Smart Crowd Management: The Data, the Users and the Solution

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Abstract

This research project is situated in the domain of smart crowd management, a domain that is gaining importance because of the challenges that arise from urbanization, but also the opportunities that come with smart cities. While our cities become more crowded every day, they also become smarter, for example by employing pedestrian tracking sensors. However, the datasets that are generated by these sensors do not allow smart crowd management yet, because they are sparse and not linked to the perception of the crowd. This research will tackle these issues in three steps. First, pedestrian counts will be estimated on streets that have no tracking data by use of deep learning and space syntax data. Next, the perception of crowdedness within the crowd will be linked to the objective pedestrian counts by conducting two user studies, and finally, the resulting subjective pedestrian counts will be used as weights for a routing algorithm. The last step has already been developed as a proof of concept. The routing algorithm, that uses partly simulated data and partly real-time tracking data, has been embedded in a webtool to show stakeholders the potential and goal of this innovative project.

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Supplementary Material *Software (Source Code)*: `https://github.com/laudcock/Smart_crowd_management`

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1 Introduction

As the gathering of a crowd can lead to hazardous situations, public safety is a major concern for local authorities [21]. In the past 20 years, more than 100 stampedes occurred with over 5000 deaths [10]. These numbers highlight the need for a flexible system that can monitor crowd dynamics in an urban environment. A need that will be even higher in the future, as the population growth in urban areas is projected to increase to 68% of the world's population by 2050 [4, 19]. Urbanization will go hand in hand with the development of smart cities,

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which will facilitate urban sensing [4]. This opens the door to a smart solution for crowd management, because crowds can be tracked throughout the urban environment. However, this sensor data has a few limitations. First of all, the sensors that are employed in urban environments are sparse as it is unfeasible to place them in every street [5, 16]. This means that pedestrian tracking datasets almost never fully cover an urban street network. Second, the objective number of pedestrians that is counted by tracking sensors does not necessarily reflect the subjective feeling of crowdedness within the crowd [1]. This research project aims to tackle the issues mentioned above by focusing on three components: the data, the users and the solution. In the remainder of this section, the state of the art of each component will be outlined.

The data

As pedestrian tracking data with full-coverage is rare, models are being developed to simulate the dynamics of a crowd. There exists a wide variety of models, but no model has all criteria to enable crowd modeling in practice, leading to a gap between theory and implementation [24]. There are two reasons for this [9]:

- Human behavior and decision making are influenced by numerous individual factors that are difficult to capture in a general set of model rules and equations.
- The varying environmental context makes it hard to introduce universal models that work in every context.

In this research project a model will be developed that provides an answer to both issues. The first will be resolved by using data-driven techniques, such as deep learning. Unlike theoretical models and simulations (e.g., cellular automata), deep learning algorithms do not need previous assumptions on the data, which has already been shown to be an advantage in several studies. Wang et al. (2019) found, for example, that deep learning methods were better than traditional ones when crowd movements during an evacuation experiment were more complex [23]. Given these promising first results of deep learning for crowd modeling, this project will use this technique, but enhance it with geodata to resolve the second issue mentioned above, i.e., the varying environmental context. Raubal et al. (2020) distinguish two types of geodata: tracking data and context data. While the availability of tracking datasets for research purposes remains limited, there is an increasing number of urban context data sources [18]. One specific type of context data known to correlate particularly well with pedestrian movement flows is space syntax [12]. The space syntax theory was defined in 1984 by Hillier and Hanson to "quantify space in a way we socially experience it" [11]. Its representations (e.g., axial lines, isovists, visibility graphs) and measures (e.g., integration, connectivity, occlusivity, controllability) have been used by designers, spatial planners and researchers to quantify the structure of cities and buildings ever since (e.g., [7, 22]). Space syntax has been proven very useful for crowd modeling purposes as well [20]. Zampieri et al. (2009), for example, combined space syntax and other spatial data with deep learning to estimate pedestrian counts [25]. The resulting model had a correlation coefficient of more than 90% for both the training and testing set, but they did not use crowd tracking sensors as the pedestrians were manually counted. Therefore, in this research project space syntax and deep learning will be combined for the first time to estimate pedestrian counts based on urban sensor data. The resulting model will estimate crowdedness on every street of an urban network.

