SENSING BEHAVIOUR FRAMEWORK: ACQUISITION AND COMMUNICATION OF OCCUPANCY BEHAVIOUR DATA.

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ABSTRACT

Architects and building owners often lack a systematic way to understand how their buildings are used, making it difficult to improve designs. To address this, the Sensing Behaviour framework provides methodologies and tools to gain insights into the behaviour of building users. The framework connects pre- and post-creation loops to learn from past examples and inform future designs. Sensing Behavior uses object and relation detection algorithms on video streams to understand occupant behaviour. The framework couples detected objects and persons and their interactions as nodes and edges in a time-based graph representation. This paper describes the technical development of Sensing Behavior, related workflows, and protocols, and its implementation in a real-world use case as proof of concept. The framework's capability to record and analyze occupancy behaviour has the potential to inform future architecture and create sensor systems for better building design.

Keywords: Behaviour, Occupancy Analysis, Computer Vision, Machine learning.

1 INTRODUCTION

Architecture has always been a knowledge-based field (Schön 1984, Visser 2010), however, academic design research is slow to expand the field's knowledge from the design processes to analytic knowledge based on real behaviour within buildings. More specifically, the field is lacking tools for capturing and analyzing occupant behavioural data, even though, the potential of behaviour-driven and human-centred insights for improving life inside buildings, has been long identified (Brazil 2016, Becker and Douglass 2008).

Since the 1980s the mapping of a building's occupants' behaviour has followed the same methodology (Gehl 1987, Gehl and Svarre 2013a). Even though some computational frameworks have been developed, these mainly focus on gathering quantitative occupancy data by means of human observation (Gehl 1987). The automated collection of data on occupancy is limited to the detection of data, such as occupant *presence*, *counting* and *tracking* (Dong 2017). However, there is to our knowledge no such tool, yet, to document the qualitative aspects of occupied buildings. Therefore, new methods for documenting and thus understanding occupant behaviour in the built environment should be investigated. These could assist the development of the field (RoyalAcademyofEngineering 2015) and elevate the design processes with more information.

The research project "Sensing Behaviour: Occupancy-Informed Architecture by Customisable Situational Mapping with Computer Vision" (SBF) investigates the utilization of Computer Vision methods (CV) on affordable sensor systems to capture and communicate occupancy behavioural data (Jorgensen, Tamke, et al. 2020). Sensing Behaviour is developed in collaboration with CITA - Centre of Information Technology in Architecture and the architectural practice 3XN Architects/GXN Innovation. In Sensing Behaviour, methods for documenting and analyzing occupancy behaviour are explored, with the ambition to help architects understand and react better to the implications of their designs for current and future users.

The theoretical framework underlying Sensing Behaviour (Jorgensen, Tamke, et al. 2020) suggests the definition of the term *Behavioral Situation* as the actions that cause observable interactions between occupants and inanimate objects. Therefore, a behavioural situation can be described by observable objects, the relations between them, and the context within which they emerge. The research project consists of three stepping stones:

1. *Data Acquisition:* The realization of a sensor system capable of capturing socio-spatial information of occupancy behaviour,
2. *Storage:* The set-up of a database to host the acquired time-based relational information, and
3. *Analysis:* The development of a notational system that allows the analysis and visualization of behavioural architectural data.

In this paper, we briefly demonstrate the technical development of the SBF along with its implementation on a case-specific example. The ambition of the project is to establish a global mapping of behavioural data within buildings. The project's development, at the moment, consists of the detection of objects and their relations through Computer Vision methods on RGB images, along with the deduction of their spatial relations in the built environment from depth images. As a proof of concept, an in situ data collection and analysis of occupant behaviour from the co-working community BloxHub in Copenhagen is realized and showcased.

2 BACKGROUND AND LITERATURE REVIEW

Occupancy analysis is a methodology that involves assessing the use and occupancy of a building or space. In recent years, new technological apparatuses and computer vision have become valuable tools in the context of occupancy documentation. These technologies can be used to automate the process of occupancy analysis and provide a higher level of information about the usage of space. In this section, the notion of occupancy analysis, new technological apparatuses, and the use of Computer Vision technology in the context of occupancy documentation are briefly explained and evaluated.

2.1 Occupancy Analysis

The observation of occupant behaviour in the life of buildings is nothing new in itself. Behavioural data acquisition methods were developed by architects in the 1970s and 80's (Gehl 1987). However, these methods were practical *systematic observations* (Gehl 1987, Gehl and Svarre 2013a), conducted by human actors counting *people-oriented indicators* in situ, to gather information of interest. These methods are labour-intensive and difficult to scale (Sylvest 2017). (Becker and Douglass 2008) shape a complete method regarding the aspects of manual recording of occupancy behaviour. Post Occupancy Evaluation (POE) serves as a mediator between social sciences, technical performance evaluation, and design. POE has enabled architectural practices to inform their designs on specific parameters acquired from the occupants' behaviour, and therefore enable designers to formulate inclusive and behaviour-specific architecture.

