Visual Analysis Tool for a BLE Technology based Tracking Data

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Keywords: Internet of Mobile Things, Data Visualization, Indoor Positioning, Data Mining, Information Systems.

Abstract: Several systems deal with human mobility. Most of them are for outdoor environments and use mobile phones to capture data. However, there is a growing interest of enterprises to consider indoor movement to take employees and client classes into account. Moreover, they usually want to assign semantics to the visited locations. We propose a visual exploration tool for analyzing the dynamics of individual movements in an indoor environment in this work. We present the use of suitable charts and animations to explore these complex data better. Finally, we argue that one could use our solution to monitor social distancing in indoor environments, which is a sensible thing during the current COVID-19 pandemic.

1 INTRODUCTION

Global navigation satellite systems (GNSS) enabled the estimation of a target's position at a given location. This technology has numerous functionalities, which have since been improved in outdoor environments (Kaplan and Hegarty, 2005). It allows us to identify a position of a car to suggest a better route, share people's location between family groups, and even identify iceberg displacements for environmental monitoring. In indoor environments, it is also possible to estimate a specific target location, in particular, of people (Dardari et al., 2015).

Nowadays, many enterprises want to increase the digitization of their data and improve their operational efficiency. To do so, they started to collect and analyze data about their internal workflows, business processes, employees' movement, and the resources used (Curran, 2018). Employees' higher mobility within the enterprise is a clear sign of their higher operational efficiency because employees become more adaptive and better collaborate with colleagues to manage the production process and possible problems (Melamed, 2016; Marini, 2019).

Although there are systems for analyzing human mobility in indoor environments, these systems do not have embedded semantics. Usually they are agnostic to a specific business field, and they do not consider the participants' classes.

In this work, we propose a visual exploration tool for analyzing the dynamics of individual movements in an indoor environment. To do so, we first developed a low-cost tracking system for indoor environments (Schneider et al., 2021). This system detects, collects, processes, and stores users' movement and presence data. It also considers the users' classes and the semantics of the location. We collected these data in two university buildings used by faculty, staff and students.

Using this exploration tool, we report the results comprising the data collection and visual exploration to answer some questions about individuals' indoor mobility. We propose the use of suitable charts and animations to analyze these complex data better.

We organized this paper as follows. Section 2 describes some related work about visual analysis and visualizations for indoor mobility data visualization systems. Section 3 presents the research questions that guided the development of this work. Section 4 reports a visual exploration tool developed and the visual analysis of a real case study. Section 5 concludes this work and proposes future directions.

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Schneider, F., Branco, A., Rodrigues, A., Carvalho, F., Barbosa, S., Endler, M. and Lopes, H.
Visual Analysis Tool for a BLE Technology based Tracking Data.
DOI: 10.5220/0010454202320239
In *Proceedings of the 23rd International Conference on Enterprise Information Systems (ICEIS 2021) - Volume 1*, pages 232-239
ISBN: 978-989-758-509-8

2 RELATED WORK

The related work presented in this section addresses visual tools for analyzing indoor individuals' movements and the most common visualizations used for this analysis.

2.1 Visual Analysis Tools of Individuals' Movements

This subsection presents some related work to visual tools for analyzing individuals movements.

According to Oppermann and Munzner (Oppermann and Munzner, 2020), current visual data analysis tools do not suffice to support decision making about indoor space usage over time. They designed and implemented a visual decision support tool centered around location-based counts of the Sensible Building Science (SBS) commercial product. Taking advantage of WiFi networks available at some vendors, SBS uses real-time location services (RTLS) to record the number of devices per zone at regular intervals. As These data are non-trajectory location-based counts, the analysis of movement flows is not supported. Their visualization system addresses multiple levels of space and time granularity. Since our focus is not only on space and time, our solution is not dependent on RTLS WiFi capability.

We developed some interactive charts for user trajectories and occupancy in time versus location. In addition to movement flows, we also want to visually analyze the relation between individuals, locations, and user trajectories.

Andrienko and Andrienko (Andrienko and Andrienko, 2013) surveyed methods, tools, and procedures focusing on visual analytics of outdoor movement on spatial and spatial-temporal analysis, and limited the scope of their work to movement data of discrete objects whose spatial positions can be represented by points. They grouped their objects of analysis in four categories: trajectories, inside trajectories, birds's-eye view on movement and investigating movement in context. According to them, the most usual movement visualizations for discrete entities are static and animated maps and interactive space-time cubes. From their example, they pointed out that showing multiple trajectories in maps or space-time cube (STC) may suffer from visual clutter and occlusions and provides a limited representation of many movement characteristics and their changes. They suggest that visualizations of changes of movement characteristics over time may be better represented on a time graph. They considered spatial aggregation of movement data by locations (space compartments) and pairs of locations for presence and density analyses.

