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PZ Smart Flooring System: Spatiotemporal Occupancy Analyses for Architecture

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Abstract

This paper introduces, first, the value of obtaining dynamic information through smart environments for Architecture feedback at building scale. Second, it describes the co-evolution of the systems design for specific sensitivities required to perform meaningful analyses for the different scales. Third, it presents the significance of obtaining spatial and temporal occupancy data of high resolution, allowing significant new architectural analyses to emerge. Furthermore, it concludes by describing the vision for the future trajectory of this line of research.

Keywords Smart Environments, Smart Buildings; Smart Flooring Systems; Post-occupancy Analyses; Spatiotemporal Occupancy; Piezo-based Flooring.

INTRODUCTION

We envision the future of computational design integrated with smart environments –at city, campus, building and human scales. Specifically, the inclusion of dynamic information into the computational models. The long-term goal is to integrate dynamic stochastic data, such as human behavior, into the models, for the development of analyses at four levels: Systems automation for smart environments, building performance outcomes, organizational performance outcomes, and feedback for buildings redesign.

This research focuses on smart building environments, presenting a co-evolution between the design and development of a pressure sensing flooring system (Piezo-flooring or PZ-flooring) for human behavior data acquisition (Figure 1), as well as the set of analyses based on spatiotemporal occupancy data [Gomez, 2017]. The objective is to present a framework of the importance of spatiotemporal occupancy and behavioral data for architecture analyses and feedback

Current research in the leading architecture offices focuses on the analytics of information at the earliest as well as latest design stages, with the purpose of optimizing some aspects of architecture designs, such as the layout organization, building orientation and façade design, energy consumption and light quality, among others. The goal is to achieve the optimization of certain aspects as well as achieve some standards (i.e. LEED or Leadership in Energy and Environmental Design standards). Building energy simulations are one of the most popular analytics, with the highest revenues for the clients and the industry; However, the occupant modeling does not yet include the actual occupancy of a building (Kim, 2016).

Building Information Modeling (BIM) allows some separate analyses, such as programmatic spaces, building circulation, energy consumption, and preliminary cost [Sanguinetti et al., 2012]. However, these analyses are currently using passive information based on stored historic data (codes, weather data and climate zones), which does not consider the nuances and granularity of real-time variations. Our long-term goal of including dynamic information about spatial occupancy in architectural analyses implies several challenges, at numerous levels. First, at a highest level, it requires obtaining occupancy data of high temporal-and-spatial resolution; second, it implies determining meaningful assessments based on the characterization of the data obtained, which, in turn, requires the development of the right sensing system. These challenges cannot be isolated from each other since there is a direct correlation between type of sensors, the characterization of data they collect –their accuracy, precision and resolution– and the analyses we can obtain from such data.

Within this context, this paper presents the framework for a line of research that comprises two branches: First, collaborative technology-development research on Smart Flooring Systems, and second, the analytics implemented for meaningful Architectural outcomes. The goal of both branches combined is to support the optimization of layout design and organizational performance, developing new and dynamic building performance analyses.

SMART ENVIRONMENTS

Smart Environments is derived from the paradigm of ubiquitous computing, which is defined as “a physical world that is richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives, and connected through a continuous network." [Weiser, Gold, and Brown, 1999]. According to Dey, Abowd and Salber (2000), “One of the goals of a smart environment is that it supports and enhances the abilities of its occupants in executing tasks. These tasks range from navigating through an unfamiliar space, to providing reminders for activities, to moving heavy objects for the elderly or disabled.” In this research, we are extending this vision further. Our goal is to enhance not only the tasks and experience for users, but to obtain a deeper feedback for the building analytics, which can be useful for several stages of the building lifecycle, from design to post-occupancy.

