Modelling and Visualizing People Flow in Smart Buildings: a Case Study in a University Campus

Rita Tse
ritatse@ipm.edu.mo
School of Applied Sciences - Macao Polytechnic Institute
Macao

Silvia Mirri
silvia.mirri@unibo.it
University of Bologna
Bologna, Italy

Su-Kit Tang
sktang@ipm.edu.mo
School of Applied Sciences - Macao Polytechnic Institute
Macao

Giovanni Pau
giovanni.pau@unibo.it
University of Bologna
Bologna, Italy

Paola Salomoni
paola.salomoni@unibo.it
University of Bologna
Bologna, Italy

ABSTRACT

The tremendous CoVid-19 outbreak has had a significant impact on the lives of people anywhere in the world. Several approaches have been presented with the aim of helping in limiting and mitigating the effect of CoVid-19 infections. This paper proposes a system that exploits Internet of Things (IoT) and Data Visualization to monitor the flow of people in buildings, with the aim of providing policymakers with a tool that visualize and highlight critical issues. The case study considered is a Smart University Campus located in Cesena, belonging to the University of Bologna.

CCS CONCEPTS

• **Information systems** → **Spatial-temporal systems**; • **Human-centered computing** → *Visualization*; • **Computer systems organization** → *Sensor networks.*

KEYWORDS

People Flow Modelling, Internet of Things, Data Visualization, Human-Centered Design, Smart Campus

ACM Reference Format:

Rita Tse, Silvia Mirri, Su-Kit Tang, Giovanni Pau, and Paola Salomoni. 2021. Modelling and Visualizing People Flow in Smart Buildings: a Case Study in a University Campus. In *Conference on Information Technology for Social Good (GoodIT '21), September 9–11, 2021, Roma, Italy.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3462203.3475877

1 INTRODUCTION

Nowadays, the Internet of Things (IoT) is employed in different contexts such as enhancing people inclusions [21] and improving buildings accessibility [11]. With the unprecedented outbreak of CoVid-19 [19], more and more research has been conducted with the aim of designing and developing tools to monitor, limit and mitigate the effect of the global pandemic [6]. From contact tracing [15] to wearable smart helmets with a thermal camera to measure fevers [20], passing through robots that can help in the diagnosis by collecting throat swabs samples from patients [22], many IoT-based systems have proven to be effective. Given the high risk of infections in indoor environments [16], it is important to have tools for monitoring such environments [14], for example by evaluating the occupation of spaces, the flows of people, and compliance with the rules [24].

In this paper, we present our research proposal to design and develop a tool to monitor the flow of people in smart buildings, exploiting IoT and Data Visualization. Our objective is to implement a tool that supports policymakers, highlighting critical issues and situations that happen inside the building and that help them in adopting corrective policies with the aim of contrast them. Given the current global health emergency, this tool could be useful to determine a policy that can help to limit the spread of the virus in the indoor context. Our methodology comprises the following steps: i) deploy a sensors infrastructure to count people using cameras or WiFi access points, ii) define a model to map the flow of people in a building, iii) develop a data visualization layer to display hyper-local data both real-time and historically, and iv) determine a set of thresholds to automatically identify critical situations. The case study is based on the smart campus in Cesena, part of the University of Bologna. It is home to several degree courses, including Architecture and Design, Biomedical Engineering, Computer Science and Engineering, and Electronic Engineering. It has been chosen since it is equipped with several convenient infrastructures and systems, that could be the starting point for this specific research. In particular, a sensors layer has already been deployed together with a data visualization layer able to display the collected data [28]. Thus, a model of the building has already been defined for the building way-finding system [27].

The rest of the paper goes as follows. Section 2 describes some works related to this research. Section 3 presents our research proposal and the related methodology while in Section 4 we details our case study, explaining the motivation behind our choice. Finally, Section 5 closes the paper, highlighting the future directions of this research.