The limitations of manual systematic observation methods provide datasets that lack temporal longevity and socio-spatial granularity (Wagner, O'Brien, and Dong 2018). Consequently, the development of digital occupancy analysis tools is quickly moving toward the realization of more adequate tracking sensor systems. Occupant-sensing technologies should be implemented for behavioural research within architecture since data-driven design processes are improving not only the design itself but also the functions and operations of buildings (Thomsen, Tamke, et al. 2015). Occupant behaviour documentation is based on observations of factual interactions, and therefore, can facilitate an immersive development in the design field and architecture considering building-occupant relations. State-of-the-art sensor frameworks focus on documenting occupant *existence*, *population* and *tracking* (Wagner, O'Brien, and Dong 2018), but are inadequate for assessing qualitative aspects of occupancy behaviour.

2.2 State of the Art technologies for Occupancy Analysis

Most research attempts to monitor and understand occupancy behaviour are facilitating one of the following three technologies:

1. Environmental or ambient sensors (Ioannidis, Tropios, Krinidis, Stavropoulos, Tzovaras, and Likothanasis 2016) , detecting e.g. $CO2$ emissions or water consumption
2. Tracking of people using attached sensors, e.g. wearable devices or smartphones (Betti, Aziz, and Ron 2020)
3. Tracking with computer vision technology

Computer-Vision-based occupant analysis methods are popular since they allow the classification, recognition, and tracking of people, objects, and activities, through images. Computer Vision (CV) is used in commercial and academic settings for occupant tracking (Wagner, O'Brien, and Dong 2018, Stisen, Mathisen, Blunck, Kjærgaard, Prentow, et al. 2016). Frameworks, implementing this technology, can acquire data that contain the population, positioning, and trajectories of occupants. Prominent suppliers of CV-based occupancy analysis systems are: Ubiqisense (Ubiqisense 2022), a company that developed its sensor system capable to record the movement of employees in office buildings to maximize building and office space utilization. Xovis sensors (Das, Sangogboye, et al. 2019) are addressing larger scale infrastructures, such as airports, where they allow to track people flow. Xovis technology provides scalable means to track individuals and masses of people in real time. It has applications in the industry but also in academia. Further Vision based techniques have been developed on the base of surveillance cameras e.g. the retail industry for the tracking and handling of customer movements (Mora, Nalbach, and Werth 2019).

While these frameworks are established and versatile, there are some setbacks regarding their usability, as these sensor systems usually require complex setups, infrastructures, and computational systems, and are designed with a specific application in mind (e.g. people counting, capturing the utilization of offices, people flow). This specialisation does not allow customization towards other purposes and questions (Jorgensen, Tamke, et al. 2020). Moreover, state-of-the-art technologies focus on the tracking of individual occupants in or through space but lack tools capable of mapping occupant relations and interactions with other occupants, objects or the environment they are in.

3 METHODS

The system architecture of SBF in its current state is similar to any computer vision system and can be seen in fig. 1. More specifically, the project aims to capture images and process them to acquire relational/behavioural data. The data are then uploaded to a remote graph database, to be visualized and communicated. Several processes were tested to acquire suitable data for the Sensing Behavior framework. Protection of the individual's privacy, as they are manifest in the GDPR (Goddard 2017a), has been guiding the development of our framework. Our software architecture allows isolating Data capture and Detection algorithms on a camera with a pre-trained Vision and Detection algorithm. In this way we leverage Edge-Computing to assure privacy, as only anonymous data would leave the device and privacy by default can be achieved by instant deletion of any non-anonymous data and removing any detection steps, that would filter off blacklisted attributes, such as gender. For this study and future training and validation phases of the framework, other means to ensure the protection of individuals' rights for privacy have been found.