Figure 1: Conceptual Image of the Smart PZ-flooring system

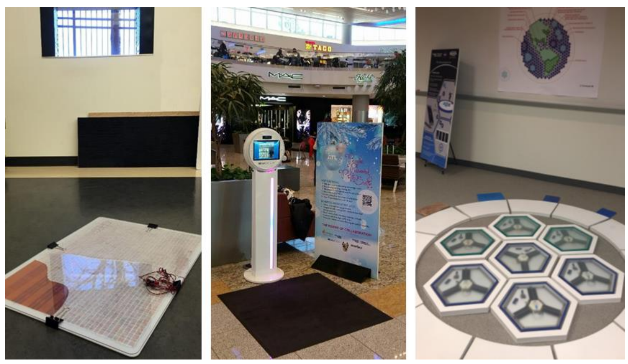
BUILDING ANALYTICS

On the one hand, areas of Architectural research, such as Space Syntax and Evidence-based Design (EBD), have focused on understanding the influence of space configuration on human behavior, with an emphasis on binary occupancy, directional movements, and social interactions as counters (Bafna, 2003; Hillier 1984 a and b). However, the traditional methods utilized to collect behavioral data are resource intensive and require observation and manual inputs to acquire relative accuracy [for details please reference to Gomez, 2017, Chapter 2]. Those methods require human interpretation to be precise, but they still lack high spatial and temporal resolution to allow meaningful architectural analytics (Gomez, 2014). On the other hand, the area of simulation and modeling for evaluating building use (i.e. energy consumption, or building organizational schedules), had conventionally used a set of existing agent-based simulation models. These analyses have provided an approximation of results, which are used to make design decisions at all design stages, from early design stages such as massing design, to late design stage decisions including specifying HVAC systems. Researchers have compared those results, finding an important difference between the calculated models and the real post-occupancy outcomes (Kim, 2016), determining that agent-based simulation models should include stochastic factors, imported from real post-occupancy analyses.

Differences between the architectural models and post-occupied buildings naturally emerge, especially in how the spaces were intended to be used and how they are actually used. Based on the work of several authors that make a distinction between the ideas of “program” and “programming” of a space (Markhede et al., 2007 and 2010; Koch and Steen, 2012), Gomez (2014 and 2017) presented the concept of incorporating the real spatial programming and actual occupancy into the digital models, and compared them with actual occupancy. This includes the real-time number of occupants as well as changes over time of organizational schedules and space functions. The goal was to demonstrate that human behavior is not only influenced by the layout configuration, as conceived in the early literature presented above, but also by the space functions assigned and modified over time, the organizational programming, and the actual activities being performed. In this context, smart environments bring the opportunity to advance the behavioral data collection towards larger volumes of spatial and temporal data with more resolution, accuracy, and precision. This article presents two concepts: The technology definition to capture such data, introducing the challenges faced during the development and installation of one of the largest smart flooring prototypes (200 ft2) (refer to figure 6); and the correlation between the aspects definitions for the design of a technology and the final analytic outputs to be achieved.

PIEZO-BASED FLOORING SYSTEMS

Our smart and sustainable Piezo-based flooring systems are designed for three scales: Body, Building and Campus scales (figure 2). The indoor building PZ smart flooring system specifically, is designed as an under layer for building applications. This indoor system has three functionalities: (1) Pressure sensing though an electronic floor underlay; (2) data capturing, transmission, and storage; and (3) data analysis, mapping, and visualization.



(a) **(b)** **(c)**

Figure 2: The evolution from (a) the first PZ-flooring laboratory concept; to (b) an interactive Photo booth system installed at the ATL Hartsfield Jackson international airport; to (c) a Campus scale PZ-tile for the Kennedy Space Center installation.

The substrate consist of a high-density array of sensors, which are able to capture pressure when squeezing the piezo material. From that signal output, we developed a set of algorithms that provides the data to calculate occupants' foot position, occupants' spatial and temporal distribution, and specific "events", such as steps or falls. These data are recorded in real time, providing positioning data points of a high resolution.

Custom designed electronics are responsible for capturing the pressure values and wirelessly transmitting the data to a server. The data includes the time stamp (t) in milliseconds and a single dimensional column-first base 64-byte array of the voltages (V) sampled from the transimpedance amplifier that is interpreted as the pressure at each sensel. The spatial coordinates (x,y) of each sensel are implicitly defined in the ordering of the single dimensional column-first structure of the values.

From the 4D array of data points, a set of specific algorithms were custom developed to interpret and analyze the types of activities that may occur, such as occupants' position, occupants' spatial and temporal distribution, and expected repetitive events, such as steps or incidental events such as falls, occur. This information is post-processed into occupancy values per square foot, or "cells" to obtain a weighted 'occupancy grid' for further analysis of spatial occupancy patterns at the room or building scale.