Some commercial tools, such as Tableau (Tableau, 2003), allow the creation of charts and data analysis without programming. However for indoor individuals' movements, visual analysis chart bring essential pieces of information combined with other kinds of visualization. Tableau, like other visual data analysis tools, does not support these types of visualizations.

2.2 Visualizations of Individuals' Movements

This subsection presents some related work to the visualizations of individuals' movement.

Martella et al. (Martella et al., 2017) explore the use of data provided by low-cost mobile and fixed proximity sensors to understand behavior of museum visitors. To show insights about behavior of museum visitors, they proposed path visualizations. A visitors' position heatmap in the museum layout and matrix shows the relation between visitors and each exhibition. The qualitative results indicated the immediate benefits of the use of these analytics in practice. Their work is interested in extracting which pieces of an exhibition the visitors are interested in, the places they visited, and how long they remained in each location. However, the relations among locations, users, and presence at a specific time are not relevant to their study.

Another approach for creating flows and graphical visualizations is by using process mining methods (Van Der Aalst, 2011). There are already some studies using this process mining applied to customer path analysis. Dogan (Dogan, 2020) showed supermarket customer flows created with process mining and compared the flows of purchasing and non-purchasing customers. Dogan et al. (Dogan et al., 2019a) applied process mining to a data set of locations in a shopping mall to discover customer path and to classify genders. And in another paper, Dogan et al. (Dogan et al., 2019b) focused on inferring a graphical representation of human behavior by implementing process mining techniques. We also adopted this approach in our work to compare other kinds of visualizations.

Krueger et al. (Krueger et al., 2015) presented three interactive visualization methods to identify patterns and individuals' movements behaviors, and to -based scarf plot. Scarf plots show gaze transitions among areas of interest on timelines, but they are not sufficient for many areas of interest and do not provide spatial information. Their interactive visual analysis has three views: the first one to identify sequence patterns using scarf plots, Space-Time cube visualization to identify the room and topic transitions, and the third one using venues maps for predicted and recorded occupancy of rooms comparison. However, they were not interested in how long persons remained in each place, the relations among locations, users, presence in specific time periods.

3 RESEARCH QUESTIONS

In the literature, there is no consensus on indoor individual movement visualizations. For this study, we examined some visualizations to answer questions about an individuals' indoor mobility, including:
RQ1: How long does a specific individual remain in each place?
RQ2: What is an individual's indoor trajectory within a certain period?
RQ3: How many individuals are at each place at a given timestamp?
RQ4: How long do two individuals stay at the same place?
RQ5: What is the relation between the places in users' trajectories?

4 VISUAL EXPLORATION TOOL

This section proposes our Visual Exploration Tool for analyzing individual movements' dynamics in an indoor environment. Our purpose is to understand movement behaviors and patterns with a dynamic visual tool to analyze such data.

Based on the analytical tasks involving individuals' movements dynamics and the research questions we defined in the previous section, we defined some design goals for the tool.

G1: Provide a visual representation for length of stay analysis;

G2: Provide a visual representation for trajectory analysis;

G3: Provide a visual representation for space occupation analysis.

In the next subsections, we explain in detail the solutions proposed for each design goal. To illustrate the explanation of these solutions, we use a dataset acquired through the Internet of Mobile Things low cost system (Schneider et al., 2021). This system collects, processes, and stores individuals' movements in an indoor environment in two university buildings used by faculty, staff, and students. It provides two kinds of data: raw and processed. In the system, each individual has a BLE (Bluetooth Low Energy) beacon device associated with them, and the places of interest are equipped with at least one fixed gateway. The system periodically records the BLE beacons advertisements that are within the radio range of each gateway.

Raw data is the exact data originated in the gateways of the IoT system, without any processing. The dataset comprises 456,094 movements of 12 individuals, captured by 20 installed Gateways over 501 hours. We used the gateway names instead of the places names and represented the persons by using their beacon identification number to maintain their privacy in the database.

