Data Acquisition for Ad-Hoc Evacuation Simulations of Public Buildings

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ABSTRACT

Crowd simulation is suitable to evaluate evacuation strategies but its validity strongly depends on the quality of input data. The acquisition of adequate input data is particularly challenging when simulating the evacuation of public buildings such as universities. As they are publicly accessible, the exact number of persons on site is unknown. Yet, to investigate specific emergency situations by means of simulation, e.g. amok or fire, information is required about distribution and amount of people within the building at a specific point of time. Due to data privacy, public buildings do not implement access control. However, data artifacts are available in various information systems, e.g., wifi data, room administration. Our hypothesis is, that the acquisition and fusion of such data artifacts is sufficient to enable data-based ad-hoc simulation of evacuation scenarios as decision support for the operations management. To this end, we introduce a procedure for the situation-dependent collection fusion of simulation input data. Furthermore, a case study is provided to demonstrate the feasibility of the approach.

Keywords

Evacuation of Public Buildings, Data Fusion, Data Aggregation, Crowd Simulation, Social Simulation

INTRODUCTION

In case of emergency situations, the evacuation of a large crowd of people is a sophisticated task for fire and rescue services as different strategies must be applied depending on the specific situation. To support the operation of rescue forces, crowd simulation is an established tool for the ex-ante evaluation of strategies. It allows for the objective measurement and comparison of different scenarios. Thus, crowd simulation gains importance for the planning of major events such as festivals or sport events but also for the construction of stadiums, arenas, or travel centers.

Compared to this, the evacuation of public buildings such as town halls, hospitals, and universities is more challenging. These buildings are publicly accessible, they usually do not require physical access control, and the quantity as well as the distribution of visitors, patients, and employees within the building is dynamic as well as unknown. In practice, additional time is required by police, fire, and rescue services to get an overview of these locations. Information regarding the current room utilization must be provided by the management of the institution. Yet, as the quantity and distribution of persons in public buildings is not documented, people in charge at the institution cannot provide the required details such that information for rescue forces is insufficient. The resulting delay of rescue operations can have serious negative effects on the safety and well-being of people staying in the building.

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From the perspective of institution's management, the problem is missing information within the decision-making. A lot of data that can be used for gaining a first impression of the current situation is electronically available in different organizational units (e.g., room planning, human resources, or IT department). Yet, it remains unused as it cannot be directly accessed and utilized in this situation. Information is distributed over and stored in different information systems. This heterogeneity of data is as much a challenge as the variability of the interfaces of the systems. With respect to technical gaps or legal contexts, e.g. data privacy, these information systems cannot be accessed centrally.

To overcome this lack of information and to facilitate the planning and execution of rescue operations, this paper aims at identifying, acquiring, and aggregating data sources. Our hypothesis is, that the use of such data enables ad-hoc simulation for decision-support within emergency situation. Therefore, we introduce an innovative approach to estimate the amount of people within public buildings by acquiring and aggregating data from available information systems. We demonstrate the feasibility in context of a case study at Trier University.

The paper is structured as follows: first we present the foundations of crowd simulation and data fusion. Then data acquisition challenges of simulating evacuation scenarios in public buildings are outlined. Finally, a case study illustrates how these challenges can be addressed using the example of Trier University.