GoodIT '21, September 9–11, 2021, Roma, Italy

ACM ISBN 978-1-4503-8478-0/21/09…$15.00
https://doi.org/10.1145/3462203.3475877

2 RELATED WORKS

This Section firstly discusses the standards for indoor modeling and then details general approaches to human indoor mobility modeling. It finishes with the description of approaches for occupancy monitoring specifically designed for the CoVid-19.

Over time, different standards have been proposed to model indoor spaces. Cantarero Navarro et al. [3] reviewed the most common standards for modeling indoor spaces, including OpenStreetMap, City Geography Markup Language, Industry Foundation Classes, Indoor Emergency Spatial Model, Indoor Geography Markup Language, Green Building XML, and Unified Building Model. Such standards and proposals have been evaluated according to nine dimensions: support for topology and geometry representations, the capacity of customization, support for semantics representations and navigation, available support, overall complexity, and user acceptance and user-friendliness. To each dimension, they assigned a value from one (poor) to four (high). Anyway, a convenient and common way to map buildings is to use graphs in which rooms represents node connected by edges that are hallways, stairs [7], or elevators [25, 26].

Different approaches have been proposed to model human indoor mobility. Li et al. [17] employ the simulation software AnyLogic in combination with Kalman filters to simulate complex people behaviours and to identify the people flow model in both simulation and real experiments. The authors employed video cameras and beam sensors to measure people's flow. Instead, Rose et al.[30], exploiting Self-Organizing Networks, introduced a new three-dimensional indoor mobility model. Such a model is based on the description of the building and it automatically identifies rooms and accommodation units. Furthermore, it is able to simulate user movements according to some activities both in office and private environments. A different approach has been proposed by Al Qathrady and Helmy in [1]. Instead of following a user-centric approach, they move to a location-centric one, with the aim of analyzing and characterizing region relationships as pertains to user flow. Instead of cameras, they exploit wireless LANs, making extensive use of the traces to quantify metrics for influx and outflux. The system has been tested involving more than three million traces relative to one hundred thousand users. Always based on WiFi, Trivedi et al. [31] tried to assess the challenges of modeling indoor mobility such as the absence of indoor mobility datasets. In their work, they proposed WiFiMod, a data-driven approach, based on Transformer, that models indoor human mobility at multiple spatial scales employing WiFi logs. The WiFi logs are preprocessed with the aim of extracting events and features to generate trajectories from smartphone digital traces. Then, for each trajectory, mobility features are extracted at both macro and micro spatial scales that will form the multi-modal embedding, that is the input of the Transformer. The idea at the base of this approach is to use multi-modal embedding to capture the mobility periodicity and correlations at different scales and to exploit Transformers to capture long-term mobility dependencies. The strength of this approach is that it first reduces the prediction space in a significant way by predicting macro-mobility and then it models the micro mobility, conditioned on the estimated macro mobility distribution.

With regard to IoT-based systems for monitoring indoor environments occupancy and social distances designed with the aim of controlling and limiting CoVid-19 infections, several approaches have been proposed, employing different techniques. Wang et al. [32] presented a smart low-cost ventilation control strategy, since ventilation has been shown to play a key role in the control and prevention of CoVid-19 infections in indoor spaces, particularly in high-occupant-density ones. Their control strategy exploits video frames captured by surveillance cameras that are analyzed by YOLO (You Only Look Once) algorithm, which performs occupancy detection. The ventilation rate is automatically adjusted by a self-developed low-cost hardware prototype based on the occupant density and considering the energy efficiency. Instead of surveillance cameras, Naser et al. [23] employed thermal sensor arrays, since they have some interesting features such as being privacy-preserving, low-cost, and non-invasive, which makes them suitable for different indoor applications. The authors proposed a novel framework using a deep convolution encoder-decoder network, which carries out a semantic segmentation of people, and then it is able to estimate the number of people and the occupancy in indoor environments and their distances from the sensor. Their systems proved to be effective using various sensors locations, with a wide range of occupants and human distance. Longo et al. [18] proposed a brand-new smart object prototype, called Smart Gate, that monitors people flow and keeps track of the occupancy levels of buildings. Such a system should be placed at one side of the entrances and it mainly exploits a pair of Time-of-Flight VL53LIX long-ranging sensors. The system can also be improved, in case of a situation in which privacy is not a constraint, with cameras whose video streams are analyzed by an external server. Such a module is also able to provide demographic information relative to people who entered the monitored area. Finally, in this context, it is fundamental to identify and adopt social and altruistic IoT approaches [13], so as to exploit and manage in a suitable way those data collected by means of mobile crowdsensing strategies [2] too.