The raw data is processed in the server to clean false positives related to the place where each individual (Beacon) was (due to gateway coverage interference) and to avoid more than one gateway set for each user at a given moment. This processing step removes unnecessary data to be consumed in the data analysis, also improving its performance. In this real case, this step reduced the raw data to 56,049 data points, 12.3% of the raw data entries, adding a delay of 1.5 minutes, which is not an issue for our study. In the next subsections we show a visual comparison of the raw and processed data.

The tool is being developed using the Python script language (version 3.7.2) (Van Rossum and Drake, 2011) with the Plotly (Version: 4.6.0) and Dash (Version: 1.16.3) packages. The tool provides multiple visualizations with filters that can be applied to many charts at the same time. It is an interactive tool that allows users to obtain more accurate information from a data point on the hover, and to zoom in/out for more/less accuracy (see Figure 1 for reference). The data is load in CSV file format.

Users of the BLEVis Tool can select the following options in the left-hand side of the dashboard:

- The database to be loaded for visualizations;
- Specific types of information, such as length of stay, trajectory, and occupation. This selection will only present types of charts specific to the selected item.
- Filters for location, person, and time. These filters modify all charts at the same time. The user can select which places, which persons, and which time range should be considered in visualizations.

In the next subsections, for each design goal we detail the proposed visual solutions and how the research questions presented in section 3 can be answered. Some of those visualizations are still to be integrated with the dynamic visualization tool.

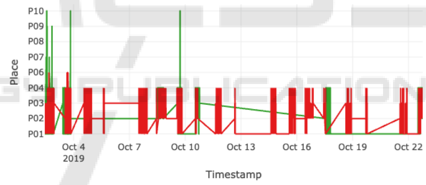
Figure 1: Visual exploration tool interface.

4.1 G1: Length of Stay Analysis

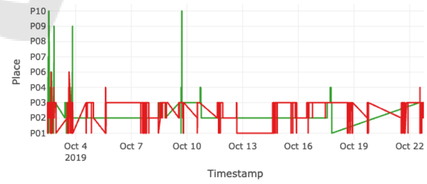
Our first design goal is to support the visual analysis of information related to the length of stay, to answer the research questions **RQ1** and **RQ4** presented in the section 3.

To answer **RQ1** (How long does a specific individual remain in each place?), we propose a `Time versus Place` interactive chart, where each `Place` is a Gateway. The name of each gateway represents a location in the chart. The time has a granularity of 30 seconds. Each line color named as `Person` represents one individual. It is possible to select each person to show in the chart. For instance, in Figure 2b, the individual represented by $U6$ (red line), moved among $P01$, $P02$, and $P03$ most of the time, and eventually went to $P06$ and $P04$. If we zoom in a certain period, it is possible to precisely get how long they remained in each place. Besides, when hovering over the cells, we can see the details of the selected data point: name, place, and time. Figures 2a and 2b show the same individuals within a certain period, comparing raw (a) and processed (b) data in the server. The charts also help designers adjust the sensors to obtain better place coverage and less interference.

As the tool allows filtering the individuals, the analyst can select two individuals to estimate how long they remained in the same place. And this same visualization allows answering **RQ4** (How long do two individuals stay at the same place?).



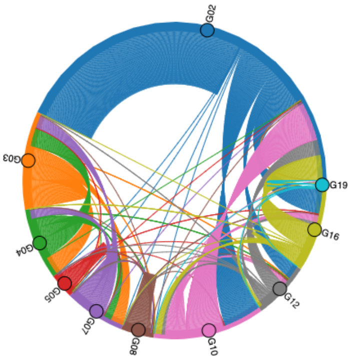
(a) Raw data



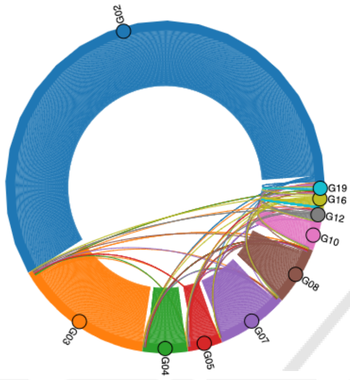
(b) Preprocessed data

Figure 2: Individual's trajectories over time versus places: (a) using the raw data; (b) using the preprocessed data.

This kind of visualization enables the extraction of unexpected movement, outliers, and groups of individuals with similar trajectories over time. In the context of this analysis, weekends, holidays, vacation periods, and specific special days may be relevant and helpful to understand patterns and anomalies.



