Face-validation of a route-choice module in a crowd simulator for confined indoor spaces in context of the COVID-19 pandemic

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Abstract. The COVID-19 pandemic has drastically changed the life of most people in the world. Governments have come up with various restrictions and measures to contain virus spreading in public (confined) indoor spaces. Simulation tools can reproduce people behaviour and assess how people react on different intervention measures, and are of high value for the related stakeholders. This research extends an existing microscopic pedestrian simulation model for this purpose, where three behavioural decision (strategic, tactical, and operational) levels are considered and adapted to capture crowd movement dynamics in a new context, i.e., indoor locomotion in tight spaces. To validate the newly developed modules, empirical data is collected in real life. This paper presents the effort of collecting empirical data that describe pedestrian route choice behaviour in one of the typical indoor spaces - restaurants. The face-validation for the corresponding route choice module has been conducted. Our study reveals influential factors (i.e., size, location) and behavioural insights regarding tactical decisions in the chosen confined space.

Keywords: Crowd simulation, Route choice, Confined indoor spaces, COVID pandemic, Face-validation.

1. Introduction

During the COVID-19 pandemic, life of most people drastically changed. Worldwide, governments had to enact restrictions to contain the virus from spreading. The virus is most infectious in the indoor environments, such as restaurants, cafés, theaters, cinemas, sport centers, schools, supermarkets, as people are gathered in confined spaces and have a high possibility of close contact with each other. Next to vaccination, a second group of measures, collectively known as non-pharmaceutical interventions (NPIs), are the primary tools for governments worldwide to reduce virus spread in indoor environments (confined spaces). Examples in this category include, keeping personal hygiene (to wash your hands thoroughly and regularly), regular ventilation (to ensure a good flow of fresh air indoors), physical distancing regulations (to keep 1.5m from others), and facemask wearing (in places where it is required by law) [1]. These restrictions and measures have led to a change in people's daily life.

Under this context, it is of great importance to understand the effectiveness of these measures and to what extent the public has changed their behaviour, and thus to balance the impact of the measures with the actual infection reduction risk. Microscopic pedestrian simulation models can serve this purpose. The key idea is to emulate pedestrian dynamics in indoor confined spaces and translate their movement into infection risk given the imposed COVID measures. Delft University of Technology (pedestrian modelling) and Wageningen University & Research (epidemiology) have jointly developed the SamenSlimOpen application (SSOapp) to assess the impact of NPI's on the virus transmission risk. The SSOapp integrates the pedestrian movement modelling with innovative virus spreading models [2]. The strength of this application is that it can explicitly model virus spread as a result of operational movement dynamics and is specifically developed for indoor spaces. This allows for a more specific and comprehensive analyses of virus transmission risks for indoor spaces.

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Several levels of pedestrian behaviour need to be taken into consideration to model the pedestrian movement dynamics in indoor spaces. Commonly, these are classified according to the strategic, tactical and operational levels [3]. The most important processes per level are: activity choice on the strategic level, activity scheduling and route choice on the tactical level, and short-term movement dynamics on the operational level. Within the SSOapp, an existing crowd simulator NOMAD [4] is adopted as the base microscopic pedestrian behaviour. This model has been developed to reproduce pedestrian behaviour in normal situations. Under the new context with COVID-19 measures, this model has been extended to describe the behaviour of people at both strategic level and tactical level for indoor confined spaces. Extension of the higher-level behaviours is required because route choice plays a very dominant role in the pedestrian movements in confined indoor spaces. The new modules for activity choice and activity scheduling have been systematically tested and validated in [5]. However, the new route choice extension has not been validated against empirical evidence. Also in literature, there is no existing work about empirical data collection w.r.t. route choice in confined indoor space or face-validation of pedestrian route choice models under this context.

This paper aims to bridge this gap by collecting such a dataset and to perform a validation analysis on the tactical behaviour module of the simulation model. Various influential factors on pedestrian route choice in confined space will be identified and the corresponding sensitivity analysis will be conducted to determine the extent of these factors on influencing routing decisions. The actual route choices collected from a Dutch restaurant will be used in the validation case studies.