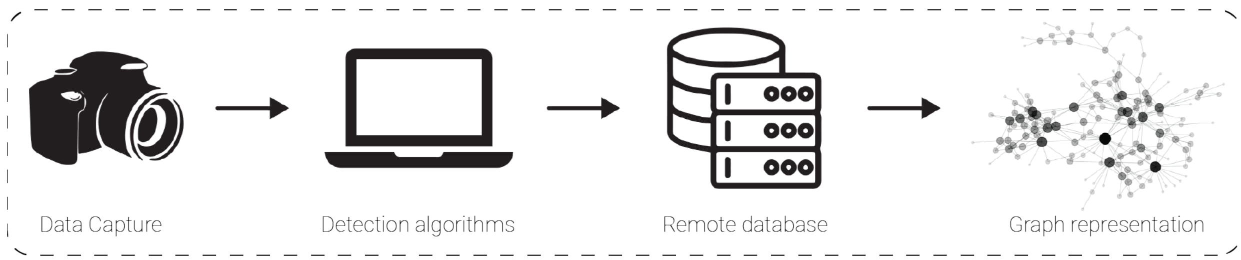

Figure 1: The System Architecture of the Sensing Behavior Framework.

3.1 Data capture

For the data-capturing processes of the SBF, the Azure Kinect DK was used. The implementation of the sensor was accomplished through the pyKinectAzure library (Gorordo 2021). Initially, the camera is activated and its configurations are modified. More specifically, for the SBF, the WFOV 2x2 binned depth mode was chosen. Even though this format does not provide the longest depth range, it offers more flexibility to the remapping of the depth image. For the RGB camera, a 720p resolution format was chosen, since it can offer computationally cheap but at the same time meaningful object detection results.

The camera is capturing an RGB and a depth (D) image. For the project's purposes, the depth image needs to be mapped onto the RGB image. Moreover, after the image mapping, the same image is passing through a post-processing step, where its edges are smoothed out. This choice was made to reduce the image areas where no depth has been detected: object edges, reflective or black materials, and objects that are away from the camera's range. When the capture is finished the RGB and D images are named after the time of their capture and saved in a folder as .jpeg and .png files, respectively. All the aforementioned functions are implemented in a loop defined by the number of frames that are acquired, and the time between them. In this way, the time-lapse of a space is created to serve the SBF purposes.

3.2 Creation of the relation dataset

The creation of a dataset capable of communicating behavioural data through graphs builds upon the captured frames and consists of three steps: **a)** *sorting the captured images in groups regarding the similarity between them*, **b)** *applying object and relation detection algorithms on the images*, and **c)** *filtering the relations*. The three steps of the process are shown in fig. 2.

3.2.1 Image sorting

The first step of the process regards the sorting of images into groups of relevance, see fig. 3. Every frame captured from the Kinect is compared with its previous one. The similarity score is calculated using

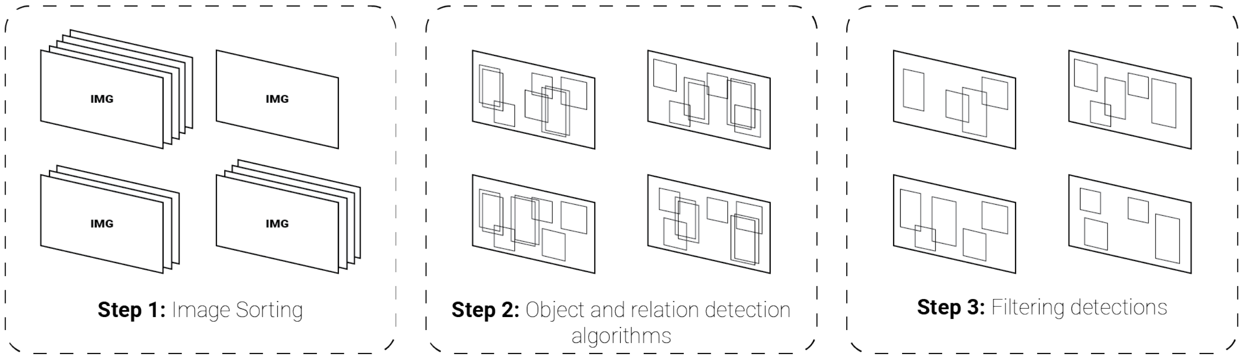

Figure 2: The steps followed in order to acquire insightful behavioural data.

the sci-kit-image library (Van der Walt, Schönberger, et al. 2014), and specifically, the `structural_-similarity` function. This quantitative measure considers three parameters namely luminance, contrast and structural information between the two images. When their similarity score exceeds the percentage of 95% then the images are merged within the same group. On the contrary, when the score is lower, then the previous group ends and a new one starts being formulated. Some exceptions were raised regarding the similarity scores, and therefore, the categories were manually over-viewed and curated. At the end of the process, a file is generated containing information regarding **a)** the total number of groups, **b)** the total number of frames in each group, **c)** the names of the frames in each group, and **d)** the similarity score of each frame with its previous one.

Following the grouping of the images, the selection of a representative image of each group took place. The selection of the representative images was realized through the visual inspection of the images by the authors.