(a) Raw data

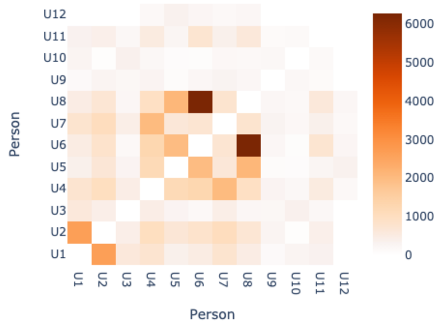


(b) Preprocessed data

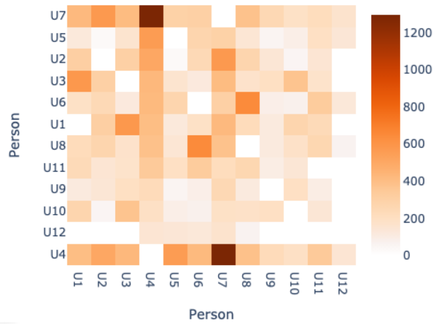
Figure 3: Flows between places.

`Chord` diagrams (Holten, 2006) represent the transitions between places and individuals. Loop lines show whether individuals remain in a place. Having a perception of the movement behavior between places and total remaining time in the same place is easier in chord diagrams. In Figure 3, each origin place is represented by one color, which identifies the direction of the movement. This figure considers all individual's movements, and it does not identify each single individual, but that is possible by filters.

Figures 3a and 3b show chord diagrams using the raw and processed data, respectively. Some relations disappeared in the second chord diagram (Figure 3b) when compared with the first chord diagram (Figure 3a). Gateway interference presented in raw data were false movements represented as relations in Figure 3a. Since this paper does not analyze the individual's paths during the transition between places, we consider that each user is in a place if they remain at least three consecutive acquisition times. The reason for that is to eliminate false positives in the pre-processing analysis. As in Figures 2a and 2b, these chord diagrams reinforce the importance of pre-processing data and removing false movements between places.



(a) All Places



(b) P03 Place

Figure 4: Heatmap: Shows the amount of time that each pair of individuals are at the same place during a given interval of time.

A `heatmap` represents a matrix, a relation between two categorical variables. The color gradient can express the intensity of a third variable. It is illustrated in Figure 4 and can also answer **RQ4** (How long do two individuals stay at the same place?). This chart indicates the relation between individuals by showing the amount of time (in minutes) that each pair of individuals stays at the same place during a given period. We can observe any patterns in the change of color intensity of cells across each axis. Besides, when hovering the cells, we can see the frequency in which each pair of users were together. The proposed heatmap can help select users and evaluate their paths through trajectory visualizations, as shown in Figure 2 (Individual's trajectories over time versus place).

4.2 G2: Trajectory Analysis

Our second design goal is related to getting information regarding trajectory analysis and answering **RQ2** and **RQ5**.

For **RQ2** (What is an individual's indoor trajectory within a certain period?), we also proposed an interactive chart of `Time versus Place` (see Figure 2) and another interactive chart of `Time versus Place per day per person`. Each line represents individ-

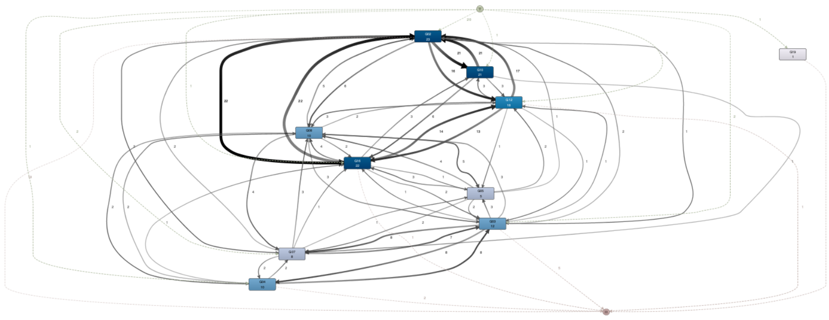


Figure 5: Process view of individuals' movement, using Fluxion Disco.