3 RESEARCH PROPOSAL

The aim of this research is to design and develop a tool that provides policymakers with information on the flow of people (be they students, professors, or administrative staff) in the building, which highlights any critical issues and allows them to adopt corrective policies such as staggering lesson times in order to avoid meetings of different classes due to simultaneous movements to the classrooms or laboratories, or to varying the access policies to the classrooms themselves. Such a tool would be very important given the current global situation, in which the CoVid-19 pandemic still represents a considerable threat and has significantly affected people's lives and a multitude of aspects of society, among which education at all levels, including the university one. In fact, some studies already analyzed CoVid-19 transmission in indoor spaces [12, 29]. In particular, Romero et al. [29] concluded their work stating that only in wide hallways, traffic should be allowed two-way while narrow hallways should be passed through one-way. Furthermore, time spent in hallways should be minimized. In their work, Duives et al. [12] investigated the spread of SARS-CoV-2 in indoor spaces through a Pedestrian Dynamics - Virus Spread model, combining insights from different areas, including pedestrian modeling, epidemiology, and IT design. Their experiments highlighted the multi-dimension challenges of the CoVid-19, which arise from the interplay between the spread of the virus and humans behaviour in indoor spaces. According to the author, a modeling strategy, taking into account the risk assessments, can be an important tool to support citizens and, in particular, policymakers. Indeed, it can empower them in designing more effective policies to limit indoor infections. With regard to the methodology, our approach could be summarized by the following steps:

(1) **Deploy a sensors infrastructure to count people**. The buildings should be equipped with a set of sensors able to count people in specific areas. Such sensors should be placed all over the building, trying to cover every area of the building as much as possible. Different sensors could be employed to count people, ranging from cameras (thermal, LiDAR, or stereo) to WiFi access points.
(2) **Define a model to map the flow of people in the building**. A general indoor mobility model should be implemented. Such a model should be able to map the history of people's movements inside the building.
(3) **Develop a Data Visualization layer**. The User Interfaces should visualize the collected hyper local data, both historically and in real-time. They should be developed following the User-centered Design, considering the policymakers as the final users.
(4) **Determine a set of thresholds to identify critical situations**. A set of parameters could be set with the aim of automatically detecting dangerous situations, such as too crowded environments.

4 CASE STUDY

Our real-world case study is based on a recently built campus in Cesena, one of the five campuses of the University of Bologna together with Rimini, Ravenna, Forlì, and Bologna. It hosts undergraduate and graduate students of Architecture and Design, Biomedical Engineering, Computer Science and Engineering, and Electronic Engineering. It is the perfect context for this research since it has different infrastructures and tools that can be successfully exploited in various steps of this research and whose architecture is reported in [28]. The campus has already a sensors layer. Currently, it employs environmental sensors that measure PM 1.0, PM 2.5 PM 10, formaldehyde, temperature, relative humidity, and air pressure, noise sensors that detect abnormal strong noises, and cameras that counts people in classrooms and in laboratories to determine their occupancy with respect to their capacity. The latter ones are particularly interesting for the first step of our research. As described in [5], the people counting system is installed in almost all classes and laboratories and it is structured on a three-layer architecture. In the first one, 1280 x 720 images are gathered every five minutes using Intel RealSense D415 Depth cameras connected to Raspberry Pi 4 model B. The second layer employs a customized YOLOv3 model to count the number of people in the room. Such a number is then stored on the Raspberry and can be retrieved through the third layer, API one, over HTTPS. Such a system has an average accuracy of 91%. Such a system could also be expanded with WiFi access points that could be used in areas that are not covered by the cameras, such as hallways and toilets.

