the systems into daily routines. The surveillance system has the highest score on passiveness and pervasiveness (1) mostly due to the power, infrastructure, and low elements of disruption but also because of its potential for an extension to natural environments and their device sizes, location, and distribution into the infrastructure.

In conclusion, from a hardware perspective, a surveillance system is by far the best choice for the objectives of this specific research, with a total score of 28 over 36 contributions, and averages of 0.82 in technical aspects and 0.78 in social aspects. Nevertheless, because the data acquisition is in video format, the scene analysis process must be complemented by implementing the second stage, video processing, in order to obtain spatiotemporal occupancy data. The assessment of this stage uncovered only two important social restrictions, cost and privacy. Video processing is the most expensive stage in terms of resources, since it requires hundreds of hours of implementation. Video processing also allows access to original videos within context, permitting the interpretation of actions, thus reducing privacy. However, from a technical perspective, this aspect allows for the generation of a model for activity and occupancy data that can be used as a baseline for data accuracy and precision, the most significant technical challenges of this stage. Overcoming these challenges is crucial, since they have a direct impact on data quality and the authentication of the results. Consequently, an entire chapter (Chapter 5) of this dissertation is dedicated to studying such parameters, designing a test to construct the baseline parameters and validating the results.

2.5 Summary

This chapter first presented a review of the traditional occupancy data collection methods utilized in architecture research, i.e., self-report and observation and mapping methods, either from fixed vantage points or with movement, such as "shadowing" a person or doing rounds. Some key variables of the traditional methods were identified, which helped construct the argument for the adoption of semi-automated systems developed in the area of computer science. These key variables are (1) the resources, including constant presence of observers, 2) the limitation in capturing dimensions and number of variables, and (3) the spatial and temporal resolution of the data collected. This chapter also reviewed the technological developments of the location systems, identifying ten criteria for exhaustively comparing them: system accuracy, system precision, range, dimensions, temporal scale, robustness, cost, privacy, passiveness and pervasiveness. The first six are classified as technical criteria and the last four as social criteria.

Additionally, a review and comparison of location techniques for people – proximity, triangulation, and scene analysis – was constructed with the purpose of selecting the most appropriate one for one for this thesis's objective of collecting spatiotemporal data of high spatial and temporal resolution in a real scenario. Some of the influences of the technical aspects were discussed, such as system accuracy and precision contrasted with the social aspects, such as privacy, passiveness and pervasiveness. Further, a specific comparison of the scene analysis systems was presented, with the purpose of supporting the selection of a surveillance system, which permits researchers to obtain occupancy data in a real scenario with minimal disruption caused by the technology. This study cannot accurately provide a depiction of the applicable scene analysis and computer vision detection methods, without first introducing a detailed description of the proof-of-concept scenario in the context of this research, which is provided in the next chapter.

CHAPTER 3

A PROOF OF CONCEPT HEALTHCARE SCENARIO

Overview

This chapter articulates the theoretical aspects of this research, as captured in the research design, through the empirical validation settings. The first section introduces the argument for selecting a healthcare facility as a proof-of-concept scenario, followed by a section that presents the previous relevant research on healthcare settings from two main architectural research perspectives: evidence-based design (EBD) and spatial analysis. The third section presents the specific scenario's spatial and non-spatial descriptions, including the main variables of a strong and complex architectural program, i.e., a hospital, and the main parameters incorporated into the scenario analysis, such as layout organization, program spatial distribution, programming of activities, and personnel schedule. The fourth section addresses hospital corridors as the specific area of interest, with an emphasis on describing them as micro-scenarios based on their adjacent spaces and their assigned functions.

3.1 Why a Healthcare Scenario?

The main goal of this research is to characterize the spatiotemporal occupancy of a building, integrating the influence of the scheduled activities occurring inside. This goal raises a question as to whether any architectural program could serve as an appropriate subject of study, since each program type would have its own particular characterization. However, this study selected a healthcare scenario, among all possible scenarios, because it presents a strong building program. A health care scenario is classified as a strong program due to its layout complexity, high spatial segregation, strong control over spatial divisions, strong control over the use of spaces and activities assigned to spaces, and strong control over inhabitants' routines and visitors' schedules. These strengths arise from the fixed relations between the spatial units, spatial labels, and spatial functions and the correspondent activities performed with minimum distortion in the space, as produced by rigid organizational mechanical systems (Koch and Steen, 2012). As a result, a strong healthcare program scenario minimizes the influence of unanticipated variables, such as unexpected activities carried out in unpredicted spaces; the range of unpredicted participants in daily scheduled or emergent activities; and the adaptation of a space supporting an activity other than what its label indicates, among other spatial and temporal variables related to users, activities, and program. As is to be expected, any such building is not homogenously programmed; consequently, neither is the sample of spaces for analysis as a proof-of-concept. Rather, the spaces will exhibit different degrees of programming depending on the organizational units and non-spatial descriptions, such as the scheduling of activities as well as the placement of object attractors, e.g., supplies (Gomez et al, 2012). In this study, strong program activities are strictly assigned to the sample spaces, allowing for minimum changes, thus allowing the isolation of a number of research variables, such as the programmed and scheduled activities by space. Therefore, these factors, as well as other non-spatial descriptions presented later in this chapter, are key variables in this research.

Over past years, healthcare settings, as strong program scenarios, have increasingly become a focus of lines in architecture research with an emphasis on improving patients and staff outcomes, such as the level of patients' recovery and nurses' walking distance (Ulrich et all, 2008) (see table2-1). Accordingly, this research uses a healthcare setting as its proof-of-concept scenario to demonstrate the feasibility –or the methods in principle– usually tested in a reduced scenario where the data may or may not be complete. The fundamental purpose of a proof-of-concept scenario is to verify that the methods developed can be used in a full study. Pondering all the aspects presented, this chapter reviews healthcare research in relationship to this proof-of-concept scenario's specific setting, with the object of establishing associations between the physical environment and health outcomes and with a final goal of developing meaningful characterizations and interpretations of the spatiotemporal occupancy outcomes.

3.2 Previous Research in Health Care Facilities

The integration of the two architectural research areas of spatial analysis and EBD, as applied to strong building programs such as hospitals, has been a strong line of research since the 50's, with the 'Studies in the Functions and Design of Hospitals: the Report of an Investigation Sponsored by the NPHT and the University of Bristol' (1955). Through the years, numerous studies have demonstrated a direct correlation between the spatial configuration of the environment and improvements in health outcomes. From a global perspective, spatial analyses have focused on the description of the configurational properties of space using space syntax methods to understand their influence on human behavior (Hillier and Hanson, 1984; Bafna, 2003). From a local perspective, the application of EBD to healthcare design involved rigorous empirical studies to link the physical environment of healthcare settings to specific patients and staff outcomes (Hamilton, 2003). Previous spatial analysis research has included evaluations of layout configuration, nursing unit typology studies, and behavioral outcome studies, such as face-to-face interaction. These prior studies include a configuration and design study in caring environments (Hanson and Zako, 2005), which analyzed the residents' active time, enjoyable activities, and environment metrics such as control and choice in relation to axial global and local spatial integration (Turner, 2001) on thirty-six residential care and nursing homes; studies of spatial dimensions of control, such as square footage of visual fields, connectivity, and integration, in three Alzheimer's units and juvenile detention centers (Peatross, 1997); a study of movements and interaction correlated with axial maps and visual fields – or Isovists (Benedikt, 1978); and research on nursing units focusing on walking distances, walking times, and visibility of patient rooms (Cai, 2012), among others.

Evidence-based Design

Evidence-based Design (EBD) research challenges architects to re-focus design toward people-centered rather than building-centered design. The application of EBD to health care relies on scientific evidence, involving rigorous empirical studies to link the physical environments of hospitals to health outcomes (Hamilton, 2003; Zimring et al., 2004). This research indicates the influence of design decisions on clinical outcomes and demonstrates how better design can generate "a less risky and less stressful environment, promoting the cure of patients" (Ulrich et al, 2008). The findings usually suggest design modifications that affect both patients and staff (Joint Commission, 2002). Thus, these studies helped to establish the widely recognized principle that "a well-designed physical environment plays an important role in making design decisions for hospitals less risky and less stressful, promoting the speedy recovery of patients and providing better places for staff to work" (Ulrich et al. 2008).

EBD researchers have conducted studies with an emphasis on three outcome categories: (1) improving patient safety through environmental measures; (2) improving patient outcomes through environmental measures; and (3) improving staff outcomes through environmental measures (see Table 3-1). In particular, this growing body of research establishes causal relationships between specific properties of the physical environment and direct improvements or specific results in health system processes, including four outcome types: 1) patient safety, such as infections, errors, and falls; 2) patient symptoms, such as reducing pain, improving sleep, and reducing stress and depression; 3) organization-patient relationships, such as duration of stay, spatial disorientation, privacy and confidentiality, and communication with patients and family members, all of which foster social support and increase patient satisfaction; and 4) organization-staff and environment outcomes, such as decreasing staff injuries and stress and improving work effectiveness and satisfaction (Ulrich et al., 2008). The resulting research findings suggest a number of recommendations for architectural design, interior design, and healthcare processes. For example, the decision to build single-patient rather than multiple-patient rooms helps to reduce hospital-acquired infections, medical errors, patient falls, and patient stress. Additionally, this design choice helps improve patients' sleep patterns, patient privacy and confidentiality, communication between patients and family members, social support, and patient satisfaction. It also decreases staff injuries and stress, while increasing staff effectiveness and satisfaction (see table 3-1).

Table 3-1. Adapted from "A review of the Research Literature on Evidence-Based Healthcare Design" (Ulrich, Zimring, Zhum, DuBose, Seo, Chou, Quan and Joseph, 2008).

	Design Strategies or Environmental Interventions											
Healthcare Ouctomes		Single-bed rooms	Access to daylight	Appropriate lighting	Views of nature	Famuly zone in patient room	Carpeting	Noise-reducing finishing	Ceiling lifts	Nursing floor layour	Decentralized supplies	Acuity-adaptable rooms
improving patient safety through environmental measures	reducing hospital-acquired infections	2										
	reducing medical errors	1		1				1				1
	reducing patients falls	1		1		1	1			1		1
Improving patient outcomes through environmental measures	reducing pain		1	1	2			1				
	improving patients sleep	2	1	1				1				
	reducing patients stress	1	1	1	2	1		2				
	reducing depression		2	2	1	1						
	reducing length of stay		1	1	1							1
	reducing spatial disorientation											
	improving patients privacy and confidential	2				1		1				
	improving communication patients and fam	2				1		1				
	improving social support	1				1	1					
	increased patient satifsfaction	2	1	1	1	1	1	1				
Improving staff outcomes through environmental measures	decreasing staff injuries								2			1
	decreasing staff stress	1	1	1	1			1				
	increasing staff effectiveness	1		1				1		1	1	1
	increasing staff satisfaction	1	1	1	1			1				

Spatial Analysis

Spatial analysis research in healthcare settings has mainly focused on characterizing the attributes of space, such as connectivity and integration, with an emphasis on visibility and accessibility and their relation to the occupancy and movements as the most important design outcomes. Connectivity and integration are metrics to characterize space based on a visibility graph analysis (VGA). Connectivity is calculated from every point in space as is integration, although the latter also factors in the distance between points (Turner, 2001). Visibility is the evaluation of a space based on connectivity, evaluating all vantage points that generate visual fields. Accessibility is also based on connectivity, but it is comprised of all accessible points at foot level. Visibility and accessibility are behavioral-spatial variables that are constructed based on the interaction of both behavioral and spatial features in an attempt to measure human experience in relation to the geometry of a space.

Visibility and accessibility are the most significant criteria for analyzing patient monitoring in healthcare settings, and these factors demonstrate that high spatial integration (Hillier, Penn, Hanson, Grajewski, & Xu, 1993; Bafna 2003) could lead to more frequent visits to patient rooms and nursing stations (Hendrich, 2003). A new measure of local visibility in buildings, targeted, or directed, Visibility, was developed by Lu et al. (2009) to propose a new model of visibility that differentiates "the origins and destinations of all lines of vision" (Lu, Peponis and Zimring, 2009). As an application of these visibility fields, Lu (2011) shows the importance of visibility patterns to architects and planners by visualizing the sight from the head of the patients' beds and correlating the findings with staff distribution in the intensive care unit of the Emory Clinic, where visual monitoring is crucial. Another research study, presented by Hendrich (2003), states that integration and visibility factors can significantly increase nurse-patient care, reducing the mortality rate of critically ill patients. Also from the visitors' perspective, the exploratory study on orientation and wayfinding in hospitals, which focuses on the spatial orientation and navigation of people in Chilean hospitals (Mora, Oats, Marziano, 2014 a and b) and demonstrates that visitors easily become disoriented after just three turns in their paths due to the complexity in the spatial configuration of hospitals. These studies were intended to extrapolate from previous research that corroborated the impact of spatial visibility on patient monitoring. The studies focused on nurse response time, decreasing the trip distance from nursing stations, and patient falls (Hendrich, Fay and Sorrells, 2002). An additional objective of these studies was to prove that visibility also affects the level of communication between staff and patients, with high visibility improving patient satisfaction, where the most important factor is good communication (Trites et al, 1970; Ulrich et al, 2004). Each of the studies and metrics presented in this section made a fundamental contribution to supporting the significance of visibility fields and surveillance in healthcare design, which will be referenced in Chapter 6.

Non-spatial Analysis Research

As reviewed in the previous section, spatial analysis and EBD have demonstrated high correlations between specific human behavior patterns and selected spatial descriptions. However, other correlations exist between behavior and non-spatial descriptions, such as organizational and programmatic factors. This section will first describe the details of spatial descriptions and then will address the non-spatial descriptions of this specific proof-of-concept study.

Previous researchers have utilized different approaches to embrace the inclusion of non-spatial descriptions, such as programming and organizational variables. In some cases, they studied the organizational flows and simulations of activities using a system engineering processing approach, focusing on where and when the activities take place. Other methodology applied the simulation of the dynamic aspects of buildings, derived from organizational workflow charts and aimed toward an understanding of the performance of complex healthcare systems. These methods focus on the optimization of workflows by simulating the existing flows and assigning activities to agents and spatial units. Specific tools, such as Flexsim Healthcare (Felixsim.com), have been used for the analysis of hospital organizational processes, adapting multi-model agent simulators such as “Anylogic” (www.anylogic.com), based on probabilistic model output from hospital databases, to model expected occupancy and movements. García et al. (2003) approached this topic in their study, “Modeling of activities: An approach to the virtual representation of human behaviors in architectural spaces tested in emergency units” (García, Baesler, Rodríguez, and Pezo, 2003). In this study, they modeled and simulated human activities in emergency units, focusing on the probabilistic evolution of activities and contributing suggestions for better spatial configurations and processes. Although both studies presented the real use of spaces, the behavior of visitors and family, which could potentially double the number of agents depending on the culture, are not included in the models. Even though these approaches have offered several useful contributions, Koch and Steen (2012) argue that "one of the main problems of finding consistent relations between workflow, organization, and spatial configurations valuable for the design of healthcare environments lies in that programmes and activities studied have been described from an organizational point of view rather than a spatial, and have been studied as efficiency machines" (Koch, Steen and Öhlén, 2012).

Discussion

Therefore, the idea of including programming of activities as a new factor in research is rather new, but at the same time, it builds on the original concept of program building categories defined by Hiller and Hanson (1984), i.e., strong and weak programs, in which the degree of influence of the program – and space – on behavior is determined by the type of activity (Bafna, Chambers, 2013). In the original definition, a strong program has minimum flexibility in relation to an activity assigned to a space, while a weak program has high spatial flexibility regarding activities (Hillier, Hanson and Peponis, 1984; Hillier and Penn, 1991). Strong program buildings were characterized as having more complex and segregated layouts than weak program buildings, having more spatial divisions and fixed uses, and imposing stronger control over inhabitants’ and visitors’ behaviors. While activities in strong program buildings are expected to follow the organization, activities in weak program buildings are expected to follow the spatial configuration. However, recent studies have demonstrated that weakly programmed buildings sometimes also follow organization in space and time, thus exhibiting the presence of some aspects of strong programs (Sailer, 2007, 2010). Therefore, Sailer et al. (2013) state that buildings can show “different degrees of programming,” suggesting that it depends on two criteria: the location of attractors, which have placement that does not necessarily follow a logical configuration, and the time restrictions placed on the space’s use as a result of constraining activities to specific schedules (Sailer, Pachilova, Kostopoulou, Radinuk, MacKinnon, Hoofwijk, 2013).

The concept of attractors previously was introduced in the "Activity Shapes" study, which focuses on presenting the influence of the nature of the activity catalyzed by the object attractor on the distribution of people in space and over time (Gomez Romero, Do, 2012). In this research, space was subdivided into a 13 x 9 grid of cells, each measuring 1.5 feet x 1.5 feet. That study concluded that activities could be differentiated by their outcomes, demonstrating that the catalyst is responsible for creating different configurations in the distribution of human occupancy in a singular space. Correspondingly, Bafna and Chambers (2013) present the argument that human behavior is influenced not only by the space, but also by the nature of the activity. They argue that habitual activities – or routines – are more susceptible to the influence of space, without the need for the inhabitants to pay attention to their environment. Concurrently, Koch and Steen present the concept of spatial practice, defining it as “the interplay between spatial configuration, organizational configuration, and the configuration of work processes and routines.” (Koch and Steen, 2012, 2013). In other words, spatial practice can be understood as the spatiotemporal patterns created in the interaction of space, routines, and activities on individual and collective levels, promoting social interaction (Koch, Steen, 2012). The concept of spatial practice. in conjunction with the concept of habitual activities, helps to construct the argument for the classification of activities by their nature. This classification introduces the differentiation between scheduled and unscheduled, or emergent, activities and constructs a baseline for comparing and contrasting their outcomes by analyzing the differences and similarities among activity patterns.

The next part of this chapter is concerned with articulating the theoretical aspects presented in the first half of this chapter through empirical settings by collecting and modeling programming information of scheduled activities assigned to specific spaces during a regular one-week period in the selected healthcare scenario: The Navy Hospital.

3.3 A proof-of-concept scenario: The Navy Hospital Spatial and Non-Spatial Descriptions:

This section presents a description of the proof-of-concept selected scenario: the navy hospital in Chile, from both the spatial and non-spatial perspectives. The first of these perspectives, as the name indicates, includes the description of the layout organization and spaces characterization. The non-spatial perspective, includes the organizational descriptions and programming approaches, the personnel involved, and their activities and schedules. The purpose of this section is to clarify the hospital functions and organizational workflows as a complement to the building analysis from the spatial practice perspective stated by Koch and Steen (2012, 2013).

Navy Hospital

Located in Vina del Mar – the central zone of Chile – the Almirante Nef Navy Hospital is the largest campus of the Navy health system in Chile with six buildings and more than 37.000 m2 built (www.hospitalnaval.cl). It was designed by the Chilean architectural firm of Alemparte Barreda Wedeles Besancon (ABWB.cl), and was constructed in 1990. For this research, a proof-of-concept study suffices to demonstrate in principle the methods proposed. The study's specific areas of interest were selected from inside the hospital's seven-story Hospitalization Tower (shown in cyan in Figure 3-1) for two reasons that respond to the research design. First, the building has six mirrored levels, with hospitalization wings on the second to the seventh floors, producing twelve almost identical and thoroughly comparable scenarios that allow for isolation of the organizational and programming information. And second, these twelve scenarios are covered by surveillance cameras, permitting the scene analysis data collection necessary for this research.

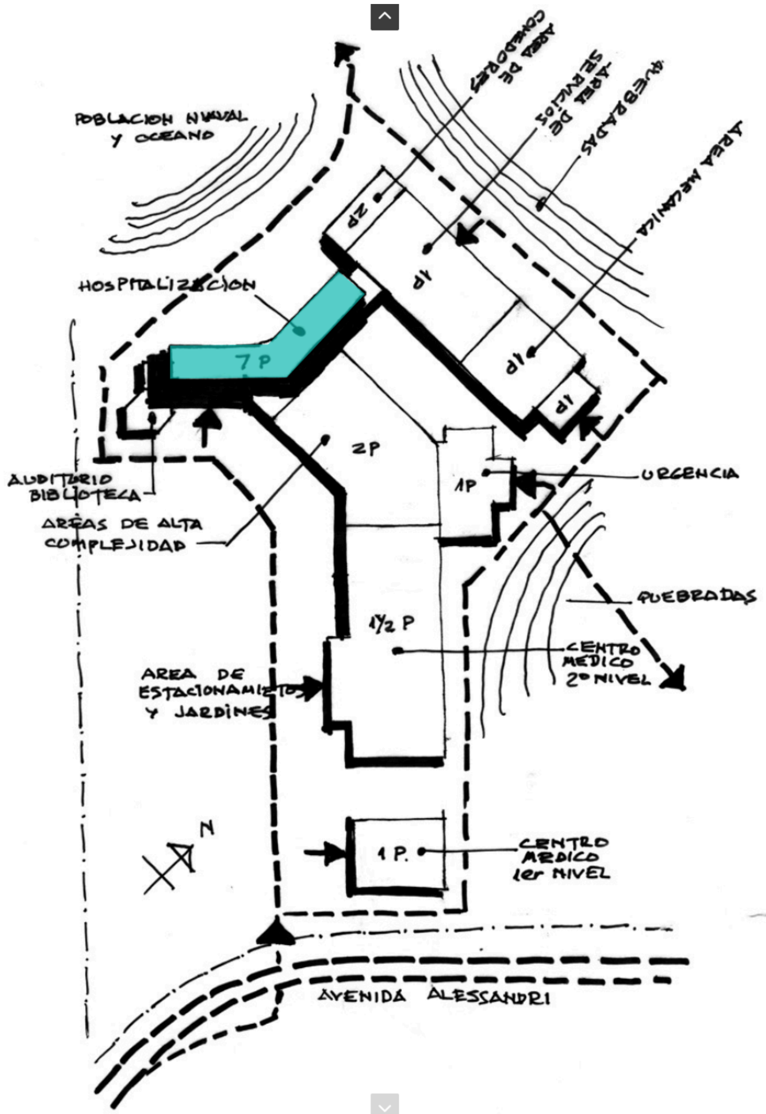


Figure 3-1. Original drawing of the general layout of the Vina del Mar Navy Hospital Campus in Chile, provided by the architectural firm Alemparte-Barreda Wedeles Bensancon (ABWB). Hospitalization tower shown in Cyan.

Figure 3-2. Picture of the Navy Hospital Hospitalization Tower taken from the beach.

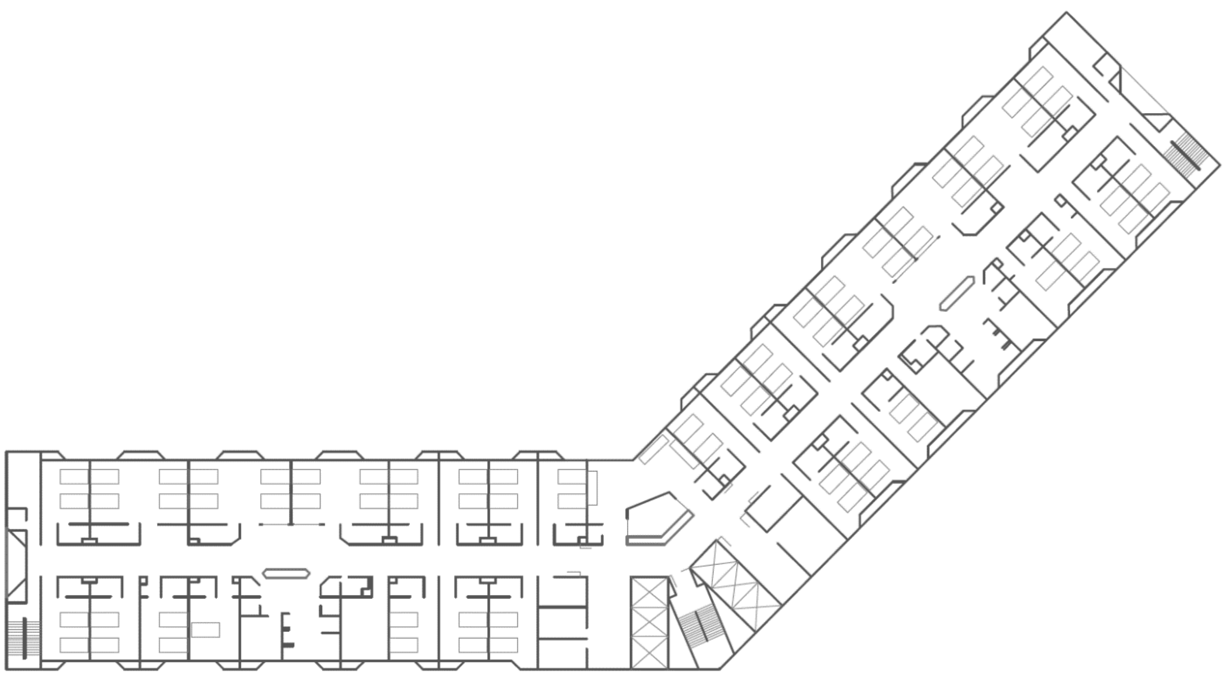


Figure 3-3. Drawing of a general floor plan layout of the Hospitalization Tower. In this figure, the South wing is located in the lower-left side of the figure; and the North wing is located to the upper-right part of the figure.

Spatial and Non-Spatial Descriptions

The Hospitalization Tower consists of a seven-floor building, with a wide-angle L shape (as shown in Figure 3-3), which contains 85,638 square feet (1,136.6 m2) and 450 beds. Each level has 12,234 square feet (almost 8,000 m2) and 70 beds that are distributed 33 to 35 per wing from the second to sixth floors and 15 per wing on the seventh floor, which is a private hospitalization unit floor with single-bed patient rooms. The spatial description of the Hospital Building references two aspects of the building. First, it is a strongly structured building, permitting almost no flexibility for spatial layout changes by allowing for only small layout adaptations from one unit to another. From the second to sixth floors, the layouts are extremely similar. This symmetric design is a classic characteristic of almost any building type in Chile due to the existing seismic geographic conditions. Second, the characterization of spaces includes patient rooms, nurse station, storage spaces, and circulation spaces. Each floor has 19 room spaces per wing. Depending on the organizational unit, between 11 to 15 of those spaces are patient rooms, and a few are used as offices or storage rooms. The offices and storage rooms, as well as the staircases, are located mostly on the east façade of the building, facing the hospital campus. Therefore, the majority of the patient rooms have an ocean view, including the intermediate-care rooms for each unit, which are located at the center of each wing.

In contrast, the non-spatial description of the Hospital Building refers to all the parameters that are not included in a geometrical model of the building, such as the organizational units, organizational boundaries within the units, personnel distribution and their schedules, and the general schedule of activities. The Hospitalization Tower is organized in eight specialty units distributed by floor, as follows: the trauma and obstetrics-gynecology units are located on the second floor's north and south wings, respectively; the pediatric unit is located on the north wing of the third floor, and the intensive care unit (ICU) is located on the its south wing; and the general hospitalization units are located on the fourth, fifth-south, and sixth floors, while the private (single-bed) patient rooms are located on the fifth-north and seventh floors. The critical care units are the general intensive care, cardio intensive care, intermediate care, and neonatal intensive care units, and they are distributed along respective units in the center of the wings. The first floor consists of the entrance, admissions administrative unit, cafeteria, gift shop, and the offices of the directors. The obstetrics and gynecology units, for example, consist of five two-bed rooms for general care and two four-bed rooms for post-operatory recovery and high-risk patients. These last two rooms have larger interior windows and are located in front of the nurse's station, increasing the level of patient monitoring. The emergency unit of obstetrics and gynecology is located at the entrance of the corridor.

Table 3-2. Navy Hospital's Organizational Units by Floor

Floor North Wing	Unit	Floor South Wing	Unit
1	Entrance, Admission, Administration, Cafeteria, Gift shop and Offices		
2N	Maternity	**2S**	Trauma
3N	Pediatric	**3S**	ICU
4N	General	**4S**	General
5N	Private / Ambulatory	**5S**	Oncology
6N	General	**6S**	General
7N	Private	**7S**	Private

a. Personnel by Unit

The number of patients usually varies from four to twelve per organizational unit-wing, never exceeding the capacity of each wing. The personnel consist of thirty-four members by unit, as follows: sixteen technical nurses, nine nurses, six medical doctors, one secretary, one service assistant, and one cleaning assistant (see Table 3-3). Their schedules and shifts are not exactly the same in each unit, resulting in different activities scheduling. This non-spatial information is key to this research, since the hypothesis is that the scheduling of activities has an influence on the spatial and temporal occupancy of the building.

b. Planned and Scheduled Activities

The term “planned activities” refers to the activities that are programmed by the organization. These activities are essential for the proper functioning of the hospital. “Unplanned activities,” on the other hand, are activities that are not programmed by the organization (see Table 3-4). These activities could either be scheduled or unscheduled. Scheduled activities are those that are programmed and have a specific timetable, e.g., 8 a.m. medical rounds. Unscheduled activities are activities that could be prearranged by either the organization or the users but do not have a specific agenda, e.g., cleaning after a spill. Some unplanned activities could have a regular frequency, making them routine, e.g. the daily staff breakfast after morning rounds. These activities are not essential for the proper functioning of the hospital, but they help improve the work environment.

Table 3-3. Examples of activities classified by nature.

		Organizaitonal Planned Activities	Organizational Unplanned Activities
Scheduled	**Regular frequency**	i.e. Medical Rounds	i.e. Staff Breakfast
	Irregular frequency	i.e. Visitors in-and-out	--
Unscheduled	**Regular frequency**	i.e. Linen distribution	--
	Irregular frequency	i.e. Cleaning after spill	i.e. Cellphone calls

In the case of the navy hospital, the predominant planned and scheduled activities are hours of operation, work hours, programmed shifts, scheduled services, and visiting hours. The Hospitalization Tower operates twenty-four hours per day, seven days per week; however, certain specific tasks are distributed in space and time as follows: major shift changes occur at 8:00 a.m. and 8:00 p.m., and they last approximately one hour in each unit because they include a medical round. Minor shift changes, such as when the chief doctor and the specialist leave the unit, occur at 10:00 a.m. and 12:00 p.m. (see

for details). The majority of the personnel start their work day at 8:00 a.m. The medical evaluation rounds start at the same time and last for around one hour, regardless of the number of patients. The order in which the medical team visits each patient room is determined by the level of the patient's health risk – from higher to lower – and the visits are not necessarily performed in a particular spatial sequence. However, as a general rule, because most critical patients are located in front of the nurse station, the personnel usually start their rounds there.

