Building Rhythms: Reopening the Workspace with Indoor Localisation

Guilherme Spinoza Andreo*, Ioannis Dardavesis*, Michiel de Jong*, Pratyush Kumar*, Maundri Prihanggo*, Georgios Triantafyllou*, Niels van der Vaart *,**, Edward Verbree*

* Faculty of Architecture and the Built Environment, Delft University of Technology

G.SpinozaAndreo@student.tudelft.nl; I.Dardavesis@student.tudelft.nl; M.D.deJong-1@student.tudelft.nl; P.Kumar-12@student.tudelft.nl; MaundriPrihanggo@student.tudelft.nl; G.Triantafyllou-1@student.tudelft.nl; C.G.vanderVaart@tudelft.nl; e.verbree@tudelft.nl;

**Esri Nederland

Nvandervaart@esri.nl

ABSTRACT

Indoor localisation methods are an essential part for the management of COVID-19 restrictions, social distancing, and the flow of people in the indoor environment. Moving towards an open work space in this scenario requires effective real-time localisation services and tools, along with a comprehensive understanding of the 3D indoor space. This project's main objective is to analyse how ArcGIS Indoors can be used with location awareness methods to elaborate and develop space management tools for COVID--19 restrictions in order to reopen the workspace for TU Delft Campus. This was accomplished by using six Arduino micro controllers, which were programmed in C++ to scan all available Wi--Fi fingerprints in the east wing of the Faculty of Architecture and the Built Environment of TU Delft and send over the data to an ArcGIS Indoor Information Model (AIIM). The data stored on the AIIM is then accessed using the app on the user's Android device using REST Application Programming Interface

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(API) where a kNN based matching algorithm then identifies the location of the user. The results show that the localisation is not consistent for rooms that are directly above each other or share common access points. However, when functioning to locate different tables inside a room, the system proved to uniquely distinguish between the specific tables. As a result, we can conclude that based on the size of the rooms, more Arduino devices should be installed to achieve an ideal accuracy. Finally, recommendations are made for the continuation of this research.

Keywords: Indoor localisation system, Wi-Fi fingerprinting, ArcGIS, Indoor model, Machine Learning

1. Introduction

Recently, the success of outdoor positioning methods has provided the means for high accuracy positioning technologies research to slowly shift towards the indoor environment (Brena et al., 2017; He & Chan, 2016; Liu et al., 2016). This new wave of indoor localisation technologies has been growing at a rapid pace, however, most of them are considered to still be in the early phases of development (Xia et al., 2017). The core aspect of Wi-Fi fingerprint localisation systems is established on the set of measurements of the signal strength from different Wireless Access Points (WAPs). They can be used as a radio-map, or reference points, that can be applied to estimate and match a location of a given device according to its signal strength (Torres et al., 2016).

Indoor models, in broad terms, are a hierarchy of unique classes of different building elements, spaces, topological and semantic information (Liebich, 2009 cited in Tran et al., 2018). Specifically, the topological information model of a building, which can be obtained from either CAD or BIM data, is the first component of creating an indoor localisation and navigation system. These 3D models are vital for the development of navigation assistance applications and emergency responses (Tran et al., 2018) .

Indoor localisation methods are an essential part for the management of COVID-19 restrictions, social distancing, and the flow of people in the indoor environment. To move towards an open workspace in a restricted occupancy scenario requires effective real-time localisation services and tools, along with a comprehensive understanding of the 3D indoor space.

This project consists of three parts which have their own goals and expectations. Accordingly, all of them are combined and each of them subdivided in more specific sections in order to form the final product. The initial one is the main goal of the ”Synthesis Project” course from the MSc Geomatics which aims to combine and apply all the knowledge, skills and insights gained during the core programme (T.U. Delft, 2020b).

The second part relates to the wider TU Delft project ”Building Rhythms” which aims to investigate the impact of COVID--19 on campus life through public data visualisations with high respect to privacy preservation (T.U. Delft, 2020a). Although the general project targets all of the campus, in this project, the focus is only about the indoor environments.

The third and last part is set by the client and stakeholders, mainly by Esri Nederland. Therefore, one of the main goals of the project is to explore the possibilities and capabilities of ArcGIS and ArcGIS Indoors with the combination of a real--time indoor location system with Fingerprinting produced by open source micro-controllers (Arduino MKR-WiFi) and a native mobile application.

To sum up, the combination of these three parts leads to the main research question of the project:

"How can ArcGIS Indoors be combined with indoor Wi-Fi fingerprinting localisation awareness techniques to create a real-time application for understanding COVID-19's impact in the indoor environment of TU Delft with high respect for privacy of the users?"