BACKGROUND

For the planning of buildings and events as well as for the evaluation of evacuation strategies, crowd simulation is increasingly used, e.g., for evacuation planning of football stadiums (Bateman and Majumdar 2018). Advantages over conventional methods such as investigating flows of individuals using real persons or expert assessments are, among other things, that no people are endangered and that simulations can be repeated as often as required under controlled conditions. This enables the testing of a large number of different scenarios while decreasing costs. Various elements such as global and local route planning, local collision avoidance, behavioral modeling such as integration of personalities, stress or emotions, and movement generation are implemented in crowd simulations (Narain et al. 2009). In many models, the relevance and characteristics of these components differ significantly. Two basic types of models can be distinguished: *Macroscopic* and *Microscopic Models*. Macroscopic approaches consider the crowd as a whole, which offers great computational advantages especially for large crowds. The crowd's behavior is not attributed to specific individuals with their possible and own unique behavior. However, this results in a lack of realism, as individual behavior exists in crowds. Microscopic models, e.g. agent-based social simulation models, aim at precisely reproducing each individual's behavior (Lorig and Timm 2014). Due to increasing computing capacities, these microscopic models are more and more applied and research activities in this field predominate. There is, for example, research on social cohesion (Adam et al. 2019), emotional contagion (Xu et al. 2018), or social capacity of the actor (Valette et al. 2018) in crowd simulations. These factors can influence evacuation behavior, e.g. social cohesion helps to evacuate individuals who would otherwise not be able to evacuate on their own. Another advantage of the increase in computing capacities is that simulation is increasingly used not only to validate security concepts but also as real-time simulation, e.g. Löhner et al. 2018. In this way, simulation can be used as decision support system. Especially in dynamic environments, such as public buildings, this can be useful as not all potential scenarios can be simulated due to their amount. Nevertheless, limitations due to computing capacity may still occur. To this end, so-called *Hybrid Models* are used that combine aspects of both model types such as a parallelization approach to calculate particularly large crowds (Yu et al. 2015). Further details on different models of crowd simulation can be found in the surveys of Pelechano et al. 2008, Zhan et al. 2008, Thalmann and Musse 2013, Ijaz et al. 2015, among others.

Due to the distinctive research in the field of crowd simulation, there is a high quality in behavior generation of actors. However, the models' validity as well as the results' transferability to reality strongly depend on the quality of input data, e.g., the number and the exact position of the persons on site. As a result of insufficient data validity, the operational validity is also low, i.e., the accuracy of the transfer of the results into the problem domain (Sargent 1991). For this reason, there are studies that deal with the use of data from the Global Positioning System (GPS) in real-time simulations (Wirz et al. 2012) and also consider the significance of errors (Zhang et al. 2019). One approach that has been neglected in research in the context of data collection for pedestrian flow simulations so far is the use of several data sources to compensate for missing data and errors. In sensor networks and distributed information systems, data fusion is a common instrument to compensate discrepancies between different sensors and to fill gaps in individual sensors by integrating and aggregating different data sources. The basic principle for this is that intersections exist in the informative value among the individual sensors, which are exploited by many methods and algorithms. For instance, similar approaches use methods such as Bayesian Inference, Dempster-Shafer Inference or Fuzzy Logic (Nakamura et al. 2007). Further methods are presented by Dong and Naumann 2009 as well as in the surveys of Smith and Singh 2006, El Faouzi et al. 2011 and Castanedo 2013. They can also be transferred from their application context to the given scenario. A similar and widespread approach is the visual evaluation of crowd video material by neural networks to derive behavioral rules of individuals for behavioral prediction in real time (Wei et al. 2018; Bera et al. 2015). These are also data fusion methods, which are not used to increase the validity of the data but to increase model validity.

Summarizing, there is increasing research on crowd simulations but the acquisition of input data is not considered thoroughly even though the simulations' validity depends on input data. Therefore, this paper addresses this research gap by proposing a process for the identification of appropriate heterogeneous data sources as well as fusion of data to simulate crowds in public buildings.

PROCESS OF SIMULATING EVACUATION SCENARIOS IN PUBLIC BUILDINGS

This section proposes a process for simulating evacuation scenarios in public buildings regarding heterogeneous data sources. The process consists of three sub-processes, which shown in Figure 1. It is related to the *JDL Data Fusion Model*, which consists of five levels: *Level 0 - Sub-Object Data Assessment, Level 1 - Object Assessment, Level 2 - Situation Assessment, Level 3 - Impact Assessment, Level 4 - Process Refinement* (Steinberg et al. 2008). In this section, challenges and methods related to identification of data sources, data fusion, and agent-based simulation are outlined in detail.