Moreover, a way-finding system, called Almawhere, has been deployed in the campus, as detailed in [27]. Within such a project, the whole campus has been mapped as a graph. A node has been added in order to map all turning points and the dead-end corridors. Then, all the Point of Interests (classrooms, laboratories, offices, and so on) are associated with the nearest node, which can hence have 0 to N PoIs. If there are PoIs that do not have a near node, new nodes are added to the graph so that each PoI is close to one and only one node. The edges are instead represented by the hallways, stairs, and elevators and their weights depend on their length. A new table can be added to the current AlmaWhere Data model, containing the number of people detected in a given instant in a PoI or in an edge. The information relative to the maximum capacity of any location could also be added for each PoI and edge. Hence, such a graph that maps the building can also be used to map the flow of people, that is the second step of our methodology. The data relative to the people flow in the building, as well as being used for monitoring the smart campus, could also be used by the wayfinding system in calculating the route. In fact, people with disabilities may prefer slightly longer but less crowded routes.

Finally, the smart campus system has already a data visualization layer [28], mainly composed of a rich web application that displays the map of the campus, depicted in Figure 1. The map has been developed with standard web technologies, HTML5, CSS3, and JavaScript. Some Javascript libraries have also been employed for the data visualization part, such as D3.js[1] and Chart.js[2]. The map is enriched with the hyperlocal data (e.g., classes occupancy, environmental data, ...). Each floor of the building consists of an SVG image, that can be easily manipulated using Javascript to visualize the data relative to the people flow in the building. Hence, this data visualization layer could be the starting point of the third step of our methodology.

5 CONCLUSIONS AND FUTURE WORK

In this work-in-progress paper, we have presented our research proposal of a system able to provide policymakers with data relative to the flow of people in a building, highlighting critical issues. This tool should allow policymakers to monitor the situation in the building and that leads to the adoption of any corrective policies. We have also detailed our methodology, mainly composed of four main steps, and the case study of this research. Such steps still need to be completed. Concerning the first one, WiFi access points have to be integrated into the system with the aim of mapping all the areas of the building such as hallways that are not covered by the counting people cameras. While in the data visualization layer, a specific UI that allows displaying historical and real-time information of the flow of people has yet to be developed.

In addition to the completion of the presented steps, this research can be extended in several ways. Once the whole system has been fully deployed, the data collection process can begin. And the collected data could be used to train a machine learning model. In

[1]https://d3js.org/
[2]https://www.chartjs.org/

Figure 1: Map of the Cesena Smart Campus.

fact, machine learning algorithms have been proven effective in different contexts [4, 9, 10], and could be employed also for people flow prediction within a smart building, always keeping in mind the limitations of such approaches [8]. The prediction system could be also integrated with the class schedules, so that some flows can be easily determined.

ACKNOWLEDGMENTS

A special thank goes to Chiara Ceccarini, Giovanni Delnevo, Wang Luoyu (Vivia), and Jiayi Wang (Joey) for their precious support.

REFERENCES

[1] Mimonah Al Qathrady and Ahmed Helmy. 2017. Location-centric flow flux for improved indoor mobility models. In *2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. IEEE, 313–318.

[2] Luigi Atzori, Roberto Girau, Salvatore Martis, Virginia Pilloni, and Marco Uras. 2017. A SIoT-aware approach to the resource management issue in mobile crowdsensing. In *2017 20th Conference on Innovations in Clouds, Internet and Networks (ICIN)*. IEEE, 232–237.

[3] Rubén Cantarero Navarro, Ana Rubio Ruiz, Javier Dorado Chaparro, Felix J Villanueva Molina, Maria J Santofimia Romero, David Villa Alises, and Juan C Lopez Lopez. 2020. A Proposal for Modeling Indoor–Outdoor Spaces through IndoorGML, Open Location Code and OpenStreetMap. *ISPRS International Journal of Geo-Information* 9, 3 (2020), 169.

[4] Luca Casini, Giovanni Delnevo, Marco Roccetti, Nicolò Zagni, and Giuseppe Cappiello. 2019. Deep Water: Predicting water meter failures through a human-machine intelligence collaboration. In *International Conference on Human Interaction and Emerging Technologies*. Springer, 688–694.