2. Methodology

The methodology of the project can be summarized into five key stages: Data Acquisition, Indoor modelling, Indoor localisation with Wi-Fi fingerprinting, and, Testing and Visualisation. The indoor model was based on (Computer Aided Design) CAD files with minor adjustments, in order to represent the current floor-plans of the Building of the Faculty of Architecture and Built Environment, TU Delft. The CAD files, combined with an excel file containing information about the layers, were imported into ArcGIS Pro, so that the CAD layers could be transformed into GIS layers.

To accomplish the scope of this project, only the ground and first floor of the Faculty's east wing were investigated. Furthermore, the database, which contains the information about the rooms of the building, was enriched with additional information, such as capacity, occupancy and room types, provided by TU Delft Campus Real Estate and Abdullah Alattas (Alattas et al., 2018). Points of Interest were created for rooms of high importance, such as offices and lecture rooms, based on which the interior network of the model was created. The created model was published in ArcGIS online portal, as a web scene, which works as the main view of the android application and the part of the end product of this project.

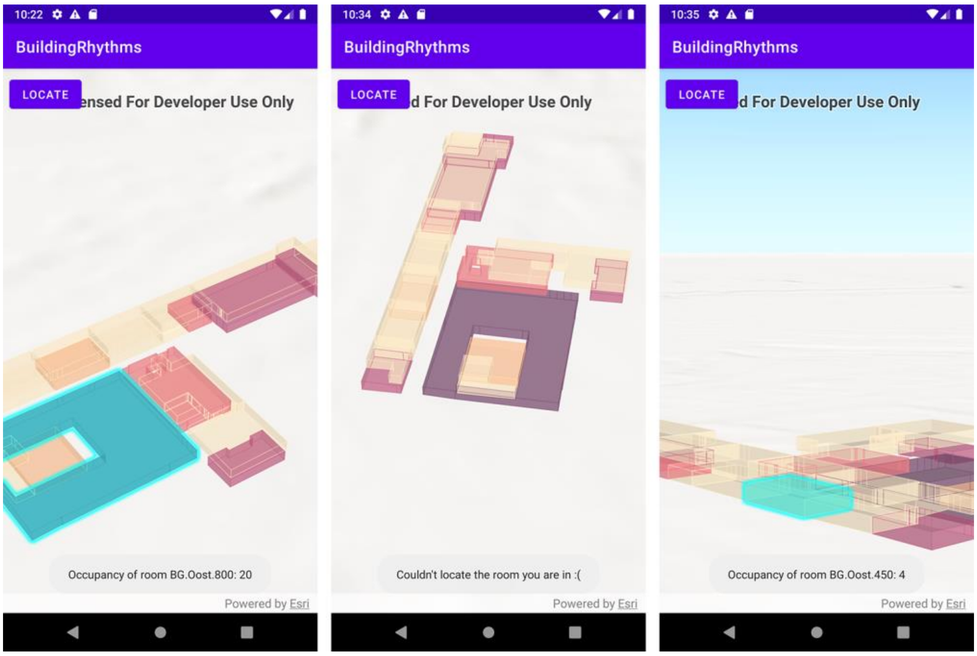

Figure 1: Android Application

To find out if live radio maps combined with Wi-Fi fingerprinting can accurately be used as an indoor localisation system, we use a setup where the rooms we want to test are equipped with a Wi-Fi enabled microcontroller which creates a live radio map of the static Wi-Fi networks at the Campus, and sends this to the server. Studies such as those from (Abdul et al., 2019; Lee et al., 2019), indicate that the microcontroller needs to have an ESP8266 module on board, which acts as both a Wi-Fi access point which scans for Wi-Fi signals in the vicinity as well as a device which connects to a pre-set Wi-Fi access point and pushes data to our server set up on ESRI ArcGIS

Online Server (ESRI, 2021c). The pushed data includes the RSSI, BSSID, SSID and a location tag specific to the location where the particular chipset is located and this is achieved through the use of Arduino MKR 1010 Wi-Fi controller.

The pushed data is then used as input for a simple user app we developed that uses a local user Wi-Fi scan and a kNN machine learning algorithm to match the user to a fingerprint location which is semantically linked to the indoor model. For the purpose of the matching algorithm, different techniques could have been employed, as illustrated by (Lee et al., 2019), a random forest model could be used, or a deep learning-based model (Ayyalasomayajula et al., 2020) could be used, however, the chipset employed returns only about 20 Wi-Fi scan values in one push to the server, hence the amount of data samples involved is not sufficient to train a deep learning or random forest based model. Deriving from studies of (Dai et al., 2019; Ge & Qu, 2016; Hoang et al., n.d.; Oh & Kim, 2018; Yu et al., 2014) , kNN proves to be the most reliable and fast model to predict the room the user is located in. This matching is done locally on the user device, ensuring no user Wi-Fi data is being used anywhere except on the users phone itself. Using this, we can then update the indoor model with live occupancy data on a room level of detail, ensuring that no privacy sensitive data is sent to the server.