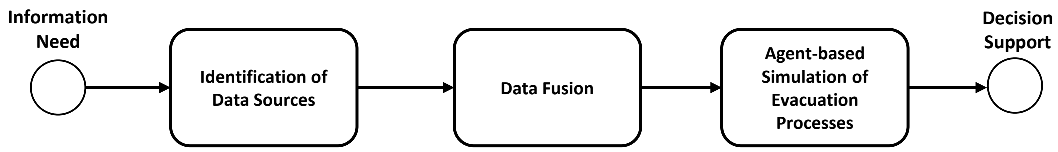

Figure 1. Identified Subprocesses for Using Heterogeneous Data Sources for the Simulation of Evacuation Scenarios

Identification of Data Sources

In a first step, which corresponds to Level 0 of the *JDL Data Fusion Model*, relevant data sources for the subsequent data fusion are identified. This subprocess is necessary because publicly accessible service institutions usually have numerous information systems which either do not provide any information gain or to which direct access is not permitted for legal reasons, e.g., accounting systems. Therefore, the targeted identification and selection of information sources ensure that a sufficient amount of information is recorded.

The process addresses two aspects: First, the emergency services' requirements on information and data quality are identified. Secondly, we outline how the consideration of the structure of the system landscape can positively influence the selection of data sources.

It must be ensured that data sources generate not only data but a **gain in information** which arises when a decision maker, e.g., the police, benefits from the knowledge of this data. However, this presupposes that the user has contextual information and that data is correct as well as not manipulated. In the context of special threat situations, the information requirement of the emergency forces contains two aspects: the evaluation of the threat situation on the one hand, as well as an estimation of when, where, and how many people with which characteristics are present in the area to be evacuated on the other hand (Vreugdenhil et al. 2015). If the number and location of people in the building is known, rescue and evacuation measures can be initiated more quickly and in a more targeted manner.

The second aspect tackles the influence of the **structure of the system landscape** on the selection of data sources. Most of the system landscapes in a building of public services can be characterized by a high degree of network connectivity and interdependencies. The result is that similar or even redundant data is recorded in different systems. For example, if a documentation system depends on the availability of an Internet connection, it could be sufficient and possibly more convenient to monitor Internet access alone, since both systems offer conclusions about the same information gain, i.e., the number of people on site.

However, aggregating more or less redundant data sources can also be advantageous as described in the following subsection. The decision to integrate a system with intersections of information into an already integrated system depends on the information gain generated by the integration of the new system. It is possible to end up with one system that contains a sufficient amount of relevant information but this probably depends on the homogeneity of people and the way they use information systems. In a public building, people are more likely to show heterogeneous usage patterns, suggesting that one data source is not sufficient. It is therefore necessary to aggregate data.

Data Fusion

After identifying relevant and useful data sources, data is usually not yet usable in the application context. Even if data is prepared for technical reasons, e.g., interface preparation, inconsistencies between different data sources can occur and gaps in the database are frequent. Therefore, data fusion aims at the homogenization of data by using several data sources, which probably increases the overall quality of data. This process corresponds to levels 1 to 3 of the *JDL Data Fusion Model*. Data fusion merges the data to avoid inconsistencies and gaps and make the data more accurate and useful. The fact that data from different systems originates from the system landscape of a service of general interest means that it may be available in different formats and that different strategies are pursued to collect measurement data, e.g., cyclic and acyclic measurement. Therefore, we need this process to ensure a basic applicability of the data.

Depending on the information and its source, different forms of information fusion can be classified, which also apply to data fusion: *Complementary, redundant, and cooperative fusion* (Durrant-Whyte 1988). Complementary fusion is characterized by the fact that a composite data image is generated from different information sources. Redundant fusion brings together data sources that basically describe the same information. However, since inconsistencies or gaps may exist in both data sources, the redundant fusion achieves a higher data quality. Cooperative fusion describes the process by which new information is generated by deduction during the merging of information of different data sources. The problem in practice is that the quality of data sources or information is often unknown. Particularly in redundant fusion, it is uncertain which data sources has a higher quality as well as information content and should therefore dominate during calculating the data. In the application context of threat situations in public buildings, it can be assumed that the information systems chosen as information sources diverge to a certain extent from actual reality. The uncertainty is therefore even greater than in a classical Wireless Sensor Network (WSN). For this reason, an empirical study is essential to value the quality of data and it is necessary to differentiate between types of data, the measurement method of the data, and the temporal as well as spatial dimension. This results in three classes of problems which have to be considered in the given application context:

1. the discrepancy between the measurement and planning data of the information systems and the real situation,
2. the discrepancy between the measurement time of the information system and the specific simulation time, as well as
3. the estimation of an exact geo-localization of individuals in the building.