Table 3-4. Personnel Schedule on Weekdays

Staff on Weekdays	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Chief Doctor	1	1	1	1																				
Specialist (UCIM Nurologist)	1	1																						
Resident A	1	1	1	1	1	1	1	1	1	1	1	1												
Resident B													1	1	1	1	1	1	1	1	1	1	1	1
Nurse in Chief	1	1	1	1	1	1	1	1	1															
On Call Nurse A	1	1	1	1	1	1	1	1	1	1	1	1												
On Call Nurse B	1	1	1	1	1	1	1	1	1	1	1	1												
On Call Nurse C													1	1	1	1	1	1	1	1	1	1	1	1
On Call Nurse D													1	1	1	1	1	1	1	1	1	1	1	1
Nurse Technician A	1	1	1	1	1	1	1	1	1	1	1	1												
Nurse Technician B	1	1	1	1	1	1	1	1	1	1	1	1												
Nurse Technician C	1	1	1	1	1	1	1	1	1	1	1	1												
Nurse Technician A2													1	1	1	1	1	1	1	1	1	1	1	1
Nurse Technician B2													1	1	1	1	1	1	1	1	1	1	1	1
Nurse Technician Variable													1	1	1	1	1	1	1	1	1	1	1	1
Nurse Technician in charge	1	1	1	1	1	1	1	1	1	1	1	1												
Service Assistance	1	1	1	1	1	1	1	1	1	1	1	1												

Table 3-5. Scheduled activities for the function of the Hospital

Scheduled Activities	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Meal Service **7:30/11:30/15:30/18:30**				1				1			1													1
Medical Rounds / Shifts	1												1											
Medicine Distribution	when needed																							
Service Cleaning	outside																							
Linen Distribution	once a day / by patient																							
Staff Lunch Round 1 12:30/13:30					1																			
Staff Lunch Round 2 13:30/14:30						1																		
Staff (unofficial) Breakfast **9:30/10:00**		1																						

Beside shifts and medical rounds, other daily scheduled services are meal service, medicine distribution, cleaning service, linen distribution, and staff lunchtimes.

Meal service and medical rounds are scheduled at a fixed time every day (see tables 3-5). Medicine distribution, service cleaning, and linen distribution, however, are incorporated, but not fixed, in the hospital schedule. Medicine distribution depends on each patient's treatment schedule, which is uniquely designed for that patient. The cleaning service and linen distribution are programmed once a day, in the morning with no fixed schedule; instead, these services are organized sequentially by patient room. The staff is divided in two groups for lunch breaks, either from 12:30 to 1:30 p.m. or from 1:30 to 2:30 p.m., in order to maintain an uninterrupted surveillance of patients. The ICU unit varies its lunch schedule by one-half hour, starting at 12:00 p.m. Also, a planned but unscheduled activity is the staff breakfast, an unofficial routine that occurs every day after medical rounds finish for approximately one-half hour.

c. Visiting Hours

Visits to patients comprise another scheduled activity. Visiting hours are scheduled by unit (as shown in Table 3-5). The patient admission office, located on the first floor of the Hospitalization Tower, attends to patients and visitors from 8:00 a.m. to 5:00 p.m. After these regular operating hours, the admission function takes place in the hospital's emergency unit, located in another building. Visiting hours vary from unit to unit. Six units receive visitors for only two hours per day, from 3:00 to 5:00 p.m. The single-bed hospitalization wing patients receive visitors continuously from 3:00 to 8:00 p.m. Intermediate and intensive care units, receive visitors two times a day, for time periods of one hour each, from 12:00 to 1:00 p.m. and from 4:00 to 5:00 p.m. Other rules for visiting patients depend on the age of the visitor. Visiting hours for visitors under 10 years old are restricted to between 4:00 and 5:00 p.m. Therefore, the time period from 4:00 to 5:00 p.m. is the only one in which all units are receiving visitors simultaneously.

Table 3-6. Programmed and Scheduled (but irregular) activities: Visiting Hours by Healthcare Unit.

Visit Hours	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	1	2	3	4	5	6	7
1st Floor Admission	1	1	1	1	1	1	1	1	1															
2nd Floor S Trauma								1	1															
2nd Floor N Maternity									1	1	1													
3rd Floor N Pediatric								1	1															
3rd Floor S ICU					1				1															
4th Floor N General Surgery								1	1															
4th Floor S General Surgery								1	1															
5th Floor S Oncology								1	1															
5Th Floor N Private Ambulatory (2d max)								1	1	1	1	1												
6th Floor NS General Surgery								1	1															
7th Floor NS Private								1	1	1	1	1												
ICU					1				1															
ICU General					1				1															
Intermediate CU					1				1															
Psychiatry							1	1	1															
Neonatology (Pediatry)		1	1	1	1	1	1	1	1	1	1													
Kids under 10 as visits									1															

For purposes of this research, the organization and schedules presented above are considered nominal activities, or activities that are considered in the presumed hospital schedule. These nominal activities are planned activities and are thus programmed by the organization. In contrast, actual activities are those that are observed in reality, which may or may not be programmed or scheduled; therefore, they can differ from the presumed hospital schedule. Actual activities are observed in practice and are also captured by the video surveillance system. Theoretically, the difference between nominal activities and actual activities should be the unscheduled and the emergent activities. The challenge was to develop a methodology to collect behavioral data of sufficient spatiotemporal resolution to allow for the characterization of both nominal and actual activities, differentiating planned and scheduled from un-scheduled and emergent activity patterns. The hypothesis is that scheduled and unscheduled types of activities will influence the occupancy characterization of spaces, determined by the following two factors: (1) the hospital's fixed schedule and (2) the influence of the probabilities of un-scheduled and emergent activities. Accordingly, the specific research questions about the characterization of particular activity types will be led by the accuracy and resolution of the behavioral data collected, which, in turn, depends on the methods used for collecting it.

3.4 Defining the Micro-scenario

Therefore, in attempting to address the goal of characterizing the spatiotemporal occupancy of a healthcare scenario, this research is designed to recognize the influence of scheduled as well as unscheduled activities within an area of interest. This section presents the methods that allow this study to investigate in detail a real micro-scenario subset, separating spatial influences from activity-type influences on occupancy, beginning with a description of the selected micro-scenario of public corridors in the hospitalization units during a one–week period.

In defining the micro-scenario, the physical area of interest (corridors) as well as the temporal sub-sets (schedules) are considered as variables of the research that determine selected EBD outputs. Circulation spaces, such as corridors, are very well-defined and advantageous as proof-of-concept micro-scenarios for several reasons. First, they are public spaces, which means that they are accessible by every type of user, not only staff and patients but visitors as well. Second, corridor spaces have a single and straightforward assigned function of connecting one space to another space. As there is no other program or function associated with a corridor space, hospital corridors are frequently used for overflow of equipment and sometimes, in extreme conditions, even patients. Third, corridor spaces could be characterized by the features of its adjacent spaces, as it could become a supporting space for certain activities, such as meal service, medicine distribution, cleaning service, and linen distribution. The twelve corridors of the hospitalization wings meet the above criteria and present twelve almost identical and thoroughly comparable micro-scenarios, allowing a researcher to isolate the spatial, organizational, and programming variables. The goal is to study one of the hypotheses presented earlier in this chapter, i.e., If all corridor layouts are almost identical, what is the influence of non-spatial information on the occupancy patterns?

These 12 micro-scenarios are covered by the hospital video-surveillance system, permitting the collection of data for the scene analysis necessary for this research.

3.5 Summary

The goal of this chapter was to present the research design in the context of a healthcare scenario. First, a strong program scenario was selected for the purpose of reducing the number of variables involved in the occupancy distribution. Second, a strong healthcare program was selected based on the evidence produced by the EBD and spatial analyses fields and the interest that healthcare has received because of its organizational complexity and its effects on people's well-being. Third, because of challenges in developing methods for achieving a characterization of occupancy, the main goal of this research, the scope of this research was restricted to a proof-of-concept scenario.

The third section of this chapter introduced the specific proof-of-concept scenario chosen for this research – the hospitalization corridors of the navy hospital. The scenarios were described from the spatial as well as the non-spatial perspectives, incorporating the main spatial and organizational parameters into the scenario analyses, such as layout organization, , program spatial distribution, programming of activities, and personnel schedule; introducing the concepts of the nature of the activities as scheduled or unscheduled; and characterizing the corridors by their adjacent spaces. These concepts help to construct the framework that defines the spatiotemporal occupancy characterization, articulating the two theoretical aspects of this research: architectural significance and technological applications. The next chapter presents a set of methods for obtaining the spatial and temporal occupancy data required to validate the framework.

CHAPTER 4

SCENE ANALYSIS COLLECTING SPATIOTEMPORAL OCCUPANCY DATA FROM SURVEILLANCE VIDEOS

Overview

This chapter presents the scene analysis methodology adapted and developed as part of this research to capture people's occupancy data from video surveillance cameras and store it for further analysis. These methods include acquiring and processing the surveillance videos to obtain spatial and temporal occupancy information automatically. After a brief review of scene analysis in the first section of this chapter, the second section, Video Acquisition, describes the process of collecting the videos from the existing surveillance system at the hospital, including the details of exporting and storing the resulting high quantity of data. The third section, Video Processing, describe two developments. First, it explains MATLAB's Computer Vision System's feature location algorithms utilized and adapted for recognizing and automatically extracting the position of people in each video frame. And second, it introduces the post-process of converting people's position-in-frame data to people's position-in-corridor data, i.e., the spatial and temporal coordinates of people's occupancy. The accuracy of these methods and the precision of the spatial positioning data obtained will be presented in Chapter 5, which is dedicated to building the regression model of occupancy detection to explain the parameters that determine its accuracy.

4.1. Scene Analysis

Scene analysis was first introduced in Chapter 2 as the selected method for automatic indoor positioning because several of its technical and social characteristics fit with the purpose of this research. Scene analysis refers to the set of methods developed for analyzing a scenario captured on video with the final purpose of recognizing features or objects by identifying structures and features of objects in a real environment and generating mathematical or symbolic information to 'understand' the results (Nalwa, Klette, 2014; Morris, 2004; Shapiro and Stockman, 2001; Jähne and Horst Haußecker, 2000). Scene analysis methodology consists of three stages: video acquisition, video processing, and video analysis (Figure 4-1). The first two stages are presented in detail in this chapter, while video analysis is presented in the next chapters.

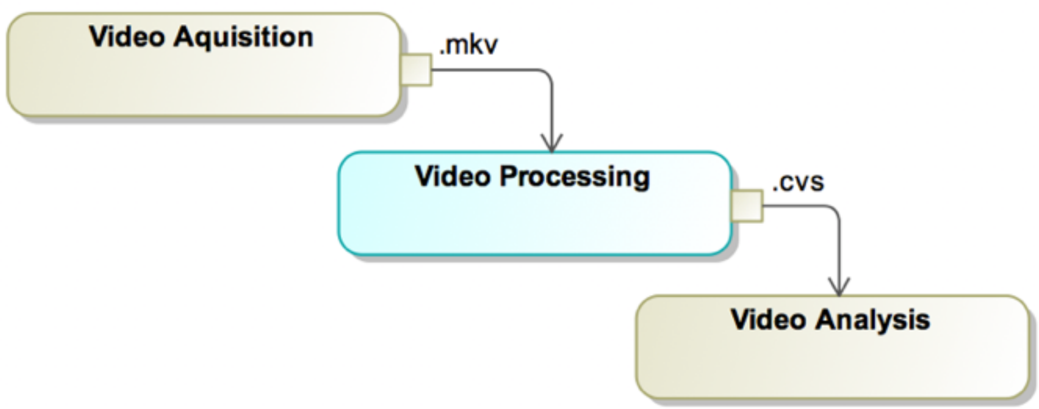


Figure 4-1. Scene analysis consists of three stages: video acquisition, video processing, and video analysis.

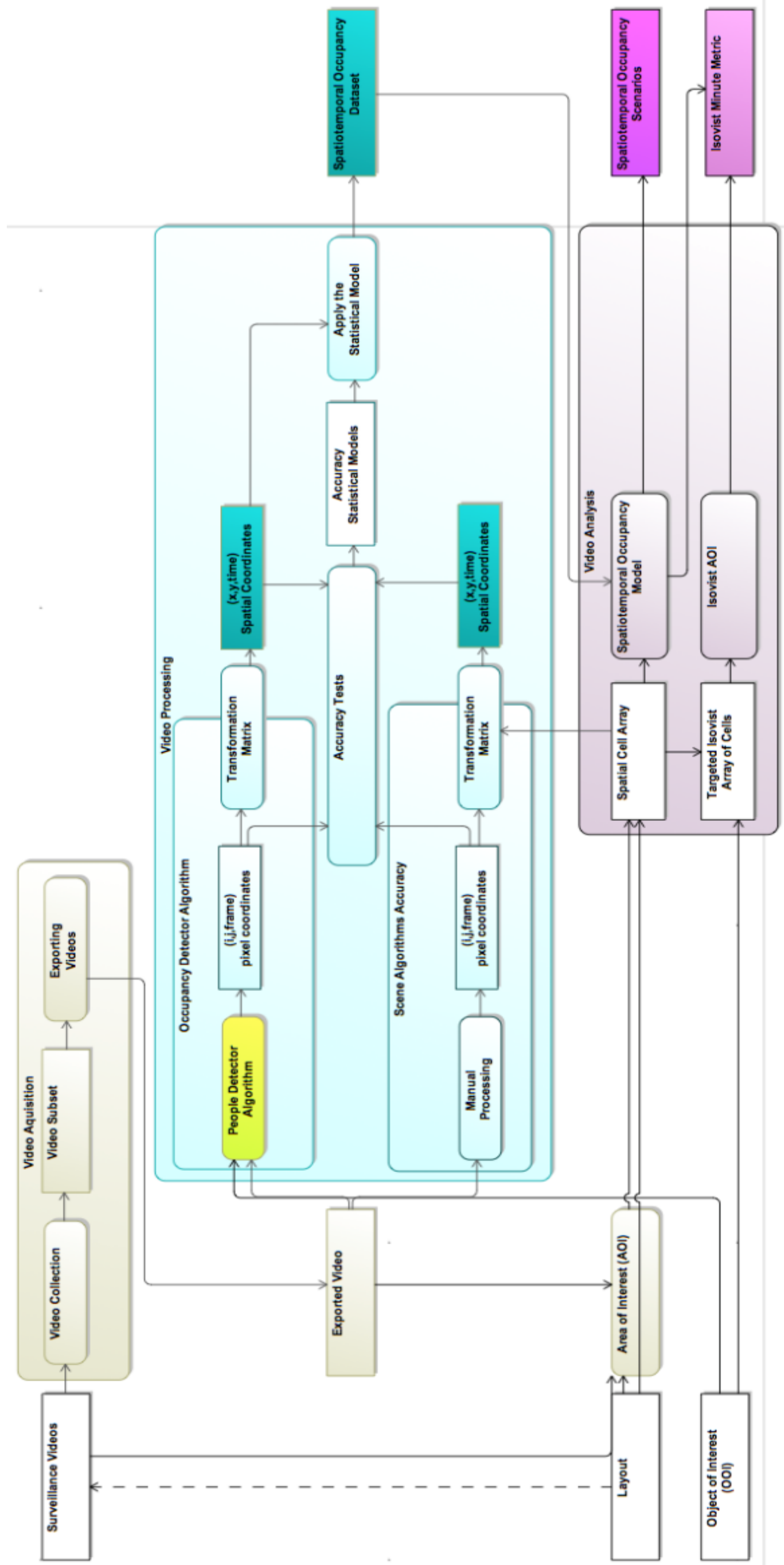


Figure 4-2. Detailed Activity Diagram of the Scene Analysis, from the Surveillance Video Input to the Spatiotemporal Model output

4.2. Video Acquisition

This section describes the existing hospital surveillance system, the process of collecting the surveillance videos obtained from the system, and the details of accessing and exporting such data, including the protocols for controlling privacy. The selection of the video surveillance files to be analyzed for this research must also consider the areas of interest and the objects of interest, as well as variables such as the process of selection and storage of the video surveillance datasets and the appropriate exporting format for video processing.

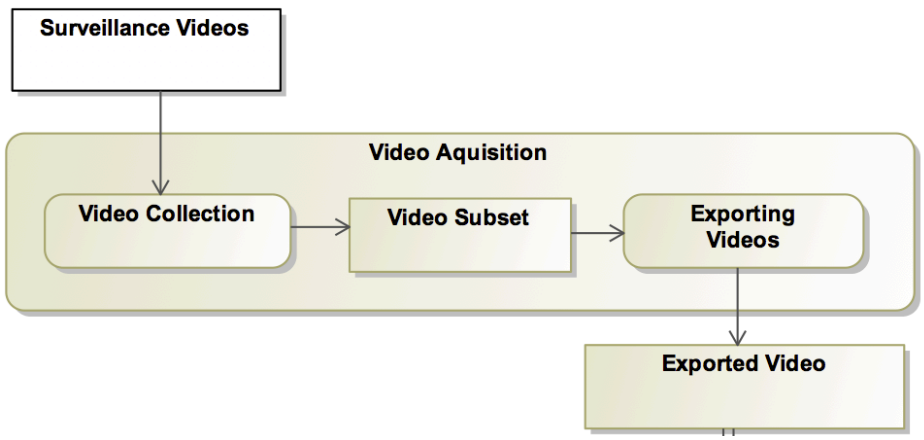


Figure 4-3. Video Acquisition subset of the Activity Diagram, including the Surveillance Video and Layout inputs.

Hospital's Surveillance System

As discussed in Chapter 2, one of the objectives of this research is to rely on a passive, as well as non-pervasive, technology in order to maintain social acceptance and low pervasiveness due to familiarity of users with the 5-years surveillance system, and therefore collect data as close to reality as possible by capturing every single participant who transits through the areas of interest. Consequently, this study uses the existing hospital surveillance videos as the source for evidence collection. For this research, the hospital granted access to only one of its servers, which stored video surveillance from twelve cameras that ran twenty-four hours a day for one week during the winter season, a high demand season for healthcare systems. These 12 cameras correspond to the ones located in the public corridors of the Hospitalization Building.

The surveillance system utilized by the hospital relies on Milestone XProtect, an open platform IP video management software (VMS). Milestone systems offer a range of software and hardware for easy-to-manage surveillance systems. The hospital's entire surveillance system consists of forty-one cameras, which are administrated by two Milestone systems, XProtect Essential and XProtect Professional (www.milestonesys.com).The first system supports up to 26 connected cameras per recording server, while the second one supports up to 64. Each system requires two independent servers (A and B) with one and two terabytes (TB) to store one and two weeks of data, respectively. Each database consists of 24-hour video surveillance (1.73GB each in average), stored as a PQZ database file and a set of .PIC images, starting at 12:00:00 and ending at 11:59:59. Each video database file is stored in a folder, created specifically for that day, with one subfolder for each camera. The folders are replaced by the end of their recording period (one or two weeks depending on the system) and the previous file is overwritten. For example, if the system records one week of video surveillance, the previous six days of complete surveillance video will be stored, along with the current day's videos. At noon of on that day, Monday for example, the prior week's Monday folder will be overwritten, and the same overwriting process occurs each day of the week. Beside the cameras and the servers, the surveillance system also includes the presence of one or more observers, who monitor the total number of cameras in real-time in a monitoring room located in a different building. When the observers visually detect a security "event," they copy the content of that folder onto another server. For this research, the hospital decided to grant access to footage that does not contain such events. Additionally, the hospital granted consent to store the videos on the condition that all institutional review board (IRB) regulations were met and that ethical, safety, confidentiality, and privacy provisions were guaranteed by secure and confidential handling of the videos. Therefore, the videos were recorded on an external hard drive and access was granted only to the researchers participating in this research, by way of password authentication and other restrictions. IRB regulations also require the deletion of original videos once the research is completed (see Annex A).

Selecting and Acquiring Video Datasets

For this research, the video acquisition consisted of one week of stored videos, from a Monday to a Sunday, during midwinter, the healthcare high traffic season. The surveillance footage was first stored on server A, in twelve files per day (one per corridor), which correspond to the collection of twenty-four hours of video files per camera. In total, this research had access to 84 video database files. The size of each video database depends on the video resolution and the amount of movement captured when motion-detection sensors actuate the recording. The list of the cameras and the correspondent hospital wings are presented in Table 4-1, and a correspondent visualization of them is presented in figure 4-4.

Table 4-2. Navy Hospital's Organizational Units by Floor

Floor North Wing	Unit	Floor South Wing	Unit
2N	Maternity	**2S**	Trauma
3N	Pediatric	**3S**	ICU
4N	General	**4S**	General
5N	Private / Ambulatory	**5S**	Oncology
6N	General	**6S**	General
7N	Private	**7S**	Private

Figure 4-4. Collection of surveillance Cameras Views, from second floor (first row) to seventh floor (last row); North wings to the left and south wings to the right.

In order to store this amount of data, an external drive of 2TB was required. The Video Acquisition process took approximately 63 hours in total, using a USB 3.0 external hard drive. The transfer took eighty minutes per camera file, per day of recording, requiring approximately nine hours to transfer data from twelve cameras per day of video-recording. Since the entire week could not be recorded at once due to the folder overwriting function discussed in the previous section, two transfer sessions were scheduled, one on Thursday, to record data from Monday at 00:00:00 to Wednesday at 23:59:59 and another on Monday to record data from Thursday at 00:00:00 to Sunday at 23:59:59. These transfer sessions took about 27 and 36 hours, respectively. This strategy allowed time for reviewing the videos to determine if the files were corrupted before the folder was overwritten. Some corrupted files were found in the first two attempts at data collection, so the data in this research was acquired in the third attempt.

Exporting the selected evidence

XProtect Smart Client is an easy–to-use application that allows videos to be reviewed, selected, and exported from the native database and manages any Milestone surveillance system. Using XProtect Smart Client to export the videos presented many advantages as well as a few challenges. First, Smart Client provides an interface to visually review up to four videos simultaneously, increasing their speed up to 16x (Figure 4-5). Second, the application provides a calendar and a time stamp, which allow the selection of the date and the exact start and end times of the video to be exported (Figure 4-6). Third, the export time depends on several factors, such as the length of the video, the version of the system used, the video format, and the storage location. During the first tests, because this system was installed in the hospital a decade ago, the default player took about one hour to export one hour of video. Afterwards, the Smart Client application was updated and installed separately from the rest of the system on a different computer. The decision to use a separate computer reduced the export time to 15 minutes. As more fully discussed below, the .MKV format of the video was selected for exporting based on its export time and file size.

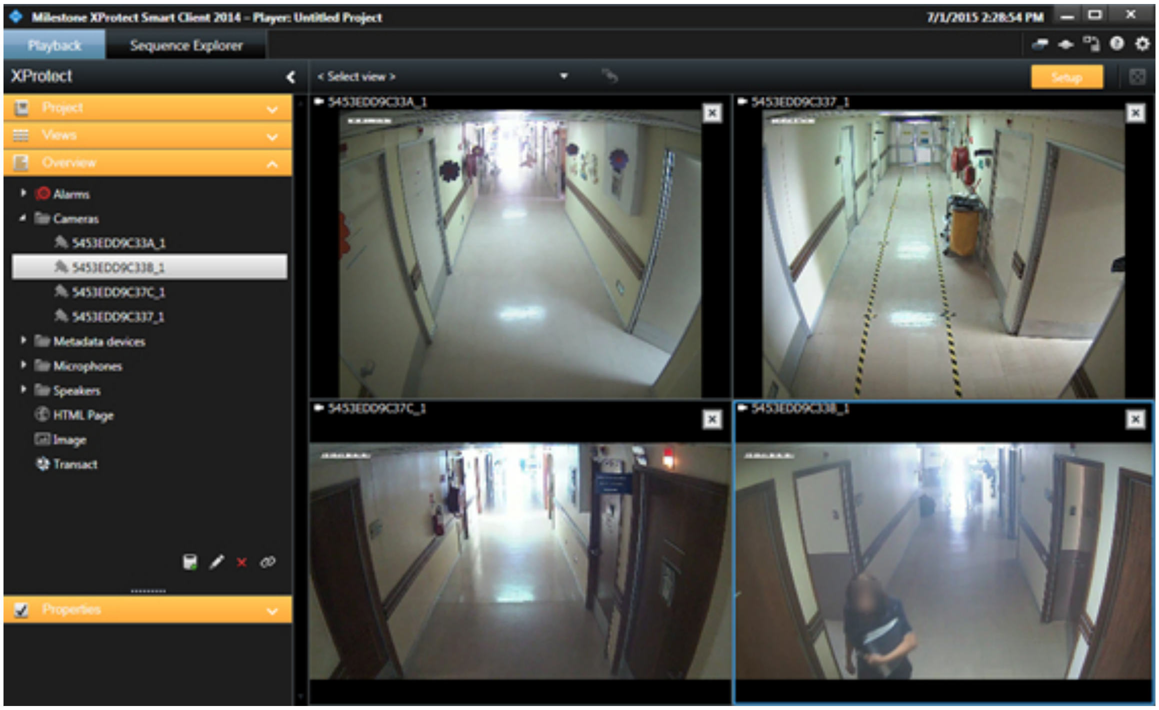


Figure 4-5. XProtect Smart Client application screenshot, showing the original surveillance database import process. Camera name is highlighted in the left column.

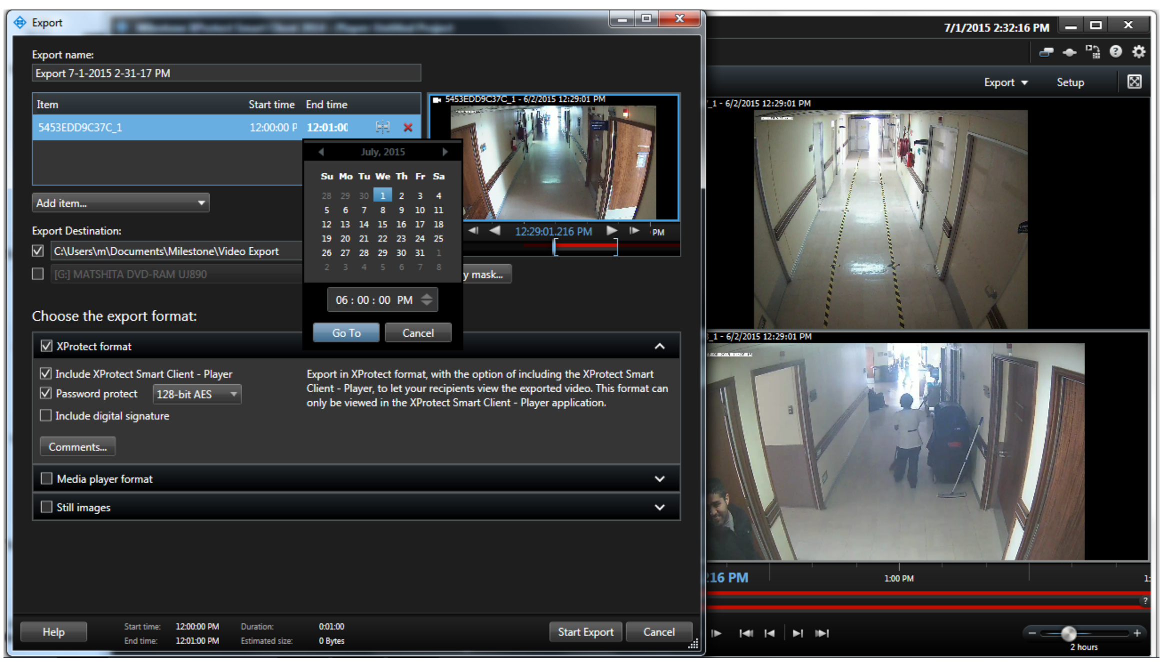


Figure 4-6. Screenshot of the XProtect Smart Client application showing the easy to use interface for exporting evidence by determining the exact date, time, and duration of the videos.

Video Format

The Smart Client application supports JEPG, AVI, and MKV export formats for images and videos, respectively. JPEG is an acronym for the Joint Photographic Experts Group, which created the standard. AVI stands for Audio Video Interleaved, a multimedia container format introduced by Microsoft in 1992, and .MKV stands for Matroska Multimedia Container, an “open standard free container format” that can hold several videos, audios or pictures in one file. To give a sense of the comparable file sizes, a one-hour video exported in JPEG pictures is about 2.5 GB; a one-hour AVI video-only file is approximately 5 GB depending on the amount of frames per second (fps) exported, the movements recorded, and light changes; and a one-hour .MKV video-only file, with the same ambient conditions, is almost 1 GB, about one fifth the AVI file. All videos were exported as .MKV files, in their original size, due to the file sizes and the characteristics of the data necessary for processing the exported videos. Afterwards, for the Video Processing stage, the videos were imported into MATLAB (matlab.com) as inputs for the automatic occupancy detector algorithm, providing the opportunity to modify their sizes for normalization purposes.

4.3. Video Processing

The final goal of video processing is to obtain people’s positions in space and time (x, y, time). Video processing is composed of the following three stages: the “automatic occupancy detector” algorithm, the “video observation detection” method, and a post-stage of location data processing. The three stages include adapting and developing algorithms for obtaining people’s occupancy with high spatial and temporal resolution from the video files. To facilitate a complete understanding of video processing, this section begins with a description of computer vision and the functions that concern this research.

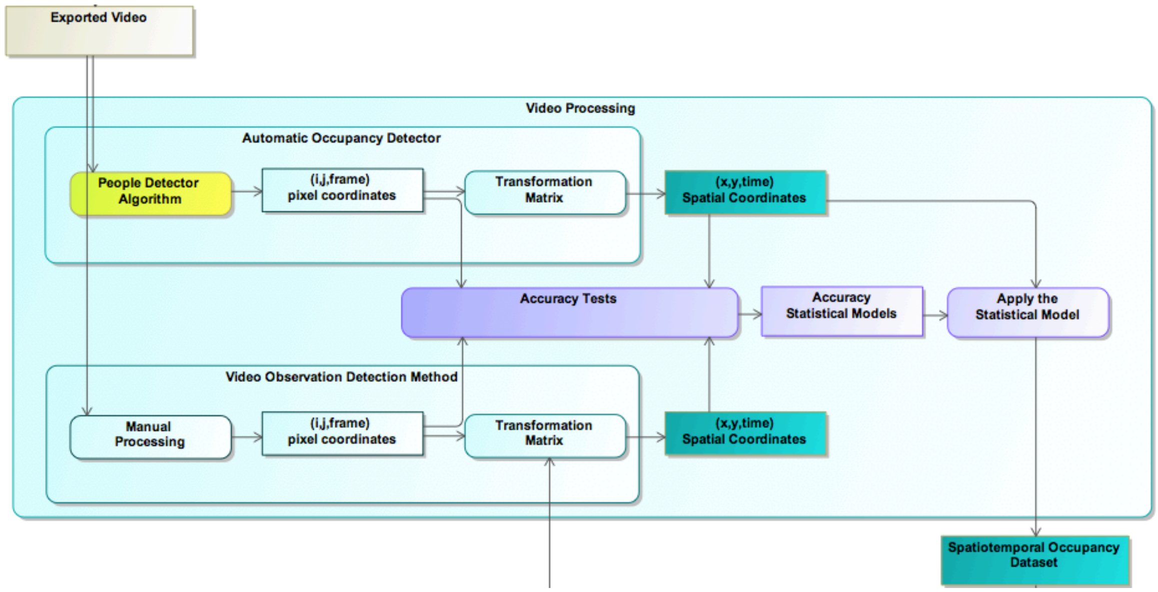


Figure 4-7. Activity Diagram of Video Processing including Automatic Occupancy Detector Algorithm and Scene Accuracy.

Computer Vision in MATLAB

Scene analysis methods rely on computer vision, which refers to the "understanding" of digital images or videos. Computer vision works by computationally recognizing meaningful patterns of categories of images and by utilizing certain statistical methods (such as classifiers) to "understand" and "predict" those patterns. The final purpose is to recognize a feature or an object by classifying it as one of a category. While computer vision relies on the fundamentals of image processing, it also has algorithms to detect, identify, classify, recognize, and track objects or features through a sequence of images (www.mathworks.com/videos).