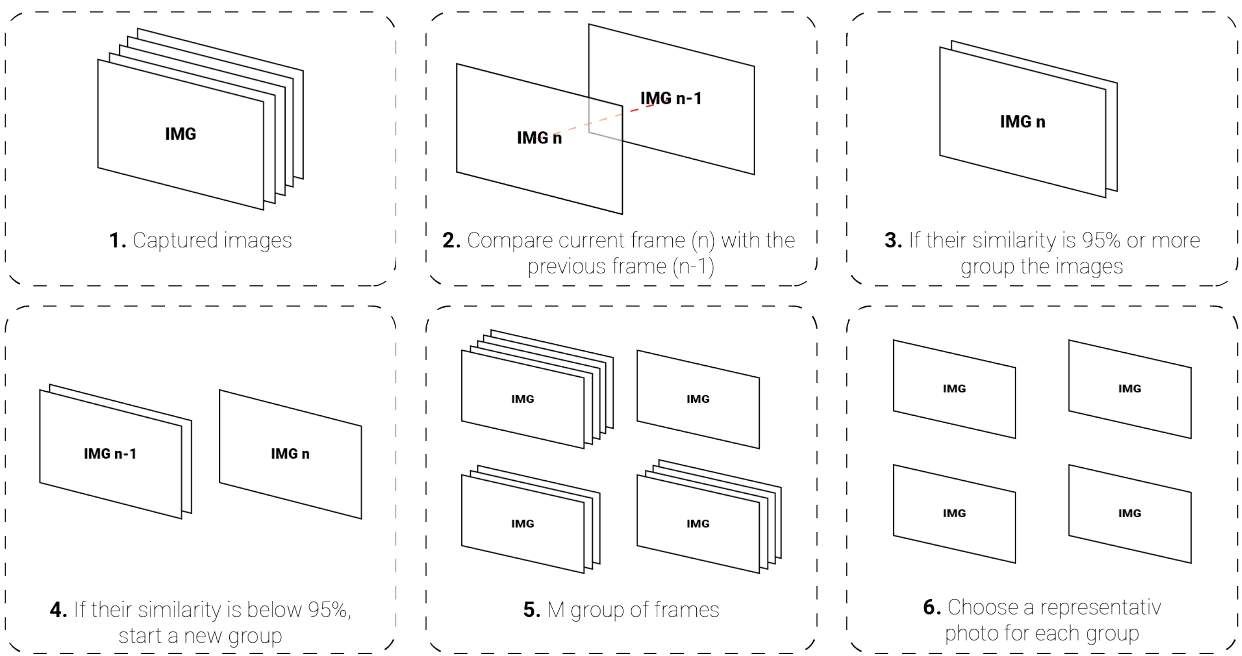

Figure 3: Separating the images into groups regarding their similarity.

3.2.2 Object and Relation detection algorithms

The RGB images acquired from the sensor are being processed through the mask R-CNN object detection algorithm (He, Gkioxari, et al. 2017). The algorithm can detect 150 different objects within a broad range of categories, from animals to humans, and furniture to vehicles, buildings, or plants/fruits. After the detection of every object in the scene, a bounding box and its centre are plotted upon the resulting image. The pixel coordinates of the centre of the detected objects are used to calculate their real-world coordinates regarding their depth value extracted from the acquired depth maps.

Both object and relation detection is realized through the Scene Graph Generation (SGG) Benchmark (Xiaotian, Jianwei, et al. 2021) based on the maskrcnn-benchmark model (Facebook 2021). The SGG algorithm can detect 50 relations concerning spatial relation, ownership, activity, adjectivity, etc. After the detection is completed for every selected representative frame of the captured time-lapse, a relation dataset is exported containing information about subjects, objects, and the relations between them.

3.2.3 Filtering Relations

The algorithm can understand approximately 100 relations between the detected objects within a frame. However, most of the detected relations are inaccurate or irrelevant to the purposes of the project. For example: `detected_object_1`: woman, `detected_relation`: is_wearing, `detected_object_2`: jacket (meaning: A woman is wearing a jacket). A relation as such, in the case-specific example, that we are analysing through the SBF is irrelevant. That said, there is a need for filtering these detections to acquire meaningful information regarding the space.

Automated Filtering: Initially, the dataset created is refined by an automated filtering script. The script's structure can be seen in fig. 4 and its 4 steps of operations are the following:

1. *Remove irrelevant objects*: Delete all the relations that have been detected between objects of no interest (e.g. body parts, building components, clothing etc),
2. *Anonymizing the dataset*: Remove gender and age information from the occupants.
3. *Merge operations*: Check the overlap percentage of the bounding boxes of two detected objects that share the same label. When this percentage exceeds 90% then the detected object with the higher detection accuracy is replacing the other one.
4. *Check distance*: Filter the detected relations regarding the spatial distance between the objects in the physical world. For our case-specific example, we set this value to 1.5 m. All the relations with a higher distance between the related objects were eliminated from the dataset.