The first problem is, that a certain discrepancy can be assumed between the measurement and planning data of the information systems and the real situation (1). For instance, during the work process in an administrative office for citizens, the system which measures the number of employees logged on to an information system may differ from the real number of people on site, as not all employees necessarily have to use this system for their work or several employees have different logins to this system. Furthermore, visitors can be counted in this public office by measuring the visit dates in the calendars of the employees. However, the number of visitors on site can deviate from this as on the one hand visitors may skip an appointment and on the other hand they may appear without an appointment. Simultaneously, there is an uncertainty whether the information of different data sources is complementary or redundant. Possible double counts can create a discrepancy between measurements and reality.

The second challenge is that there may be a discrepancy between the measurement time of the information system and the specific simulation time (2). This challenge can be divided into three aspects: First of all, with period-related data, a conclusion must be drawn about the time of simulation. For example, visitors to the administrative office for citizens can be late for an appointment. Secondly, in rare cases, measurements are collected continuously. Mainly, these are discrete measurements that are carried out in a certain time interval. In the above example of the registrations of the employees of the public office at an information system, if the data are collected in a cycle of 15 minutes, an interpolation must be carried out to determine the data of a simulation time, which lays between the collection of times. Finally, a measured time or information at a time (planning data) can have an effect on pre- or post-states. If a visitor of the public office has an appointment with an employee, he or she may be in the building long before the appointment, e.g., to be on time, or still be in the building after the appointment, e.g., to complete documents.

The third class of problems is that with many systems, especially in combination with the second category, an exact geo-localization cannot be carried out (3). If an employee of the administrative office logs in at a wifi access point, this person can be in the entire transmission area of the access point. During appointments, employees and visitors can be located anywhere in the specified room. This may be irrelevant for small rooms with a few people present but in large rooms with a large number of people present this can seriously effect an evacuation event. However, observations and other knowledge can be used, e.g., queues or explicit waiting and sitting areas where people are more likely to stay.

We believe that all three problem classes can be addressed by methods of data fusion. Established methods like heuristics and Machine Learning mentioned in Section 2 will be used to remove gaps and inconsistencies. However, both aspects require a reliable evidence about real data, which is why an empirical data collection is essential to determine the error probabilities and to adapt the measured data to the real data. The overall aim of the data fusion's synergistic multiple use of different information sources is to produce more accurate and consistent data than could be produced by any single data source alone. This has to base on the measurement and planning data.

Agent-based Simulation of Evacuation Processes

Once data has been aggregated and adapted to the state of reality, an agent-based simulation of an evacuation process can be carried out, which corresponds to level 4 of the *JDL Data Fusion Model*. This sub-process is recommended because it allows us to react objectively to the numerous possible scenarios that can occur in buildings with high dynamics. It assumes that a model of the public building to be investigated exists in crowd simulation software. Usually respective simulators allow for the execution of a number of simulation experiments with systematic parameter combinations. By varying a large number of parameters, the best evacuation strategy can be determined without performing experiments within the real system.

Summarizing, the process of simulating evacuation scenarios in public building regarding heterogeneous data sources consist of three sub-processes: During identification of data sources, it must be ensured that there is a gain in information by integrating systems, whereby the structure of the system landscape can be regarded. In the sub-process of data fusion there are three main problem classes which have to be handled to generate consistent and accurate data. By using this data, the the validity of the crowd simulation can be increased. The applicability of the proposed methodology is demonstrated in the following case study.