[5] Chiara Ceccarini, Silvia Mirri, Paola Salomoni, and Catia Prandi. 2021. On exploiting Data Visualization and IoT for Increasing Sustainability and Safety in a Smart Campus. *Mobile Networks and Applications* (2021), 1–10.

[6] Vinay Chamola, Vikas Hassija, Vatsal Gupta, and Mohsen Guizani. 2020. A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact. *Ieee access* 8 (2020), 90225–90265.

[7] Matteo Ciman, Michele Donini, Ombretta Gaggi, and Fabio Aiolli. 2016. Stairstep recognition and counting in a serious Game for increasing users' physical activity. *Personal and Ubiquitous Computing* 20, 6 (2016), 1015–1033.

[8] Giovanni Delnevo. 2020. A Study on The Limits and Potential of Machine Predictions from a Human-Big Data-Machine Interaction Perspective. In *Proceedings of the 6th EAI International Conference on Smart Objects and Technologies for Social Good*. 234–235.

[9] Giovanni Delnevo, Roberto Girau, Chiara Ceccarini, and Catia Prandi. 2021. A Deep Learning and Social IoT approach for Plants Disease Prediction toward a Sustainable Agriculture. *IEEE Internet of Things Journal* (2021), 1–1. https://doi.org/10.1109/JIOT.2021.3097379

[10] Giovanni Delnevo, Andrea Lipparini, Marco Roccetti, and Maurizio Sobrero. 2018. Human intelligence, ambidexterity and ai: Reflections on a data cognification case study in an underwater scenario. In *2nd annual science fiction prototyping conference*. 50–55.

[11] Giovanni Delnevo, Lorenzo Monti, Federico Foschini, and Luca Santonastasi. 2018. On enhancing accessible smart buildings using IoT. In *2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)*. IEEE, 1–6.

[12] Dorine Duives, You Chang, Martijn Sparnaaij, Berend Wouda, Doris Boschma, Yangfan Liu, Yufei Yuan, Winnie Daamen, Mart CM de Jong, Colin Teberg, et al. 2021. The multi-dimensional challenges of controlling SARS-CoV-2 transmission in indoor spaces: Insights from the linkage of a microscopic pedestrian simulation and virus transmission models. *medRxiv* (2021).

[13] Ivan Farris, Roberto Girau, Michele Nitti, Luigi Atzori, Roberto Bruschi, Antonio Iera, and Giacomo Morabito. 2015. Taking the SIoT down from the Cloud: Integrating the Social Internet of Things in the INPUT Architecture. In *2015 IEEE 2nd World Forum on Internet of Things (WF-IoT)*. IEEE, 35–39.

[14] Marco Furini, Federica Mandreoli, Riccardo Martoglia, and Manuela Montangero. 2016. Iot: Science fiction or real revolution?. In *International Conference on Smart Objects and Technologies for Social Good*. Springer, 96–105.

[15] Enrique Hernández-Orallo, Pietro Manzoni, Carlos Tavares Calafate, and Juan-Carlos Cano. 2020. Evaluating how smartphone contact tracing technology can reduce the spread of infectious diseases: the case of COVID-19. *IEEE Access* 8 (2020), 99083–99097.

[16] Jos Lelieveld, Frank Helleis, Stephan Borrmann, Yafang Cheng, Frank Drewnick, Gerald Haug, Thomas Klimach, Jean Sciare, Hang Su, and Ulrich Pöschl. 2020. Model Calculations of Aerosol Transmission and Infection Risk of COVID-19 in Indoor Environments. *International Journal of Environmental Research and Public Health* 17, 21 (2020), 8114.

[17] Keyu Li, Kai Zhang, Xiangbao Li, Jie Xi, Hui Fang, and Zhen Jia. 2016. Building occupancy estimation with people flow modeling in AnyLogic. In *2016 12th IEEE International Conference on Control and Automation (ICCA)*. IEEE, 669–672.