Because access to the Wi-Fi chip was paramount for the development of the user app, and with Apple not opening this up for developers in iOS, this led us to start the development of an Android user app. The home screen of the user app is a 3D Scene of the Indoor Model of the study area which is directly added from ArcGIS Online. The main functionality of the app is to provide a visual representation of the real time occupancy of the study area, and to allow the user to locate themselves in this study area (given that they are in a room that is covered by the system).

The ArcGIS Online REST API (ESRI, 2021b) was used to load the table which contains the updated Wi-Fi fingerprints from the Arduino sensors located at different nodes, being hosted on the ArcGIS Online server. The HTTP request returns a JSON string which is then parsed to be loaded into a table, with the columns for MAC address, RSSI values, and Room ID. The Wi-Fi signals received from the Android device are parsed as a JSON string, and loaded directly to a table, which is then cleaned to contain two columns, one for the MAC addresses and one for the signal. Once this is done, the x and y variables for the kNN algorithm are extracted. This is done by the following means: Firstly, in order to take the MAC addresses into account when running a matching algorithm, all the MAC IDs are aggregated and each unique MAC address is given a unique number. The x variables for training data set then are the Unique MAC numbers and their corresponding RSSI values. The y- -variable is the label containing the rooms name from which a particular MAC number and a RSSI was obtained. For the test data-set, only the x- variables need to be created, which should be in the same format as the training data-set, so a unique MAC identifier and RSSI values are needed. To prepare the x-variables for the test data, the MAC addresses are matched to the fingerprint MAC addresses and the unique number assigned to a MAC in fingerprint is given to matching MAC addresses from the test data-set. If a MAC in test data cannot be found in fingerprint data, it is discarded along with its RSSI values, as that particular MAC address would not help us in matching. The y-variable in the case of the test data-set is supposed to be our final label for the room to locate the user's position.

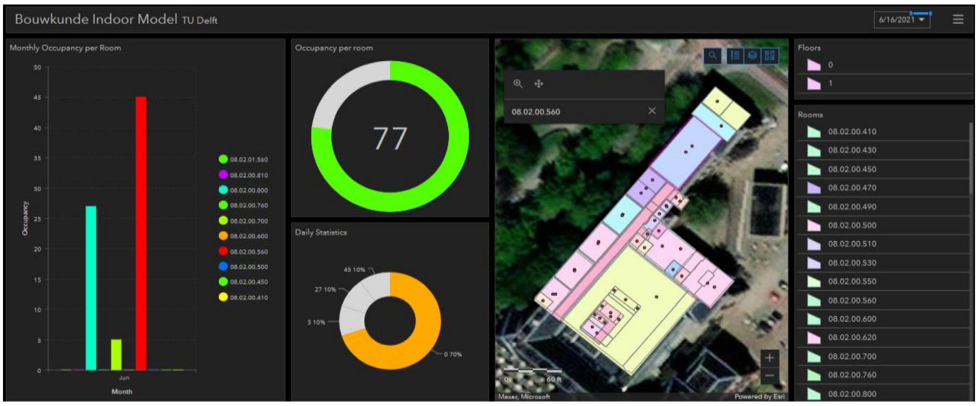

Figure 2: ArcGIS Online Dashboard

On the back-end, to actually implement the updating of the occupancy without storing any more data then needs be, a simple updating function was developed. This function uses the output of the matching algorithm, which will either be a string with the NAME attribute of a feature, or it will output the error string *"Couldn't locate the room you are in :("*. If the output is the error string, nothing happens, as no new occupancy data has not been generated. If the output of the matching algorithm is not the error string, the updating function will be called once or twice, depending on if there is a previous room known to the app or not. If the previous room is known, the app will decrement the occupancy in the previous room, and increment the occupancy in the current room.

One of the main goals of this project was to investigate and analyse the impact of COVID-19 in the indoor environment. The manager of a building, the Faculty of Architecture of TU Delft in this case, should be able to have access to statistics, including movement patterns inside a building, as well as occupancy data, so that the peak hours of movement and occupancy could be identified. This data aids towards optimizing space planning and avoiding overpopulation of rooms. To accomplish that, a dashboard was created using ESRI ArcGIS Dashboards (ESRI, 2021a), additionally to the main application, in order to provide hourly, daily and monthly statistics, based on occupancy data provided by the Arduino sensors. The dashboard uses the created indoor model of the map and provides several capabilities, such as monthly and daily occupancy per room, as well as information on which rooms are the most populated at the current time. The dashboard is interactive and the included graphs are updated real-time with a small refresh rate.