The field of computer vision has been attractive to researchers due to its fundamental goal of understanding and interpreting human perception by learning and building models about the real world; however, computer vision's biggest challenge has been to recognize three-dimensional objects from a set of two-dimensional images. While it is currently a very active research area, the origins of computer vision dates from the 1960s, and some classical areas of its application include tracking, robotics for identification and description of objects, aerial images for improving images and espionage, astronomy for chemical composition, medicine for diagnoses and procedures planning, chemistry for molecular composition, and atomic physics for finding new particles and identification of tracks (Ballard and Brown, 1982). Recently, computer vision has been flourishing in several areas due to the number and variety of problems that are about to be potentially solved by its technological advances (Forsyth and Ponce, 2003). Architecture research, however, is a relatively new area for computer vision applications. Only a few studies have used some of its methods to relate human movements with space (Tomé and Heitor, 2012, 2013 and 2015 a and b; Romero et al, 2008). These studies were exhaustively reviewed in Chapter 2, where the social and technical reasons for using the scene analysis approach were described.

Computer vision algorithms are not bound to a specific programming language. Open Source Computer Vision (Open CV) provides a library of programming function that is mainly aimed for real-time Computer Vision. It has C, C++, Java and Python interfaces and supports Windows, Linus, Mac OS, iOS and Android (http://opencv.org/). However, due to the focus of this thesis is on the overall methodology and not on the detection algorithms improvement, MATLAB presents a robust platform for the required functions for several reasons. First, the language allows object-oriented programing design and does not require programming low-level tasks like “declaring variables, specifying data types, and allocating memory” (www.mathworks.com). Second, MATLAB provides a complete range of computation methods for iterative exploration, design, problem solving and analysis, built-in graphics for visualizations and custom data plots, and interaction, allowing multidisciplinary collaboration. But more significantly, MATLAB also offers specific packages for specific tasks. Among these are the computer vision system toolboxes, which supply pre-built algorithms, functions, and applications for tracking and detection of features and objects for image and video processing. The Image Processing Toolbox “provides a comprehensive set of reference-standard algorithms, functions, and applications for image processing, analysis, visualization, and algorithm development.” (www.mathworks.com/products/image). In comparison, the Computer Vision System Toolbox (www.mathworks.com/products/computer-vision) provides algorithms, functions, and applications for the design and simulation of computer vision and video processing systems.

Image processing has some key features such as image analysis including segmentation, morphology, statistics, and measurements; image enhancement , filtering and de-blurring; image geometric transformations and intensity-based image registration methods; image transformations; Large image workflows, including block processing, tiling, and multiresolution display; Visualization apps, including Image and Video Viewer; and Multicore- and GPU- enable functions, and C-code generation support (www.mathworks.com/products/image/features). The Computer Vision System’s capabilities include object detection and tracking; training of object detection, object recognition, and image retrieval analysis; camera calibration for single and stereo cameras; 3D point cloud processing and video processing. It also includes video display, and graphics, video file I/O, feature detection, extraction and matching, and C-code support generation (www.mathworks.com/products/computer-vision/features). This research will focus on the feature-detection and tracking capabilities, including the Viola-Jones, Kanade-Lucas-Tomasi (KLT), and Kalman filtering methods, as well as training of object detection, object recognition, and image retrieval systems, including cascade object detection and bag-of-features methods.

4.4. Object Detection and Tracking

Detection and tracking have captured the attention of computer vision and image processing researchers for decades. In computer vision terms, detection refers to the recognition of an object in an image by distinguishing its features through recognition of an abrupt change in pixel information, which corresponds enough to a significant incident in the scene to recognize a boundary or an edge. Detection relies on “matching, learning, or pattern recognition algorithms using featured-based techniques, including edges, gradients, Histogram of Oriented Gradients (HOG), Haar wavelets, and linear binary patterns." (Haar wavelets, and linear binary patterns). Tracking focuses on the detection of moving objects in a video from a static camera. It has several applications such as activity recognition, traffic monitoring, and automatic safety (Yilmaz, Javed and Shah, 2006). It uses a subtraction background algorithm based on Gaussian mixture models, eliminating background noise. Later, it applies blob analysis to detect groups of connected pixels (Sookman, 2006). Object detection and tracking enable a researcher to do more than what was traditionally achievable with image processing. While image processing has supported object detection for a long time, it uses two primary techniques, blob analysis and template matching. Blob analysis works well when an object can be found by segmentation and followed by measurement of the segments' properties. However, it does not work well in more complicated images where segmentations are difficult or there are different types of objects. Template matching searches for a match using a normalized cross-correlation that measures similarities of series. Commonly used with machine vision, it does not present a robust method for detecting rotation, occlusion, or changes in object size.

Feature-based and Learning Algorithms

The feature-based object detection model uses a reference object, detects its features, and matches them on the scene, extracting the object. Feature matching is similar to, but more robust than, template matching, since it is able to overcome occlusion, scale and rotation issues. The algorithm reduces an object's dimensions by representing only its important features, estimating their geometric transformation (for which it needs seven points). To locate the transformed referenced object, Random Sample Consensus (RANSAC), an iterative method used to "estimate parameters of a mathematical model from a set of observed data." (Martin A. Fischler & Robert C. Bolles, 1981), is applied. RANSAC traverses the features found and creates a geometric model to locate the specific region of interest in the image, discarding outliers. Features and descriptors are fundamentals used by many computer vision algorithms, such as image registration, object detection, classification, tracking, and motion estimation. Object detection recognizes a group of features by using both matching and RANSAC; however, it is limited since it does not refer to a general categorical object detection.

Categorical Object Detection

To detect more general types of objects, such as faces in general, regional descriptions plus machine learning or classifiers, are integrated together. Learning or supervised algorithms, as the names state, “learn” from observations by identifying patterns. The more observations the better the performance. “Specifically, a supervised learning algorithm takes a known set of input data and known responses to the data (output), and trains a model to generate reasonable predictions for the response to new data.” (http://www.mathworks.com/machine-learning).

Category detection is commonly used for content-based image retrieval, people detection, face recognition, texture classification, and video stabilization. In this research, the occupancy detector is based on MATLAB’s vision.PeopleDetector System object (“PeopleDetector”), a learning algorithm that was adapted and tested for detecting standing people in space. In this research scenario, this algorithm demonstrated a better detection rate when some of its properties were adapted. The Computer Vision System Toolbox comes with several pre-trained classifiers that use the Viola-Jones algorithm (Viola and Jones, 2001, 2004 and 2005) for detecting faces, upper bodies, and standing persons, among other objects. “However, these classifiers are not always sufficient for a particular application,” and they must be trained (www.mathworks.com/help/vision/ug/train-a-cascade-object-detector). The cascade object detector is the general learning algorithm, which can be trained using the “trainCascadeObjectDetector”, which allows for training a custom classifier. An example of a classifier is “People,” which is stored in a classification model. (Please refer to Annex B for Training sessions).

PeopleDetector includes a classification model ("UprightPeople_128x64" or "UprightPeople_96x48"), which is composed of the images used to train the models. The numbers refer to the size of the bounding rectangle that inscribes the person, including the background pixels around one person, and, therefore, the size of the detected person is always smaller than the training size (i.e 128 x 64). A classification threshold is a tunable positive value, which typically ranges from 0 to 4, that "controls whether a subregion gets classified as a person. The higher the threshold value, the more stringent the requirements are for the classification." When there are many false detections, the value should be increased.
(http://www.mathworks.com/help/vision/ref/vision.peopledetector-class.html).

"MinSize" and "MaxSize" are also properties of PeopleDetector. Together they comprise a two-element [width, height] vector, which refers to the smallest and largest regions containing a person. Where they are not specified, the detector sets the minimum as the region used to train the classification model and the maximum as the entire image. MinSize and MaxSize values are tuned to reduce the computation time. Additionally, the "ScaleFactor" property consists of a numeric value greater than 1.0001, which "incrementally scales the detection resolution between MinSize and MaxSize. . . . Decreasing the scale factor can increase the detection accuracy. However, doing so increases the computation time." With the exception of ScaleFactor, all values are in pixels. "WindowStride" is another two-element [x, y] vector that specifies the number of pixels the detection window will slide across the image in x and y directions. "Decreasing the window stride can increase the detection accuracy. However, doing so increases computation time. Increasing the window stride beyond [8 8] can lead to a greater number of missed detections." And MergeDetections and SelectStrongestBbox controls duplication of similar detections (http://www.mathworks.com).

Classification Models

"ClassificationModel" is a trained cascade classification model specified as a Comma Separated Values (CSV) pair consisting of ClassificationModel and a string, as follows:

```
detector = vision.CascadeObjectDetector(Name,Value)
```

The "vision.CascadeObjectDetector" ("CascadeObjectDetector") detects object categories with an aspect ratio that does not vary significantly, such as stop signs, cars from the side, people's facial features (e.g., noses, eyes, or mouths), or upper bodies. The detector creates a system object and configures it to use the custom classification model specified with the XML file (human and machine readable) input. The CascadeObjectDetector detects objects by traversing the image with a detection window to determine whether it contains the object of interest. Because the aspect ratio of the target should not change much, training a single detector sometimes does not work with 3D rotations. The detection classification model can be trained with a determined object of interest using the trainCascadeObjectDetector model, explained later in this chapter.

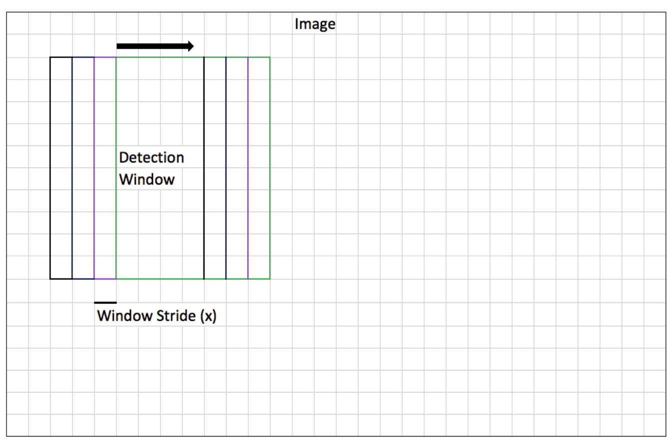


Figure 4-7. Vision.CascadeObjectDetector process, where the detection windows slide through the image (represented by cells), in a Window Stride range determined by the number of pixels.

The object of interest to be detected and tracked is defined by the specific research goal. In this research, the object of interest is people occupancy, which is the physical presence of a person; therefore, the occupancy detector is essentially based on PeopleDetector.

4.5. Automatic Occupancy Detector

Collecting great amount of high resolution occupancy information is one this thesis objectives, therefore the automatic “Occupancy Detector” algorithm was developed based on MATLAB’s Computer Vision package described above, specifically, based on People Detector. *Occupancy Detector* inputs the hospital’s surveillance footage, and outputs spatial and temporal information of people’s occupancy in the corridor space (x,y,time) in a Comma Separated Value (CSV) format (see figure 4-8). The following section describes in detail the Occupancy Detector algorithm and its adaptations for this specific scenario, from the input to the outputs, in a sequential order following the activity diagram (figure 4-8).

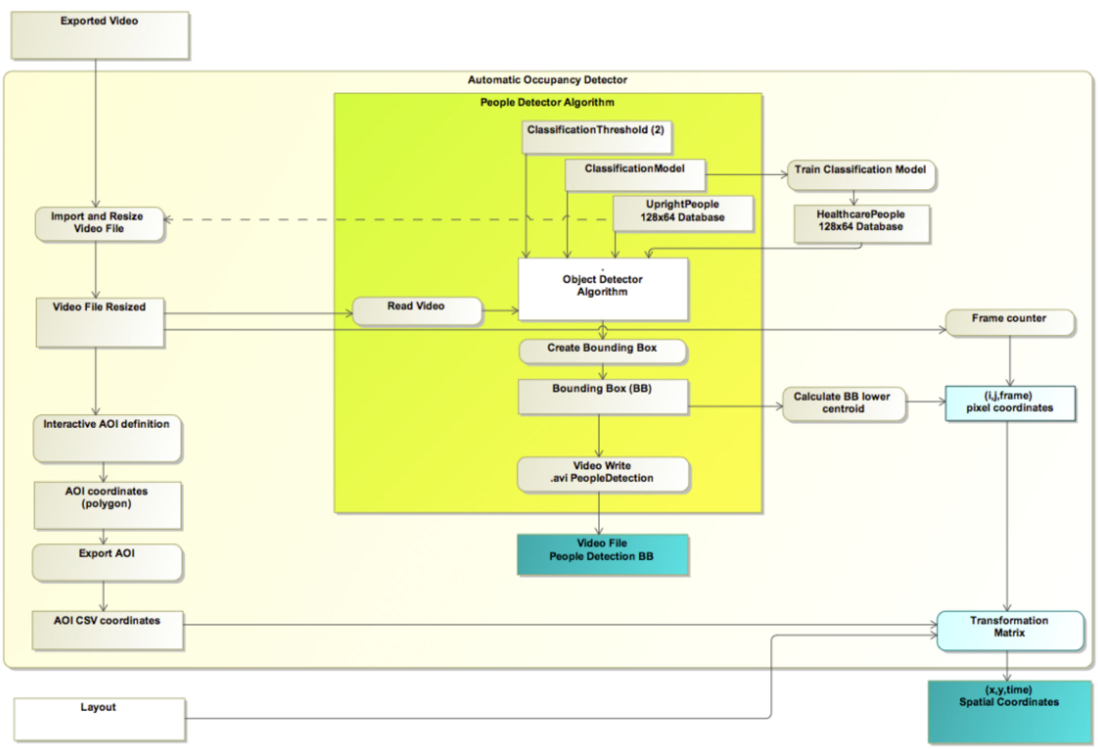


Figure 4-8. Activity Diagram of Occupancy Detector Algorithm. The two main inputs are the Exported Video and the Spatial Layout. The diagram also indicates the core “Object Detector Algorithm” in yellow; and the 3 key outcomes: Video File detection, Positions in pixel coordinates, and Spatial Coordinates in dark cyan.

Video input

As mentioned above, the videos were exported in .MKV video format, in their original size, and stored in one folder. Each video corresponds to one hour of video in one level and wing of the hospital. During the video processing stage (figure 4-7), the videos were imported in sequence into an automatic occupancy detector, using MATLAB's "VideoReader" function. The automatic occupancy detector algorithm produces a set of spatial occupancy data that corresponds to a one-hour video and that is stored in independent CSV files. The CSV output files are named by the hospital's level and wing and by the hour of the day that corresponds to the video, for example "2N_1800", for the second level North wing, from 18:00:00 to 18:59:59.

People Detector

As its name indicates, PeopleDetector is a system object that detects upright people using "HOG features and a trained support vector machine (SVM) classifier" (http://www.mathworks.com/help/vision/ref/vision.peopledetector-class.html). People detection is based on "object detection," which "identifies instances of category of objects, using feature-based and learning models, such as image segmentation using background subtraction and blob analysis. Object detection is commonly used for image retrieval, face detection, tracking, security, surveillance, and automated vehicle parking systems." (http://www.mathworks.com/discovery/object-detection.html). For the human body figure, the distribution of features is based on the appearance of a human body, creating a model. This model can be built for the entire body or just parts of it, such as upper bodies or faces, using blob-based models. The tracking of articulated body parts is possible, but it requires more complex, efficient, and specialized tracking algorithms (Han, 2016). For purposes of this research, `peopleDetector = vision.PeopleDetector(MODEL)`.

PeopleDetector distinguishes people within a rectangular search region, or ROI, which must be specified as a four-element vector [x, y, width, height]. The properties of PeopleDetector are properties of a feature-based as well as a learning algorithm.

Classification Model and Classification Threshold

In order to calibrate the automatic people detector algorithm toward its most accurate detection capacity, different classification models and classification thresholds were tested for different corridor scenarios, and the best combination was selected after a few tests. First, both pre-defined classification models that comes with the Computer Vision System package, UprightPeople_128x64 and UprightPeople_96x48, were tested.

The test consisted of a one-minute video, changing the classification threshold from value 1 to value 5, using both classification models. The recognition rate based on false positives (Type I error, when something else is recognized as a person) and false negatives (Type II error, when the presence of a person is not recognized) was as follows:

Table 4-1. Vision.CascadeObjectDetector process, where the detection windows slide through the image (represented by cells), in a Window Stride range determined by the number of pixels.

Classification Threshold	**'UprightPeople_128x64'**	**'UprightPeople_96x48'**
1	1,104	23,787
2	217	3,326
3	35	209
4	0	7
5	0	0

A test involving 1170 frames was run to determine the optimum classification threshold and classification threshold for this scenario conditions. While the smaller MinSize of the images (96x48 pixels) together with a lower classification threshold (1) produces more recognitions, it also produces more false negatives. The 'UprightPeople_128x64 and classification threshold with a value of 1 produces more false positives, recognizing doors as people. The same model with a classification threshold with a value of 3 does not accurately recognize people with matching-background color cloth, such as nurses. Also the same model with a threshold value of 4 and 5 does not recognize people at all. The most accurate results were obtained utilizing the default classification model UprightPeople_128x64 and the classification threshold with a value of 2.

Occupancy Coordinates

PeopleDetector performs multiple scale object detection on each frame (RGB image), returning an M-by-4 [x, y, width, height] matrix, defining M as the number of bounding boxes (bbox), each of which circumscribe one detected person. PeopleDetector also returns the confidence value for the detections. The bbox represents people detected within an ROI in pixel units. For occupancy, the detection information is extracted from the bbox as occupancy coordinates [i, j], which correspond to the position of people's feet in pixels (see figure 4.10), calculated as

$$[\, i,j \,] = [\, \text{bbox}\ (x) + \text{bbox width}/2 \ ,\ \text{bbox}\ (y) + \text{bbox height} \,],$$

where the bbox position is [x, y] in pixel coordinates and the bbox's dimensions are [width, height] in pixels. The occupancy coordinates should also include the timeframe, therefore its occupancy output is [*i, j, frame*]. The information is written into a CSV file, where the first two columns correspond to i and j information, and the third column corresponds to the frame number. If more than one person is detected in the same frame, the CSV file writes a new row with the information, repeating the frame number. This way, the CSV file is sequentially written row by row, taking in information from upper-left to bottom-right corner.

a *b* *c* *d*

Figure 4-9. a) Automatic recognition algorithm; b) Bounding box position (x,y, width, height); c) Calculation of horizontal occupancy (i = bbox (x) + bbox width/2); d) Calculation of vertical occupancy (j = bbox (y) + bbox height); e) Area of interest represented by magenta area.

Occupancy Spatial Coordinates

To transform occupancy coordinates [i, j, frame] into occupancy spatial coordinates [x, y, time], it is necessary to determine the physical area of interest – the corridor – by determining the four corners of a polygon that contains it in the image (see Figure 4-11, 4-13).

Figure 4-10. Activity diagram of the transformation of pixel coordinate position (i,j,frame) to spatial coordinate positions (x,y,time).

The transformation of the pixel coordinates to real spatial coordinates is done by using a projective transformation. Projective transformation supports nonisotropic scaling in addition to translation and tilting. The transformation matrix is calculated using the location of the four corners of the polygon to be transformed as first input, as well as the four points of the expected transformed polygon. The real physical dimensions of the corridor are seven feet in width by 120 feet in length. The physical area of interest will be represented from now forward, as a bi-dimensional array of 7 by 12 cells, of 1 by 1 foot each, as shown in Figure 4-12).

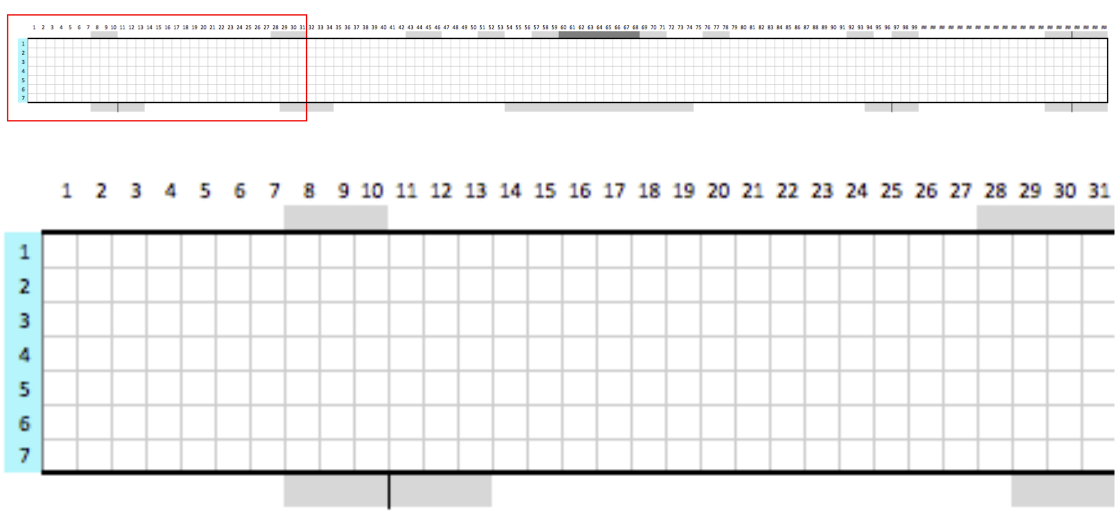
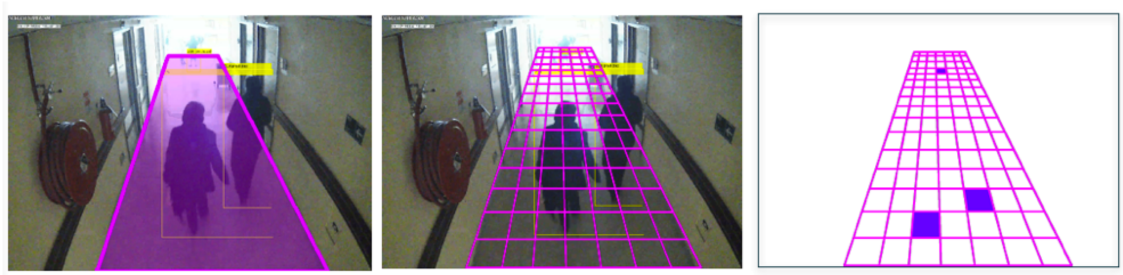


Figure 4-11. 2D cells array representing a corridor of the hospital. Gray areas next to it represents openings such as door (light gray) and open areas (darker gray). The cyan mark to the right represents the access to the corridor from the core of the building.

The transformation script uses the “vision.GeometricTransformEstimator System object” (“GeometricTransformEstimator”), which computes the Transformation Matrix P from two sets of points, the projected area of interest and the real area of interest. The first set of points is stored as a set of coordinates in pixels [x1 y1; x2 y2; ...; xN yN], where N is the number of points. The second set of points is bounded by the corners of the real area of interest [i1 j1, i2 j2, i3 j3, i4 j4] in cell units, which in turn correspond to square feet. The ‘GeometricTransformEstimator calculates’ “projective, affine, or non-reflective similarity transformation using robust statistical methods, such as RANSAC and Least Median of Squares.” (www.mathworks.com/help/vision/ref/vision.geometrictransformestimator-class), expressed as TFORM = step (H,MATCHED_POINTS1, MATCHED_POINTS2).



a *b* *c*

Figure 4-12. a) Area of interest represented by magenta area; b) Cells array displayed in perspective in the image; c) Representation of occupied cells in perspective; d) Representation of occupied cells transformed to real spatial.

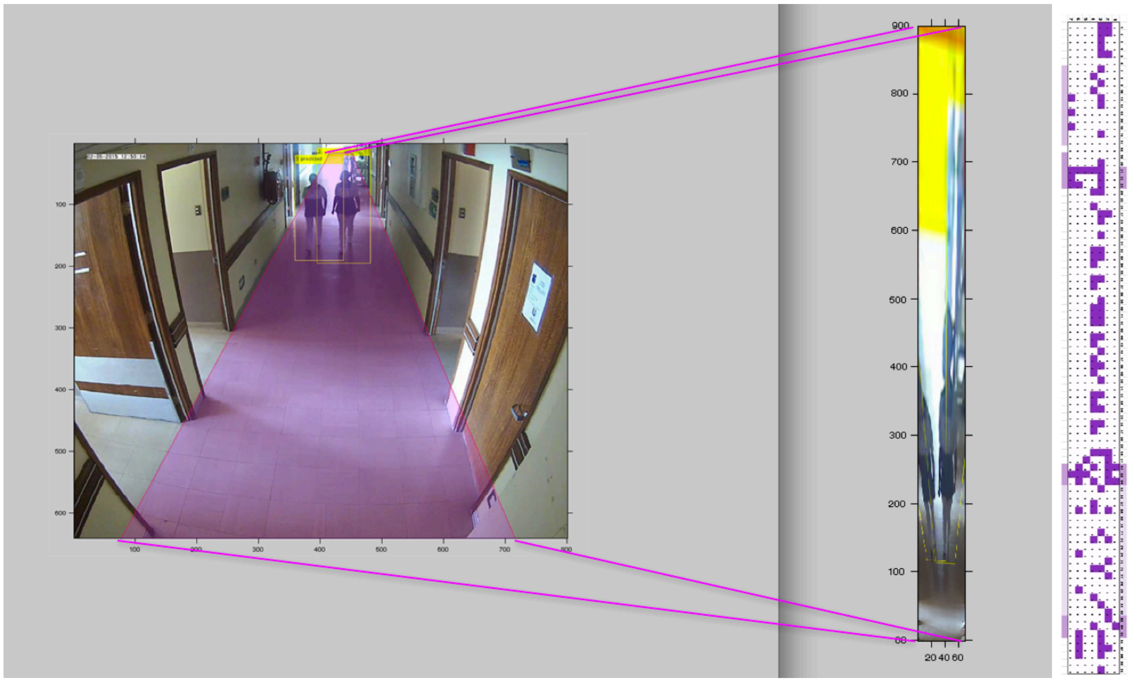


Figure 4-13. Transformation matrix applied to an image, and then modified to be applied to a bi-dimensional array transformation.

When the transform property is set to projective transformation, the output is a 3-by-3 matrix *(*geometrictransformestimator-class). The original occupancy data were first exported to a CSV file in pixel coordinates. The transformation matrix P was applied to the original CSV file to obtain a spatially transformed CSV dataset, corresponding to the corridor layout, in foot coordinates. Spatial coordinate writing in a CSV file is produced during the transformation, writing one row of information at a time. The “frame-to-time” transformation is a linear proportion between the frame number and the number of frames per second of the video (24.97). Both spatial and temporal information is clustered by ranges. Pixels coordinate to cells in feet and timeframes to time stamps in seconds. Since the pixels in the upper part of the picture represent a greater physical distance than the ones in the lower part of the picture, the occupancy accuracy is not homogenous along the corridor. The hypothesis is that the further from the camera, two types of error, recognition accuracy and position precision, increase.

Occupancy Analyses

In order to obtain accurate results, the research should study the influence of the scenario conditions, such as background or activity conditions, on the occupancy detector. These conditions are usually very specific to each scenario and their effect on the accuracy of the algorithm could be monitored, in order to find the precise variation for each scenario. With that goal in mind, “Video Observation Detection” was developed as a user interface application in MATLAB, to manually map the exact position of each person’s feet on the scene, creating a “truthful” or 100% level of confidence dataset. This approach involves a frame-by-frame video analysis.

After the 100% level of confidence dataset was obtained, it was compared to the automatically computed dataset, in order to measure the level of the algorithm’s accuracy, understand the output’s errors, and measure any differences. These differences, called accuracy and precision errors, are extensively explained in the next chapter. A later application of the spatial and temporal occupancy results will be presented in detail in Chapter 6, with the video analysis process, which offers an interpretation of the occupancy data automatically obtained from the methods presented in this chapter. The assumption is to find patterns of occupancy in space as well as in time, under some specific perspectives and goals, depending on the scenario. In this specific case, this scenario corresponds to a hospitalization building.

4.6. Practical Issues and Challenges / Discussion

This chapter presents a series of methods to capture occupancy, which presented a large number of technical and practical challenges, from data volume to accuracy of the results. This section presents the challenges by category. First, the volume of the data, which includes the number of cameras, the files storage and transfer capacity, the exporting process and computational requirements, the database sizes and manageable exported files.

As discussed earlier in this chapter, the servers stored up to 2-weeks of video surveillance due to the sizes of the server and the video databases, where each file correspond to 1-day video surveillance in one corridor. Therefore, the transfer to an external hard drive was challenging and had to be scheduled in 2 sessions, in two different days, since the transfer of files took longer than the speed of files replacement, making 1-session transfer impossible. 1-week videos used almost 1TB of storage, therefore the files were kept in an external hard drive. This decision made the export sessions longer, since the data was constantly transferred through a USB 3 cable. Sometimes, the exporting was corrupted, and it was necessary to re-do it. Another factor that impacted the exporting time was the XProtect surveillance application used at the hospital, which was not updated. The version used for this research was updated to make the exporting more time efficient. Due to the reasons explained above, plus the difficulty to manage large video files (i.e.12 hours), the length of the videos exported was restricted to one hour. Adding to those reasons the theoretical reasons of analyzing videos by scheduled activities, which are usually by hour, each 1-hour videos were analyzed independently.

Due to the aforementioned reasons, the number of video files exported increased to 288: 24 1-hour video files by corridor. The sizes and qualities of the videos vary depending on the camera calibrations and quality, and video resolution (1280x720, 1280x1024, and 768x576). Therefore, the algorithm had a resize calibration, in order to be able to compare the data outputs. The MKV video export format was decided because it allowed the smaller file version maintain the data quality. Naming the exported files became another issue at two stages. First, the video exported contained the corridor and initial hour of exporting, for example 6N-18000 correspond to level sixth, corridor north, recording from 18:00 hours to 19:00 hours, stored in a different folder by day. Afterwards, the occupancy data exported shared the initial name, and the frames started counting from 0 are stored in a 2D array. This becomes an issue again when merging 1-day of video in the Video Analysis stage, and it will be explained in the last chapter.

Furthermore, a number of details related to the algorithms' variables emerge. First, the differences in the surveillance camera lenses and video sizes, which depend on the camera type and quality since some cameras are as old as the installation of the surveillance system, and other (2) were replaced last year. This issue cannot be resolved in general for all the cameras, but for each camera in particular, where each field of view varies enough to modify the *Area of Interest* in pixels' coordinates, disrupting the outcomes. Therefore, for this case an input variable was added, storing the different *Areas of Interests* from camera to camera, as a set of coordinates points. The cameras quality also could impact the accuracy and precision of the data processed, therefore the accuracy tests should include different video sizes, defining the sub-physical-areas that allow higher level of confidence of the occupancy data.

A conclusion is that any surveillance video is able to produce occupancy data with the right levels of confidence, when run against the right classification model. Theoretically, the possibility of training the classification model allows the possibility of more accurate recognition rate, and also opens the possibility of train specific dataset to interchange the object of study, from generic person to a specific role person –nurses, staff, patients or visitors–, or to a specific object –such stretchers, carts, or wheelchairs, among others. In this specific case the training did not produced a better people detection classification model for general persons, as the number of images and the number of stages were much smaller and lower than the default dataset.