CASE STUDY

On 24th November 2017, a student of Trier University threatened to use armed violence on the campus. Although police was able to identify and arrest the student at an early stage, they carried out an extensive intervention at the university and cordoned off the campus. At that time it was not certain whether possible accomplices existed or whether hazardous material or weapons were already on the campus. The campus of Trier University is characterized by its wide accessibility, since there are entrances in all directions. This implies that situation assessments take a great amount of time and that decision makers in special situations can only plan and carry out a necessary evacuation after a delay. Ultimately, the specific threat was not confirmed at Trier University but the incident has revealed exactly such delays. Therefore, there is still a lot of potential in the aggregation of information, especially since the information was actually available in various systems. The following case study is carried out using the example of Trier University respecting the specific described challenges. Its purpose is to show the applicability of our process using heterogeneous data sources for the simulation of evacuation scenarios in public buildings. Our study is initially limited to one building, which, however, has a particularly high dynamic in the number of persons on site. It contains the largest lecture hall of the university, the Auditorium Maximum, with over 500 seats, and the main canteen on campus (see Figure 2). The building has entrances and exits in all directions and the canteen consists of three open floors.

Figure 2. Site plan Auditorium Maximum and canteen (Floor 1)

Data Sources

In a first step, relevant data sources are identified to satisfy the need for information regarding the location of persons at specific points in time. We identify three useful data sources: the integrated campus management system of Trier University (**PORTA**), the **wifi access points**, and the **canteen cash system**.

PORTA provides information on events at the university's facilities. Each room has a capacity of seats and a list of events, e.g. lectures, taking place in the room. Participant lists exist for the events, since online registration is mandatory for participants to take part in a lecture or event. By using the PORTA system, conclusions can be drawn about the future planned occupancy of the Auditorium Maximum. Deviations from this plan can occur, for example, due to the short-term cancellation of an event or the absence of registered attendees.

Another source of information is the number of registered devices that are connected to a **wifi access point**. This is logged by the university's IT department. Each student and employee receives an ID which they can use to access the university-wide wifi. The SSID of all access points is identical, which guarantees a login at the best transmitting access point (probably the closest one). There are currently four access points in the selected building: two in the Auditorium Maximum (AP03 + AP04), one in the foyer area of the building (AP02), and one in the canteen (AP01). A further access point in the Mensa will be installed soon. Figure 3 shows an example of a day with wifi use in the corresponding building. The increasing number of registered devices at the access point at lunchtime (middle of the diagram) is obvious. It is characteristic of the two access points in the Audimax that the number of registered devices is relatively stable over the period of the lectures. The rapid rises and falls in the number of registered devices correspond to the times when the lectures begin and end. Between these events there are peaks of the access point in the foyer area, where most students enter and leave the building for visiting lectures.

Since the canteen also sells food to people who do not belong to the university, there may also be people on site who have not yet been registered by the two sources of information mentioned above. For this reason, the **canteen cash system**, which logs every meal sold, is also a relevant source of information to be used in the case study. A customer group, e.g. students or guests, is logged for each purchased meal, which is helpful for the subsequent data fusion process.