3. Results

A fully functional hosted indoor model has been implemented using ArcGIS Indoors, with the initial testing of the Android app has proved to successfully obtain the Wi-Fi fingerprints from the selected research area and match them statically to a fingerprint in the database. After expanding to real-time fingerprinting, we found that while for some rooms, the accuracy is very high, for other rooms the accuracy is far lower, due to a number of reasons. The accuracy of the system of both testing setups is presented in table 1 and 2 below.

Room ID	Accuracy in center [%]	Accuracy along sides [%]
BG.Oost.560	100.00	100.00
01.Oost.560	10.00	0.00
BG.Oost.700	30.00	40.00
BG.Oost.800	100.00	100.00

Table 1: The accuracy of our indoor localisation system with n=10

Table ID	Accuracy in center[%]
2.031.O	100.00
2.032.O	100.00
2.033.O	100.00
2.034.O	100.00

Table 2: The accuracy of our indoor localisation system within a room with n=3

After looking at table 1 it would seem that the localisation system we designed is not functioning well, be-cause there is low accuracy on at least two out of four rooms upon first glance. However, when diving into the testing deeper we do see that there are some reasons for this outcome, and then these results are not unexpected.

The first thing to consider is the placement of the rooms, namely the pairs BG.Oost.560 and 01.Oost.560 and BG.Oost.700 and BG.Oost.800. For the two .560 rooms we know that these two rooms are directly above each other, which leads to lots of shared access points, and could lead to a less unique fingerprint for each room, leading the fingerprint matching algorithm to wrongfully assign the BG.Oost.560 room when in the 01.Oost.560 room and vice- versa.

In the case of 700 and 800, the fact that often when the user was in 700, the algorithm would match the user to 800 erroneously is also due to their proximity, with room 700 sharing a wall with windows with room 800. This could also be the reason that the accuracy for room 700 is higher near the walls of the room, the 40% accuracy are the 4 measurements taken nearer to 800 than to the location of the Arduino.

Another thing to consider is the fact that the ratio of different rooms varies quite a bit, with an over-representation of room BG.Oost.560, and an under representation of room 01.Oost.560, leading us to theorise that, this is another reason that 01.Oost.560 is has a very low accuracy. To solve this, in the second testing setup we tried to watch the ratio of the Arduinos feeding their data, and the high accuracy presented in table 2 shows this does have an effect.

4. Discussion and Conclusions

With this project, we demonstrate the development of an ArcGIS Indoor Model created from CAD data in ArcGIS, which is later applied to an external Android app to display real-time occupancy of the Faculty for COVID-19 scenarios. The process of creating the ArcGIS Indoor Model was easy to follow, given the information provided by Esri, however, there were some issues with the initial structure of the CAD data, therefore, for it to function properly within the ArcGIS Indoors software required some manual adjustments. We have yet to conclude our project, however we believe that there is potential to expand and implement it as a privacy-preserving indoor localisation system, with location information available on a room scale. We think that the system could be expanded to include routing and navigation.

When defining the product, it became quite clear, early on, that we would need to design, develop and test a system that would try to answer the need created in the research question, namely: the combi-nation of ArcGIS Indoors with a privacy proof Wi-Fi fingerprinting localisation technology. To this extent, we have achieved what we wanted, with different levels of success on individual aspects of the system design.

On a more specific level, the system isn't exactly production ready. But we did make a big initial step to show that a reasonably accurate, versatile, cheap and scalable system can be created to provide an answer for the need stated in the research question. In terms of privacy, which was a very important value and key reason the entire system is set up this way, as opposed to using something like Indoors (the native ArcGIS IPS), we have achieved what we wanted. There is no personal data required to display and store occupancy information for an indoor environment like the Faculty of Architecture. Furthermore, we managed to completely separate the client and server side in the sense that the user is not required to share any data with the server concerning Wi-Fi or location as of yet.

Furthermore, we have developed a robust pipeline for converting often readily available CAD data into a semantically rich indoor model suitable for indoor localisation on a room level, using ArcGIS Pro/In-doors. This pipeline can be applied to any indoor environment for which this data is available, which is essential for the scalable nature of the system in its entirety.

In a technical sense, we have shown that using a single scanning point inside a room to create live radio maps can lead to a reasonable accuracy level, and deploying this setup can yield similar levels of accuracy as when constructing a very time consuming radio map at regular intervals as in the traditional Wi-Fi fingerprinting setup. With our system having lower initial time investing, as the scanning devices operate independently and autonomously, this project serves as a proof of concept.

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