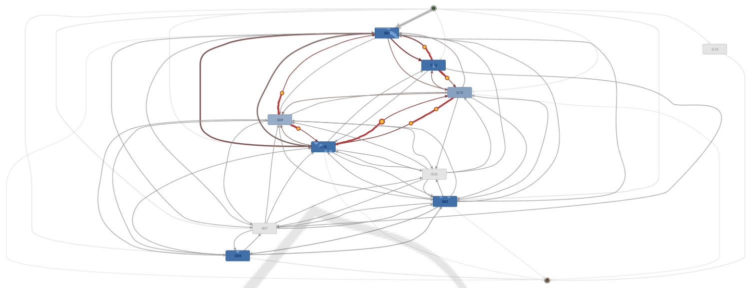


Figure 6: Animation view of individuals' movements, using Fluxion Disco(c).

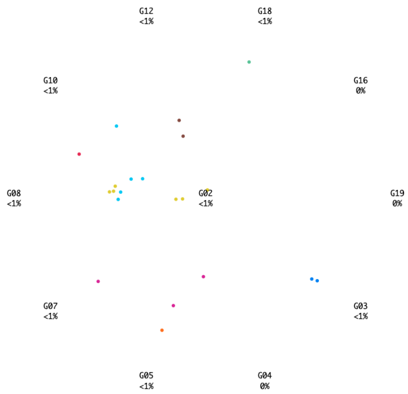
Activity	▲ Frequency	Relative frequency	Median duration	Mean duration	Duration range
G02	1,022	28.77 %	7 mins, 30 secs	2 hours, 8 mins	5 days, 18 hours
G03	647	18.22 %	30 secs	15 mins, 53 secs	1 day, 2 hours
G16	534	15.03 %	30 secs	15 mins, 48 secs	2 days, 16 hours
G07	471	13.26 %	1 min	13 mins, 58 secs	19 hours, 58 mins
G10	418	11.77 %	30 secs	4 mins, 6 secs	4 hours, 13 mins
G12	227	6.39 %	0 millis	3 mins, 54 secs	6 hours, 44 mins
G04	180	5.07 %	30 secs	43 mins, 4 secs	15 hours, 49 mins
G08	35	0.99 %	30 secs	15 mins, 28 secs	3 hours, 52 mins
G05	17	0.48 %	0 millis	31 secs, 764 millis	2 mins, 30 secs
G19	1	0.03 %	1 hour	1 hour	0 millis

Figure 7: Place statistics.

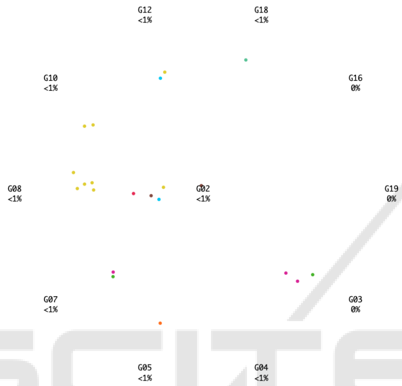
uals' trajectories through places and the time spent at each one. Each graph of the `Time versus Place per day per person` chart represents each day of a person in one different color. The daily charts support the visualization of path patterns and behavior identification between days and persons. As previously mentioned, the data on a certain person can be selected from the chart according to the period of interest. From one to all persons can be selected.

We may also analyze individuals' movements through specific process mining visualizations, like the ones provided on the Disco process mining commercial software[1]. This tool allows analyzing the performance metrics directly and intuitively and animates the movement history on the model. We converted the data into an event log, where individuals' ids became cases, and places became the activities in a process mining context (Van Der Aalst, 2011). Figure 6 shows the frequency of different individuals in a specific path (from one place to another). Here, the boxes and lines represent the places and the trajectory from one place to another. A similar view with absolute frequency or the maximum number of repetitions is also available, instead of frequency of cases. Another useful Disco view is the animation, which dynamically presents the history of user movement within a specific period, and shows, for instance, an evaluation of bottlenecks, illustrated in Figure 6. Figure 7 presents statistics on places, which show that 29% of individuals appeared in G02 and presented a mean duration of two hours for five days and 18 hours. Figure 8 shows two different snapshots of an animation that represents individuals' movements through places configured with gateways in a dynamic visualization. Each colored point identifies one individual. Each place is illustrated in the figure by a gateway number. For instance, place 01 is G01. This visualization enables the analysis of dynamics of individuals' movements in an enterprise within a certain period or in real-time. This dynamic visualization was inspired

[1] https://fluxicon.com/disco – last visited in September 2020.