[18] Edoardo Longo, Alessandro EC Redondi, Massimo Bianchini, Patrizia Bolzan, and Stefano Maffei. 2020. Smart Gate: a Modular System for Occupancy and Environmental Monitoring of Spaces. In *2020 5th International Conference on Smart and Sustainable Technologies (SpliTech)*. IEEE, 1–6.

[19] Silvia Mirri, Giovanni Delnevo, and Marco Roccetti. 2020. Is a COVID-19 Second Wave Possible in Emilia-Romagna (Italy)? Forecasting a Future Outbreak with Particulate Pollution and Machine Learning. *Computation* 8, 3 (2020), 74.

[20] MN Mohammed, Halim Syamsudin, S Al-Zubaidi, Ramli R AKS, and E Yusuf. 2020. Novel COVID-19 detection and diagnosis system using IOT based smart helmet. *International Journal of Psychosocial Rehabilitation* 24, 7 (2020), 2296–2303.

[21] Lorenzo Monti and Giovanni Delnevo. 2018. On improving GlovePi: Towards a many-to-many communication among deaf-blind users. In *2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)*. IEEE, 1–5.

[22] Mohammad Nasajpour, Seyedamin Pouriyeh, Reza M Parizi, Mohsen Dorodchi, Maria Valero, and Hamid R Arabnia. 2020. Internet of Things for current COVID-19 and future pandemics: An exploratory study. *Journal of healthcare informatics research* (2020), 1–40.

[23] Abdallah Naser, Ahmad Lotfi, and Junpei Zhong. 2020. Adaptive Thermal Sensor Array Placement for Human Segmentation and Occupancy Estimation. *IEEE Sensors Journal* 21, 2 (2020), 1993–2002.

[24] Michele Nitti, Roberto Girau, Luigi Atzori, and Virginia Pilloni. 2017. Trustworthiness management in the IoT: The importance of the feedback. In *2017 20th Conference on Innovations in Clouds, Internet and Networks (ICIN)*. IEEE, 325–327.

[25] Gustavo Patow. 2010. User-friendly graph editing for procedural modeling of buildings. *IEEE Computer Graphics and Applications* 32, 2 (2010), 66–75.

[26] Saša Pešić, Miloš Radovanović, Mirjana Ivanović, Milenko Tošić, Ognjen Iković, and Dragan Bošković. 2020. Graph-based metadata modeling in indoor positioning systems. *Simulation Modelling Practice and Theory* 105 (2020), 102140.

[27] Catia Prandi, Giovanni Delnevo, Paola Salomoni, and Silvia Mirri. 2021. On Supporting University Communities in Indoor Wayfinding: An Inclusive Design Approach. *Sensors* 21, 9 (2021), 3134.

[28] Catia Prandi, Lorenzo Monti, Chiara Ceccarini, and Paola Salomoni. 2020. Smart campus: Fostering the community awareness through an intelligent environment. *Mobile Networks and Applications* 25, 3 (2020), 945–952.

[29] Van Romero, William D Stone, and Julie Dyke Ford. 2020. COVID-19 indoor exposure levels: An analysis of foot traffic scenarios within an academic building. *Transportation Research Interdisciplinary Perspectives* 7 (2020), 100185.

[30] Dennis M Rose, Thomas Jansen, Sören Hahn, and Thomas Kürner. 2013. Impact of realistic indoor mobility modelling in the context of propagation modelling on the user and network experience. In *2013 7th European Conference on Antennas and Propagation (EuCAP)*. IEEE, 3979–3983.

[31] Amee Trivedi, Kate Silverstein, Emma Strubell, and Prashant Shenoy. 2021. WiFiMod: Transformer-based Indoor Human Mobility Modeling using Passive Sensing. *arXiv preprint arXiv:2104.09835* (2021).

[32] Junqi Wang, Jingjing Huang, Zhuangbo Feng, Shi-Jie Cao, and Fariborz Haghighat. 2021. Occupant-density-detection based energy efficient ventilation system: Prevention of infection transmission. *Energy and Buildings* 240 (2021), 110883.