In this specific research, one could argue that ideal would have been to have had access to a higher number of cameras per area of interest. However, one of the arguments in Chapter 2 is about using existing pre-installed systems due to the pervasiveness of outside systems. Both constraints –the number of existing cameras and not adding external supplementary cameras– provoked to propose a way to "correct" the data accuracy under some conditions. The focus is not on having a perfect mapping of the current actual occupancy of this specific week, but constructing a statistical model that is able to simulate the probability of future results under the same environmental conditions, to be able to extrapolate the occupancy models. At this stage of the research, the question that arises is:

> *"What is the level of confidence on the spatiotemporal occupancy datasets obtained using the automatic methods?"*

By the time of this publication, Computer Vision will most probably have enhanced many of the recognition algorithms utilized in this research. However, the focus of this thesis is not the perfection of the computer vision algorithms themselves, but developing a consistent methodology for demonstrating the importance of such approach and application in Architecture research, proposing to expand the research about space use and occupancy.

4.7. Summary

This chapter has presented the first two stages of the scene analysis method developed to automatically process a set of videos to capture the occupancy data: video acquisition and video processing. First, video acquisition describes the process of collecting the dataset of interest from the hospital's existing video surveillance system. This section explained how the videos were collected and stored, including all the technical and practical challenges. Second, the video processing section includes the two methods implemented in MATLAB for collecting occupancy data, automatic detection and observation and mapping.

The automatic occupancy detector uses the Computer Vision System's feature location algorithms to automatically extract people's position in the video. This section explained the specifics of the occupancy algorithms, including the translation of people's location in the image to real spatial and temporal occupancy coordinates, including all technical and practical challenges. These challenges raise questions about the accuracy and precision of the occupancy data obtained, which introduces the next chapter of this thesis. The following chapter presents the accuracy and precision tests, the statistics behind the video processing, and introduces some of the findings of spatiotemporal occupancy. Video analysis, the third stage of scene analysis method, focuses on the spatiotemporal specific findings, which are introduced in Chapter 6.

CHAPTER 5

ACCURACY AND PRECISION OF AUTOMATIC OCCUPANCY DETECTION

Overview

The goal of this part of the research is to determine the accuracy and precision of the automatic occupancy detection method developed in this study, with the goal of improving the accuracy of the automatically obtained datasets. First, this chapter introduces an assessment of the accuracy of the scene analysis' automatic occupancy methods by comparing a sample of the automatic dataset, which was obtained using the methods described in the previous chapter, with a 100% confidence occupancy dataset obtained by observing and manually mapping people's location. Second, it presents an application specifically designed and developed in MATLAB that allows to observe the videos and manually map the location of people as well as environmental and activity related variables of the scene for further analyses on their impact on occupancy at both the data collection and occupancy outcomes levels. Third, the chapter introduces logistic regression, the statistical model selected to describe the accuracy and precision of the datasets based on the distance of the test subjects from the camera. For purposes of this study,"accuracy" refers to the percentage of correctly recognized people on the scene, while "precision" refers to the distance error between the actual position of people and the position automatically collected. Both errors are associated with environmental influential factors, algorithms, or dataset parameters that will influence the results; therefore, this study describes the accuracy by a multiple regression statistical model. The chapter concludes with a presentation of the probability surface of recognition, which will be utilized to improve the automatic occupancy dataset based on the location and scene conditions.

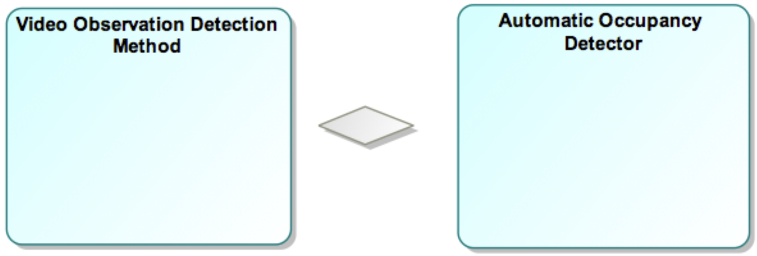
5.1 Accuracy and Precision

Over the past decades, the accuracy comparison and validation of the algorithms developed in the area of machine learning research have become increasingly important. The focus of these methods has been on the statistical comparison of two or more learning algorithms on a single dataset and more recently on multiple datasets. Demsar (2006) studied all the statistical analyses, published in the proceedings of the International Conference on Machine Learning from 1999 to 2003, to rank the classification accuracy of two or more algorithms against a single dataset or multiple datasets. Since “there is no established procedure for comparing classifiers over multiple datasets … researchers adopt different statistical and common-sense techniques to decide whether the differences between the algorithms are real or random.” (Desmar, 2006). Among them, the parametric (paired t-tests and ANOVA), the non-parametric (Wilcoxon signed-rank and Friedman tests), and the Sign test were compared, concluding that from the samples, non-parametric tests were preferred, since they do not assume normal distribution of variance and, “as such, they can be applied to classification accuracies, error ratios or any other measure for evaluation of classifiers, including even model sizes and computation times.” (Desmar, 2006).

This research compares the pre-built algorithms when using the default and trained classification models (please refer to Annex B) with the video observation-and-mapping dataset obtained manually on a sample of the almost identical twelve corridor scenarios presented in the previous chapter. The method for calculating the accuracy of the algorithms in this research has been adapted towards a re-formulated goal: understanding the factors of these specific scenario conditions that would impact the classification accuracy. The objectives are 1) to recognize the factors that would impact the occupancy detection results and 2) to provide a list of parameters to be considered for further algorithm developments. Furthermore, the research had a second objective of utilizing the same datasets to obtain the characteristics of the spatiotemporal occupancy, such as the occupants' roles, the activity they are performing, and their body posture.

These factors helped to construct a statistical model to compare the spatiotemporal patterns of occupancy within certain periods of time.

As described in the previous chapter, the automatic PeopleDetector algorithm was calibrated toward its most effective detection capacity by adjusting the specific variables of the script and functions, such as the “classification model” and “classification threshold” values, until the algorithm reached the highest detection accuracy and produced the desired results, minimizing errors for every scenario condition. Nevertheless, accuracy (Provost and Fawcett, 1997; Provost et al., 1998; Fawcet, 2006) and precision (Hofer, Straub, Koulechov & Dietz, 2005) must be measured to determine the level of confidence in the results. As noted above, accuracy refers to the percentage of the true values of recognition, providing a comparison between the detected and the observed in reality. Precision, in turn, refers to the distance between the detected person and his actual location, by determining the difference between location coordinates. The central hypothesis is that the accuracy and precision of the automatic detection algorithm will be higher the closer the target is to the camera and that errors would arise from environmental conditions or the database characteristics for object recognition when not modifying the parameters of the algorithms. To test the hypothesis, it was necessary to measure the detection accuracy by comparing the automatic occupancy dataset to an absolute or known occupancy. The absolute occupancy is defined as 100% accurate occupancy information and is considered the baseline for data occupancy. This baseline is obtained by observing the videos and manually mapping human location as shown there collecting pixel coordinates in the process.



Absolute occupancy ~100% <> Automatic detection occupancy x%

Figure 5-1. Comparison between Video Observation and Mapping outputs and Automatic Detection outputs.

5.2 Accuracy Process

The main goal of the "accuracy test" was to measure the accuracy of the data produced by the automatic algorithms developed in this study to capture spatiotemporal occupancy with high spatial and temporal resolution. The intent was to use these measurements to understand the spatial distribution of the algorithms' accuracy. The first objective was to obtain two comparable datasets, the "automatic occupancy" and the "manual occupancy" datasets, in both pixels (i,j,f) and spatial (x,y,t) coordinates. The second objective was to specify the aspects of the datasets that have an impact on the accuracy of the occupancy data in order to understand each aspect's relative influence on both datasets and the spatial distribution. The "video observation" and "mapping method" approach proposed herein combined two established methods: "video observation" and "observation and behavioral mapping", as presented and scrutinized in Chapter 2. Observation and mapping of a video allows the researcher to freeze the video, providing time for mapping occupancy either frame by frame or second by second, permitting the researcher to take as long as necessary to correctly map every person on the scene. Since the results can be undone and revised, the assumption is that this method offers 100% accuracy, and this dataset is utilized as the baseline for location detection in this research.

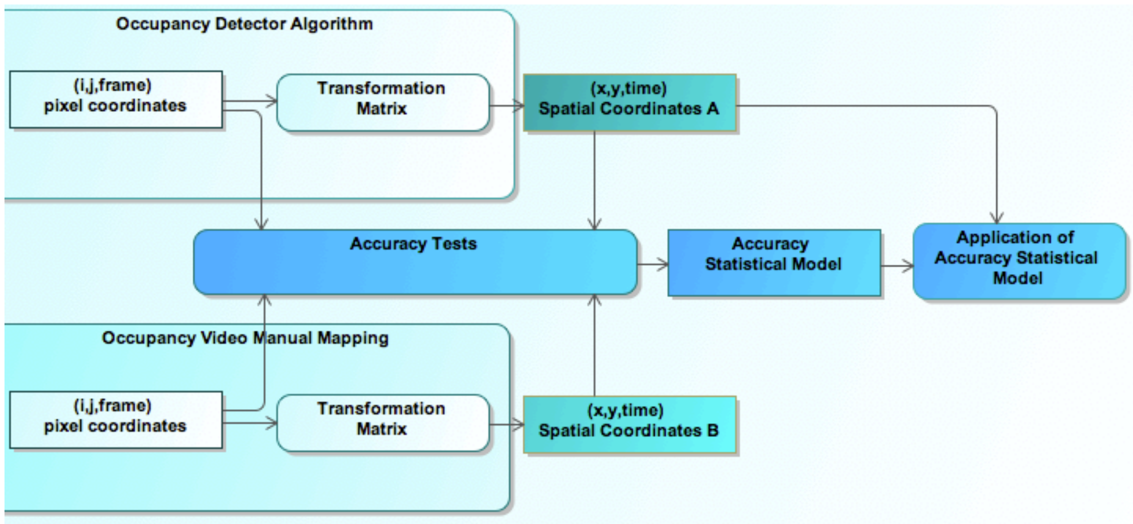


Figure 5-2. Accuracy test process shown in blue, along with its two necessary inputs and three stages: accuracy test, accuracy statistical model, and application of the accuracy statistical model to the occupancy data.

Accuracy Test

Accuracy test involves four sub-processes: (1) obtaining the automatic occupancy database, using the algorithms described in the previous chapter; (2) selecting a sub-set of random frames from the total database from specific one-hour time periods defined by the type of activities performed in order to characterize the scenarios; (3) observing and manually mapping occupancy and the environmental and the occupancy factors in the "Video Mapping" application developed in MATLAB for this specific purpose; and (4) comparing both occupancy datasets, by frame, using regression models to determine the recognition accuracy and the influence of the environmental and occupancy factors on the results. This section begins with an explanation of the process for selecting a statistically representative sample of frames.

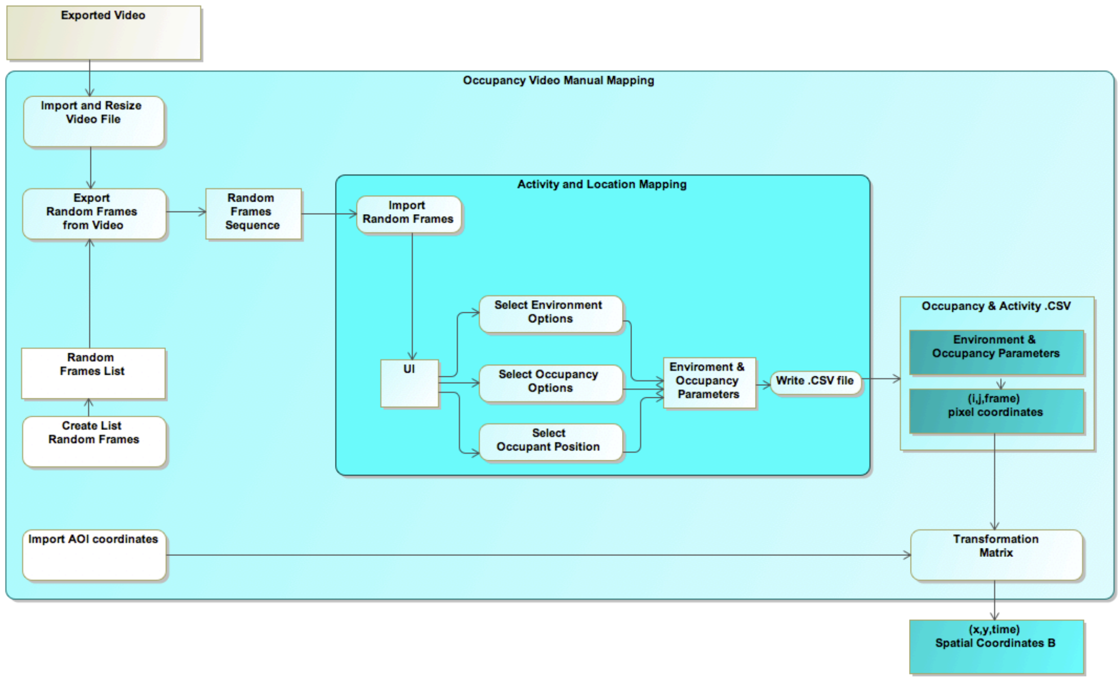


Figure 5-3. Activity diagram of the "Video Mapping" method for occupancy collection with 100% accuracy and precision. This method inputs a video and exports a Comma-Separated Values (CSV) file with spatial and temporal coordinates.

Accuracy Statistical Model

For both the one-minute and one-hour videos, this study selected a random sub-set of frames for performing the manual occupancy mapping, considering the desired occupancy confidence level in determining the appropriate sample size for both types of video. The confidence level options were 90%, 95%, or 99%, with an acceptable margin of error that varied from 1% to 5%, in increments of 1%. Because most advanced detection algorithms provide around a 90% confidence level, this study chose a 95% level of confidence (most common value), with +/-5% as an acceptable confidence interval (or margin of error), resulting in a sample size of 383 frames per hour of video recording (see Table 5-3. Summary of Classification Matrix calculations). This level of confidence is comparable to some indoor location positioning system technologies such as UWB, Infrared, or Ubisense, which have an accuracy of 90-95% and is similar the highest algorithm detection systems in scene analysis from surveillance cameras, multi-cameras, and hybrid environments, which have an accuracy of 80%-90% (see table 2.3).

$$ss = \frac{Z^2 * (p) * (1-p)}{c^2}$$

Where:

Z = Z value or margin of error (e.g. 5 for 95% confidence level)

p = Percentage of positive of negative values in a sample, expressed as decimal (0.5 in the worst case scenario)

c = Confidence interval, expressed as decimal (e.g., .05 = ±5)

Correction for finite population:

$$\text{New ss} = \frac{Ss}{1 + (ss-1 / \text{total population})}$$

Table 5-1. Alternative statistical calculations of sample selection based on various population sizes for accuracy tests. These calculations are based on http://www.surveysystem.com/sscalc.html

	Margin of error that is acceptable (+/- %)				
Population Size 108000 frames (1 hour)					
Desired Confidence Level (%)	**5**	**4**	**3**	**2**	**1**
90	270	421	746	1665	6365
95	383	597	1057	2349	8819
99	659	1027	1812	3994	14379
(24 hours video)					
90	6480	10104	17904	39960	152760
95	9192	14328	25368	56376	211656
99	15816	24648	43488	95856	345096
Population Size 86400 frames (1 hour)					
	5	**4**	**3**	**2**	**1**
90	270	421	745	1659	6273
95	382	596	1054	2336	8643
99	658	1024	1805	3957	13916
(24 hours video)					
90	6480	10104	17880	39816	150552
95	9168	14304	25296	56064	207432
99	15792	24576	43320	94968	333984
Population Size 3600 seconds (1 hour)					
	5	**4**	**3**	**2**	**1**
90	252	378	622	1151	2350
95	347	515	823	1441	2619
99	560	805	1219	1927	2958
(24 hours video)					
90	6048	9072	14928	27624	56400
95	8328	12360	19752	34584	62856
99	13440	19320	29256	46248	70992

The researcher first, selected a random sample of 383 one-minute videos for the automatic detection of people. Second, they added the one-minute videos together and randomly extracted 4608 total frames for video mapping, resulting in the collection of more than 7000 people location points. This process allowed the researchers to calculate detection accuracy by matching both datasets by frame number. For the first model, the data obtained was a sample of any environmental and activity types, resulting in aggregated results that described the overall healthcare micro scenario. For the second model, and to assure the representativeness of the activity types, the original surveillance videos were subdivided into one-hour videos, synchronized with the activities scheduled by the organization (presented in Chapter 2). Then, a sample of 383 frames for each one-hour video were randomly selected. Both samples represent a confidence detection level of 95% with a 5% margin of error.

For the first part of the study, 383 frames were randomly extracted from every one-minute video representing the global healthcare scenario conditions. This portion of the study focused on finding environmental or algorithmic causes of any detection errors. For the second part of the study, also 383 frames were randomly extracted from the one-hour videos, representing different activity scenarios. The required number of timestamps were randomly created in Microsoft Excel using the RAND function, selecting them from the total population size of 86,400 and 108,000 frames, respectively, which corresponded to the number of frames in each selection. Using the RANDBETWEEN function (1, PopulationSize), a list with timestamp values was created in a CSV format. Afterward, a one-hour video and the CSV list containing these numbers were imported into MATLAB for the purpose of generating a list of .jpg frames, indicating the name of the corridor, the hour, and the frame number as follows: FloorNumber – N or S – RNDframeNumber .jpg.

5.3 Video Mapping Application

The next stage of the accuracy test consisted of observing and mapping the location of people in the video frame, as well as annotating other environmental aspects.

With the aim of obtaining 100% accuracy in the occupancy data, the researcher implemented “video mapping” in MATLAB, which imported either videos or frames, displayed a user interface displaying the current frame to be analyzed (figure 5-3), and exported a dataset with the location information as well as other occupancy aspects that were relevant to this research. The final goal was to statistically explain the influence of these factors on the accuracy levels of the automatic “occupancy detection” algorithm.

For this research, the video mapping process was performed by a single researcher, who previously completed 40 hours of training based on a pilot study, using the same video cameras but different video samples. The goal of the training was to standardize the classification criteria relating to three conditions: 1) determining the exact location of a person, which was defined as the lower pixels located right under the feet closer to the camera, a decision that resulted in that an individual’s gait stand and swing phases (figure 5-4) would be interpreted as “jumps” in the occupancy data, not interpolating the position of the head; 2) determining the boundary conditions for aspect classifications, such as partial occlusion and occlusion (partial occlusion occurs when less than half of the body is occluded by another object, while occlusion occurs when half or more than half of the body is obstructed); and 3) defining the limits between classification groups such as determining when an activity or body posture changes. This factor corresponds to the human body’s center of gravity, initial propulsion for an activity, or posture change. (i.e., walking toward the camera versus away from it was determined when one foot was pointing in a different direction).

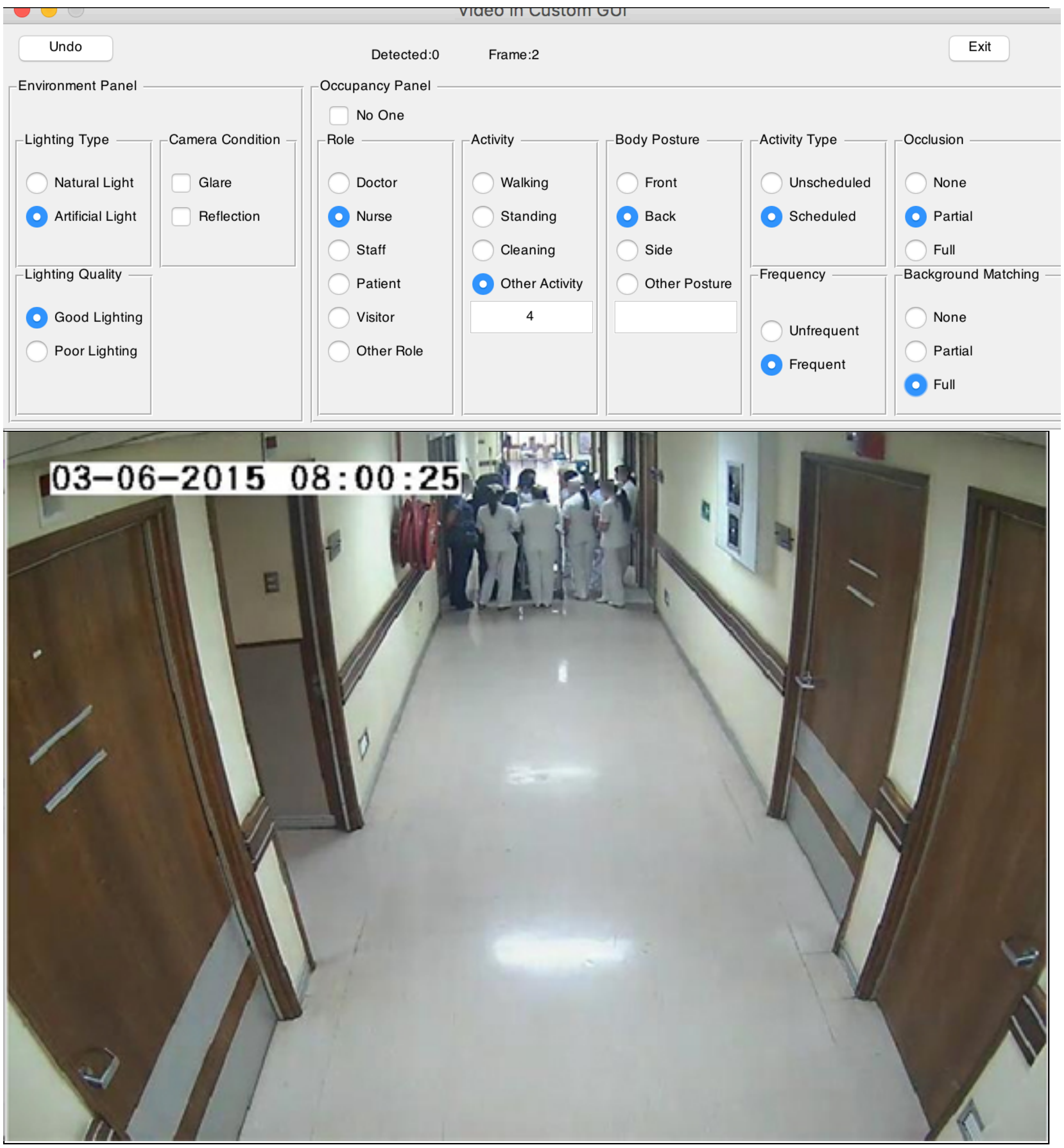


Figure 5-4. Video Mapping's Graphic User interface. It displays all buttons in an upper panel, and the video frames or random frames in the lower window.

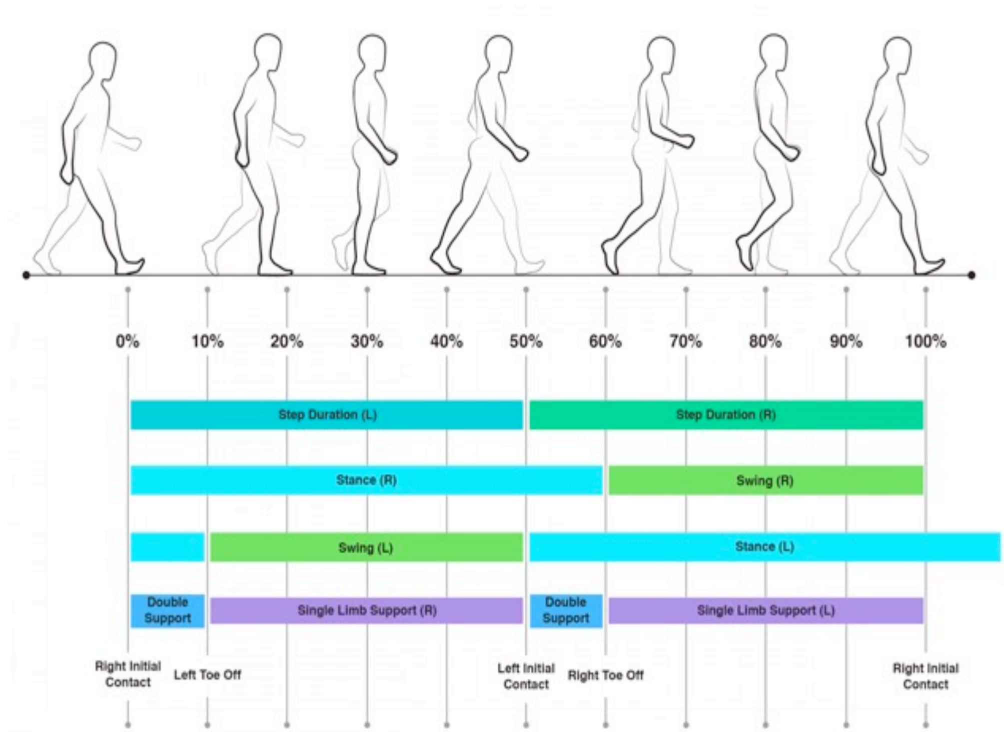


Figure 5-5. Phases of human gait (adapted from [http://www.apdm.com/mobility/)](http://www.apdm.com/mobility/) presented with the purpose of explaining in detail the factors of the precision error detected.

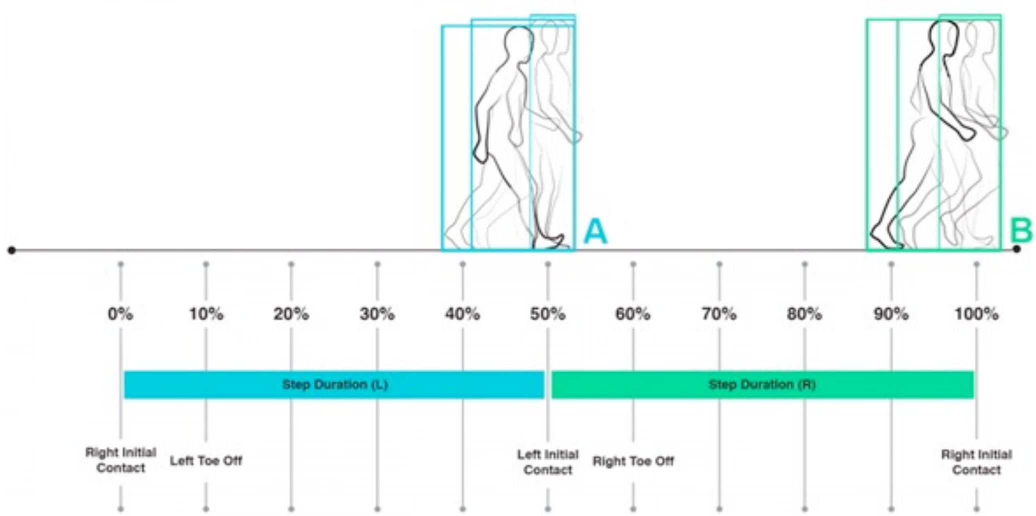


Figure 5-6. Sequence of feet position on the floor A and B. Location A during 40% of the total gait time, while the right foot marks the position closer to the camera. Location B during the other 40% of the time, while the left foot is the closest to the camera, and 20% of the total gait is the transition between A and B.

Correspondingly, background changes were identified when the presence of one canceled the other, for example, the presence of artificial light over natural light. Glare, in turn, was detected when the profile of a person was blurred due to the lighting contrast. Also, the researcher's prior training helped to redefine a number of newly emergent classification groups, such as cloth color matching, roles, activities, postures, and activity types.

User interface

The Video Mapping's graphic user interface (GUI) displayed all global variables as radio or check buttons to enter the information that this study required. The application allowed the user to enter three types of information: 1) the coordinates of the occupants' position in the video frame (i,j,frame), which was inputted with a mouse left-click at the location of their feet; 2) a number of environmental aspects that help characterize the background conditions, such as lighting and camera conditions; and 3) a number of aspects that collect occupancy information about individuals, such as their role, the specific activity each one is performing, the activity type (added for the second part of the study), their body position, the extent that the color of their clothing -matched the background, and the occlusion information.

Graphically, the buttons were distributed in one upper panel, subdivided by the category of information. In the upper part of the main panel, two global variables were displayed as return feedback from the process, i.e., the current frame and the number of people detected. "Exit" and "Undo" buttons were also displayed in the upper panel as a general control for data storage. All other global variables were displayed in the environment and occupancy sub-panels. These variables were globally visible from every function of the script, so their values remained constant until they were modified by the user. All radio buttons allowed the user to choose only one option among the predefined ones, including "other", which in turn enabled the user to type a new option. Each "lighting", "occlusion", "activity", "body posture", and the clothing color in terms of “background matching” was stored as a categorical value represented by integers, from 0 to the number of elements in each category.

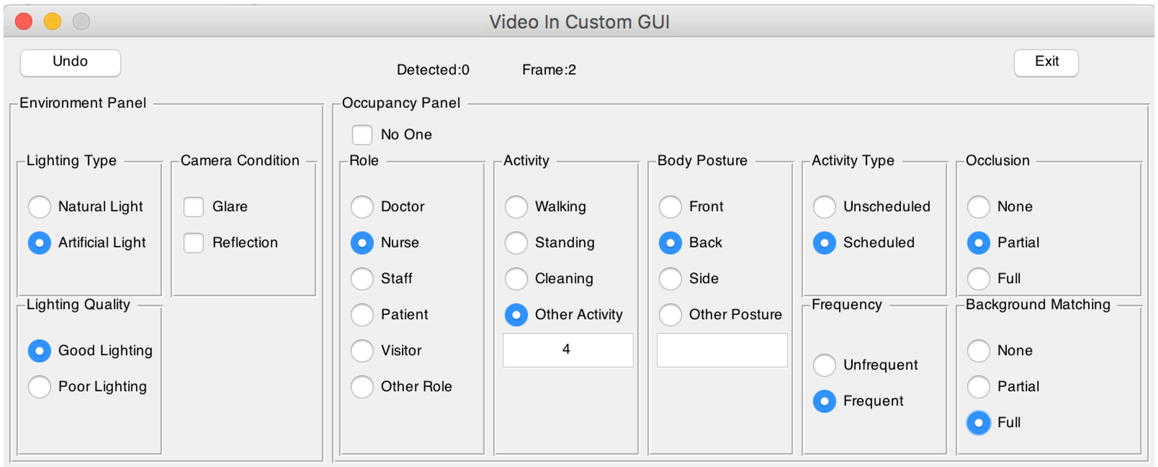


Figure 5-7. ‘Video Mapping’ application. This image presents the Environment and Occupancy panels, including their radio and check buttons for each factor taken into account. These factors are subject to change, depending on the research question.

Environment panel

The environment panel included the categories of “lighting” and “camera conditions”. “Lighting type” could be classified as “natural” or “artificial” or “good” or poor”, updating the values to one and two, respectively. “Lighting” could produce “glare” and “reflection” depending on the camera’s properties, such as its location and orientation, the presence of reflective surfaces, and the hour of the day. In the chosen hospital scenario, the environmental conditions lasted for several hours since they depended on lighting conditions, which primarily changed during sunrise or sunset. The only check button option addressed “camera conditions”, since it was the only option that did not require classification values; therefore, both conditions, “glare” and “reflection”, could co-exist because they arose, indistinctively, from the sun’s position and a surface’s reflective quality.