The rest of paper will be organized as follows: Section 2 provides an overview of the related works on this topic. Next, a short recap on the route choice model in NOMAD is given in Section 3. Afterwards, the methodology and the procedure of the validation study on the tactical level are presented in Section 4, and it is followed by the validation case study using empirical data in Section 5. Lastly, the main conclusions are discussed in Section 6.

2. Related work

This work focuses on the second level of pedestrian behavioural choice. At the tactical level, existing routing models provide static map navigation for decision-making in the operational level. The values in the static floor filed (cost navigation map) are calculated based on the environmental information (such as walls, obstacles, …), based on for instance the shortest path navigation algorithms: wall follower, depth first search algorithm, flood fill algorithm [6]. To validate the plausibility of the chosen algorithm, empirical data should be obtained.

Field observations are the traditional method to study pedestrian route choice behaviour and to collect empirical data in real life [7]. The idea is to collect information about pedestrians who move and make choices in realistic and natural environments (including both normal and emergency situations). The data collection approaches range from manual counting/recording, to using digital recording devices (e.g., cameras) or more sophisticated monitoring systems (e.g., GPS, Wi-Fi, Bluetooth) [8]. Given its unobtrusive nature, this method aims to minimize the influence of the observers and/or observation techniques on pedestrians who are being observed. For instance, Proulx et al. [9], Shields & Boyce [10], Kobes et al. [11] and Galea et al. [12] used video recordings to study pedestrian route/exit choice behaviour in apartment buildings, retail stores, hotel rooms, and a theatre, respectively. More recently, Imanishi and Sano [13] and Rahouti et al. [14] analysed evacuees' movements during evacuation drills in a theatre and a hospital respectively, featuring pedestrian route and exit choice. However, to the authors' best knowledge, there is no empirical field observation taken place in confined indoor spaces, like particular, office rooms, cafés or restaurants. The activity-scheduling and route choice behaviour in such an environment is still unclear.

3. A short recap on the route choice module of NOMAD

NOMAD is a microscopic simulation model that simulates the operational movement dynamics of individuals. The NOMAD route choice module developed by Hoogendoorn and Bovy (2004) is utility-based. It makes use of the minimum walking cost principle. In essence, individuals balance their desire to move towards their destination with other needs, as the result of an optimization process on, for instance, travel time, physical effort, closeness to attractive sights/places of interests. In this implementation of NOMAD, only the need to avoid static obstacles (e.g., tables, bar areas) in their surroundings is accounted for. This module is built on top of the shortest path toward destinations.

Using a floor field approach for both global and local route choice, the walking costs are computed for the complete walkable area of the pedestrian infrastructure. Each destination has its own floor field. When a pedestrian is traversing the walkable space to reach his/her destination, it requests a desired direction from the floor field accompanying this destination at every time step. A cost matrix is created whereby the desired direction of a cell is determined by the gradient between the cost of itself and the cost of its neighbouring cells.

In particular, a grid of rectangular cells (0.1x0.1m) is adopted, each of which contains a cost value. Based on the static cost map, the desired direction of an individual in the center point of each cell can be determined using the steepest descent method. Here, individuals are walking orthogonal to the equi-cost (contour) lines. A continuous representation of the desired direction can accordingly be calculated on-the-fly by means of linear interpolation between the current location of an individual and the four nearest locations for which the desired direction was already computed. See Figure 1 for an illustration of three trajectories that could be the result of this routing model.

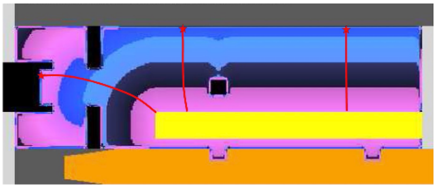


Figure 1: Static floor field in NOMAD with three resulting trajectories (Floor field image from Campanella et al. (2009) [15]). The color of the contour map denotes the same static floor field (cost) value, where the star is the origin, and the yellow bar is the destination.