The users

As opposed to the data and modeling component of crowd management, there is few research on the perception component [1]. However, several researchers agree that the perceived crowdedness can substantially differ from the objective density (i.e., the number of people per unit of space) [6, 14, 17]. Li and Hensher (2013), for example, compared the results of a survey which measures the passenger loads with the results of a survey which asked 2500 train commuters for feedback on the rail services. According to the first survey there was no substantial crowding problem, while in the second survey 55% of the commuters indicated there was [14]. Besides in public transport, this mismatch between objective counts and perception can also be found in urban green spaces. Campagnaro et al. (2020) found, for example, that crowding in a park was experienced as a negative thing for most participants, while other studies show that moderate crowding increases the feeling of safety [3]. This does not only show that there is a difference between objective and subjective crowding, but also that their relationship is complex and not linear [6]. This is because the perception of crowding is influenced by numerous factors. The two most obvious factors are space and people, which is why some authors differentiate between spatial density and social density [2, 17]. This shows that we must go beyond the physical space when discussing crowding and also analyze the behavioral or cognitive space, something that is rarely done within the field of crowd modeling, but more common within the field of space syntax [17]. As the environment has an important influence on the link between crowd counts and crowdedness perception, we feel that quantifying space by use of space syntax might be an essential step to determine this link. Once this link has been made, the perceived crowdedness can be deduced from the objective counts, which are generated by the model described in the previous section.

The solution

Determining the link between objective and perceived crowdedness is important as Li and Hensher (2011) have shown that the willingness to pay for reduced crowding is often as high as for reduced travel time [13]. However, most routing algorithms today minimize travel time or distance by calculating the shortest or the fastest path, even though scholars agree that users of navigation systems do not always prefer these paths [15]. Muller et al. (2017) state that many subjective parameters determine the route choice, but that it is not straightforward to include these parameters as weights in a routing algorithm, because that would require data of the user's perception [15]. The lack of data is one of the reasons that crowdedness has long been overlooked as a weight for pedestrian routing algorithms, although it clearly can be a decisive factor. This research project aims to fill this gap, by generating perceived crowding data on a city-scale and incorporating it in a routing algorithm. This algorithm will generate the least perceived crowded route, which can be used by local authorities and safety officials for crowd management purposes, but also by pedestrians as a route planning service. In the next section is explained how we will reach this result.

2 Materials and methods

The data

In the first step of the methodology a model will be generated that interpolates pedestrian counts in between sensor locations. In this modeling phase two concepts will be combined for the first time in the domain of sensor-based crowd tracking: space syntax and deep learning. Both local (area, perimeter, compactness, vista length, occlusivity) and global (integration, depth, control, controllability) space syntax measures will be calculated for every street with the isovists.org software. Tracking data will be obtained from Telraam, a Belgian citizen-science project that helps citizens to install a tracking device in their front window (for more information on the technology and sensor locations, see `https://telraam.net`). The data of these devices can be freely imported in custom applications through an API. In a next step, a graph will be created for each timestamp of the street network of the study area, and the space syntax measures and Telraam counts of a certain timestamp will be added as attributes to the edges. The motivation to use a graph is twofold: first, the spatially enhanced graphs will serve as input for a graph convolutional network (GCN) to estimate the counts on the graph edges without Telraam sensor, and next, the resulting graphs with an estimated pedestrian count for every edge will be used as input for a shortest path algorithm.

The users

In the first step, objective tracking data was used as input for the model, but in the second step the bridge will be made to subjective crowding data. Therefore, the link between objective and subjective crowding must first be determined. To this end two user studies will be conducted: one in the field and one in virtual reality (VR). For the first study, we will ask pedestrians how crowded they find the street where they are walking on two days in three different contexts: the main shopping street in Ghent (Langemunt), the main bar street in Ghent (Overpoort) and the main metro station in Antwerp (Groenplaats). For all three locations, objective tracking data will be collected by the radio frequency sensors of Crowdscan during the survey (for more information on the technology, see `https://www.crowdscan.be`) [8]. This way, both objective and subjective crowding data will be obtained for three different activities (shopping, nightlife and public transport) on two different days. The second user study will be conducted in VR, as influencing parameters (e.g., the weather) can be easier controlled with this medium than in a field study. Different scenarios and levels of crowding will be simulated for participants while they will be asked the same question: how crowded do you find this place? Based on the datasets, resulting from the two user experiments, and the space syntax measures of the environment the link between objective and subjective crowding will be determined, so that for each Telraam count we can calculate the corresponding general subjective crowdedness. In summary, the result of this step will be a graph with subjective crowdedness levels for every edge.

The solution

The resulting graph of step 1 and 2 can be used as input for a routing algorithm. As a proof of concept, the routing algorithm has already been developed and embedded in a webtool. The tool uses real-time Telraam pedestrian counts and simulates the interpolated data that will be generated by the model in the future. In the next section the code is explained in more detail.