Occupancy Panel

The “occupancy panel” allowed input of the existing occupant conditions, including “occlusion”, “activity”, “body posture” and “background matching”. The study hypothesized that any automatic occupancy detection errors most probably resulted from these factors. The study also posited the theory that “activity”, “activity type” and “role” were the most important factors in determining occupancy distribution. Occlusion indicated when the view of a person’s body was partially obstructed. These situations arose, for example, when nurses were carrying a wheelchair that occluded their legs or when people disappeared from the camera’s field of view by entering another convex space. Activity identified the activity each occupant in the frame was performing. The activities were listed in order from the most to the least probable to occur in a particular corridor, providing an option to add peculiar and recurrent activities in the text box. Since the inputs were stored as integers, other additional activities were classified beginning with the digit five (5), as assigned by the researcher. In this study, the most recurrent activities were: (5) a cell phone call, (6) reaching for supplies, (7) sitting, (8) pushing a cart, and (9) providing laundry or cleaning services. Body posture, which is highly related to the activity, indicates the position of the body toward the surveillance camera, i.e., (1) front, (2) back, (3) side and ‘other’, including (4) sitting and (5) crouching, while performing a specific activity. For example, an individual could be walking toward the camera (walking-front) or from one side to the other side of the corridor (walking-side). Cloth color was another variable that the study hypothesized would be an important cause of error recognition, but only when contrasted with the background color; therefore, this variable is not categorized by color, but rather by the percentage of matching between the clothing color and the background color. The options offered for each variable were defined from the most to the least recurring potential causes for errors in recognition. This list evolved during the training stage after several iterations, by modifying the structure of the GUI and aggregating or modifying variables, resulting, for example, in the separation of the activity variable from the body posture variable.

The occupant’s “role” and “activity type” were variables added in the second part of the research, which focused on the study of spatial and temporal occupancy characterization rather than detection accuracy. “Role” and “activity type” variables were created when the data were selected by hour, representing the activities that, in theory, were programmed by the organization to occur at the selected time. During the training stage, the researcher identified six roles and three types of activities. The roles were: “doctor”, “nurse”, “staff”, “patient”, “visitor”, and “other”. Roles classified as “other” usually referred to an administrative role, such as a worker from another administrative hospital unit. The “activity types” were categorized as “scheduled” and “unscheduled” at the organizational level and as “regular-” or “irregular-frequency” activities. Regular-frequency activities include those activities that are fundamental for the successful functioning of the hospital, but which are not exactly scheduled by hour at the organizational level, e.g., cleaning or linen distribution.

Process of Data Storing

Once the first frame from the random sample list was displayed, the researcher defined all the environmental conditions, which generally remained constant within a single one-hour period, unless sunrise or sunset occurred during that time. Next, the researcher defined one person to be mapped and identified all of that individual’s occupancy characteristics, as discussed in the previous section. Once these parameters were defined, the location of the individual’s feet was left-clicked, storing the [i,j,frame] pixel and temporal coordinates, as well as all the environment and occupancy variables, using the “dlmwrite” function into a CSV file, as shown in the Table 5-6. These two last steps were repeated in that exact order for every person present in each frame. If the wrong data was annotated, the researcher could use the “Undo” button to erase all the information for that frame. When several occupants were present in the same frame, each occupant was identified by clicking the position of his or her feet on the screen, as previously defined. This data input was repeated as many times as the number of occupants in the frame required. Although the environment and occupancy parameters could change, as well as the position, the frame number remained constant until the frame was completely analyzed. After all individuals in the frame were mapped, the next frame would be displayed by clicking ‘enter’ or ‘right click’, and all previous information was stored in the CSV file. Iteratively, the researcher should have repeated all the steps until the frame list was complete. However, if an error in the process was detected after appending the data into the CSV file, the Undo command could not delete the last appended lines; therefore, to edit that information, the CSV file was opened and edited manually. The final number of rows that every frame provided depended on the number of people present in that frame.

When a frame was unoccupied, the “No one” button was checked in order to overwrite all the occupancy panel values for that frame with zeros (“0”). When the researcher un-checked the “No one” button, all the occupancy values return to their last stored value. This process was intended to expedite the occupancy evaluation. In practice, when the scenario to be analyzed was very crowded, the set of frames were analyzed in rounds or layers of mapping in order to avoid modifying every aspect for each occupant several times over in the same frame and instead to enable the researcher to come back to the recorded values on the next frame. Hence, for the busiest hours, the layers of mapping rounds were defined by role. The mapping process could be finished at any time and re-initiated in a determined frame number when necessary by entering the initial frame number into the code, so the test re-started where the researcher left off. The CSV file continued appending the information, unless the CSV file name was manually modified, or another video was imported. All the above description is summarized in the following pseudo code:

{Write the Video Mapping information types into a CSV file}

```
While frames = 1: total population sample, do {                    // 383 is the total data sample
        for each frame
            set current global Environment variables;
                for each occupant {
                    set current global Occupancy variables;
                    mouse input (left click) on current occupant feet’s coordinates (local variable);
                    (i,j) coordinates, frame number
                    append all information into a row into the CSV file;
                next occupant; next row
                }
        undo or append rows;
        next frame;
}
```

Outputs

The expected output of this "video mapping" script was a bi-dimensional array (row, col) of spatial and temporal occupancy information, exported as a CSV file. The first three columns were expected to be exactly like the ones obtained from the automatic occupancy method. However, the "video mapping" CSV files also stored the environment and occupancy quantitative information from rows four (4) to thirteen (13) (see figure 5-6). Afterwards, the first three columns of both occupancy datasets were transformed using a transformation matrix, into spatial occupancy coordinates [x,y,time], as explained in Chapter 2.

Manual_X	Manual_Y	Manual_frame	Light_Poor	Light_Artifi	Light_Natur	Light_Glare	ReflexionWall	ReflexionFloor	Occlusion_People	Occlusion_	Occlussion_St	Color_Cloth	Body position
776.42	191.48	2	1	0	0	0	0	0	0	0	white	0	0
776.42	191.48	3	1	0	0	0	0	0	0	0	white	0	0
785.45	189.91	4	1	0	0	0	0	0	0	0	white	0	0
722.26	196.19	5	1	0	0	0	0	0	0	0	white	0	0
784.45	189.91	5	1	0	0	0	0	0	0	0	white	0	0
728.27	193.05	6	1	0	0	0	0	0	0	0	white	0	0
778.43	192.26	6	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	7	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	8	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	9	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	10	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	11	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	12	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	13	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	14	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	15	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	17	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	18	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	19	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	20	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	21	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	23	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	24	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	25	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	26	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	27	1	0	0	0	0	0	0	0	white	0	0
778.43	190.7	28	1	0	0	0	0	0	0	0	white	0	0

Figure 5-4. A screenshot of a sample of the CSV table that stores the occupant's values as indicated. When the frame number is unique, it indicates the presence of only one individual. When the frame numbers are duplicated 'N' times, it indicates the presence of 'N' number of individuals in that frame.

5.4 Statistical Models

The data from the two studies was amenable to multiple methods of analysis that would achieve useful insights. The selection of the proper method, however, required a focus on the objectives of the study's statistical analyses: first, to calculate the accuracy of the automatic occupancy algorithm and determine each parameter's influence on such accuracy; second, to calculate the precision of the location algorithm to correctly determine the occupants' positions; and third, to demonstrate that the spatiotemporal patterns of occupancy are influenced by scheduled activities as well as by the space in which they occur, by showing that the differences in occupancy distribution in space and time were not the result of chance. The first two objectives are presented in this chapter and the third one is introduced in the next chapter.

Thus, the selection of the proper statistical analysis depended on the nature and the number of the dependent and independent variables. In the case of this research, occupancy, the dependent variable, is a categorical variable that takes two values: occupied or unoccupied.

Classification Matrix

Calculating the performance of the Automatic Detection Algorithm lead us to recognize the existence of two types of errors: Type I (False Positives), which refers to detecting an occupancy that is not present and Type II (False Negatives), which refers to failing to detect an occupancy that is present (Hofer et al., 2005). In recognizing the nature of the errors, the analyses detoured from pure accuracy to measure the performance of a classifier using a “classification matrix”, also called a “confusion matrix”.

Table 5-2. Classification Matrix

		True Conditions	
Predicted Condition	Total Population 7266	**Positive Condition 5117**	**Negative Condition 2149**
	Predicted Positive Condition 1824	**True Positive** 1824	**False Positive (Type I error)** 0
	Predicted Negative Condition 5442	**False Negative (Type II error)** 3293	**True Negative** 2149

A “classification matrix” allows more detailed calculations than “accuracy”, which presents the overall ratio between the correct guesses and the total population, in order to help explain the statistical models and the causes of error in more detail. These calculations include “sensitivity”, which measures the proportion of positives that are correctly identified as such (“true positives”); “specificity” (SPC), which “measures the proportion of negatives that are correctly identified as such” (“true negatives”); the “false positive rate" (FPR) or fall-out, which measures the proportion of Type I error over the total negative conditions; and the "false negative rate" (FNR) or miss rate, which calculates the proportion of Type II error over the total positive conditions.

Table 5-3. Summary of Classification Matrix calculations

Accuracy (ACC)	(True positive + True Negative) / Positive Condition	3973/5117 = 0.776
Prevalence	Positive condition / Total population	5117 / 7266 = 0.704
Sensitivity or True positive rate (TPR)	True positive / Positive Condition	1824 / 5117 = 0.356
Specificity (SPC) or True negative rate (FNR):	True negative / Negative condition	2149/2149 = 1
Miss rate or False Negative Rate (FNR)	False negative/ Positive Condition	3293 / 5117 = 0.644
Fall-out or False Positive Rate (FPR)	False positive / Negative Condition	0 / 2149 = 0

Therefore, Classification Matrix's calculations such as "accuracy", "prevalence", "sensitivity" and "specificity" were computed based on the true detections and the two types of errors. Then, Logistic Regresion was used to model occupancy, by first constructing a bivariate model to study the effect distance on occupancy on data stratified by different categories, and then constructing a multiple regression logistical model to make a comprehensive model which could be used to predict occupancy rates for the setting studied here to test an independent group of variables, i.e., "distance" from the camera, "background conditions", and "occupancy conditions. The premises are that the distance from the camera has an effect on the automatic recognition of peopla, and that while the distance from the camera increases, it the probability of recognition will decrease. This premise also assumes that other factors, such as the environmental and occupancy conditions, will influence the recognition. To corroborate this, a set of one-minute video data samples were used for the five main calculations mentioned above in order to obtain a complete overview of the data sample (Table 5-2. Classification Matrix). Then, "accuracy" was cross-measured against distance using “logistic regression” and against environmental and occupancy parameters using “multiple regression” (categorical vs. categorical variables).

Logistic Regression

The Logistic Regression model, or “logit model”, is a statistical method used when there are one or more independent variables that impact a categorical dependent variable with two opposite outcomes (i.e., successful or unsuccessful recognition of an individual). The objective in this study was to meaningfully explain the influence of the underlying factors on “occupancy recognition” true positive and false negative values. This study demonstrates the influence of distance from the camera on recognition as:

$$logit(p)= \beta_{0.}$$

Logistic Regression Model by Distance

The Logistic Regression model is also used for predicting binary dependent variables – in this case, recognition and non-recognition – with a Bernoulli distribution of y | x, showing that the residuals are not normally distributed. Logistic regression first reflects the likelihood that recognition or non-recognition happens for the different values of the independent variable, i.e., distance. Then, it takes those odds’ radio (which is continuous but cannot be negative) to create its logarithm. This is referred to as the logit or logarithm of the odds (log-odds). The function’s parameters represent a probability ***p***, and the logit function outputs the log-odds. The logit of a number ***p*** between 0 and 1 is shown by the formula:

$$logit(p) = \ log\ p/(1-p)$$

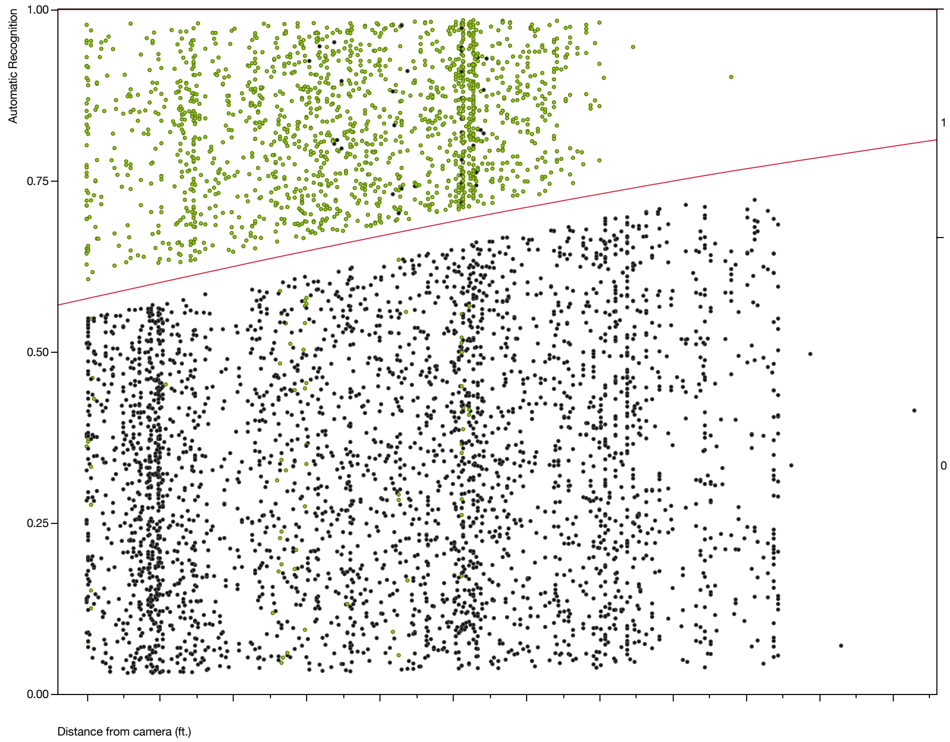


Figure 5-5. Logistic Fit of Automatic recognition by Distance from the camera. The ratio varies from 57.52 to 80.93% of not recognition.

For this analysis, the Whole- Model Test, which shows that the 'Chi-Squared test', or the sum of the squared errors, was used to attempt rejection of the null hypothesis that the recognition data are independent from the distance to the camera [*dist Y*].

Table 5-4. Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	29.71	1	59.43	<.0001*
Full	3140.65			
Reduced	3170.36			

Table 5-5. Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.31	0.06	30.19	<.0001*
Distance cam	0.0019	0.0002	58.40	<.0001*

For log odds of 0/1

The “logistic fit model” indicated that distance had a significant effect on the probability of recognition, the Whole Model Test showed that the probability of obtaining a ChiSq value of 59.42938 by chance, for one degree of freedom, is less than 0.0001 (p-value). This meant that the null hypothesis that “the distance has no effect on automatic recognition” could be rejected.

The parameter estimates analysis shows that the change in odds is 1.01. This means that for every one-distance-unit (i.e., one foot) closer to the camera, the odds of recognition, which are a numerical expression of the likelihood of that event, will increase by 1.36 times, and that the change of log-odds [p/(1-p)] is 0.00195102.

Series of Logistic Regression Models by Factors

The aforementioned model presents a clear correlation between the distance from the camera and the recognition of an individual. While performing the “video observation” and “mapping”, observations and questions emerged regarding the influence of scene-related factors (see image 5-7). Environmental factors depend on conditions pre-established in the setting, such as the lighting type and quality, as well as the camera condition, including the type and position of the cameras and the glare or reflection captured by each camera position. Algorithm- and database-related factors were associated with the scene occupancy, including the number of people present and the occlusion produced due to the occupancy density factor. For the database using the people detector “classification model,” the clear hypotheses were that the cloth-background color-matching, as well as the activity performed and body posture, were influential factors on people recognition.

To determine the influence of each factor, two statistical models were proposed: first, a “logistic regression model” to literally visualize the influence of activity and body posture and second, a “multiple regression model” to calculate the correlation of all the factors in the recognition prediction models.

Logistic Regression by Activity

In general, logistic regression measures the relationship between the categorical dependent variable –occupancy– and one other independent variable by estimating the probabilities of specific outcomes using a logistic function, or the cumulative logistic distribution. Based on the observations made during the manual input of video occupancy data, questions arose regarding the nature of influence of activity type and body posture on automatic recognition. These questions led to the dissection of the data; addressed by a series of logistic regression models of subsets of data, by "activity" and "body posture". Among the activity data subsets, "walking", "standing", "cleaning", and "crouching" were the most frequently occurring activities. The hypothesis H_{actv} for this analysis was that each activity's accuracy model would be statistically different, and would vary by the relative distance of the subjects to the camera.

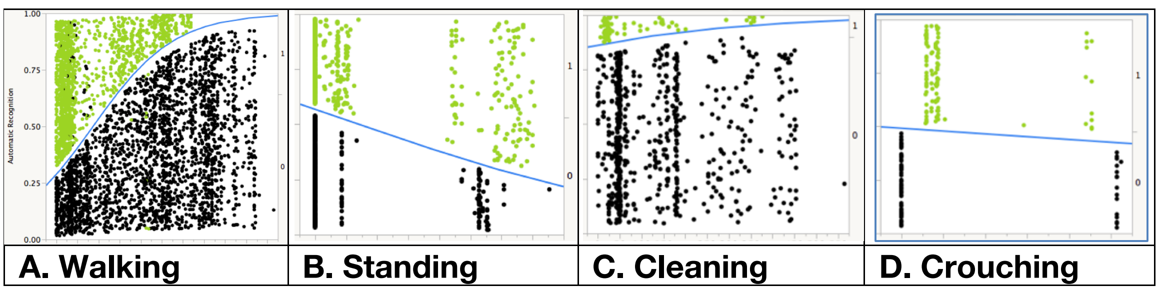


Figure 5-8. Logistic Regression Models of data subsets by 'activity'. The four most frequent are: 'walking'; standing'; 'cleaning'; 'crouching'.

A. Walking

Table 5-6. Whole Model Test of Walking Activity

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	593.48	1	1186.97	<.0001*
Full	1965.93			
Reduced	2559.42			

Table 5-7. Parameter Estimates of Walking activity

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.91	0.057	249.05	<.0001*
Distance cam	0.01	0.000	804.92	<.0001*

For log odds of 0/1

B. Standing

Table 5-8. Whole Model Test of Standing activity

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	23.59	1	47.19	<.0001*
Full	1024.67			
Reduced	1048.27			

Table 5-9. Parameter Estimates of Standing activity

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	0.28	0.056	24.42	<.0001*
Distance cam	-0.00	0.000	43.10	<.0001*

For log odds of 0/

C. Cleaning

Table 5-10. Whole Model Test Cleaning activity

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	4.06	1	8.11	0.00044*
Full	237.55			
Reduced	241.61			

Table 5-11. Parameter Estimates for Cleaning activity

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	1.84	0.17	110.67	<.0001*
Distance cam	0.003	0.001	6.83	0.0090*

For log odds of 0/1

D. Crouching

Table 5-12. Whole Model Test for Crouching activity

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.19	1	0.38	0.5355
Full	237.55			
Reduced	241.61			

Table 5-13. Parameter Estimates for Crouching activity

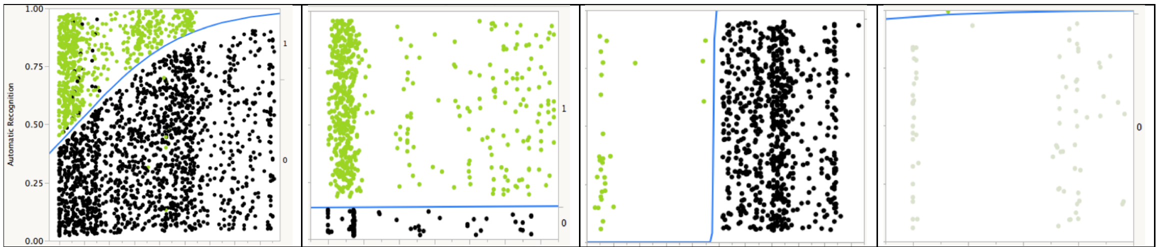
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.33	0.172	0.04	0.8491
Distance cam	-0.001	0.001	0.38	0.5386

For log odds of 0/1

Logistic regression analyses of recognition accuracy versus distance demonstrated that each activity's recognition accuracy was associated with a different distribution. For example, walking, which is by far the most common activity in the corridor, decreased recognition logarithmically the further the individual was from the camera. The chance that these results were random is 0.0001 (ChiSq). When associated with standing, recognition increased the further the person was from the camera (ChiSq 0.001). This result was unexpected, showing that a clear definition of a body's boundaries has more influence on recognition than the distance to the camera and that a static perspective image of a person closer to the camera is more difficult to recognize. Cleaning, is a non-frequent activity, and although recognition was very unlikely due to the body posture and the external elements (cleaning devices), distance did have an impact on recognition (ChiSq 0.0044). Crouching, however, was not a frequent activity, and thus the sample of data was small compared to the other activities. The relationship between recognition and distance from the camera was weak for crouching subjects since the probability is 0.053. (ChiSq). The ChiSq values resulting values in Crouching activity, shows that the "Distance from the camera" is not a variable that has an effect on recognition; therefore, any results based on crouching subjects have a chance to be random. The hypothesis is that the body posture of this activity, is not included into the Classification Model used to train the algorithms. Furthermore, people recognition is not defined for this body posture.

Logistic Regression by Body posture

While "walking" was the most frequent "activity", the four "body postures" tested were the most recurrent ones. "Front", "back", "side", and "hidden hands" were the most common body postures that occurred in the collections of scenes analyzed in this study. The hypothesis H_{pos} was that each activity's accuracy logistic model would be statistically different from the others, and their distribution by the distance to the camera would also vary differently.



A.1 Front	**A.2 Back**	**A.3 Side**	**A.4 Hidden hands**

Figure 5-9. Logistic Regression occupancy data plots by 'body posture'.

A.1 Walking-Front (towards the camera)

Table 5-14. Whole Model Test for Walking-front

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	211.76	1	423.52	<.0001*
Full	1298.26			
Reduced	1510.01			

Table 5-15. Parameter Estimates for Walking-front

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.330	0.07	21.37	<.0001*
Distance cam	0.009	0.00	320.14	<.0001*

For log odds of 0/1

A.2 Walking-Back

Table 5-16. Whole Model Test for Walking-back

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.008	1	0.016	0.8990
Full	260.648			
Reduced	260.656			

Table 5-17. Parameter Estimates for Walking-back

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.83	0.146	156.81	<.0001*
Distance cam	0.0001	0.001	0.02	0.8987

For log odds of 0/1

A.3 Walking-Side

Table 5-18. Whole Model Test for Walking-side

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	122.52	1	245.05	<.0001*
Full	1.203e-8			
Reduced	122.52			

Table 5-19. Parameter Estimates for Walking-side

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-301.84	151518.72	0.00	0.9984
Distance cam	1.25	614.51	0.00	0.9984

For log odds of 0/1

A.4 Walking-Hidden hands

Table 5-20. Whole Model Test for Walking-hidden hands

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.36	1	0.73	0.3930
Full	4.95			
Reduced	5.31			

Table 5-21. Parameter Estimates for Walking- hidden hands

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	3.53	1.155	9.32	0.0023*
Distance cam	0.013	0.017	0.56	0.4553

For log odds of 0/1

The logistic regression analyses demonstrated that recognition accuracy was associated with a different distribution when associated with facing the camera (front), back to the camera, side to the camera, and texting, or holding objects (hidden hands). Thus, a person walking toward the camera was more likely to be recognized within the first 25 feet from the camera. A person walking away from the camera, was very likely to be recognized in any position, independently of the distance from the camera (ChiSq 0.8990). Furthermore, a person walking across the corridor (presenting a side view) was likely to be recognized within the first 23-24 feet but unlikely to be recognized at all from that distance and further. Hidden hand positions were very unlikely, and when they occurred, the people associated with this position were not recognized, regardless of the distance from the camera (ChiSq 0.3930). This result presents a challenging goal to develop algorithms that recognize individuals presenting from a side view and with hidden hands but the development of such algorithms will be necessary to improve the recognition outcome in future research. While these findings are informative, environmental parameters also were embedded in the error factor, their inclusion in the statistical model becomes extremely important.

Multiple Logistic Regression

As previously noted, regression analysis estimates the relationship among variables and is commonly employed to predict uncertain events based on experience or knowledge (ref.). The goal of multiple logistic regression is to find the equation that best predicts the probability of the dependent variable ***Y***, as a function of several independent variables (ref), and is represented by the following equation:

$$\boldsymbol{Y = \beta_1 * x_1 + \beta_2 * x_2 + \ldots + \beta_n * x_n.}$$

All environmental and occupancy factors from the global data sample are included in the model, presenting the influence that each has on recognition.

Table 5-22. Multiple logistic regression. Whole Model Test for all factors

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	1445.59	12	2891.19	<.0001*
Full	1724.76			
Reduced	3170.36			

Table 5-23. Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	1405	890.04	1780.094
Saturated	1417	834.72	**Prob>ChiSq**
Fitted	12	1724.76	<.0001*

Table 5-24. Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.53	0.16	10.01	0.0016*
Y manual	-0.00	0.00	11.79	0.0006*
Corridor[]	-	-	-	-
Corridor[2N]	0.19	0.34	0.32	0.5724
Corridor[2S]	-5.32	0.57	86.92	<.0001*
Corridor[3N]	-1.59	0.33	22.14	<.0001*
Corridor[4S]	4.74	0.36	166.24	<.0001*
Activity [walking]	-	-	-	-
Activity[cleaning]	3.29	0.17	367.17	<.0001*
Activity[crouching]	-3.17	0.22	206.54	<.0001*
Activity[standing]	-1.81	0.15	133.74	<.0001*
Body Posture[side]	-	-	-	-
Body Posture[back]	-4.79	0.24	370.07	<.0001*
Body Posture[front]	-0.48	0.21	5.05	0.0246*
Body Posture[hidden hands]	4.99	0.57	75.03	<.0001*
Color Cloth[mix-matching]				
Color Cloth[bckg matching]	2.18	0.30	51.90	<.0001*
Color Cloth[no-matching]	0	0	.	.
Lighting Condition[Good]	-	-	-	-
Lighting Condition[Poor]	0	0	.	.
Glare [no glare]	-	-	-	-
Glare[glare]	0	0	.	.
Reflexion[1]	-	-	-	-
Reflexion[0]	0	0	.	.
Reflexion[Floor]	0	0	.	.

For log odds of 0/1

Table 5-25. Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Y manual	1	1	11.80	0.0006*
Corridor	4	4	1245.47	<.0001*
Activity	3	3	632.83	<.0001*
Body Posture	3	3	937.41	<.0001*
Color Cloth	2	1	150.36	<.0001*
Lighting Condition	1	0	0	.
Glare	1	0	0	.
Reflexion	2	0	0	.

The multiple regression analyses showed that most of the variables have a non-random influence on occupancy detection. First, the different datasets obtained from different corridors cannot be determined by randomness, making the case about the different scenario conditions influence on occupancy, independently of their almost identical spatial layouts. Only one of the corridors [2N] is an exception to these analyses. It is important to notice that the corridors not present in this analysis are the ones that were discarded due to technical reasons. The second factor of influence, as described in detail before, is the distance from the camera. Same occurs with Activity Type and Body Posture factors, which have high impact on occupancy detection. While these findings are informative, the crucial future step is to be able to recognize the presence of these environmental and occupancy parameters in each spatiotemporal scene, to be able to characterize the scenarios and apply a probabilistic model of occupancy. The inclusion of these factors in the statistical occupancy model becomes particularly important.

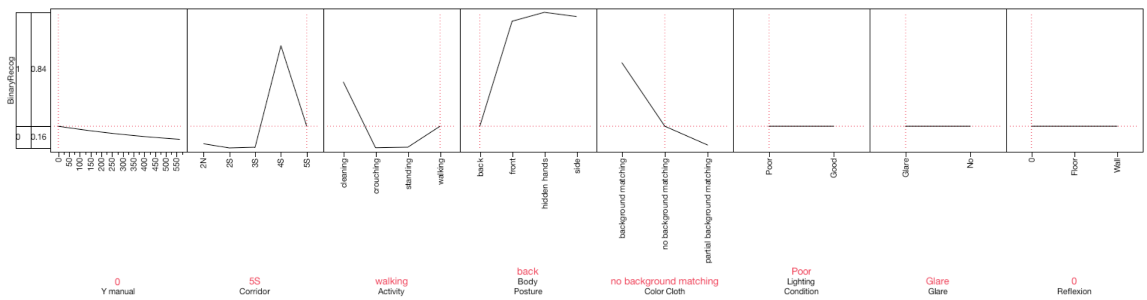


Figure 5-10. Prediction Profiler

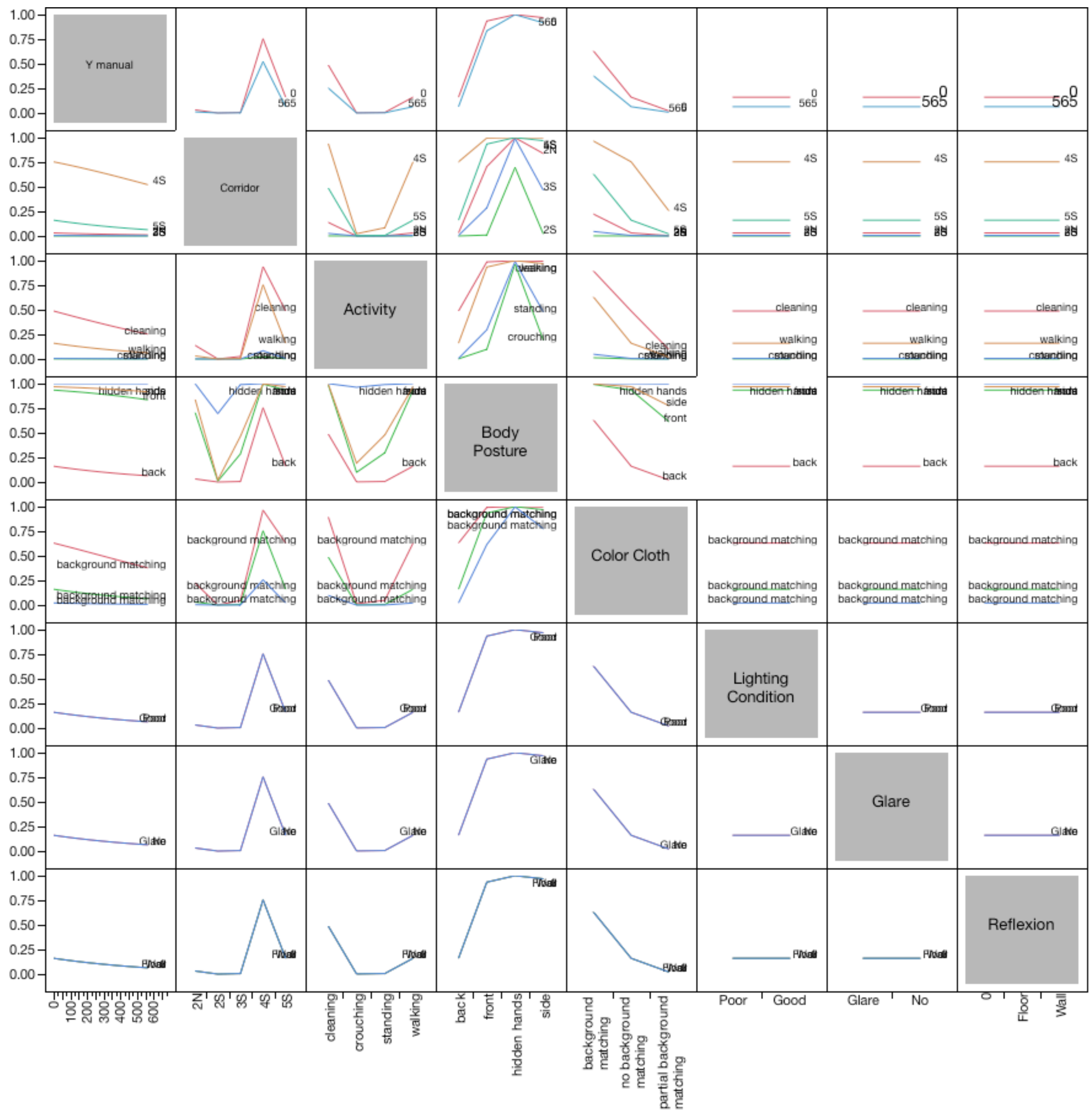


Figure 5-11. Interaction Profiles

The resulting outcomes present a probability for recognition (p[1]) or non-recognition (p[0]) based on the set of factors that define the scenario (see image 5-12). The value of p varies from 0 to 1 showing a percentage of recognition probability, as follows:

$$\boldsymbol{p[1] = num\ [1]\ /\ n}.$$

5.5 Applying probabilistic models to datasets

The probabilities of recognition by location, determined the impact of other environmental and occupancy factors, can be used for practical purposes, such as correcting the automatic recognition data to model scenarios of occupancy. The process of applying such probabilistic models included first constructing a set of statistical models based on the programmed activity, which necessarily includes the time of day at which the activity is performed. After running the accuracy test, probability factors per cell emerged.