The two types of obstacles identified in NOMAD are ‘real’ obstacles and ‘virtual’ obstacles, respectively. The first type refers to the infrastructures that do not allow pedestrians to walk over them. In the context of confined indoor spaces (such as the case in restaurants), these obstacles include walls, tables, bar areas, cashier counters, etc. For walls, pedestrians cannot ‘see’ over them. For the rest, pedestrians can ‘see’ through them (and thus pedestrians might potentially interact with others at the operational level – implemented at the operational level). As for the ‘virtual’ obstacles that only in certain circumstances are treated as obstacles, such as chairs (in restaurants), pedestrians can either stand at their location or need to move around them. This obstacle type is an obstacle for all pedestrians other than the one who considers it as its activity destination. So the word ‘virtual’ refers to the fact that there is no physical (route) blocking, and that the obstacle can also act as a destination. A flooding (flood-fill) algorithm is applied, which means to flood the cost value at the current cell to its surrounding cells in the cost matrix. This is an iterative process where after the initial flooding an iterative algorithm iterates over the cost matrix until it converges.

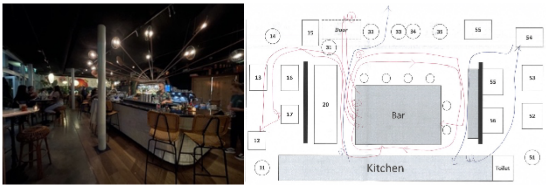
4. Validation analysis and method

Model validation is the process of determining whether the model accurately represents the behavior of the targeted system/network [16]. Model validity should be evaluated both conceptually (i.e., by determining whether the theory and assumptions underlying the model are justifiable) and operationally (i.e., by determining if model output agrees with observed data). Conceptual validation is always feasible. For the latter, simulation models can be validated by comparing model output to independent empirical (experimental or field) data sets that align with the simulated scenario. This process is subjective to the availability and the quality of the data (representativeness of the targeted system, suitability of the data for validation). In this work, operational face-validation is conducted for the route choice module in NOMAD to see how realistic the simulated environment appears to the observation. Please note that we will not look into the predictive validity of the model as required for practical applications [17]. Moreover, we take a restaurant case as an example of confined indoor spaces. The empirical dataset was collected at a Dutch restaurant and featuring the local route choice (routing) of pedestrians. The layout of this restaurant is shown in Figure 2. The general idea is to compare the generated local route choice (routes) from the simulation with the actual routes taken by the restaurant staff members and customers observed in reality.

Figure 2: Layout (floor plan) of the observed restaurant featuring realistic dimensions.

4.1 Empirical data collection and analysis methodology

Due to privacy constraints, we conducted a non-invasive empirical observation – covert observation - in the chosen restaurant (see Figure 3.a). As for the people being observed, no personal identifiable information was collected. No video recording was used since the observations were kept anonymous and unobtrusive. The observers manually recorded the movement behaviour (i.e., their activity scheduling and routing) of customers and staff members in the restaurant using pre-printed restaurant maps (a reporting example is shown in Figure 3.b).



(a) (b)

Figure 3: (a). snapshot of the restaurant area; (b). example of manual recording - route tracking using conceptual map (trajectories of two staff members for a short period – NB. The numbers in the map are irrelevant)

After analyzing the empirical routing samples, it is obvious that the route choice sets of staff members are not always the shortest paths between two locations. The distance factor (regarding travel time/cost) plays a major role, but factors like context information along the routes (e.g., combined activities: order taken, serving, checking-out, table-cleaning, feedback acquirement) might also influence the route choice decision. This should additionally be encapsulated by the activity scheduler at a higher level. This observation shows a clear distinction of this type of indoor space from other walking facilities (such as train/metro station areas) where the shortest paths generally prevail. Particularly, in this restaurant layout, at least two alternative routes were identified via observations for each destination point (e.g., tables to be served) – and were actually used by the serving staff.