SYSTEM SPATIOTEMPORAL RESOLUTION

The spatiotemporal resolution of a grid of sensors varies depending on the scale of the project and the intended analyses that relate to that scale. During this research, we tested different grid resolutions, from four (4) sensors per square foot to half (½) of a square inch, in different patterns. For example, for a building scale, a resolution of 1 square foot (Figure 3), which corresponds to the size of a carpet tile as well as a personal space bubble (defined by Hall, 1960), is sufficient to study the building patterns of activities between spaces, across weeks. While for body scale, a resolution of half (½) square inch is appropriate for detecting the pressure distribution of a human footstep, and to therefore study the walking patterns of users (Figure 4 and 5). The adjustment of temporal resolution also varies from application to application, from 1 to 60 times per second. For example, a temporal resolution lower than 15Hz does not allow the recognition of a running activity, due to the high frequency of steps on the surface.

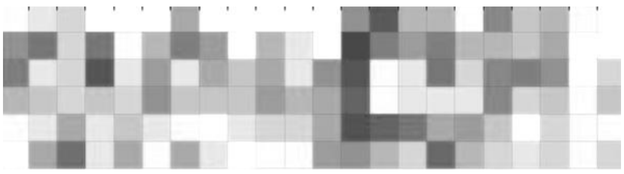


Figure 3: Example of an Occupancy Grid of 1 ft. x 1 ft on a corridor. Intensity of color gray indicates the amount of time that cell was occupied, in intervals of 1 second, for a 1-hour period.

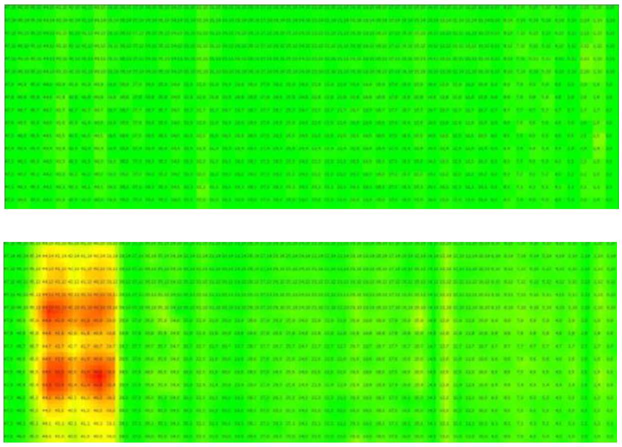


Figure 4: Upper image: Spatial sensor grid with a resolution of ½ inch x ½ inch, and no pressure on the area. The bottom image shows a person standing in the area: Heat map indicates the intensity of the pressure on the cell, at intervals of 60 times per second.

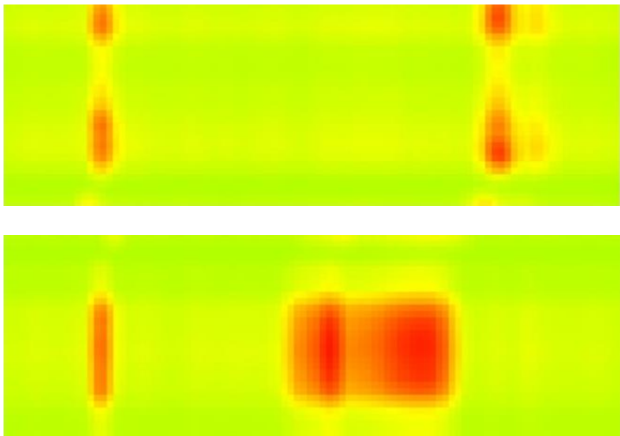


Figure 5: Example of a spatial sensor resolution of ½ inch by ½ inch. Heat map indicates the intensity of the pressure on the surface, 60 times per second. Upper part of the image shows someone doing push-ups along the surface, while the bottom part of the image shows the pressure of someone sitting on the floor.

Projects at the building scale face several challenges related to spatiotemporal resolution. One such a problem is the use of thin film sensors to maintain uniformity in the system thickness. Additionally, the decisions on data granularity and density depend on the output analytics. Each sensing flooring unit (e.g. carpet tile or square inch) is read independently. The smaller the sensor, the fewer signal impulses are sent, but the higher the spatial resolution the system can provide. Therefore, the intelligent calibration point should be tuned between the sensor capabilities and desired spatial resolution.

Figure 6: 200 ft^2 prototype installation of a senior care living area, at Leading Age (2017), Upper image shows the real-time visualization of steps.