We expect that by applying the probability of recognition **p[1]** factor of a data subset, which was calculated from the general sample, the occupancy recognition surface would predict the occupancy expected for each cell in each subset scenario as it is presented in Chapter 6. The objective was to complement the automatic occupancy datasets with the predicted occupancy. The final goal was to improve the automatically collected occupancy data sample obtained from the Scene Analyses video –or any other technology that might cause detection errors– by identifying the error that was produced by the influence of each environmental as well as behavioral variable on each scenario.

5.6 Precision

Precision refers to how close are two measurements, which reflects the difference in distance between the positioning information collected using the automatic algorithm and the information collected from manual mapping. The goal of measuring precision was to correct the positioning information. The hypothesis was that precision would vary along the corridor (X axis), and would be fairly constant across the corridor (Y axis).

The testing revealed that the precision decreases by some inches at the beginning of the corridor and up to four feet at the end of the corridor. Because the occupancy grid resolution is measured in square feet, the first 25 feet of the corridor did not exhibit precision errors, but the errors began incrementally increasing at around one foot to approximately 25 feet, with a mean of response of -24. 3472 by 1/10 foot. In the X axis, however, the error was less than one foot, with a few exceptions, which corresponded to the less frequent activities, such as cleaning, primarily due to the subject's body position during such activities. Because the precision factor was very reliable, and the errors in the Y axis were always produced toward the camera, making that the error negative, this factor should be added to the automatic occupancy algorithm to correct the positioning. Although it could be argued that the difference in Y can be assumed to be a time error, in the sense that 1 second later the individual would most probably be in that exact predicted location, precision is significant at the moment of calculating the fields of vision from the patient's bed.

Precision Regression Along the Corridor (axis Y)

The precision from the camera starts in -0.9 ft., which means that the automatic recognition detects position further than the actual position. This is due the perspective of the body when too close to the camera. At distance between 8 and 20 feet, precision error is less than 1 ft. Afterwards it increases, as shown in the profiler, up to 6.2 feet at the end of the corridor.

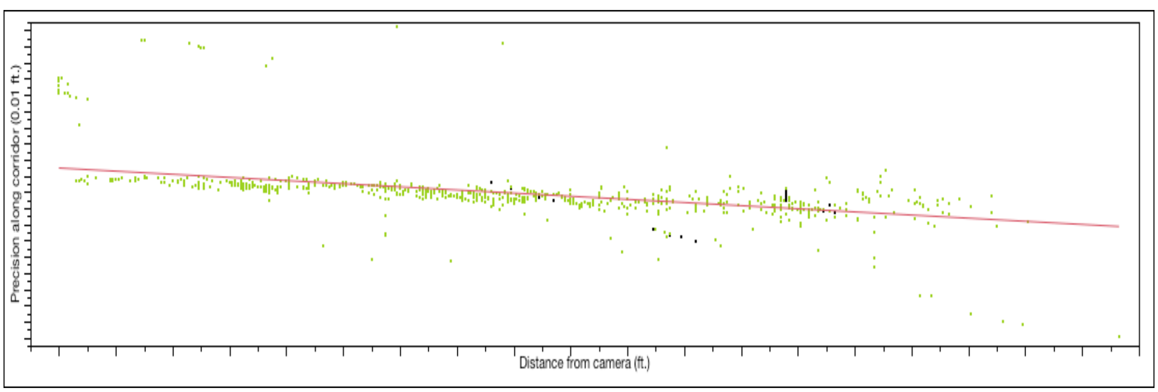


Figure 5-11. Plot of occupancy precision, distributed along the corridor (Y axis). It shows the distances between the real occupancy position and the detected position. The unbalanced horizontal distribution is due the un-centered camera focus.

Table 5-26. Summary of Fit

RSquare	0.32
RSquare Adj	0.32
Mean of Response	-2.44
Observations	1081

Table 5-27. Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	1	285035.29	285035	511.4731
Error	1079	601308.41	557	**Prob > F**
C. Total	1080	886343.70		<.0001*

Table 5-28. Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	9.58	1.66	5.75	<.0001*
Distance from camera	-0.19	0.00	-22.62	<.0001*

Table 5-29. Profiler

Distance from camera (ft.)	**Precision (ft.)**
0	0.9
18	-0.8
36	-2.6
56	-4.4
90	-6.2

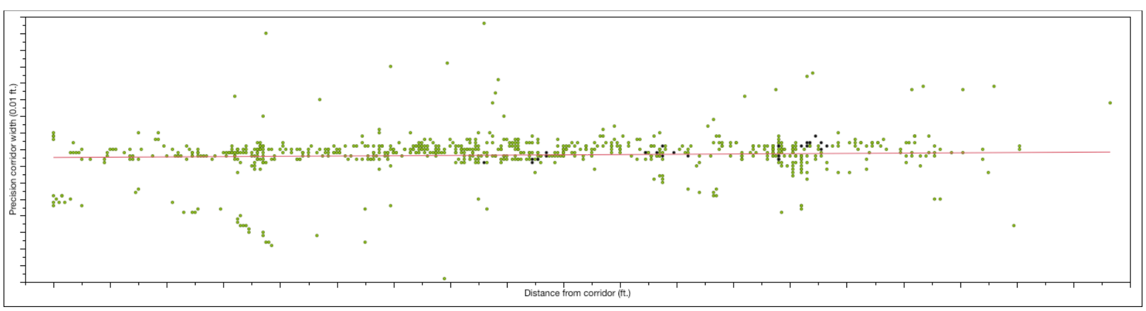


Figure 5-12. Precision Regression for Corridor Width.

Table 5-30. Summary of Fit

RSquare	0.00
RSquare Adj	0.00
Root Mean Square Error	5.32
Mean of Response	-1.70
Observations (or Sum Wgts)	1081

Table 5-31. Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	140.15	140.15	4.9389
Error	1079	30619.05	28.37	**Prob > F**
C. Total	1080	30759.21		0.0265*

Table 5-32. Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	251	12615.75	50.26	2.3116
Pure Error	828	18003.30	21.74	**Prob > F**
Total Error	1079	30619.06		<.0001*
				Max RSq

Table 5-33. Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2.46327	0.37625	-6.55	<.0001*
Distance from camera	0.0043144	0.001941	2.22	0.0265*

Table 5-34. Profiler

Distance from camera (ft.)	Precision (ft.)
0	-0.24
24	-0.21
43	-0.19
60	-0.16
90	-0.08

Table 5-35. Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	19.10	8.19	2.33	0.0199*
Y manual	**-0.28**	**0.014**	**-20.19**	**<.0001***
Activity[cleaning]	18.37	12.97	1.42	0.1569
Activity[crouching]	-8.83	5.66	-1.56	0.1190
Activity[standing]	-5.72	5.36	-1.07	0.2857
Activity[walking]	-3.81	5.71	-0.67	0.5043
Body Posture[back]	-2.14	7.02	-0.30	0.7606
Body Posture[front]	1.81	7.07	0.26	0.7977
Body Posture[hidden hands]	-16.99	20.05	-0.85	0.3968
Body Posture[side]	**17.32**	**7.95**	**2.18**	**0.0297***
Color Cloth[background matching]	-19.39	10.36	-1.87	0.0616
Color Cloth[no background matching]	**16.13**	**5.77**	**2.79**	**0.0053***
Color Cloth[partial background matching]	3.25	5.41	0.60	0.5474
Lighting Type[Artificial]	**16.86**	**7.98**	**2.11**	**0.0350***
Lighting Type[Natural]	**-16.86**	**7.98**	**-2.11**	**0.0350***
Lighting Condition[Poor]	-14.68	8.78	-1.67	0.0949
Lighting Condition[Good]	14.68	8.78	1.67	0.0949
Glare[Glare]	0	0	0.00	1.0000
Glare[No]	0	0	0.00	1.0000
Reflexion[0]	-31.56	16.31	-1.93	0.0533
Reflexion[Floor]	0	0	0.00	1.0000
Reflexion[Wall]	31.56	16.31	1.93	0.0533

The multiple regression results showed that only few of the parameters had a direct influence on precision (with a significant effect at 95% level). They are: Distance from the camera, Body posture [side], Color Cloth [No background matching], and Lighting type[artificial and natural]. The "precision" outcomes involve distances that show the difference between the two positioning methods, automatic and manual, once people are recognized. The distance between the two systems is added to correct the instrumental error when calculating spatiotemporal occupancy (ref. Chapter 6).

5.7 Discussion

The main goal of this part of the research was to demonstrate that even when the technology used for positioning produces some data with errors, a statistical approach can predict the adequate expected data, up to a determined accuracy. For the accuracy test, the first objective was to determine the accuracy of the automatic people recognition algorithms used for this research, in order to measure the reliability of their outcomes. We expected an increase in the accuracy error rate the further the detection was from the camera and that other parameters, such as environmental and activity-related ones, would have an undetermined influence on the measurements. The second objective was to understand the impact of each environmental and activity parameter on recognition, with two purposes: 1) to understand how the parameters' variations define the scenario for recognition; and 2) to understand the probability of recognition depending on these parameters.

Environmental factors change slowly compared to activity factors. Therefore, the lighting and camera conditions are classified in few categories, and can be considered mostly constant during time slots of one hour. On the contrary, activity conditions such as the activity type and body posture are in permanent change and are the main causes of classification model errors for people detection. These findings are expanded in the conclusion section, providing valuable feedback to improve future research in the area of machine learning by refining the classification model training process. They could be useful to address classification accuracies, error ratios, or any other measure for the evaluation of classifiers, including model sizes and computation times. Future work in this area could include the automation of the process for collecting environmental and occupancy information, extending the algorithms for specific recognition patterns. Additionally, the probability of recognition is derived from the influence of each of the aforementioned parameters that affect recognition. This research proved that each parameter impacts recognition individually and in association with each other and that they are related to the environment as well as to occupancy. In fact, the object of our analyses, the scenarios, were essentially composed by the environmental conditions, including the time of the day, which in turn implied the activity performed, and thus the occupancy factors. Occupancy factors such as occlusion, which is the most recognized and common factor that impacts visual recognition, depended primarily on the number of people present in the scene. This result varied depending on the activity scheduled and the number of people involved. Therefore, determining the probability of occlusion by shorter periods of time, such as one hour, would help to create a probabilistic model with higher resolution, which would explain the variability in the recognition probability.

Both Accuracy and Precision depend on the units of measurement employed. For this research, spatial measurements were taken in pixels and the temporal one in frames. Pixels were later transformed to spatial dimensions of feet including decimals. Once the spatial position was determined and the accuracy and precision were calculated, the units of analysis were rounded to feet and the frames to ¼ of a second. At this resolution, the errors were reduced and the unit for occupancy measurement was in square feet by 0.25 seconds [sqft/sec]. The “occupancy unit” could become the actual resolution, defined as the average of time during that second –or one to four selected occupied frames– eliminating from the sample those frames that were not recognized, thus increasing the accuracy according to the temporal resolution.

5.8 Summary

Acknowledging that the “scene analysis” accuracy was lower than 50% in some zones of the corridor areas, this section of the research proposed to improve that occupancy recognition accuracy by applying probabilistic models. The first step necessarily involved the design and development of an “accuracy test” to measure the accuracy and precision of the “occupancy algorithm”. This test entailed two parts. The first step, “video mapping”, consisted of observing and manually mapping occupancy in the videos, as well as the activities performed and the environmental factors that might influence the occupancy data outcome.

The second step involved comparing the outcome of the “video mapping” of sample frames with a sample of the automatic dataset to determine its accuracy and its precision. The application of regression models determined the impact of each environmental and activity factor on occupancy accuracy, including the distance from the camera. To determine the precision of detected location, precision was calculated as the distance between the manual and automatically detected positioning coordinates, with the final goal of correcting them. Finally, this chapter presented a predicted occupancy dataset, and it will continue on Chapter 6 by applying a probability detection factor given the location compared with the automatically collected datasets. Later, the precision distance was subtracted to correct these positions. The improved occupancy datasets are later contrasted with a 100% confidence dataset collected manually to validate the results.

CHAPTER 6

ANALYZING SPATIOTEMPORAL OCCUPANCY AND DEFINING A NEW BEHAVIORAL-SPATIOTEMPORAL METRIC FOR HEALTHCARE SETTINGS: ISOVIST-MINUTE

Overview

This chapter presents the framework for the spatiotemporal analyses and spatiotemporal occupancy-related metrics in the field of architecture. The three central topics are addressed in this chapter: 1) the modeling of spatial and spatiotemporal occupancy with a specific focus on recognizing the influence of organizationally scheduled activities on people's behavior; 2) the characterization and comparison of specific scenarios by analyzing the spatiotemporal occupancy datasets to understand occupancy distribution and finding emergent outcomes such as the spatiotemporal occupancy-related metrics, which embodies a relationship between spatial layout and occupancy patterns; and 3) the design of spatiotemporal occupancy-related metrics and specific analyses to facilitate the healthcare outcome of patient surveillance. The chapter starts by introducing the concepts of occupancy grids and occupancy cells, the fundamental units of occupancy mapping used in this research; continues with the characterization of specific scenarios for occupancy comparison; and concludes with a validation of the proposed methodology by defining a spatiotemporal occupancy-related metric, the Isovist-minute. This metric measures the probability of achieving patient surveillance in specific locations within a spatial setting, given certain scenario conditions, including spatial, environmental, and occupancy aspects, as well as programmed and actual activities.

6.1 A Model for Spatiotemporal Occupancy

A spatiotemporal occupancy model refers to the structure and presentation of the collected occupancy data, organized and displayed to support its exploration. Its purpose is to facilitate the identification of occupancy patterns to explain the theoretical influence of "organizationally scheduled activities" on people's behavior, with the main goal of characterizing the occupancy patterns of a particular building.

As discussed earlier in this document, The spatiotemporal occupancy data is stored not in a database but tabular form and because it provides a manageable file size to accommodate the amount of data stored in this case. Each occupancy record consists of three fields in the automatic data collection (x, y, and time) and ten fields in the manual data collection besides x, y, and time. These ten fields include lighting type, lighting quality, and camera condition as environmental conditions, and role, activity, body posture, activity type, activity frequency, occlusion, and cloth color as occupancy conditions. Each CSV file contains occupancy data by hour and by corridor. The mechanisms for exploration are the accumulation of a set of hours or the comparison among a set of files. The graphic display of the data is structured as x and y on a two-dimensional (2D) occupancy grid and with a z-axis temporal dimension to construct a three-dimensional (3D) "occupancy cube," referencing Mario Romero's work on 'activity cube' (2008), both defined in the next section.

6.2 Occupancy Grid (OG)

The spatial occupancy grid in this research is a fine-grained 2D map composed of a collection of cells representing the continuous space of possible locations in the scenario, reducing the spatial complexity. Additionally, a set of 2D occupancy grids are sequentially aggregated together by time instances in a Z-axis to create a spatiotemporal 3D occupancy cube. Both the 2D occupancy grid and the 3D occupancy cube are based on a grid-based approach, which is computationally easy to build and represent, providing independent locations. The first grid-based map was originally proposed by Elfes (1987) and Moravec (1988), who assigned an occupancy binary value to each cell to determine its occupancy. Occupancy grids have also been defined in the area of probabilistic robotics, the goal of which is to “estimate the posterior probability over maps given the data” (Thrun, Burgard and Fox, 2005).

The 2D OG coordinate system has a location index, which begins at (1,1), starting at the bottom-right corner of the area of occupancy. The maximum size of this specific grid based on the area of interest (AOI) defined in the previous chapter is 7 x 120 cells. Each occupancy cell in the grid is assigned a binary value as either occupied (1) or unoccupied (0) (see figure 6.1). The model imports the occupancy values obtained from the automatic recognition method for each cell in the grid. Each OG represent a time stamp, and the aggregated occupancy grids represent the aggregated time.

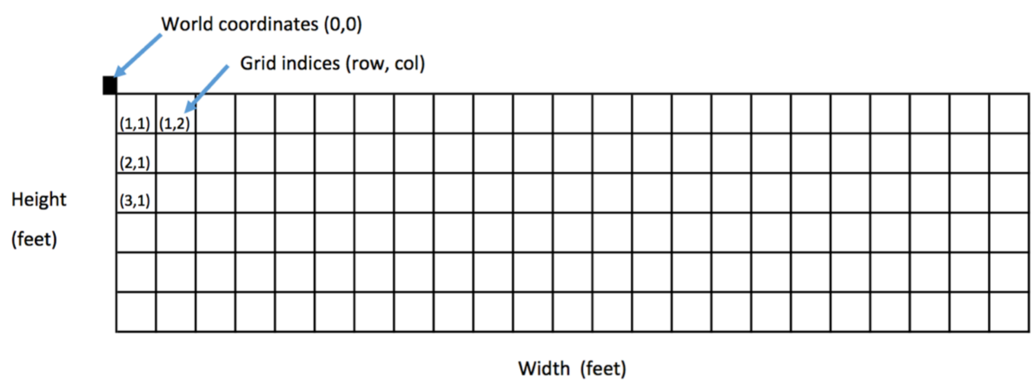


Figure 6-1. Indicates the 2D gird size and grid indices (row,col), staring at the upper left corner.

The resulting aggregated 2D occupancy grid stores a set of the binary occupancy values (0 and 1) assigned to each cell, resulting in a 2D binary occupancy grid or a weighted occupancy grid (see figure 6.2). The weighted occupancy grid (figure 6.2) reflects the aggregated results of the temporal occupancy grid, defined as “occupancy over a number of different timescales” (Arbuckle, Howard, and Maratic, 2016). The values for each cell refer to the total amount of time the cell was occupied during a particular period of time, representing the percentage of the total time the cell was occupied. Also, each occupancy cell imports the occupancy probability values calculated from the regression models presented in the previous chapter (see figure 6.2). The occupancy probability grid ‘adds’ a value between 0 and 1 to each cell, representing the probability of a cell having been occupied. Values closer to 1 represent a higher chance that the cell is occupied in certain conditions.

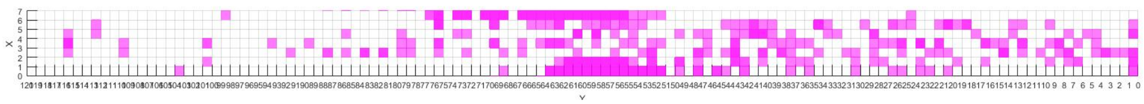


Figure 6-2. Binary Occupancy Grid (yes and no, or 0 and 1, values).

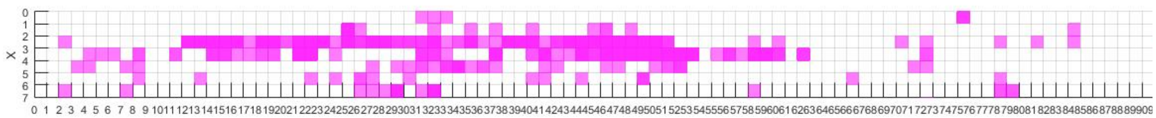


Figure 6-3. Weighted Occupancy Grid (0 to total number of time stamps, represented as continuous values between 0 and 1).

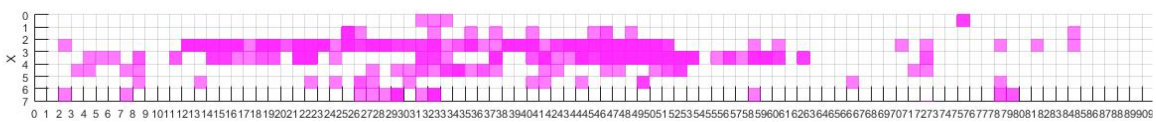


Figure 6-4. Occupancy Probability (values between 0 to 1).

The fundamental differences between occupancy probability and weighted occupancy are that the occupancy probability values are calculated from the accuracy results and are expressed as percentages, while the weighted occupancy values are calculated as the sum of the occupancy temporal duration during a determined period of time. These results are expressed first as integers, representing the time units that the cell was occupied, and later, normalized as percentages.

6.3 Analyzing Spatiotemporal Occupancy

The purpose of analyzing spatiotemporal occupancy is to understand the fundamental characteristics of occupancy in terms of spatial and temporal distribution in different scenarios, with the main goal of determining key indicators for a building's data-driven occupancy performance. The spatiotemporal analyses consist of the following four stages: 1) a visual exploration of the data by importing subsets of activity types to provide insight about the occupancy distribution of sample scenarios; 2) the quantitative analysis of occupancy distribution to compare the scenarios, determining their statistically significant differences; 3) the definition of spatiotemporal parameters based on the visual understanding of the occupancy data subsets; and 4) the definition of spatial-behavioral metrics based on the spatiotemporal parameters to specify precise built environment performance indicators.

Visualization of Sample Scenarios

The visualization of the sample scenarios is aimed at providing an overall understanding of occupancy patterns, accompanied by further visual exploration of the data to uncover more specific calculations. The quantitative analyses are based on the research-specific queries, which are answered through data-driven calculations.

The visualizations of the spatial and temporal occupancy distribution were created in MATLAB, allowing the exploration of the full datasets by providing the necessary manipulation and interaction on the variables, such as filtering and selection. The analyses provided a set of embedded calculations for some key quantitative analyses on the imported datasets. The implementation is structured as shown in the activity diagram (figure 6.4) and includes the following steps: (1) importing the two datasets of interest, the spatiotemporal occupancy dataset, which is the occupancy data obtained over time and the area of interest by corridor; (2) creating an occupancy grid and a occupancy cube figures, which are the platform for the 3D visualization, and adding an occupancy counter, which is fundamental for all calculations; and (3) creating a spatiotemporal matrix for the spatiotemporal occupancy accumulative data on the occupancy grid. At this point, the analyses offer two outputs: a 3D visualization that plots the occupancy cube and that allows interaction for data visual exploration and export of a JPEG file, and the quantitative analyses, which export the results as a CSV file.

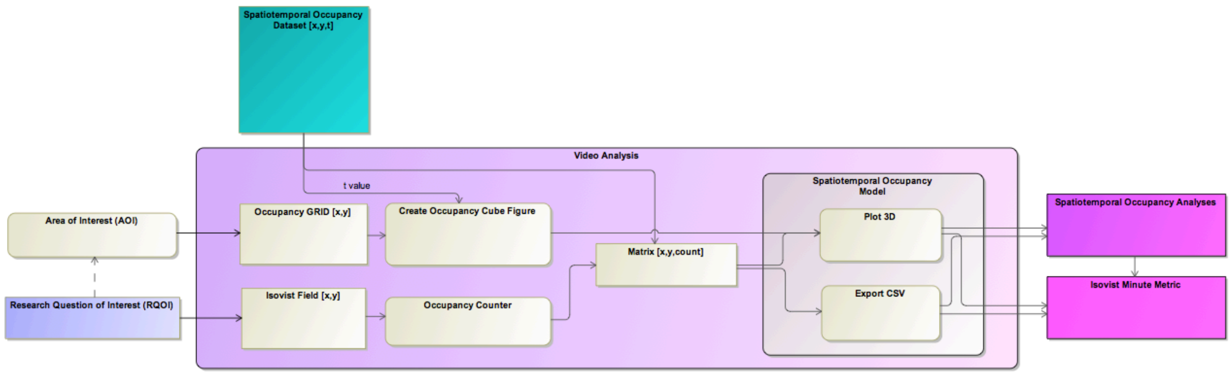
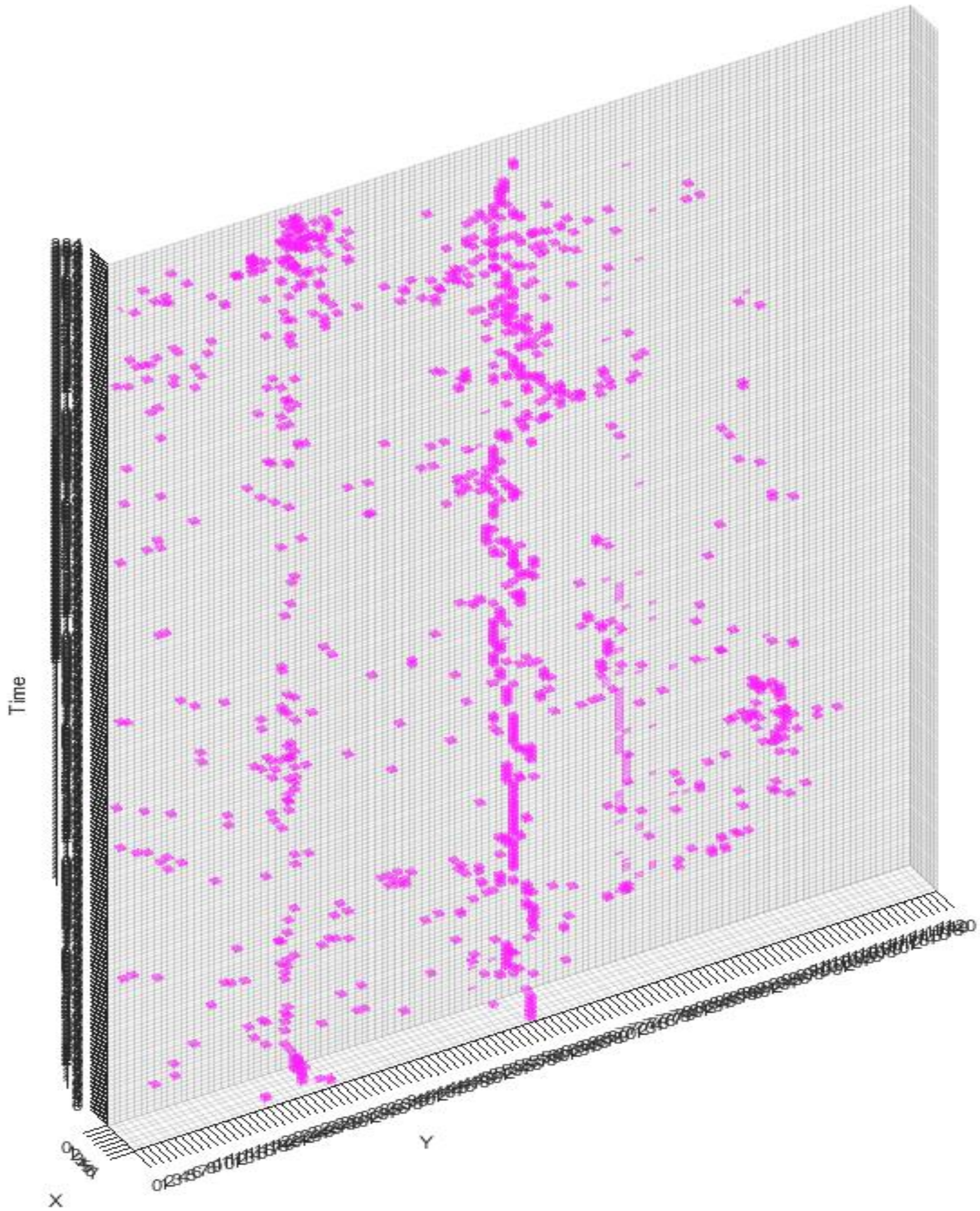


Figure 6-5. Activity diagram for the implementation of spatiotemporal occupancy analyses

Characterization of Scenarios

The visual exploration of the spatiotemporal occupancy dataset allowed for recognition of some fundamental characteristics of occupancy in terms of spatial and temporal distribution. The visual comparison of data sub-samples helped us determine specific aspects of the occupancy characterization, e.g., the influence of programmed activities. The premise is that when comparing two or more scenarios, occupancy distributions show different results based on the following three factors: spatial configuration, programmed activities, and organizational schedule, which in turn is related to activities actually happening at specific times. In this research, spatial configuration was discarded as an influential factor because the twelve corridor scenarios are close to geometrically identical, with the exact same spatial organization. Thus, the most influential factors impacting occupancy distribution were the programming, the scheduled activities and the activities actually performed, which occur in certain periods of time and imply the presence of a certain number of people. To corroborate the specific influence that programming and scheduled activities have on certain patterns of occupancy, a sample of nine scenarios were defined for comparison (see figure 6-7).

The goal of comparing samples scenarios was to unveil the differences in occupancy distribution based on the type of activity. The comparison occurred between several of the scenarios' occupancy patterns under the same spatial conditions but different programming and scheduling conditions. The nine sample scenarios selected to show these differences were medical rounds, visiting hours, and no scheduled activities in two corridors and on different days of the week. The three types of activities occurred at 8 a.m., 4 p.m., and midnight respectively, in all corridors. The corridors selected had two different organizational programs: the 7th floor, which contained private rooms, and the 3rd floor, which contained the ICU. The two days of the week selected were Wednesday and Saturday (Figure 6-7).



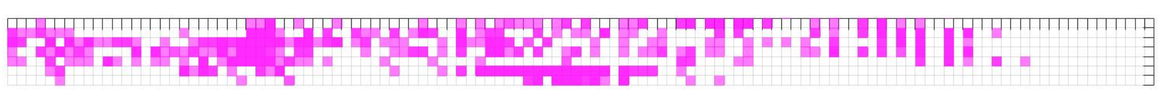


Figure 6-6. Perspective and top view occupancy on a sample scenario for visiting hours, from 4pm to 5pm.