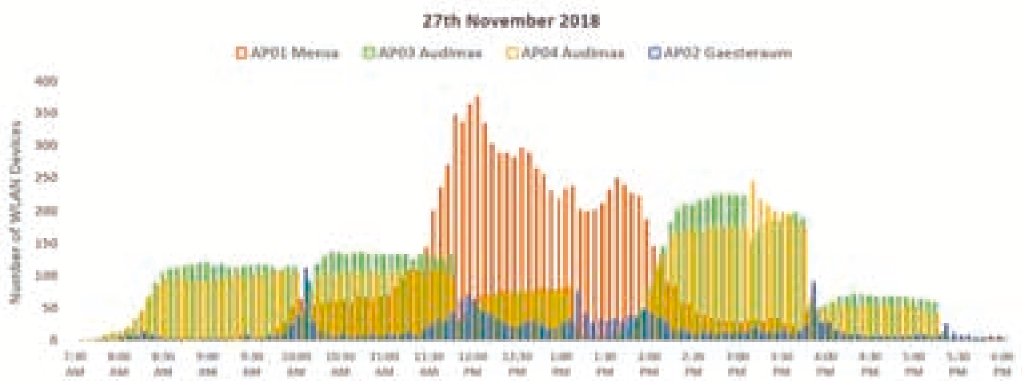

Figure 3. Number of devices logged at wifi access points

Data Fusion

Classical applications of the data fusion process can often determine the actual form of the information. Redundant fusion generates a sufficiently accurate measure that is often sufficient in practice. The given application case differs from these classical redundant fusion systems in that highly heterogeneous data sources are available and the problem classes described above occur simultaneously (cf. Sec. 3.2):

The first problem is that there may be a certain discrepancy between the measured as well as the planning data and reality (1). For example, if a system measures the number of registered devices at a wifi access point, this does not necessarily correspond to the actual number of people in the area of the access point. On the one hand, there may be people who are not logged in with a wifi-enabled device. On the other hand, persons may own more than one mobile device with which they are logged in. Furthermore, in the case of a system that documents student registrations for courses the number of students on site may differ significantly from the number of registered students. The question arises what is the real situation, since the examples show that both systematic overfitting and systematic underfitting are possible. Simultaneously, it is difficult to determine whether data is more redundant or complementary. For instance, double counts by logon to wifi and purchase of a meal are possible. Due to the heterogeneity of the data and the lack of knowledge of the probability of errors in the data, it is not possible to approximate the most probable real state. For this reason, empirical surveys were carried out at various times during the semester in which the number of persons on site and the number of wifi devices used per person were counted. This data serves as fixed points (training data) to implement a valid approximation, e.g. by using neural networks to predict the real situation. Currently, we cannot assess the success of overcoming this problem. Nevertheless, both redundancy and complementarity allow us to limit the possible variable space by a lower bound (full redundancy) and an upper bound (full complementarity), which should be very helpful in the subsequent simulation experiments.

The second challenge is that there may be a discrepancy between the measurement time and the specific simulation time (2). As explained in Section 3, this challenge has three aspects, which are explained below: First, the PORTA data source is a period-related data source. Conclusion about a specific point in time can be subject to certain patterns. For example, it is possible that students regularly arrive too late for an event. These patterns can be detected using wifi data. Furthermore, the wifi data source represents an information source at a time measured in a cycle of 5 minutes. If the time to be simulated is not exactly such a measurement time, an approximation must be made, which can be done by interpolating the two adjacent measurement times. Finally, the information source of the food sold in the canteen has a time reference which, however, has a high impact on subsequent states. Thus, it can be assumed that a person who buys a meal in the canteen is highly likely to remain in the canteen for a specific period of time. The wifi data again helps to draw a conclusion from the time a meal was bought to the length of stay in the canteen.

The third problem is how to deduce the exact geolocation from the data collected (3). When logging on to the wifi, the person with the mobile device can be in the entire coverage area of the network. In room reservation plans, the registered number of persons can also be in the entire room. This problem is particularly serious because small deviations from reality can have fatal consequences in the evacuation process. We meet this challenge by dividing the area inside the building into zones. Using the wifi data, the PORTA data and an empirical survey of agglomerations, we suggest that specific zones are likely to be occupied.

At the end of the data fusion process, the fused and approximated data is provided in an SQL database to be accessible to decision makers from multiple systems, such as a dashboard. The completely fused data as well as the adjusted data of different data sources can be retrieved in separate tables. This ensures flexibility in the use of the data. Figure 4 summarizes the data fusion process of the three chosen data sources considering their specific interdependencies.