3 Results

The code and link for the webtool can be found on `https://github.com/laudcock/Smart_crowd_management` and the general workflow is summarized in Figure 1.The webtool allows you to choose two points on the map in the city of Aalst in Belgium (the case study of the webtool) and shows two routes between these points: the shortest one and the least

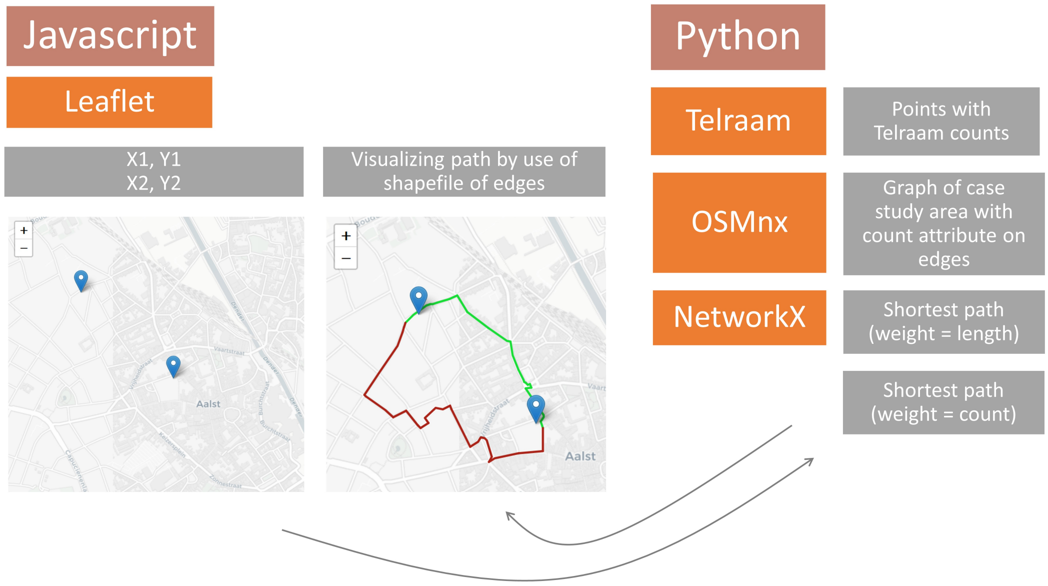

Figure 1 General workflow of the crowd routing webtool.

crowded one. The coordinates of origin and destination and the visualization of the routes is handled by a javascript code, for the calculation of the routes a python script is called. First, the real-time Telraam counts are loaded through an API. Next, a precalculated graph of the study area is loaded and the count attribute is added to the edges. The 25 edges that correspond with a Telraam sensor in Aalst case study get the real-time count, the edges without Telraam sensor get a random number between the mean − SD and mean + SD of the Telraam counts, to simulate the interpolation of crowd data in between sensors. It is important to note that each time a new route is requested, the edges get new (real-time or random simulated) count values. Finally, two shortest paths are calculated, one with the length attribute of the edges as weight and one with the count attribute.

4 Discussion and future research

As this research project is in an early phase, there is a substantial amount of future research to be done. It might seem extraordinary that we started developing the final phase of the project (i.e., “the solution”), but this had two reasons. First of all, it gives quite a good idea to stakeholders of the outcome. Second, by starting from “the end product” the prerequisites for the preceding steps of the workflow become clear. For example, the result of the modeling phase (i.e., “the data”) will have a graph-like structure as we decided to use a GCN. Although large parts of the methodology have been clarified by starting from the solution, there are still some questions that need answering. For example, it might be hard to find a good model that explains the trend in the data without overfitting. We aim to maximize the success rate by choosing a type of model that fits the data (GCN), but we might have to look into other deep learning algorithms as well. Additionally, it will be challenging to determine the link between the objective and subjective crowding as besides the environment numerous contextual and personal factors influence this link. Therefore we conduct two studies: a first explorative one in the field to identify the influencing parameters, and a second one in VR the determine the specifics of the relationship in a controlled environment. By anticipating possible fallbacks, we tried to maximize the success rate of our proposed method.

5 Conclusion

Pedestrian routing algorithms almost always use length or travel time as the weight of the path, while crowdedness can also be a decisive factor for the route choice. However, crowd-steered routing is not that straightforward because of a lack of crowd data. Crowd tracking sensors in smart cities might be an answer to this issue, but as it is infeasible to place sensors on every corner of every street, this tracking data remains sparse. Moreover, it is hard to make decisions based on this objective data because it does not necessarily reflect the feeling of crowdedness. This research project aims at resolving these issues, by using deep learning and space syntax data to interpolate pedestrian counts in between sensors and then linking these objective counts to the subjective perception of the crowd itself. The resulting subjective pedestrian counts of every street of a network can be used as weights for a crowd-steered routing algorithm. The coding and implementation of this last step has been presented in this paper, by use of partly simulated and partly real-time tracking data. The result is a webtool that generates both the shortest and least crowded path from a graph of the case study city. This outcome has been used to inform stakeholders and finetune the methodology of the remaining parts of this project.

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