4.2 Sensitivity analysis

To conduct sensitivity analyses is another crucial component of the model validation process. The objective of conducting a sensitivity analysis is to determine the relative influence of various influential factors (parameters, initial/boundary conditions, and alternative assumptions) on model output, to understand how each factor influences the model behaviour. The process is iterative, providing feedback that can improve the model [16]. As for the route choice module in the pedestrian simulation model, three influential factors can be identified for scenarios in the context of indoor environment: namely, a). parameters in the formulas to describe route choice behaviour (e.g., cell size, weights assigned to cost values of neighboring cells); b). the locations of infrastructures (e.g., tables/chairs, bars, cashier desks, base areas); and c). the size of infrastructures. In this study, a sensitivity study on the latter two factors is performed. That is, the default route choice parameters of NOMAD are applied in the analysis. Three types of testing scenarios are defined: Base scenario – Scenario 1 as the reference case; Scenarios of *size* – Scenario 2: slight changes in table size, and Scenario 3: slight changes in the bar size; Scenarios of *location* – Scenario 4: slight changes in the locations of obstacles, and Scenario 5: change in the location of the staff base area. The overview of the testing scenarios is provided in Table 1.

Table 1: Overview of validation scenarios

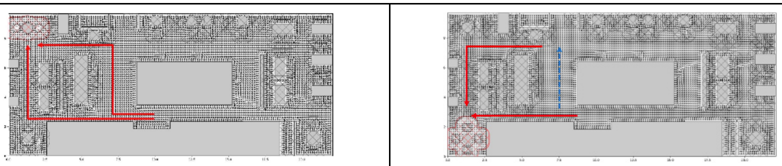
No.	Scenario category	Influential factor	Description	Comparison aspect of interests
1	Base scneario (Real dimensions)	N.A	Identify key routes Routes towards 4 corners	Route towars Corners B, C and D
2	Size	Table size	Enlarge table size (1 m for round tables; 1.5m in length for rectangulars)	
3	Size	Bar size	Enlarge the dimension of the bar	Particularly the route behind the bar
4	Location	Locations of obstacles	Obstacles: left, right, lower corridor.	Routes towards Corner D (Table 8+17 - blocked)
5	Staff location	Location of base area (source)	Vary the location of the base area for staff	Routes towards Corner C (Table 16)

In each testing scenario, four key routes towards the four corners (namely left-upper corner (A), left-lower corner (B), right-upper corner (C), right-lower corner (D), regarding the tables at these locations) are chosen for comparisons. The assessment criterion is to what extent there is difference between generated routes towards predefined destinations in the local route choice maps and the observed routing plan taken in reality. The comparison is based on the visual inspection between the identified routes (based on gradient directions) and the trajectories recorded during the experiment.

5. Validation results and discussion

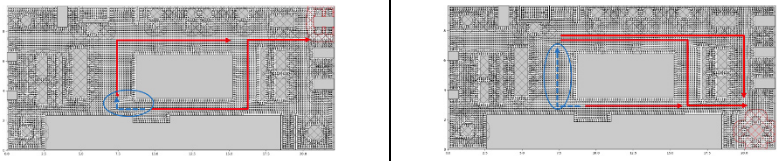
The comparison shows, the route choice module can adequately generate local route choice sets (the least-cost/shortest paths) towards destinations in the concerned restaurant. Figure 4 illustrates local route choice maps for 4 destinations at the four corners of the restaurant. As shown, no gradient directions (or cost values) are assigned to the real obstacles (tables, bar), only to the virtual ones (chairs). This means pedestrians can still move through/around them.

In data collection, we observed two or three alternative routes towards these four specific destinations/tables. This is the case in simulation, for example, the routes towards corner A - Figure 5.a. However, for some routes (e.g., towards the restaurant corners B, C, and D – see Figure 5.b, c, d), the NOMAD route choice module was only able to generate the fastest route towards the selected destination. From the static floor field map, it cannot identify alternative routes towards corners C and D, via the upper side of the bar area, as highlighted by the two circles (instead the gradient directions towards the opposite directions). Similarly, for the route to corner B, there is no connection from the base area to upper less-directional route (see the dashed line) in the local route choice map. This indicates that a modelling enhancement to update the gradient directions of the lattice cells so as to connect the origins with the observed alternative routes is needed. The disparity between the model outcomes and observations also demonstrates that distance/cost factor is not the only factor determining route choice decision in reality.