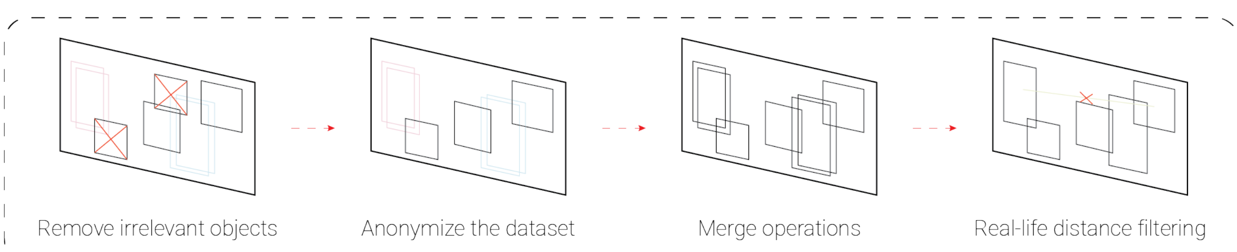

Figure 4: Automated filtering operations.

Manual Filtering: Even though, the algorithm's detections and the automated filtering results were promising, there was a lack of necessary information in the created dataset. To prove the conceptual background of the framework, we decided to add the information missing, by manually overwriting some relations that should have been detected in the scene but were not (e.g. `detected_object_1`: occupant, `detected_relation`: is_holding, `detected_object_2`: laptop (An occupant is holding a laptop).

3.3 Data Storage

For storing the data, the Neo4j Graph Database (Webber 2012) was chosen, since it's one of the graph databases with a friendly user interface, and it has been used by many big tech companies for handling big streams of data. In this part of the Sensing Behavior framework, a script was created to read the resulting dataset and upload it to the Neo4j database. The same script is uploading the data in the form of nodes for each detected object and edges between them for each configured relation.

Each detected object has the following properties: `label`: the name of the detected object (e.g. chair), `frame`: the number of the frame that it belongs to (e.g. 1, if the object was detected in the first image captured), and `dataset`: The dataset that the object belongs to (e.g. `S1`, when the detected object was captured from the sensor `S1`). While each relation is only described by a `label`: the name of the detected relation (e.g. sitting_on).

3.3.1 Time in Graph Database

In order to succeed in a temporal saving of the data, special nodes were created representing time zones, see fig. 5. These nodes are equal to the number of captured images and have the following characteristics: `label`: the name of the frame (e.g. frame_1, if the node represents the first image captured), `Time`: the actual time of the capture (e.g. 2022-11-29, 09:26:27), and `property`: the number of the frame (e.g. 1, if the node is the first one)

4 EVALUATION

For the evaluation of the Framework, a case-specific application was realized at BloxHub Copenhagen. BloxHub is a co-working community consisting of companies, organizations, and research institutions, all working with architecture, design, construction, and tech, aiming to achieve sustainable urbanization. BloxHub is located in a 9.000 m2 co-working space with 140 member companies (approx. 1.100 people). Bloxhub's interior layout promotes internal knowledge sharing and innovation and attracts attention to new co-working activities. A community-style working base is key, where meetings are the foundation for business development, synergies, and innovative processes. The conceptual and tailored decorations encourage employees to develop their own space and workstations.

For Sensing Behavior and in communication with the administration of BloxHub, we decided to set up two sensor systems and analyze one of its rest areas. The specific area was chosen due to its location, being placed in the middle of BloxHub, but also having one of the greatest views over the Copenhagen Canal, which should attract occupation.