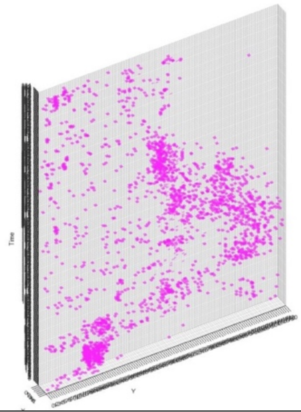
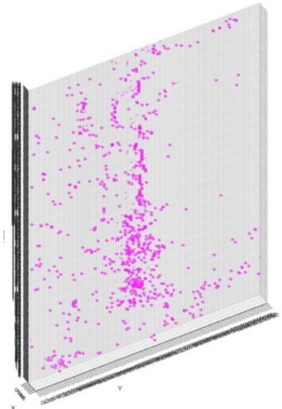
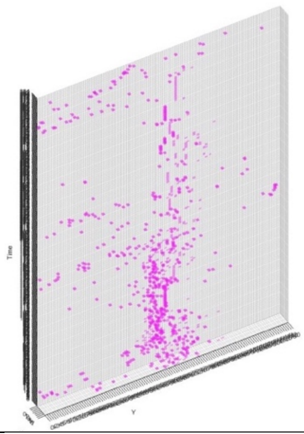
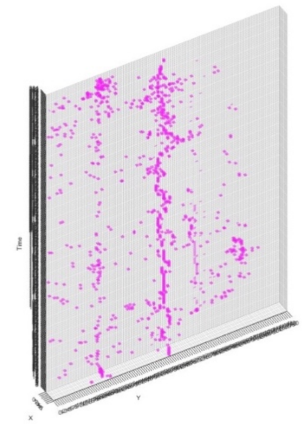
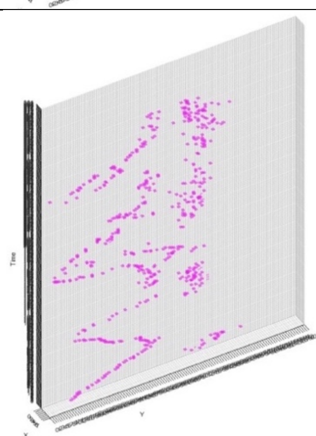
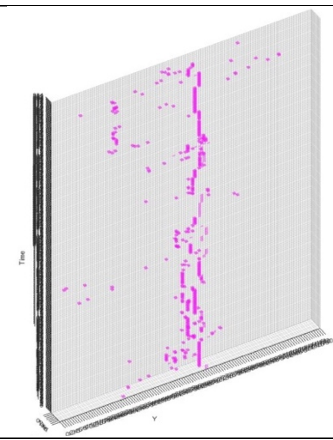
	Week day	Week day	Weekend
8 am			
4pm			
00 am			

Figure 6-7. Matrix comparison of nine sample scenarios. Columns from left to right indicate the corridor organizational unit and the two selected days: Wednesday and Saturday. Rows indicate the three one-hour samples, three times a day: Medical Rounds at 8 am (General Hospitalization and ICU); Visiting Hours at 4pm (General hospitalization Wednesday and Saturday); and No Scheduled Activities at midnight (General hospitalization and ICU).

Some findings related to simultaneous occupancy, sequences on occupancy, frequencies, and the stability of occupancy in certain areas were noticeable though visual exploration of the occupancy data subsets, providing the agenda for testing specific hypotheses. For example, the number of people that are co-present influences the occupancy counting (two to seventeen, respectively, for the no scheduled and medical rounds scenarios), while co-impacting the redistribution of people in space as well as the sequence in which the cells become occupied. In medical rounds, for example, the number of people varies from four before the round started to twelve during the round.

Spatiotemporal Analyses

Scenario comparison also includes analyses to determine the significant differences in the data subsets, which tests this specific study's initial premise regarding the influence of activity on occupancy distribution. Once the differences were verified, analyses of the aggregated and spatiotemporal occupancy were presented. Some of these specific quantitative metrics were introduced in the "Activity Shapes" previous research (Gomez, Romero and Do, 2012), providing insights about the form that occupancy takes in space and time, as well as any statistical differences[2]. In Activity Shapes, the spatiotemporal analyses were classified into three types: dispersion, gravitation, and stability of clusters. In this spatiotemporal occupancy research, the three metrics were calculated to help characterize the hospital corridors spatiotemporal distribution. Dispersion describes the spread of spatial occupancy in the corridors, and it was calculated by distances standard error; Gravitation refers to the distances from each occupied cell to attractors at a specific positions. In this case, it was calculated to the central nurse station and to the center of gravity of the scene, which refers to the average center of all individuals' positions. The center of gravity was calculated as

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[2] We acknowledge the guidance of Dr. John Peponis in this research, as well as his involvement with the implementation of the statistical model.

weighted and unweighted. Weighted refers to including the duration that the cell was occupied, and unweighted refers to including the occupied cells as a binary result, occupied or not occupied. The dispersion and gravitational distances from each occupancy cell were calculated as part of the scenario comparison.

Table 6-1. Dispersion and gravitational distances (in cell unit) by scenario.

	Week day		**Week day**		**Weekend**	
	dispersion (st err)	**gravitation (avg dist)**	**dispersion (st err)**	**gravitation (avg dist)**	**dispersion (st err)**	**gravitation (avg dist)**
Medical rounds (8 am)	5.88	49.60	8.24	37.80		
Visiting hours (4 pm)	6.21	47.93			7.85	40.77
Night shifts (00 am)	15.80	36.72	10.76	35.74		

The results show significant differences among the three scenarios in terms of dispersion and gravitational distances. First, the highest dispersion is found in scenario three, night shifts (15.80 and 10.76), indicating that participants maintain more variable distance from the nurse station. In contrast, the lowest dispersion is found in medical round scenario (5.88), followed by visiting hours (6.21), both in the private hospitalization wing, indicating that participants are less dispersed, or maintain less distance difference to the nurse station, being closer from each other than from any other pivot point. Second, the medical rounds scenarios had the highest distance to the nurse station (49.60), which means that the center of gravity of the activity moved along the corridor forming occupancy clusters. Third, the highest gravitational distance to the nurse station was found during the same two scenarios (49.60 and 47.93), while the shorter were during the midnight shift. Similarly, gravitation of the visiting hours (40.77) indicate the formation of clusters in the corridor, which represent visitors having a conversation in the corridor (as shown in Figure 6-5). These results suggest differences in occupancy dispersion and gravitation when comparing two scenarios at a time by the sum of the total distance among occupied cells and the distance from all occupied cells to the central nurse station. These results corroborate the assumption that the activity being performed has an influence on the occupancy distribution. For example, the distribution of people during the medical rounds is clustered, while in the other two scenarios, people are more dispersed. Thus, a noticeable correlation exists between the type of activity and the distribution of people in space and time. These calculations can help characterize the occupancy distribution per scenarios, helping to provide guidelines further research in occupancy simulation.

Spatiotemporal Parameters

The findings presented above, considered in the context of a high occupancy resolution of one square-foot by second, raise a question regarding the appropriate metrics for studying the spatiotemporal relationship of space and behavior. Two main parameter suggestions emerge from this study's data exploration, position-dependent and time-dependent parameters. Position-dependent parameters refer to the position of an individual in space, which also depends on the number of people simultaneously present in the space. This research presents some definitive findings, based on observations that arose during the visual explorations. First, the spatial occupancy distribution depends on the solitary or simultaneous presence of users. For example, when only one person is walking along a corridor, he or she tends to walk toward the center of the corridor, but if two or more individuals are walking along a corridor in opposite directions, each person tends to stay to his or her right. The position of a person and his relationship to space will directly affect the behavioral-spatial metrics proposed in this dissertation.

Time-dependent parameters refer to an individual's length of stay in a specific cell, either the time spent in a location or the walking speed, which also affected the total occupancy distribution. Those factors also depend on the nature of the activity (i.e., programmed vs. non-programmed and frequent vs. infrequent). While it is not possible to generalize to all scenarios from these samples, some common tendencies arose regarding activity-driven occupancy, and both position- and time-dependent parameters as the direct variables for the spatial-behavioral metrics proposed later in this research.

6.4 Healthcare Behavioral-Spatial Variables

Prior EBD studies have focused on the correlations between design strategies or environmental interventions in healthcare buildings and desired healthcare outcomes, as summarized in Table 6.2. For example, the effect of acuity on reducing medical errors and patient falls, reducing the length of stay, decreasing staff injuries, and increasing staff effectiveness, all of which relate to the field of vision surrounding patient beds (Ulrich et al., 2008). With the purpose of demonstrating the key role of spatiotemporal occupancy analysis, and based on the concepts of position- and time-dependent parameters, as presented above, this research proposes specific metrics to identify new key building occupancy performance indicators. From the standpoint of healthcare EBD, and its crucial relationship to patient safety and outcomes, the analyses and metrics developed in this research will focus on patient surveillance, a key goal for healthcare organizations.

	Design Strategies or Environmental Interventions											
Healthcare Ouctomes		Single-bed rooms	Access to daylight	Appropriate lighting	Views of nature	Famuly zone in patient room	Carpeting	Noise-reducing finishing	Ceiling lifts	Nursing floor layour	Decentralized supplies	Acuity-adaptable rooms
improving patient safety through environmental measures	reducing hospital-acquired infections	2										
	reducing medical errors	1		1				1				1
	reducing patients falls	1		1		1	1			1		1
Improving patient outcomes through environmental measures	reducing pain		1	1	2			1				
	improving patients sleep	2	1	1				1				
	reducing patients stress	1	1	1	2	1		2				
	reducing depression		2	2	1	1						
	reducing length of stay		1	1	1							1
	[redacted]											
	improving patients privacy and confidential	2				1		1				
	improving communication patients and fan	2				1		1				
	improving social support	1				1	1					
	increased patient satifsfaction	2	1	1	1	1	1	1				
Improving staff outcomes through environmental measures	decreasing staff injuries								2			1
	decreasing staff stress	1	1	1	1			1				
	increasing staff effectiveness	1		1				1		1	1	1
	increasing staff satisfaction	1	1	1	1			1				

Table 6-2. Summary of studies of the impact of design strategies or environmental interventions on healthcare outcomes (Table adapted from Ulrich, Zimring et al., 2008).

Surveillance

Dougherty (1985) first introduced the term “surveillance” in the healthcare context and defined it as the care provided by nurses, later refining that definition to include both cognitive and behavioral processes involved in the decision-making and action for the well-being of a patient (Dougherty, 1999). Today’s definition of surveillance implies a set of actions, including monitoring, evaluating, analyzing, interpreting, making decisions, and taking action based on an assessment (Titler, 1992; Schoneman, 2002), and is a broader and multidimensional concept that includes expertise, intuition, and early patient health recognition skills. Stated another way, Henneman, Gawlinski, Giuliano (2012), defined the term as “a systematic and goal-directed process focused on early identification of risk and the need for intervention.” Healthcare surveillance, therefore, encompasses a more complex process than mere visual surveillance, and includes performing rounds, monitoring, and identifying both vulnerable patients and potentially unfavorable events, with a goal of averting medical errors. While the term surveillance has been utilized throughout multiple disciplines “to describe the process of collecting, analyzing and taking action based on facts and data” (Schoneman, 2002), healthcare surveillance refers to an intermittent process, either passive or active, and is used for the purpose of collection and propagation (Thacker et al., 1989), as well as for decision-making (Kelly and Vincent, 2011). Research has shown that patient outcomes are directly related to surveillance, most frequently by presenting the negative consequences associated with insufficient or absent surveillance, such as health complications, life-threatening conditions, and higher mortality rates (Dougherty, 1999; Institute of Medicine, 2004; Kalisch, 2006; and Kutney-Lee et al.. 2009).

Surveillance is the most important strategy for patient safety, and although visual surveillance or monitoring is only one component of healthcare surveillance, it is an essential one. Analysis from 75 participating hospitals showed that direct observation of patients, i.e., visual surveillance, showed a statistically significant correlation with lower fall rates (Feil and Wallace, 2014). Other initiatives involved installing video surveillance in selected rooms in a few hospitals, which reduced the number of patient falls to only one per year (For hospitals, 2013). Consequently, visual surveillance of patients could help reduce negative health consequences, while reducing the length of stay and, correspondingly, the cost of hospitalization. Therefore, this dissertation studies the visual fields from patient beds and the actual visibility of patients in a hospital setting, with the purpose of developing a surveillance-related metric that might help improve the patient health outcomes.

Visibility and Visual Fields

Visibility is a spatial variable constructed on the interaction of behavioral and spatial features. The first and most influential work that attempted to measure human experience in relation to the geometry of a space is Benedikt's "Isovists" and "Isovist fields" (1979). An Isovist is defined as the polygonal region that is directly visible from the specific position of an habitant. A sequence of Isovists – or Isovist fields – represents the Isovist variations, which depend on the trajectory of an habitant in space. Both Isovists and Isovist fields are used to describe environments, quantitatively, from the perspective of a vantage point. Benedikt described some quantitative Isovist's geometric properties, proposing methods to measure its area, perimeter, occlusivity, variance, skewness, and circularity, which are geometrically calculated from a defined vantage point (Davis & Benedikt, 1979). In 1980, Braaksma and Cook worked on measuring the intervisibility between spaces in a transportation terminal by applying visibility graphs. They selected certain of the terminal's key spatial units to measure disorientation in such buildings. They were the first researchers to construct a visibility graph as a representation of the visual connection between spaces, in which nodes were the spaces, and connecting edges represented visual relationships (Braaksma and Cook, 1980). From the graph, they calculated the ratio between existing visual relations and potential visual relations to measure the influence of space on human orientation. Visibility graph analysis is the approach utilized by Space Syntax to construct the spatial analyses mentioned earlier in this research, such as connectivity and integration (Bafna, 2003; Turner, 2004).

Targeted Visibility

Targeted, or directed, visibility was addressed by Lu et al. in a study of targeted visibility analysis in buildings (Lu, Peponis & Zimring, 2009; Lu, 2011). They proposed a new visibility model that "separates the origins and destinations of all lines of sight." They correlated the findings with the distribution of people in an environment of crucial visual monitoring: the Emory Neural ICU. Lu applied this approach in analyzing other settings, such as virtual exhibitions. On another track, Markhede and Miranda observed how space syntax tools had disregarded the occupied space by giving priority to the potentially occupied space, or "occupiable space" (Turner, 2004). In their work on the Spatial Positioning Tool (SPOT) (Markhede and Miranda 2007a; 2007b; 2010), they measured the visibility of a space from the occupied locations. SPOT examines 360° of visual fields from occupied spaces, offering "a new insight into how we approach space syntax" (Koch, Marcus and Steen, 2009) in SSS7 proceedings, 2009 (Turner, 2009).

This dissertation, with the aim of analyzing the real visual fields in spatial environments, seeks to answer questions about actual visual surveillance of spaces by incorporating actual human positional data as inputs for spatiotemporal analyses, shifting the focus from general visibility as a property of the space to an Isovit temporal metric, or the surveillance of real observers over time in relation to patient beds. This research proposes the development and implementation of algorithms for real surveillance over time and its analysis, constructed using the spatiotemporal occupancy datasets as inputs.

6.5 A New Spatiotemporal Occupancy Metric: The Isovist-Minute

Few previous studies have proposed Isovist field metrics that originate from patient beds. The targeted visibility study (Lu, 2011), discussed above, counted the heads of patient beds that were in sight of each position from the corridor, assigning this characteristic to the space. Another study by Osman (2016), defined Isovist-connectivity as the properties of each patient bed's Isovist fields, such as its internal connectivity, determining their influence on patient's outcomes, such as mortality rates. Both metrics were founded on three geometrical – and static – parameters of space: visual fields, positions of the beds, and connectivity. These studies, however, failed to include occupancy data; which left no information about actual surveillance. Therefore, importing actual spatiotemporal occupancy data will determine the transformation of static-geometric metrics into a parametric spatiotemporal occupancy-related metric of actual surveillance, which would vary depending on the values of the time- and position-parameters. Consequently, this research proposes a new spatiotemporal occupancy-related metric for measuring the performance of the occupied space: the Isovist-minute.

Isovist-Minute

An Isovist-minute of a target is defined as the visibility of a specific target during a determined time frame. In a hospital, for instance, it can be computed for a patient's head, where it measures the amount of visual surveillance of a patient's bed from the corresponding target's Isovist areas in the corridor (see figure 6.4). The Isovist-minute is calculated based on the actual occupancy data collected automatically and corrected statistically as described in the previous chapter, measuring the real and probable surveillance of a hospitalized patient.

The Isovist-minute of the patient, or "target," measures the time that the head of a patient's bed is within any observer's sight or probable sight. This probability takes into account the statistical accuracy and precision corrections presented in the previous chapter, as well as the probable direction of the head of the occupant. The Isovist-minute output is a value that represents the total time during which the target was observed or potentially observed. Computationally, the target could be defined as a person or as an inanimate object. The Isovist-minute can hold several sub-metrics, depending on the emphasis of the key performance indicators. Among these are "temporal Isovist-minute fields," the "Isovist-minute's frequency," and its "intensity."

These three metrics are calculated utilizing the occupancy grid approach, with both values and visualizations as outputs (figure 6-2).

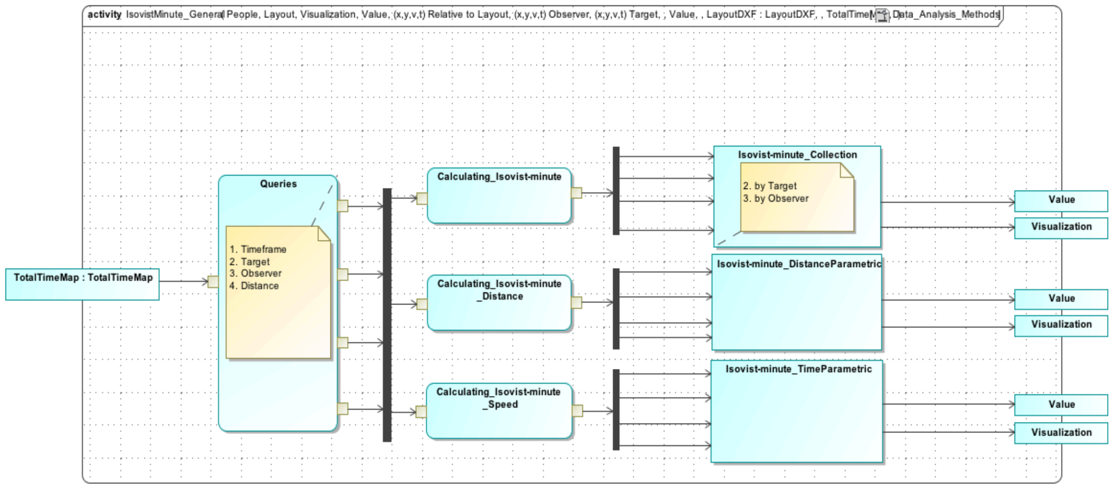

Figure 6-8. UML Activity Diagram that represents the Isovist-minute methods. It shows the input (spatiotemporal occupancy), the possible queries for computation, the three methods proposed, and their outputs as values, as well as visualizations.

"Temporal Isovist-minute fields" are essentially the analyses of the variations in Isovist-minutes over time. This metric collects the Isovist-minute information by time frames (seconds or minutes), allowing for measurement of the Isovist-minute fields' properties, such as the spatiotemporal distribution of visual fields, calculating their variation over time. The "Isovist-minute's frequency" refers to the spacing between the occurrence of events over a period of time, while the "Isovist-minute's intensity" factor is the distance between the patient and the observer, calculated by dividing the Isovist-minute by the distance in cell units. This latest Isovist intensity definition was first addressed by Do and Gross (1997) with the goal of modeling and analyzing spatial characteristics of layouts. Do and Gross created four computational methods of analyses, each addressing different aspects of spatial analysis, to support architectural design in terms of spatial perception, i.e., enclosure, Isoview, point light simulation, and shadow casting Point-light and shadow-casting. In particular, these are two algorithms that calculate the intensity of the Isovist field, which varies depending on the distance from the vantage point.

Isovist-Minute Implementation

Existing methods of spatial analyses have been constructed using different implementation approaches that influence the results of the analyses in terms of values, but more importantly, in terms of the underlying architectural concepts that they describe (Turner and Penn, 1999; Turner, 2001; Turner, Doxa, O'Sullivan and Penn, 2001). Visibility has been mathematically described and computationally implemented from two approaches, as geometry and as a graph. Geometrical visibility is a mathematical abstraction of real-life visibility, which occurs between two points in the Euclidean space. In contrast, a visibility graph is an abstraction of relationships of intervisibility between nodes (Braaksma and Cook, 1980; Turner 2001). Each node represents a location in space, and each edge connecting two nodes, a visible connection. To simplify geometrical visibility calculation, and depending on the conceptual description of space, several authors have proposed calculating visibility fields as an approximation of space in a visibility graph, using a bi-directional adjacency matrix data structure, in which each edge represents mutually visible locations, generating an array of relations from each node.

Computationally, the Isovist-minute is calculated as a sub-set of a 3D occupancy array of cells containing positioning and time information (x,y,t). This approach is based on both the ease of the computational resources required and the MATLAB language, which has characteristics that make it compatible with the description of the space as an occupancy grid. The calculation of an Isovist-minute requires a description of the patient's fields of view and of the spatiotemporal information occurring inside those fields. The first step is to describe the patient's visual fields – or Isovist-fields – from the head of each patient's bed, and the next step is to define the sub-set of occupancy cells that belong to each particular Isovist-field. The description of the patient's Isovist-fields results in the generation of several CSV files, each composed of a list of cell coordinates that belong to the corresponding Isovist-field (figure 6-9). The patient's Isovist-field, as calculated from the head of his or her bed, is defined as the maximum field of vision generated from the upper-third of the patient's bed, as shown in figure 6-10. While an occupancy cell's center belongs inside the Isovist-field area, the occupancy cell itself belongs to the Isovist-field list. Some cells, as expected, belong to several Isovist-fields (Figure 6-9). In this research, every hospitalization wing contains 22 rooms, as shown in figure 6.5 with one or two beds per room positioned either at the center of the wall (m), the corridor (c) or the window (w), thereby creating several potential Isovist areas. Once the Isovist-fields are created from the head of each patient's bed, the array of cells that belong to that Isovist is stored as an independent CSV file containing an array of cells (x,y), named as "Floor level," "Room number," and "Position of the bed" (i.e. 7N-07-w).

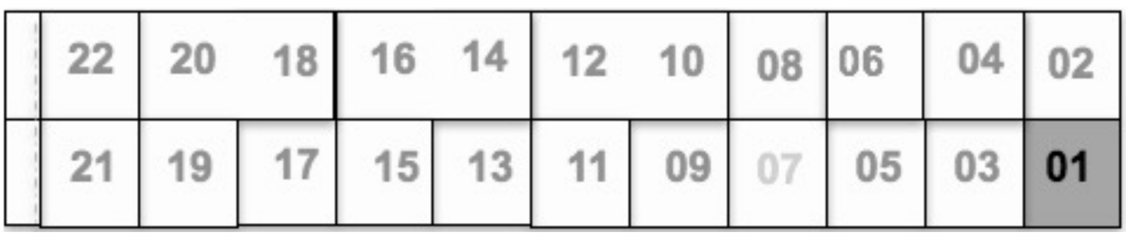

Figure 6-9. Array of rooms along the corridor, starting at the entrance.

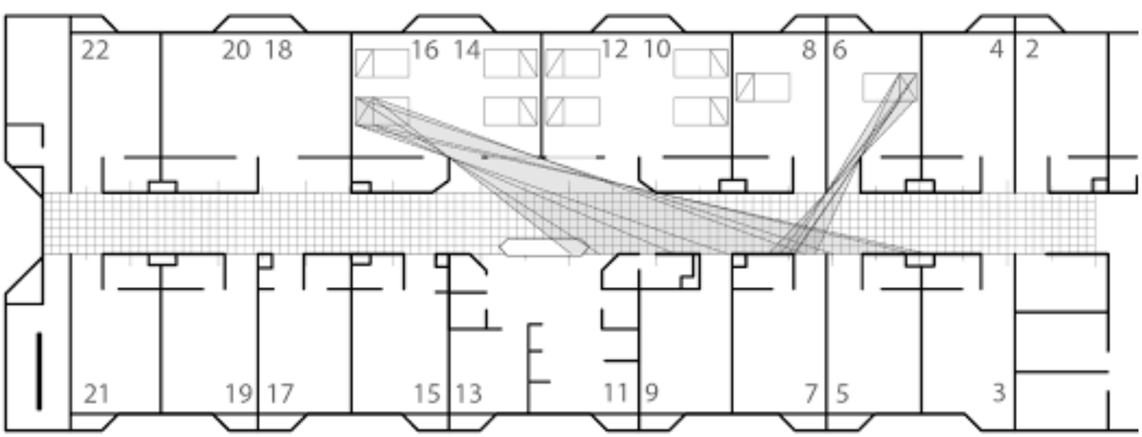

Figure 6-10. Isovist areas from patient's head of beds 6-center and 16-corridor.

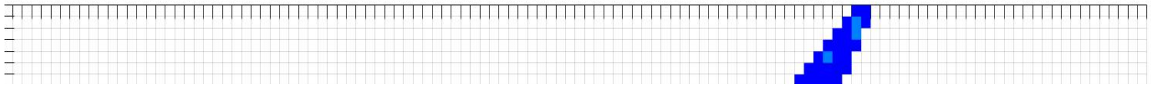

Figure 6-11. Heat map of occupied cells, indicating length of stay, in the Isovist area of patient's bed 6-center.

The computation of the Isovist-minute requires importing the spatiotemporal occupancy data and superimposing it over the patient's Isovist-fields, resulting in a number of spatiotemporal occupancy data subsets occurring inside each of the patient's Isovist-fields. Once generated, these cell subsets are used as the main input to create the Isovist-minute for each scenario. The result is a global measure of the potential surveillance under the current conditions; however, as visual fields have a theoretically inherent direction, implementing directed fields of vision will provide more resolution to the Isovist-minute results. To determine Isovist-field direction, it is key to define a second level of occupancy subsets addressing directional occupancy along the corridor, which will determine the Isovist-minutes that are meaningful in a particular context. For example, as the patient's bed in room number 8 is facing north (Figure 6-10), and the occupants are walking towards the nurse station, the actual sub-set of visual surveillance is very meaningful, showing that the very high probabilities of occupancy facing the head of the bed (compared to the opposite scenario when people were walking in the away from the nurse station, or are facing another direction, such as looking down under a cart). These directional Isovist-minutes are also calculated during one-hour periods of time, and include not only on the programmed rounds by medical staff and nurses, but also any inadvertent surveillance from the corridor areas.

Isovist-minute Scenarios

As addressed above, the Isovist-minute outputs depend on the predominant activity performed during a specific period of time, as demonstrated by the nine scenario characterizations presented below (Figures 6-12 to 6-19).

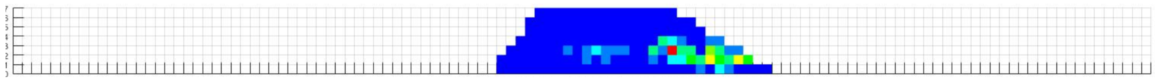

Figure 6-12. (6SN-00am) Isovist Bed-12-corridor; Heat map of Isovist-minute by cell.

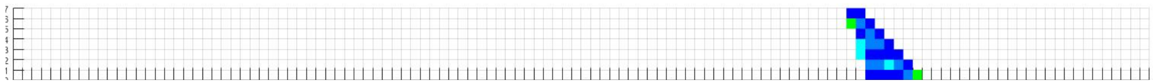

Figure 6-13. (6SN-00am) Isovist Bed-8-center; Heat map of Isovist-minute by cell.

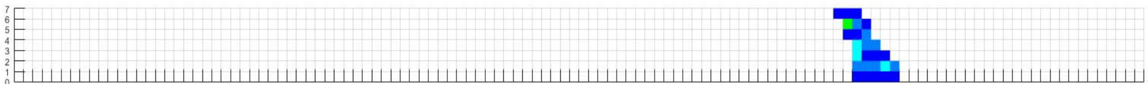

Figure 6-14. (6SN-00am) Isovist Bed-8-window; Heat map of Isovist-minute by cell.

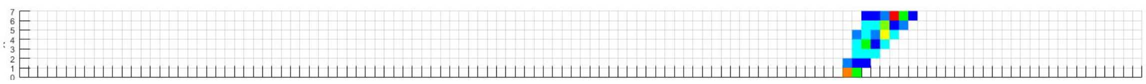

Figure 6-15. (7N-8am) Isovist Bed-7-center; Heat map of Isovist-minute by cell.

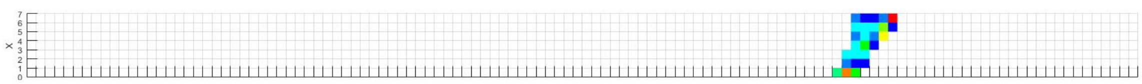

Figure 6-16. (7N-8am) Isovist Bed-7-window; Heat map of Isovist-minute by cell.

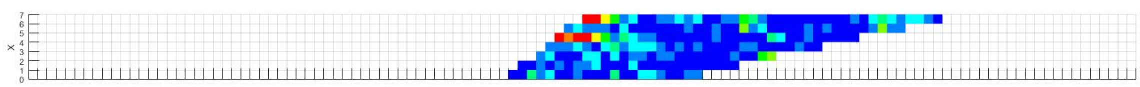

Figure 6-17(7N-8am) Isovist-minute bed-16- corridor; Heat map of Isovist-minute by cell.

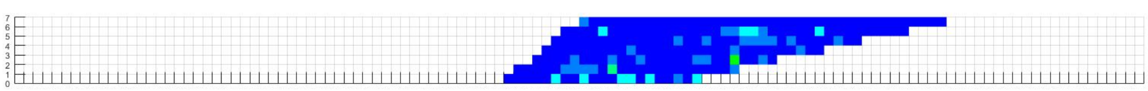

Figure 6-18. (7N-4pm) Isovist-minute bed-16- corridor; Heat map of Isovist-minute by cell.

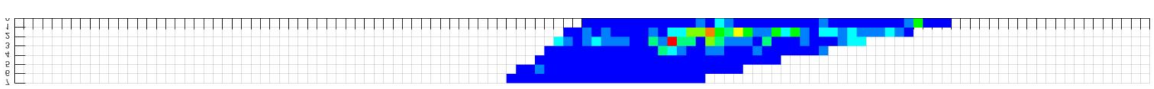

Figure 6-19. (7N-00am) Isovist-minute bed-16- corridor; Heat map of Isovist-minute by cell.

Table 6.2: Occupancy count results obtained from IsovistCount.m Matlab file, which counts the number of events per cell; total Isovist-minute in minutes, per hour, per scenario.