(a). Sce. 1 – Corner A

(b). Sce. 1 – Corner B



(c). Sce. 1 – Corner C

(d). Sce. 1 – Corner D

Figure 4: Route choice maps of restaurant simulation (scenario 1) – Small black arrows indicate the gradient directions of the static floor fields in the walking area. Red solid arrow line indicates the identified route in simulation. Blue dashed arrow line indicates the route which could not be generated by the simulation (and were seen in reality).

Scenarios 2 and 3 investigate the impact of facility size on creating static floor fields. In most cases in Scenario 2, the generated floor-field maps of various destinations are similar to Scenario 1 regardless of choice of the table size. This indicates that the influence of table size within limiting magnitude on generating route choice sets is marginal (unless oversized tables lead to the blockage of complete corridors). In Scenario 3, the size of the bar area increased. The direct outcome is the formation of a narrow corridor behind the bar area. It is noticed that even with a narrow lane, the route (gradient directions) behind the bar area is clearly identified (and used).

In the scenario of including obstacles (Scenario 4), the module was not able to generate some of the reported walking routes in some specific situations. For instance, the route towards the destination at the lower-right corner is blocked by the obstacle placed in the corridor behind the bar area. The routes towards other destinations remain reasonable and walkable under the same conditions. This indicates that the exact definition of the location of destinations plays a major role on determining route choice sets.

In scenario 5, if the base area is moved to the right lower corner towards the bar area, the model is able to identify two alternative routes towards the Corners C (See Figure 5) and D, as observed in reality. This is clearly different from the cases observed in Figure 4 (c).

Figure 5: Route choice maps of restaurant simulation (Scenario 5 – Corner C), where the destination is identified by the bold hash and the origin by the circle.

Discussion

The case studies show the route-choice module with the context extension in confined indoor spaces is able to provide route sets that are similar to the routes as observed in reality. Sensitivity analysis demonstrates that the size of infrastructure poses a marginal influence on the generated route sets. The locations of infrastructure (origins, destinations, and obstacles) can influence the creation of local route choice sets. More importantly, it is noticeable that the distance/cost factor is not the only factor impacting route choice behaviour in confined spaces. The underlying route choice module built upon the flooding algorithm for creating the shortest path should also be extended to consider other factors, like context information along the routes. This extension can be included in two ways: a. to improve the existing local route choice module by incorporating the concerned factors; b. context factors that influence routing can be encapsulated at a higher level by e.g., the activity scheduler [5].

6. Conclusions

This paper presents a pioneering study on the validation analysis on microscopic route choice module in confined indoor spaces during a pandemic. It showcases for the first time an empirical data collection featuring route choice behaviour in a restaurant environment. The face-validation of the route-choice module of NOMAD has been performed using the empirical data collected from a Dutch restaurant. The insights gained by a sensitivity analysis in this realistic setup pertain to that the size of infrastructure poses a marginal influence on the generated route sets, and the locations of infrastructure (origins, destinations, and obstacles) can influence the creation of local route choice sets significantly.

We conclude that the existing route choice module acts in a plausible manner, also if we qualitatively compare the model outcomes to the empirical observed routes. While we do not aim to show absolute validity in a quantitative way (by using pedestrian trajectories and measured shares of alternative routes), we see that the qualitative routing decision in the existing simulator is plausible, with identifying the shortest path alternatives and possible extension by connecting with alternative routes, as observed in reality. Although this validation study was performed in a restaurant case, the model can be generalized and applied to other confined spaces, like office rooms, theaters, cinemas, cruise ships. For this purpose, collecting real data in such specific contexts for refined calibration and validation (predictive validity) of the model is essential to allow for practical use of these models for engineering applications.

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