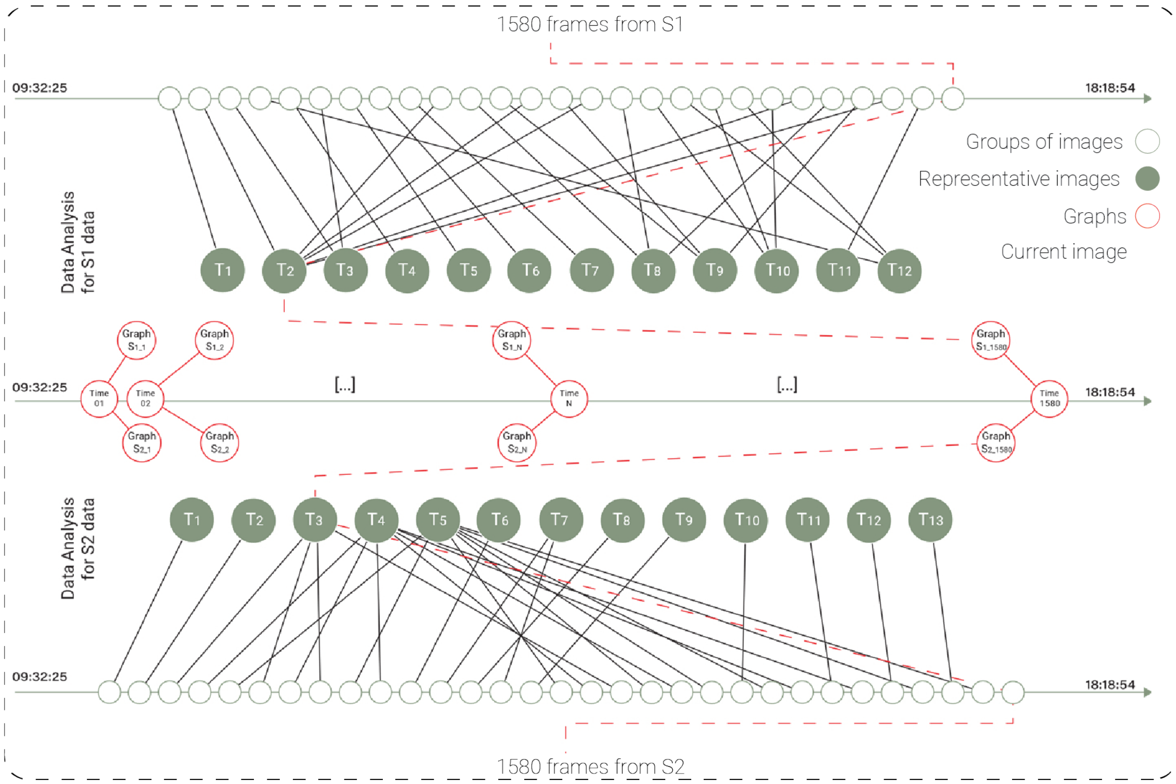

Figure 5: An illustration of the temporal timeline with the nodes and edges uploaded in the graph database can be seen in the middle line of the figure. The top nodes represent the categories within which the frames of Sensor S1 were sorted. Each of the batches created after the image sorting is represented by a situational graph, e.g. T1 (The same situational graph might represent more than one image batch). The same happens below with the frames captured from frame S2. The two chosen situational graphs are simultaneously uploaded to the graph database and connected through a timezone one after the other.

4.1 Questions

In discussion with the Bloxhub Facility Management team, four questions relevant to their management and future planning of these spaces within their facility have been identified, which should be answered through the data capture campaign:

1. How often are occupants using the rest area, and in what ways?
2. Are the occupants relaxing or working?
3. Are they alone or is it a spot for interaction and socialization?
4. Would it make more sense to have more working spaces rather than a rest area?

4.2 Sensors set-up

For the specific data acquisition, the algorithm was set to capture one frame every 20 seconds, until it reached the number of 1580 frames. The total time of the capture was approximately 9 hours, from 09:30:00 to 18:20:00. The day of the capture was midweek as it is the most representative time for office occupancy behaviour (Gehl and Svarre 2013b). Several locations were explored within the area in order to finalize the positions of the cameras that enabled the acquisition of useful behavioural data. The final placement of the two sensors can be seen in 6, while the view of each sensor is shown in fig. 7.

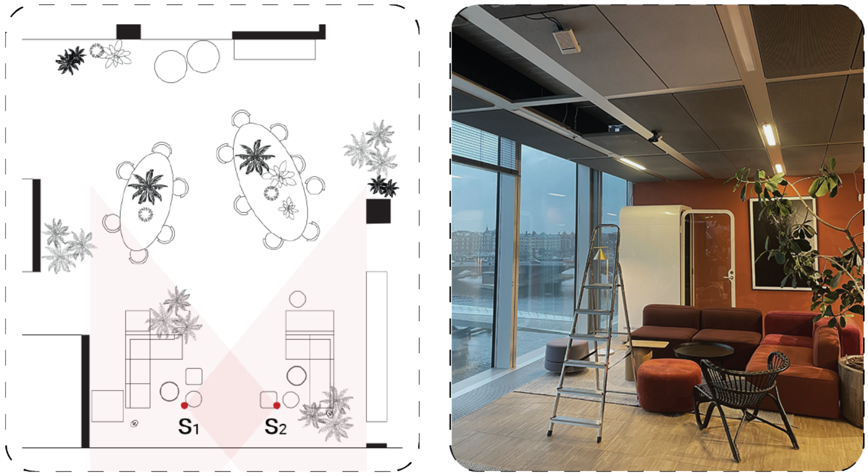

Figure 6: The positioning of the two Kinect cameras, along with a picture of the setup.