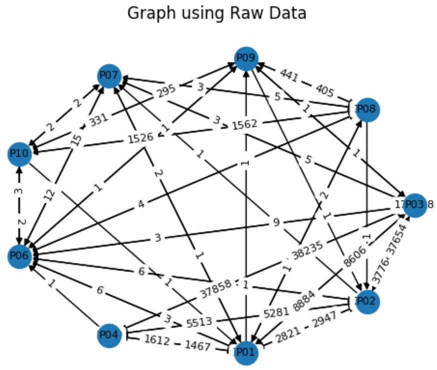


(a) Timestamp 1

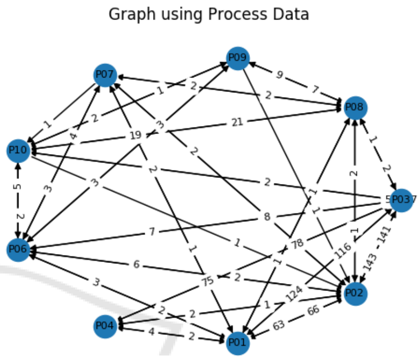


(b) Timestamp 2

Figure 8: Images of an animation of individuals' movements through places at two different time stamps. Figure based on code from https://flowingdata.com/projects/2015/timeuse-simulation/.



(a) Raw data



(b) Preprocessed data

Figure 9: Directed graph of place transitions during a period of time.

by one at Flowingdata.[2]

We propose some visualizations and animations to address **RQ5** (What is the relation between the places in individuals' trajectories?). The first one is the use of a directed graph visualization of individuals' movements. It shows relations among places, directions, and frequency of individuals' movements between places in a certain period. However, it does not evidence how long each person remains in a place. Figure 9 illustrates this idea with the raw and processed data. The second one is chord diagram (Figure3) which provides the flows between places and also evidences the time remained in each place. However, the exact number of interactions or movements between places is not as straightforward as in directed graphs.

4.3 G3: Occupancy Analysis

Our third goal is to support the visual of occupancy analysis. To reach this goal and answer **RQ3** (How many individuals are at each place at a given timestamp?), we selected a dynamic heatmap chart, as illustrated in Figure 10. This chart shows the number of people in each location over time. The time granularity is 30 seconds. The period selection directly in the heatmap is also available. One can use this information to manage and optimize the usage of places and to help with the automation of environmental conditions in offices, such as controlling lighting and air conditioning systems. In the epidemic situation that we are facing, we could use this system to monitor each place occupancy to keep social distancing requirements, being aware of the maximum number of individuals in each place. This chart is interactive: which places to see and the time range selection are available.

[2]https://flowingdata.com/projects/2015/timeuse-simulation - last visited on December 2020.

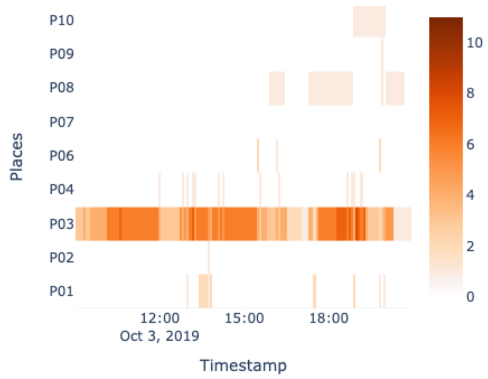


Figure 10: Occupancy of individuals in places over time.

5 CONCLUSIONS

We proposed a visual tool prototype and demonstrated it with some charts and animations to visualize a real-case scenario of an indoor movement dataset generated in two university buildings used by faculty, staff, and students. In this set, we explored the data visually to answer some questions about individuals' movements. We visualized the relations between individuals and places and the inter-relations with individuals × individuals and places × places. The contribution is how we adapted the charts and animations to answer questions in this context and to enhance analysts' experience by reducing the time spent on the analysis. Our future work aimed to incorporate more chart integration, filters, and functionalities such as event thresholds in the dash tool to (a) to facilitate environmental automation or monitoring for social-distance control for COVID-19, to adjust the air-conditioning temperature, and to estimate resources available; (b) to identify outliers and predict movement online for indoor environments; and (c) to make it more usable for human operators to derive insights about the indoor movements. Finally, we plan to test the tool by using another dataset and to conduct an empirical study to evaluate its efficiency and ease of use.

ACKNOWLEDGEMENTS

This work was partially supported by CNPq - Conselho Nacional de Desenvolvimento Científico e Tecnológico.

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