DATA COLLECTION AND ANALYSES

The PZ smart flooring system includes the implementation of a Web App that displays a visualization of the data in real-time (figures 6 and 7). We discovered that this literal visualization of a heat-pressure map was the most logical to communicate the concept to the user (Figure 8, left side). Then, more sophisticated algorithms showing the total number of steps, accumulation of movement, or more high-level interpretations such as number of visits to a room, were more comprehensive analytics, but not as easy to translate to the user (Figure 8, right side).

A prototype of a set of PZ-tiles was installed on site (See figure 6), collecting data of the daily usage, as counters of events (or steps). The amount of data coming out of this system, per second, requires some compression algorithms to be able to transmit the amount of data at the necessary speed (10Hz). The large system was a key test of the system architecture for aggregation of units, as well as the wireless data transmission and the spatiotemporal visualization. The current stage of this research is on the implementation of the most advanced analyses described in the first section for events, utilizing machine-learning algorithms to teach the system to automatically recognize specific “events”, such as falls, one of the most expensive events in any healthcare facility, for example.

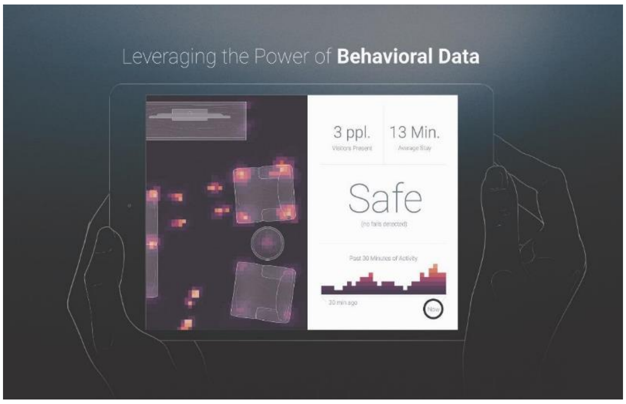


Figure 7: Concept of the Interactive PZ-flooring data visualization on an IPad.

Figure 8: Representation of a screen visualization of a “fall” event, and the comprehensive analytics to the right.

CO-EVOLUTION SYSTEM – DATA

As discussed in the previous section, the sensing capabilities and resolution of the system are influenced by a series of parameters: The thickness and stiffness of the material, modularity for fabrication and installation processes, the sensing calibration (that depends on the building structure and its natural vibration), and the area covered by each sensor, which in turn informs the spatial resolution of the system. All these parameters should be calibrated taking into consideration the sensitivity that the system requires (i.e. be able to recognize a jump, a step, or a touch), and the spatial and temporal resolution that best fit each scale. For example, at an urban or even campus scale, the resolution of 1/10 of a second is not relevant to the occupancy analyses during a day; however, for the interaction with the system, this temporal resolution is adequate. On the other hand, the sensitivity required to recognize a touch in a smart surface needs much higher spatial and temporal resolution, therefore smaller sensors distributed in high density. In addition, lower the thresholds for the signal outputs are required.

DISCUSSION

We expect that once our smart flooring system is manufactured at scale, it will act as an embedded positioning mapping system that provides feedback from the real use of a building, updating the results that are currently obtained from evaluating computational models on spatial, energy, or circulation analyses. As our spatiotemporal occupancy datasets include not only the spatial distribution of occupancy and movements, but their temporal sequence as well, the analyses accuracy improvement is not only quantitative as for data amount, but also qualitative for expanding the type of analyses offered.

The interactivity of the system allows for the automation of other systems, such as lighting systems; The real-time feedback allows for organizational improvements on the staff schedule, for example, or on the report of unexpected/unwanted events, such as falls. In addition, for building performance outcomes, further development of the system could also optimize other aspects that are based on building occupancy. For example, this real time data streaming will allow sending data to the building management system to calculate real time energy consumption to calibrate the HVAC system or the conference-room scheduling system. Once the data is stored, the databases can be updated for energy simulation models. Finally, all the information Architects will be able to gather from this type of non-invasive system, can be directly applied for re-design strategies of a building in terms of layout configurations or user experience.

The obtained feedback can be embedded into a BIM model to 1) understand the patterns of behavior to embed them later in similar design models, and 2) use the model to help building managers to make performance-based decisions about the spaces and layout configuration, as well as organizational decisions to control people’s traffic and behavior. Usually, these decisions are based on previous experience. However, during building operation, there are no reliable means to assess if the current layout is optimized to its best performance toward the expected goals.

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