Figure 7: On the left side, the view of the Kinect S1 is shown, while on the right side the view of the Kinect S2.

5 FINDINGS

Through the data querying we were able to answer some of the initial questions. This was succeeded through Charts (Needham 2020), a Neo4j Graph app which has a visual query builder that generates charts based on queries. Those queries can then be used in dashboards to create tables, bar charts, line charts, and more. The analysis of the data is described by two types of reports: *General Information*: regarding the database characteristics and the capture, as a technical process, and *Behavioural Analysis*: which consists of the *Quantitative Data*, that most existing sensors are capable of reporting, and the *Qualitative Data* extracted from the dataset.

General Information The capture started on the 29th of November at 09:32 am and lasted for approximately 9 hours. The number of created time zones is 1580, as the frames that were captured. The database consists of 46844 nodes of detected objects and 206876 relations between them.

Behavioral Analysis The Behavioral Analysis reported an occupancy percentage of 73% over time with an average of 1.6 occupants. Even though the space was occupied for most time of the capture, it wasn't used up to its full potential. The distribution of the occupants over time can be seen in fig. 8. The sofa activity captured from S1 reported an occupancy percentage of 39.5% while the data captured from S2 reported a percentage of 62.5%. Through the analysis, we were able to report 2564 instances of occupants in the space, out of which 1314 were alone while the rest 1250 instances reported occupants in groups.

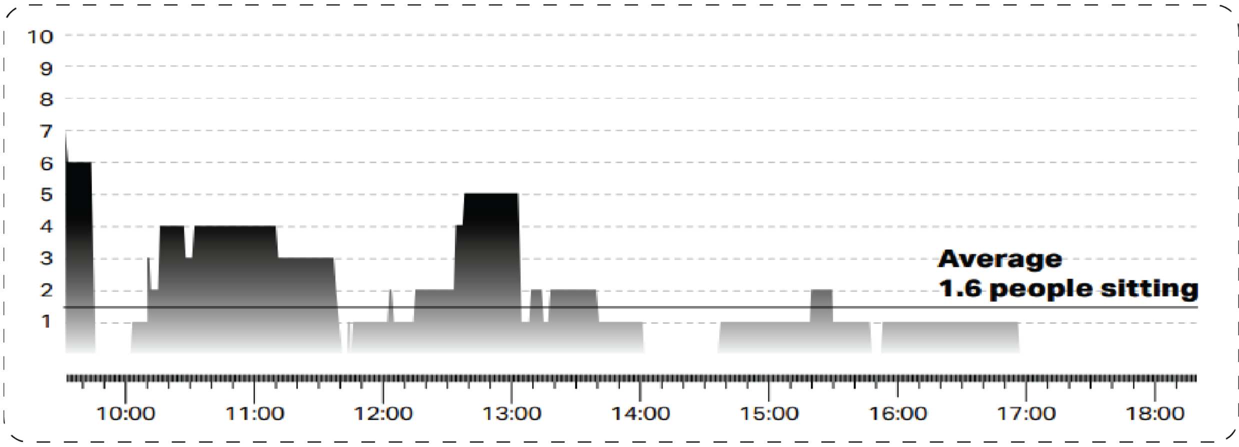

Figure 8: Occupants distribution over time from both sensors, S1 and S2.

Furthermore, the sensor systems were capable of detecting and reporting qualitative aspects of the space, such as human-to-human interactions, human-to-inanimated objects interactions and their duration through time. Fig. 9 shows the activities occurring in space. As shown in the aforementioned figure, the space is mostly used as a break-out space for work sessions. Therefore, a deeper analysis of the objects and relations describing work situations is performed by reporting the types of interactions. More specifically, we noted in both sofas, 2146 people were involved in a working situation (which is described by the nodes of occupants in relation to the nodes of laptops), 1182 out of which are working alone while the rest are working in groups of 2, 3, 4 or 6.