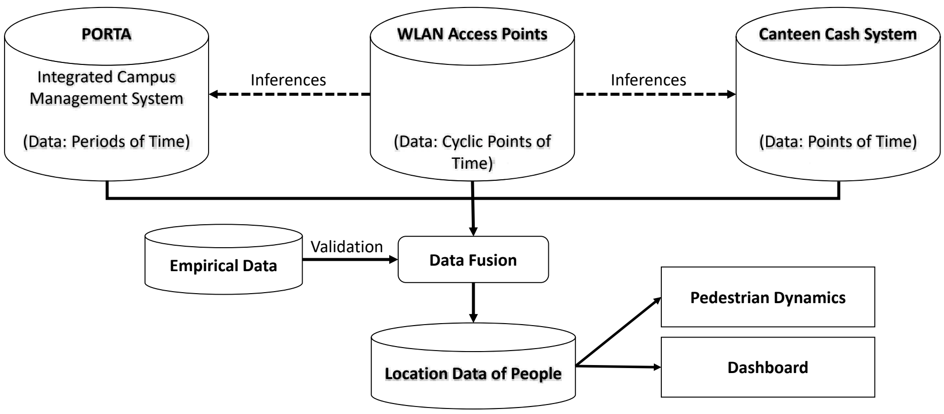

Figure 4. Used data sources for generating inferences

Evacuation Processes at Trier University

Even if a dashboard should be very useful for decision makers in threat situations to get aware of the current situation, the main goal of data fusion of heterogeneous data sources at Trier University is conducting evacuation simulation studies with focus on the flow of involved persons. The model of the relevant parts of the campus was implemented using the *Pedestrian Dynamics* simulator by *INCONTROL*. Figure 5 shows parts of the models. The challenge so far has been where valid data comes from as simulation input. We are addressing this challenge by processing the data in the data fusion process. In this way, we can achieve situation-dependent decision support concerning evacuation strategies.

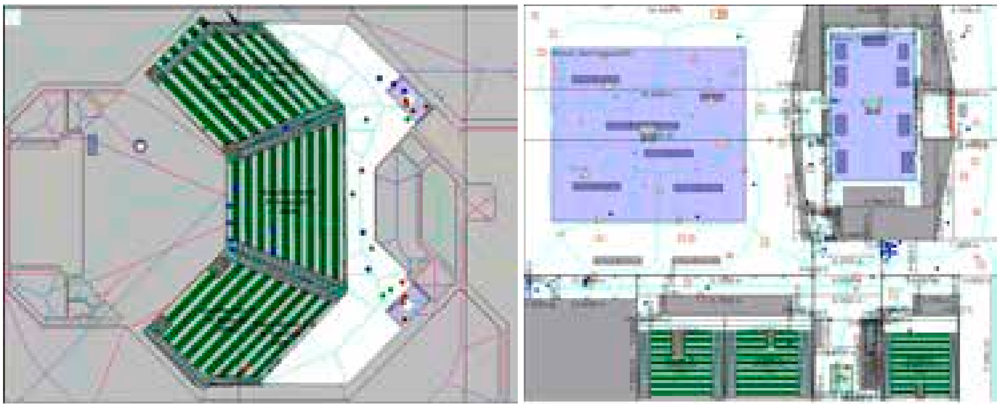

Figure 5. Pedestrian Dynamics models of Auditorium Maximum (left) and lecture halls (right) at Trier University

CONCLUSION AND FUTURE WORK

A lot of data required for gaining a first impression of the current situation in special threat situations is electronically available in different information system but remains unconsidered as it cannot be directly accessed and utilized. This paper proposes a process of the identification of appropriate heterogeneous data sources as well as the aggregation of data by means of data fusion. This process aims at supporting decision-making in emergency situations by using ad-hoc simulation of evacuation strategies. As a key aspect, we focus on increasing the quality of parametrization as well as the level of validity.

To evaluate this process a case study at Trier University is carried out. We identified and selected relevant data sources. Additionally, we built a simulation model of the campus in the software *Pedestrian Dynamics* for investigating evacuation scenarios. Currently, the necessary interfaces are being implemented to integrate the distributed available data into our workflow. In future work, we will elaborate on specific algorithmic approaches for the estimation of amount and distribution of individuals within public buildings. We will draw samples by manual people counting in our case study. Additionally, the agent representation should be extended by emotional and cognitive behavior such that realistic crowd behavior emerges.

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