	Occupancy count	Isovist-minute per hour
Bed-12-corridor (6SN-00am)	**1290**	**21.5 min.**
Bed-8-center (6SN-00am)	**180**	**3 min**
Bed-8-window (6SN-00am)	**220**	**3.7 min**
Bed-7-center (7N-8am)	**610**	**10.2 min**
Bed-7-window (7N-8am)	**640**	**10.7 min.**
Bed-16-corridor (7N-8am)	**2220**	**37 min.**
Bed-16-corridor (7N-4pm)	**540**	**9 min.**
Bed-16-corridor (7N-00am)	**1360**	**22.67 min.**

The Isovist-minute visualization outcomes were expected to predict that bigger Isovist-minutes would result from the larger Isovist areas. Additionally, the visualizations revealed that visual surveillance for beds located in front of the nurse station, was not limited to evident areas in the radius of the nurse station, but instead expanded to other areas along the corridor. Moreover, certain patient beds including the 16-c (room 16, bed towards the corridor), which was somehow hidden from direct visual surveillance from the center of the nurse station, had a bigger Isovist area (210 sqFt. compared to 155 sqFt.) as well as a bigger Isovist-minute (21.5 min. / 22.67 min.) than patient's bed 12-c (room 12, bed towards the corridor) –which is theoretically more exposed to constant surveillance– when comparing both at the same hours (please see figures 6.12 and 6.19 for details, as well as table 6.2 for results).

In addition, directional surveillance must be taken into account in determining meaningful Isovist-minutes. It was expected and corroborated that at the end of each day, the aggregation of all spatiotemporal occupancy information would be close to average, including the number of occupancy inputs facing both directions along the corridor. The findings indicate that at 8 a.m., during the medical-round scenario, the patient's beds facing south, or the entrance of the unit, had higher Isovist-minutes, because most people walk into the organizational wing in a northerly direction. In this context, even though medical rounds added exclusive surveillance-time for patients in each room, as the visits were sporadic the Isovist-minute per room were infrequent (one per hour). In contrast, during visiting hours, nurses were mostly not present when they were supposed to stay primarily at the nurse station, and un-programmed casual surveillance came from visitors, mostly those walking towards the unit, opposite to the beds facing the entrance at the beginning of the visiting period and beds facing in the opposite direction at the end of the period.

Practical and technical challenges

Both conceptual challenges and challenges in implementation development arose at this stage of the research, evolving with each iteration. The conceptual challenge involved the development of meaningful analyses in the specific context of a healthcare building, and the implementation presented several practical and technical challenges. The practical challenges concerned file management and naming; data management; and mapping data positioning from video to layout and to space labeling. The technical challenges included adding the precision error into the spatiotemporal occupancy data, filtering the data into meaningful subsets, scaling the temporal axis for the visualization to ensure the data samples were comparable, and inserting automation between several steps in the process.

The volume of data necessitated that file management and naming include strict organization of the folders and the files within them. First, spatiotemporal occupancy data was exported every hour, and the exported file adopted the name of the folder followed by the name of the video. Parsing technique was applied to recognize delimiters, such as a slash (/) and a dot (.), including the name of the folder and the video file in the name saved into the CSV output file. Managing the set of files for analyses involved a semi-automated process. The code determined each sequence of files to analyze, but they were conceptually pre-defined by the researcher. Mapping occupancy data needed global and local coordinate references. First, on the videos, the global origin was defined in the lower left corner of the area of interest, the corridor. Second, in the layout, the consensus origin was located at the lower left corner of the corridor, when looking from the camera's perspective. This means that in the actual layout, the positioning data was mirrored in the Y axis, numbering the cells from 0 to 120 on the Y axis in the north corridor and from 120 to 0 on the Y axis in the south corridor. On the X axis, however, the cells were not mirrored but rather were flipped, meaning that, when looking from a top view of the layout, the origin was located at the lower right corner in the south corridor and on the upper left corner in the north corridor. This procedure was implemented to maintain consistency in the labeling of space for the Isovists. Space labeling, however, was mirrored to the X axis as well, to maintain the relation of space labeling to space qualities, such as the relation to adjacent spaces and exterior views (see image 6.7).

Because of the number of considerations and exceptions, the automation of the transition between operations presented a substantial technical challenge that was not completely resolved in this thesis. First, although the statistical approach was defined in this research, calculating and automatically adding the changing precision error into the spatiotemporal occupancy data required the statistical model's implementation into MATLAB, since the values changed by cell, depending on the scenario conditions. Second, the knowledge needed to filter the data into meaningful subsets was defined along with the data exploration, iteratively, and it can be implemented later in a future research. Third, in order to visualize the data in a normalized scale, it was necessary to scale the Z-axis of the visualization depending on the size of the dataset (from 1:1:1/2, to 1:1:1/30), which in turn depended on the number of people present and was recognized in a one-hour time period.

Future work would include importing a set of correct files for analyses; implementing other versions of the Isovist-minute, such as an Isovist for each occupant, which would include the presence of other occupants as obstacles as well as moving objects, such as closing doors; recalculating the visual fields for every frame; storing occupancy data into a structure database for queries; exchanging data from and to the DepthmapX application or other CAD tools, such as Rhino; and packaging the database into a stand–alone application, allowing direct interaction with universal users, although this could limit the type of analyses to those pre-built in the code.

6.6 Conclusions

The spatiotemporal analyses implemented in this research focused on the theoretical influence of organizationally scheduled activities on people's behavior, confirming that the distribution of people in the space was neither homogeneous nor constant over time but instead depended on the activity being performed as well as the number of occupants in the space. Some patterns of occupancy under determined temporal parameters, such as the higher concentrations of occupants in specific locations at different times of the day, such as the higher concentration of occupants at the nurse station at midnight compared to the medical rounds (min.); or the higher concentration of occupants in the sections of corridor that are located between patients' doors, during medical rounds. In both examples, the findings might seem trivial, but the level of spatial and temporal resolution obtained is unusual.

The main goal of this section of the study was to find meaning for the spatiotemporal analyses in the context of architecture by measuring some aspects of the space-use. The result of the research was not on specific findings, but on the development of a set of spatiotemporal metrics, such as dispersion and gravitation, as well as a key-metric related to spatial configuration and environmental occupancy conditions: the Isovist-minute. In this specific research, that metric refers to a guaranteed minimum of patient surveillance per day, by patient room. This metric, the Isovist-minute, contains units of measurement that imply an area coverage during a specified period of time and allows for the recognition of certain parameters that affect its outcome, i.e., design and occupancy parameters, categorized into position of objects and proportions of the space, and positioning and time parameters, respectively. For example, one can assume that the patient's bed located in front of the nurse station would have a major and constant surveillance rate per patient. The fine-grain anayses depicted that depending on the hour of the day (and the programmed activity), some in-front-of-nurse station beds (i.e. 12c), which are expected to be highly surveilled, are less surveilled than other beds (i.e. 16c) during certain periods of times, such as medical rounds. Expanding on that example, during medical rounds, patients get at least 10.5 minutes of direct surveillance within the hour, besides the default visit to each patient room. Patients towards the entrance get the surveillance in the first third of the hour, while the rest of the beds get the surveillance later within the same hour. Also, as the order of the visits per room are determined by the diagnosis of the patient, the central rooms tend to get higher casual surveillance when the group of doctors is walking from one room to another.

Also, the position of objects in space act either as targets for, or as obstacles to, impacting the shape of the visual fields will or Isovist-fields. Also, proportions will determine both the distances between dispersed objects or persons in space, due to their radius of influence or personal bubbles (Hall, 1960), as well as the architectural elements that will either enhance, funnel, or dissuade Isovist-fields. The position of people in space, combined with their length of stay in such a position and their sequence of positions, will be a factor that impacts the Isovist-minute in terms of the Isovist field (occupancy-space relationship mapped) and the duration in minutes. Design modifications, such as the position of the bed in a patient's room, the size of the door thresholds or windows, or even changes in the hospital's organizational performance can influence the spatiotemporal metric of the Isovist-minute, and, therefore, may affect some specific patient's outcomes.

Particularly, visual calculations implemented in this research assessed visibility from a theoretical perspective of an observer with a 180° field of vision and general focus Isovists. Theoretically, observers are aware of their entire surroundings (Peponis, 1998) and vision is assumed to be horizontal at eye level, however in real life vision has a direction and a coverage range. Previously, it was reviewed that visual surveillance from public areas covers a certain range of a patient's global health state. Ambient factors, such as distance to the patient or glare coming from patient's rooms, may allow observers to focus their attention on the patient's general health status, including detecting falls, but such conditions may not allow the observer to detect more particularized symptoms, such as dehydration or fever. Therefore, Isovist-minute has particular implications for visual surveillance. In addition to healthcare environments, spatiotemporal analyses, and specifically the Isovist-minute, can be applied to retail and work environments, providing specific outcomes such as economic return or communication. Interchangeably replacing surveillance with another spatiotemporal metric that concerns occupancy, such as interactions, will allow for the extension of the list of key performance indicators to other spatial and temporal architecture aspects.

6.7 Summary

This chapter described four new metrics that capture distribution of people within a given setting both in space and over time. It further presented an empirical validation of methods by which these metrics can be estimated using Scene Analyses detection technology, combined with staistical modeling of errors. First, this chapter presented the modeling of spatial and spatiotemporal occupancy, focusing on the influence of the organizational schedule on people's behavior. Second, it presented the resulting characteristics of specific sample scenarios, describing and comparing the spatiotemporal occupancy. And third, it presented the spatiotemporal occupancy-related metric that renders the relationship of spatial layout and occupancy patterns toward an EBD healthcare outcome, a metric called the Isovist-minute, which measures the probability of an individual's surveillance in specific locations of a spatial setting, given certain scenario conditions, including spatial, environmental, and occupancy aspects, as well as programmed and actual activities.

CHAPTER 7

CONCLUSION

This research focused on capturing and analyzing spatial and temporal patterns of human occupancy in building settings, with the purpose of determining building occupancy-related metrics. These occupancy metrics were associated with the performance of key aspects of post-occupied spaces, such as inpatient surveillance during a hospital stay, which was computed as the relationship of the visual field in conjunction with the actual occupancy. The specific goal of this research was determined by the relation between a selected behavioral mapping automated system – including all its technical specifications – and an appropriate research question that the selected system was capable of answering. In this case, the characteristics of the proof-of-concept hospital scenario contributed to defining a thorough and systematic methodology, including precise aspects for the study of spatiotemporal occupancy patterns, such as automatic detection accuracy and probability. The occupancy data captured allowed for the analysis of spatiotemporal patterns and key assessments.

The outcomes and contributions of this dissertation correspond to the four main challenges in which the research was structured. The first challenge was the identification of the fundamental features of behavioral mapping that were crucial for the analyses, traversing practical, technical and theoretical inquiries, helping to define a process for capturing spatiotemporal occupancy data of high temporal and spatial resolution. Second, once the positioning system was selected based on that interrelated technology-research question. Second, adopting and adapting specific spatial analysis techniques to recognize the features the architecture research practice care about from a detection perspective. The third challenge was to determine the occupancy recognition accuracy for the large datasets gathered. And fourth, after the occupancy data were obtained, the distribution of occupancy patterns in specific scenarios became the focus of the study, which ultimately found that these patterns depended on certain programming and scheduling conditions. Also, in attempting to capture patterns of occupancy, the possibility of measuring their effect on specific behavioral outcomes became the challenge of the following stage, which outlined the Isovist-minute – a new spatial-behavioral metric. Each of these stages of research can be an independent study, yet the aim is that together they present the layout for this line of research.

7.1 The Adoption of Scene Analyses for Determining Spatiotemporal Occupancy Resolution and Social Acceptance

The research outcomes that correspond to this first stage, system selection, includes a broad survey for the selection of the data collection system appropriate for this research. The main finding was the bi-directional effect between the selection of the system and the question of interest. The nature of the research question will determine the social and technical aspects of the technology, which will have an impact on defining such question as well. For this, a parallel coordinates was plot to visualize the implications of the system selection on the research question.

Previous surveys and reviews of positioning systems, which have been exhaustively performed from the technology perspective approximately every seven years, have not addressed the systems' social aspects and implications, such as their potential social disruption and/or acceptance. Social acceptance of tracking and positioning technologies has a huge impact on the type of data possible to acquire. Also, social aspects are crucial when selecting a technology, especially in behavioral mapping, since they determine the size of the population that participates in the sample. If the sample is reduced or incomplete, the findings may not be generalizable. Although the technology with higher social acceptance usually provides greater privacy for the participants' identification, it also generally includes more subjects, allowing for the capture of more complete and exportable data, encouraging emergent findings. And as noted above, the attributes of the data that a technology can capture and the research question to be answered are interdependent factors. Other aspects to consider are the resources necessary in terms of installation, implementation, and maintenance. These factors will also determine the duration of the collection as well as the area of coverage.

7.2 Positioning Techniques

The outcomes at this second stage are set of techniques developed for spatiotemporal occupancy collection and analysis. Each technique had a set of sub-challenges at the implementation level, providing a glimpse for future work on activity detection and patterns analyses, from the perspective of applied research in the field of architecture.

The scene analyses in this specific case included all subjects in a certain distance range, capturing a spatial resolution of less than one feet and a temporal resolution of several frames per second, which determined the resolution of the spatiotemporal analyses. Additionally, aspects such as accuracy and precision played a principal role in the data acquisition process. The practical challenges included the number of cameras, each of which possessed slightly different characteristics, such as video size and quality, camera orientation, and vision angle. These challenges required setting up each corridor individually. Concepts such as “the area of interest” and the “object of interest,” as well as methods to systematically capture them, emerged. Theoretically, the training of classification models for the detection of people should be the same in all scenarios. However, this research showed that for each surveillance scenario, the levels of confidence in the classification models changed, allowing an opportunity for training specific datasets for particular environments, interchanging the “object of interest.” Computationally, the definition of object includes more than just physical objects. It also includes features that are important for detection of meaningful aspects for a research question. The object of interest could change for future research, having an impact on the methodology or system selection. For example, some objects (i.e. carts) can be tracked using sensing technologies. Therefore, create classification models for people or other more specifically defined “objects”, such as the persons’ role, their body orientation, their body posture, or the activity they are performing during certain periods of time, related to the scheduled activity, are potential next steps for research.

In this research and after performing several training sessions, the results showed much less accurate detection when using the pre-trained classification models, due to the number of images involved in the training, leading to the conclusion that for this stage of the research, the use of several approaches can help solve the challenge of accurate detection. The selection of the system set-up, including the possibility of adding extra cameras to avoid distortion and occlusion, and the ensuing technical challenges, including the particularized training of the classification model and the development of more advanced algorithms based on the environmental conditions, presented some solutions for this research. However, this thesis argues that since the technology and scenario are continuously changing, this study proposes statistical models that can help overcome data collection accuracy and precision errors, found on every technology. From the machine learning perspective, another future research direction that can branch from this stage is that similar pattern recognition techniques that the ones used in computer vision for detection could be applied to occupancy pattern learning and recognition in a layout, since both are based on a grid of ‘pixels’ or ‘cells’ to determine the “object of interest” features that are necessary to recognize.

7.3 Determining the Accuracy and Precision of the Scene Analysis Detection System

The third research stage proposes that probabilistic models can be used to derive the probability of detection of the systems, with the goal of obtaining a more reliable occupancy dataset. Further challenges arose in determining the accuracy and precision of the scene analyses system based on an understanding of the key factors that might influence occupancy data collection errors. The sources of these challenges were linked to two aspects of the behavioral mapping system selected: the environmental conditions in which the system was set up, including the number and orientation of existing cameras and the lighting conditions, and the development level of the detection algorithms. A study was designed and developed specifically to determine the influence of Background and Activity parameters on detection, and can be described by scenario conditions. It helped to determine both the exact accuracy and precision and the boundary of an adequate expected accuracy. This approach supported the use of a technology under development, even though the results were not 100% accurate. The hypothesis for this study was that the distance from the cameras, as well as environmental and activity-related factors, would have a direct influence on detection accuracy. An increase in accuracy and precision errors was expected the further the distance from the camera. The study also sought to determine the combined influence of each factor on the accuracy errors. Because the results showed less than 50% accuracy in some zones of the corridors, this study also proposed a strategy to improve occupancy recognition by applying probabilistic models.

The research demonstrated that distance had a non-linear but exponential impact on accuracy errors and a linear impact on precision in location errors. Additionally, the models developed for assessing the accuracy and precision of the scene analysis automatic detection also help us understand the sources of error that come from environmental conditions as well as the activity that is observed. Since lighting and camera conditions were predominantly constant during relatively long periods of time (i.e. one hour), the “activity”, the “body posture” were the main causes of errors related to the classification model for people detection, showing that ‘Activity Type’ and ‘Body Posture’ factors have high impact on occupancy detection. The organizational schedule will determine the probability of detecting such specific activity type, and in turn, the activity will determine the probability of detecting such body posture. The color of the cloth showed no real impact on detection, but on the classification of people’s roles. These findings provided valuable feedback to improve future research in the area of machine learning by refining the classification model training process.

The empirical study of errors also showed the value of developing models of specific scenarios. In a particular scenario, environmental conditions can be taken to be consistent as programmed activity. This means that apart from accidental change in rates of occupancy, the effect of systematically programmed activity and possible environmental conditions on error rates can be successfully predicted and accurate estimates of occupancy can be generated even when the technology or algorithms used to do so present errors. These in-context findings can be used as guidelines to improve future research in the area of machine learning algorithms development, as well as providing valuable feedback for refining the classification models, classification accuracy, errors, or other measures for the evaluation of classifiers. These findings also set a precedent for promoting the validation of video-based automatic detection incidents (Shehatta, 2008; Tsai, 2010; Sheata, 2006; Meshoui, Kardouchi, Allalim and Ait, 2011) such as the environmental and activity factors that could have a known influence on recognition probability of environmental conditions, such as glare levels, brightness and contrast levels or the degree of light reflection on surfaces.

The scenarios used for the analyses in this study were primarily determined by environmental conditions, including the time of day and thus the activity being performed. The nature of a scheduled activity necessarily affected occupancy factors, such as occlusion, the most recognized and common factor impacting visual recognition, which depended primarily on the number of people present in the scene. Consequently, the level of occlusion varied depending on the activity scheduled and the number of people involved. This study determined the probability of such occlusion, by one-hour periods of time, creating a probabilistic model that explains the occupancy recognition probability depending on the activity being performed.

Future work in this area could include developing algorithms that are adaptive to the expected environmental and occupancy conditions based on the architectural program assigned by space. Such future work would require training the algorithms to recognize not only the object of interest, but the context of interest, classifying all the aforementioned parameters, ultimately resulting in detection algorithms that are meaningful in context. Also, accuracy and precision errors depend on the units of measurement employed. This study used pixels for spatial units and frames for temporal units to detect people in videos A spatial transformation matrix then transformed the pixels into feet to obtain real spatial accuracy and precision. The matrix was modeled in general, but it took into account the specific area of interest of each camera. Thus, the generalized transformation approach had to be tailored for each camera focus and angle, determining a slightly different area of interest in terms of pixels' coordinates. The units of spatial and temporal occupancy were rounded to the nearest foot and to ¼ second, which reduced the error rates.

This study concluded by presenting a predicted occupancy dataset, obtained by applying a probability detection factor based on the accuracy of a given location. Precision also was calculated as the distance between the real and the detected location, which was subtracted at each location to correct the occupancy positions detected. The improved occupancy datasets were later contrasted with a 100% confidence dataset collected manually to validate the results. These results showed important differences in the occupancy pattern distributions, but less varied results when comparing the one-hour time periods. These results suggest that, even if it is not possible to have a predictive model for occupancy, the underlying patterns of occupancy are comparable. Accuracy and Precision analyses are methods that can be adapted to any technology. Same probability models applied to the recognition factors could be applied to occupancy patterns factors in future research.

7.4 Integrating Spatiotemporal Occupancy Analyses

The selection of a strong program scenario such as a hospital provided two advantages. One advantage is architectural program rigidity, which allowed the researcher to isolate the majority of the research variables, maintaining an almost identical geometry in each scenario and a fixed and limited set of activity and participant types. A second advantage arose from the richness of the real world scenarios, which forced this proof-of-concept study to include a number of unexpected variables into the analyses, such as the differences in occupancy outcomes based on architectural programs, organizational programming, or the programmed and unprogrammed activities that actually occurred. Compared to a simulated environment, these conditions provided the depth of detailed variables included in the research.

The aim of spatiotemporal occupancy analyses is to collect datasets that provide answers to a range of research questions, including current state-of-the-art research and other studies designed to determine more specific issues with greater resolution or multidimensional questions. Some analyses will address global patterns of behavior in specific built environments, while others will specify the spatiotemporal patterns. The ratios between occupancy and activity type, occupancy and the occupants' roles, and the occupants' distribution in space and time also can help expand the spatiotemporal question categories. Suggestions for future work include the computation of the ratio between scheduled and unscheduled activities, including the impact of some factors, such as activity programming, occupancy patterns, and the probability of occupancy, to help researchers define more detailed inputs for occupancy simulations in strong building programs. Future research to acquire more extensive datasets for occupancy detection will impact the complexity of the occupancy simulation models, by obtaining, for example, the ratio between activity types, thus providing feedback to the organizational process as well as the geometric variations of spatial configurations. Occupancy simulation models can be improved by incorporating real occupancy parameters. For example, due to the inherent nature of the activities in a strong program, most of the activities are expected to occur at certain locations and hours. However, this spatiotemporal occupancy methodology can incorporate the frequency of scheduled and unscheduled activities on certain areas of the building. Although most activities in a strong program scenario are supposed to be scheduled, they are usually linked to a designated room space. Unscheduled activities primarily occur in corridors or other types of space that do not have a specific program formally assigned.

7.5 Towards Spatiotemporal Performance Metrics by Scenario

Through the proposal and development of occupancy analyses for architectural research, this research proposes spatiotemporal analyses for building settings. These analyses included several stages: first, the modeling of spatial and temporal occupancy through the lens of organizationally scheduled and unscheduled activities; second, the characterization of sample scenarios by describing and comparing them; and third, the conception of a spatiotemporal occupancy-related metric, which measures the relationship of occupancy patterns and spatial configuration, with the goal of improving outcomes. In the case of a healthcare program, for example, an evidence-based design factor, such as patient surveillance, provides one important outcome that could give value to the built environment. In this research, the Isovist-minute mapped in a layout the probability of a patient's surveillance in specific setting, given certain scenario conditions including spatial, environmental, and occupancy aspects, as well as programmed and actual activities.

This research showed how dynamics measures of occupancy rates can be computed even when the detection systems present errors. These kinds of dynamic measures are particularly useful when the patterns of occupancy depend not just on spatial layout and program but also on activity programming and occupancy rate itself. Higher concentrations of occupants at different times of the day, at different areas, showed that the aggregated results presented in previous research tended to show only general patterns of occupancy distribution, generalizing the findings. This research does not present any specific behavioral finding due to the size of the sample. The main goal was to expand spatial analyses toward spatiotemporal analyses, adding value and meaning to the architecture evaluations, developing key metrics based on the relation of both spatial configuration and occupancy, with the objective of demonstrating the value of measuring certain aspects of the use of the space, such as a guaranteed minimum of patient surveillance per minute of occupancy. This metric, called the Isovist-minute, study the relationship among spatial variables, occupancy, and time; and it is calculated based on an Isovist or field-of-vision, activated during a specific period of time. These Isovist-minute are impacted by spatial and temporal parameters. Spatial parameters include the location of targets –such as the position and orientation of the head of an inpatient's bed–, the position of obstacles that could interfere with visual fields –such as medicine carts or closed doors– and the distance between the origin and target of the visual field. Temporal parameters that impact the Isovist-minute include the duration in time that people occupy a certain position, and the activity scheduled for that period of time.

Although this particular research assessed visibility more theoretically – as a proof-of-concept study– considering a horizontal 180° vision range, with no specific focus, these factors can be updated later for a more realistic approach, including aspects other than visual surveillance. Design parameters such as the position and orientation of patient beds, the dimensions of patient room thresholds and windows, and policies regarding visual connectivity can influence the Isovist-minute outcome and, in consequence, may have some correlation with patient health related outcomes such as reducing falls or reducing the length of a patient's stay.

This research approach shows that useful spatiotemporal metrics can be successfully developed even when the detection systems are prone to errors. This proof-of-concept study prepared the platform for using spatiotemporal metrics in architecture, at the post-occupancy evaluation stage. The system and the outcomes can be interchanged to answer a variety of research question. Hence, for example, when a more accurate location systems become available –even when it presents errors– Scene Analysis can be replaced, allowing for continuous growth and expansion of this area of research at two fronts: technological development and architectural assessment. However, each change brings with it several implications. For positioning system selection, for example, the replacement of a scene analyses system with a tracking system could impact social acceptance as well as the type of data obtained, which, in turn, could directly affect the type of calculable metrics achieved. Also, for architectural assessments goals, for example, applying the Isovist-minute to retail environments could provide an economic return as a measurable outcome. The surveillance-minute outcome could be replaced, for example, by the interactions-minute outcome, measuring the spatiotemporal distribution of communication in a workplace environment, thus expanding the range of spatiotemporal metrics in architectural assessments. In conclusion, spatiotemporal occupancy data collection and analyses methods endorse the integration of a temporal dimension into architectural research, proposing a branch of research towards the study of the relationship of spaces and their temporal occupancy dynamics.

APPENDIX A: IRB APPROVAL

File Name: H14365

SkipToMain

Protocol H14365	As Of: February 4, 2015 04:00 PM

Title: Spatiotemporal Occupancy Patterns in Hospitals: Vision-based methods for data capturing and analysis

Principal Investigator: Sonit Bafna	**Current Status:** Approved
Admin Assigned: Melanie Clark	**Last Activity:** 01/16/2015 - Supplemental Document added by Administrator
Committee Assigned: Central Institutional Review Board #1	**Original Approval Start:** 01/16/2015
Review Type: Expedited Review	**Current Approval Period:** 01/16/2015 - 01/15/2016

Protocol Details | Related Submissions

Protocol Description:

The goal of this research is to describe spatiotemporal occupancy patterns in specific hospital areas.
Patterns of occupancy can be analyzed depending on the characteristics of the data collected. Until now, the classic observation and mapping method, commonly used for post-occupancy studies in buildings, respond to questions that are limited to spatial dimensions. However, to answer finer grain questions that relate with spatial and temporal variables we required a high resolution and accurate data.
In this research, vision-based methods of analysis will be explored in great detail, using the video surveillance records for comparative empirical studies conducted in different spatial settings in the Navy hospital in Chile.

Department:

Arch

Research Personnel:

Name	Role	Certification	Documents
Sonit Bafna	PI	• Georgia Tech CITI Human Subjects Training Certification (Approved): February 20, 2013 - February 20, 2016	
Paula Andrea Gomez Zamora	Student	• Georgia Tech CITI Human Subjects Training Certification (Approved): February 6, 2013 - February 6, 2016	

The Protocol: Research Design and Methodology

A Describe the research design, including the proposed research methodology. For research directly involving human subjects, describe in chronological order the procedures that will occur. If subjects will be assigned to various conditions, describe how and why assignments will be made. (Examples of studies not directly involving human subjects, but still needing IRB approval, include prospective record reviews, observation of behavior without manipulation, and use of anonymized data).

This research will be based on a video surveillance records from the Navy Hospital in Chile. We will use videos recorded during 14 days on public areas of the principal tower of the Navy Hospital (Chile). If necessary, complementary cameras will be installed to complete the data collection. Those videos will be processed in Matlab to extract the occupancy of individuals. Original videos will not be public, and individuals will not be identified. Permission to use these videos is granted by the institution administration.

B State the duration of subject participation. How many hours, days, weeks or months? Specify number of sessions and, to the extent possible, state total amount of time for subject participation.

Data will be collected for 14 days. It consist of surveillance videos from cameras already installed in the Hospital, and few complementary cameras to fill out the missing spots. Data will be provided with the approval of the Hospital administration.

C Describe study assessments and other data collection methods. Upload all instruments, including rating scales, questionnaires, surveys, focus group and interview guides, and so on at the end of this online application in the ATTACH DOCUMENTS section.

(NOTE: The IRB recognizes that such specificity may not be possible in ethnographic or anthropological studies. In such cases, provide sufficient detail for the board to understand the study methodology).

Data input are surveillance video recordings from the Navy Hospital in Chile. The administration will provide on an external hard drive the 14 days of videos, previously recorded in a server and captured from surveillance cameras installed on the hospital. The data transfer will happen two times, the first time storing the first 7 days, and the second time storing the other 7 days. This is due the capacity of the Hospital server, that only store 7 continues days of videos. The two data sets will be collected in the same external hard drive, which is encrypted and requires a password authentication to access it, as recommended by Georgia Tech OIT security policy. The password is known by the hospital administration security footage and the researches involved in this study only. To obtain people's occupancy locations, videos will be processed using video and image processing methods in Matlab. Once occupancy data is extracted, it will be abstract data as colored spots, and no one will be able to identify individuals. Afterwards, videos will be observed by the researchers, to annotate manually the occupancy location. The goal is a comparison between automatically extracted and observed occupancy data, to compute the error rate. No other persons than the research group will have access to the original videos. After the study is finalized, the video footage stored in the hard drive will be deleted, and the hard drive formatted.

D Fully describe any potential benefits of this study. All ethical studies pose some benefit-- whether to individual research subjects, to the greater community, as a building block for further development of treatment, and so on. (If subjects will not benefit from participating, this should be disclosed in the benefits section of the consent document).

The main benefits of the study is an understanding of practical issues involved in collecting behavioral data from automated data collection techniques. Participants will not obtain a direct benefit from this study, however, they will help the success of this research. They will receive a copy of the research results, and they will be cited in the acknowledgment section of the dissertation and publications.

E Fully describe any known risks to subjects participating in this study and, to the best of your knowledge, indicate the likelihood of such risks occurring. Also state any measures to be taken to minimize or eliminate risks or to manage unpreventable risks.

No other risks than those encountered in daily life during regular working hours or visiting hours.

F Describe the statistical analysis plan, its design, and the rationale for the plan.

The video data will be used to develop automatic procedures for computing locations of subjects and from that the geometry of the paths described collectively by subjects during the recording period. During the course of analysis individual personal characteristics will be stripped from the data and only locations computed.

G What are the anticipated start and end dates for the proposed research? Include the expected number of years that data analysis will continue.

Federal regulations currently require that IRB approval remain active during data analysis (if subject data are not de-identified) even though subject enrollment and interaction may be complete. Be sure to include the period of data analysis when calculating the end date if you will maintain subject identifiers.

Data collection will start as soon as we get the IRB approval. We expect to conduct the data collection between November and January 2014, and complete the study within one calendar year of the IRB approval. No subject identifier data will be recorded or kept.

H Upload a fully annotated bibliography or reference section, including the results of the literature search done in support of this proposed study.

This material may be added in the ATTACH DOCUMENTS SECTION at the end of the online application and is required for CLINICAL STUDIES only.

This is not a CLINICAL STUDY

I If this is a **student class project**, provide the course title and number and the name of the instructor.

COA 9000 - This is a doctoral dissertation guided by Dr. Sonit Bafna.

J **GEORGIA INSTITUTE OF TECHNOLOGY INVESTIGATORS ONLY:** If funding is pending, specify the potential funding source in the field here. (IRBWISE is linked only to active awards on record in the Georgia Tech Office of Sponsored Programs and not to pending proposals). If the study is already externally funded, please select the specific project in the funding section below.

(No Answer Given)

K **GEORGIA STATE UNIVERSITY INVESTIGATORS ONLY:** Please specify the funding source in the field below. IRBWISE is not linked to GSU's Office of Sponsored Programs, so the search feature in the next question is not applicable to GSU investigators.

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