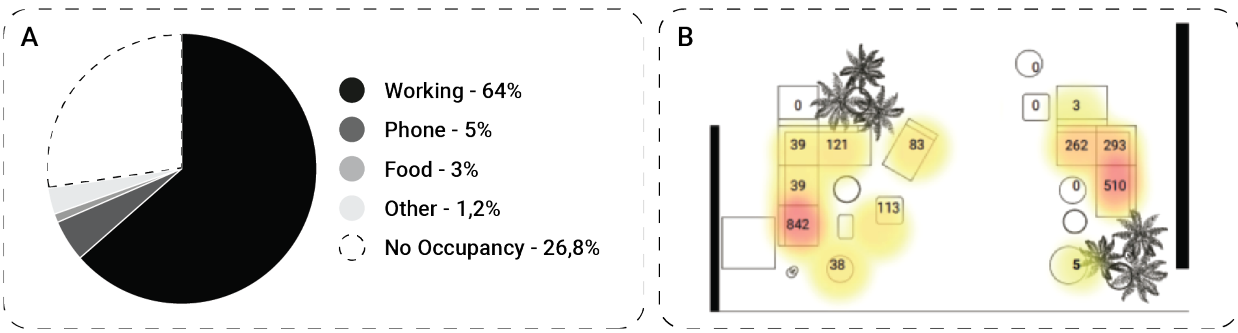

Figure 9: A. Activities of the occupants at the rest area of Bloxhub, Copenhagen. B. A heat map indicating the seat popularity of the analysed space.

6 DISCUSSION

The Sensing Behavior project aims to redefine occupancy analysis and its capabilities by adding the aspect of occupant behaviour to it. More specifically, the project's scope is to add qualitative dimensions to automated occupancy analysis by introducing quantifiable proxies for qualitative aspects of human-spatial interactions. We demonstrate the successful implementation of the framework for mapping, analyzing, and communicating occupancy behaviour within the built environment. We establish a theoretical framework for understanding behavioural situations followed by a technical framework, consisting of tools for capturing, storing, and analysis of occupant relations. The gathered behavioural architectural data are then communicated through a notational system.

In general, existing autonomous tracking systems offer the ability to collect detailed datasets while respecting personal privacy and keeping data anonymous (GDPR) (Goddard 2017b). Reassuring that the collection of data is aligned with data ethics and privacy regulations, is playing a leading role in the future development of such methods (Lapenta 2016, Stopczynski, Pietri, et al. 2014). The SBF is GDPR-sensitive between the first step of the process: capturing and the second step: the creation of the relation dataset. With respect to the legislation regarding privacy, our system has implemented privacy by default: **a.** *Storing all the captured images locally and for a limited amount of time*, and **b.** *Anonymizing the dataset by removing blacklisted objects e.g. genders*. Additionally, for the case-specific example at Bloxhub, we set up the sensor for a limited amount of time, after informing the occupants that the space is being monitored, and after clarifying the purpose and ownership of the data.

The realization of a tool capable of collecting data as such can elevate and inform the design fields. As explained in the paper, the SBF can create a schema for the behavioural situations of a specific place, and therefore, inform an architect's future decision-making processes for designs of the documented space. This is currently achieved by extensive visualisation of the data in interactive graphs and charts, which allow for a deep dive into the dataset and the detection and follow-up of emerging narratives in the data. A future step would be to use this base layer of data to deduct behavioural patterns, that could inform behavioural simulations of modified spaces or even yet unbuilt architectures. We imagine that this data could inform agent-based analysis tools, as currently used for pedestrian simulations (Ma, Lo, et al. 2013).

A major achievement of the framework is the extension of a graph database with the concept of time - a concept usually unknown to this domain. In our framework, it is possible to query for relations of objects over time in an efficient manner. The quality of these queries depends on object detection and consistent identification of persons and objects in successive time steps. We found, that there are only a limited set of objects in our space and that these have been detected quite sufficiently except for laptops. However to make the framework generally applicable our own and the used general-purpose object detection algorithms will need to improve.

After the analysis of the data acquired from the sensor system from Bloxhub, we revisited the initial questions posed by the facility management. The sensor successfully provided information for three out of the 4 questions, regarding if and how the space is used by the Bloxhub community. Answering the last question would require comparative data. Data that our framework could produce when it observes further locations in Bloxhub and for longer periods. We believe with the given information the facilitators of Bloxhub can be assisted in making decisions for the space and re-organizing it to promote a break-out workspace.

7 CONCLUSIONS

We find there is a big potential in merging social theories and contemporary technology, as investigated in this paper, to better understand our behaviour in designed spaces and to establish urgently needed feedback from the built environment to the design processes. Communicating emotional and behavioural states through data visualizations can be a powerful technique to enhance the capabilities of the design fields. Rational connections made from human experiences may provide insights into the treatment of place and can facilitate social change.

As a future development of the project, we plan to improve the detection algorithms to eliminate the need for manual effort, for example by training case-specific object detection algorithms. As a continuation of that, we aim to achieve real-time image analysis and upload of the data, eliminating all privacy concerns. Finally, to achieve a compact sensor system, we are planning to replace the use of Kinect with depth prediction algorithms (Alhashim and Wonka 2018) to acquire the objects' real coordinates in space.

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