Oppilatio - The Forecast of Crowd Congestions on Street Networks During Public Events

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Abstract At many events, the arrival of visitors depends mainly on public transport services. On such occasions, people walk from the station or bus stop to the event site. This can lead to crowd congestions since the visitors arrive in large numbers according to the schedules of the public transport services. Unfortunately, organizers of such events have very limited information about the arrival behavior of their visitors. Normaly, they only know the number of incoming visitors on the event site and the timetable of the public transport service. It is difficult to perform crowd management successfully with so little data. Oppilatio uses this limited data to determine the most likely routing paths of incoming visitors. This allows an early recognition of potential crowd congestions on the access routes and therefore the initiation of countermeasures.

1 Motivation

Size and significance of public events have increased in the last decades [1]. Therefore, research about crowd control has become more and more important. A vital aspect of crowd control is pedestrian dynamic simulations, which serves to predict the visitors' movement behavior and can be distinguished into three different model types. Macroscopic approaches describe pedestrians as flowing densities [5]

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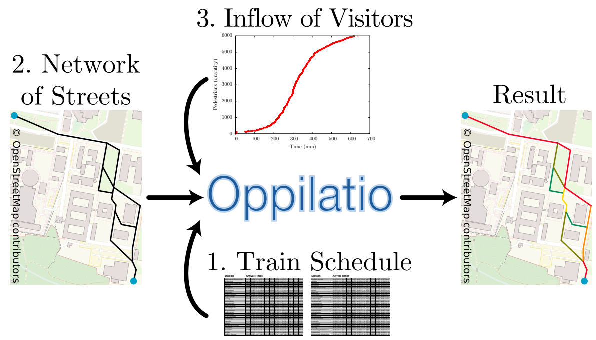

Fig. 1 Based on data commonly accessible for event organizers, it is possible for Oppilatio to calculate the routing behavior of incoming visitors to an event site.

and reduce the scenario to a simple network graph. Mesoscopic approaches describe pedestrians as discrete objects that move on a cellular grid [4]. Another model type are microscopic models which simulate individual and discrete pedestrians on a continuous scenario [8]. Each model type has different attributes according to computational effort and spatial resolution [3]. Additionally, two types of hybrid modeling exist. The first type combines pedestrian models of different spatial resolutions [3]. The second type couples pedestrian dynamic simulations with simulation models from other research fields [2]. A proper use of simulations requires valid data about all boundary conditions of the scenario (e.g. number of visitors) and background knowledge about pedestrian dynamics (e.g. for the specification of input parameters).

Unfortunately, most organizers of public events are lacking such background knowledge. Furthermore, the acquisition of valid data according to boundary conditions is difficult to achieve, especially if an event is carried out for the first time. However, knowledge about the visitors' walking behavior is essential for organizers to successfully perform crowd control. Many visitors arrive with public transport services like subways or shuttle buses. These transport services carry the visitors to a subway station or bus stop, from which they walk to the event site. Since many events take place in an urban environment [1], the access routes are often narrow and insufficient for large crowds. It is important to forecast possible congestions and therefore to prevent hazardously high densities. Broad video observation of all access routes would be useful, but this is expensive and difficult to execute due to government regulations according to data privacy. In order to fill this gap, we developed the Oppilatio method to estimate route choices based only on public transport schedules and data of arriving visitors. Oppilatio is a real time data analysis approach which helps organizers to survey incoming pedestrian streams. Contrary to simulations, no background knowledge about pedestrian dynamics is necessary and the needed input data can be easily collected (see Figure 1):

1. Arrival times of public transport services at the station
2. Accessible routes from station to the event site
3. Time-stamped counting of incoming visitors at the event site

Local transport operators provide timetables of their public transport services. Possible pathways from the station to the event site can be determined by openly-licensed geodatabases. The accessible routes are entered as a network of edges and nodes into Oppilatio: streets are represented by edges and intersections are represented by nodes. Time-stamped counting of incoming visitors can be acquired easily by event organizers (e.g. time-stamped entrance tickets). Solely based on this information, Oppilatio can calculate the most likely routes for each incoming visitor p_i, using algorithms described in sections 2 and 3.

2 Allocation of arrival times at the station

We use the arrival time t_i at the event site to determine the time a visitor p_i started at the public transport station. For this calculation, we need the pedestrian's velocity, a parameter which is unknown. Therefore, we have to estimate this value based on the classical velocity distribution by Weidmann [13]. It is a normal distribution with a mean value of $v_\varnothing = 1.34\,\mathrm{m\,s^{-1}}$ and a standard deviation of $\sigma_v = 0.26\,\mathrm{m\,s^{-1}}$. We assume a minimal velocity $v_{min} = v_\varnothing - 2\sigma_v$ and a maximal velocity $v_{max} = v_\varnothing + \sigma_v$. The assumption is based on our field observation, that visitors of public events have a significantly lower minimal velocity, since many of them stop on their way to the event site to communicate and socialize with other visitors.

$$\varphi_i(v_i) = \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left(-\frac{(v_i - v_\varnothing)^2}{2\sigma_v^2}\right) \tag{1}$$

A new velocity v_i has to be determined if a velocity value larger than v_{max} or smaller than v_{min} is calculated by Equation 1. Parameter Λ describes the set of all accessible routes $\lambda_l \in \Lambda$ from the station to the event site. The length d_l of a route λ_l is the sum of all straight route section lengths $|\mathbf{s}_{l,m}|$. The index $m = 1...M$ classifies the singular edges and nodes of a route λ_l. The sequence of indices describes the chronological order a pedestrian on route λ_l visits the nodes and edges. Therefore, the length d_l of a route λ_l with M nodes can be calculated as:

$$d_l = \sum_{m=1}^{M-1} \left|\mathbf{s}_{l,m}\right| \tag{2}$$

The parameter d_{min} defines the length of the shortest route $\lambda_{min} \in \Lambda$, and d_{max} the longest. Therefore, we can determine a minimal walking time $\Delta t_{min} = d_{min}/v_{max}$, or maximal walking time $\Delta t_{max} = d_{max}/v_{min}$. If a pedestrian enters the event site at t_i, he or she has left the station in the time interval $\tau_i \in \Delta D_i = [t_i - \Delta t_{max}, t_i - \Delta t_{min}]$. Thus, only arrival times of public transport services during this time interval can be starting times of a pedestrian p_i. If multiple transport services arrive at the station during the time interval ΔD_i, a clear assignment of starting times τ_i is not possible. In this case, we assume a normal distribution as a probability distribution to distinguish between multiple possibilities of starting times:

$$\psi_i(t) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(t-\mu_i)^2}{2\sigma^2}\right) & t \in \Delta D_i \\ 0 & t \notin \Delta D_i \end{cases} \tag{3}$$

The expected value $\mu_i = t_i - \frac{1}{2}(\Delta t_{max} + \Delta t_{min})$ describes the mean value of the time interval ΔD_i. The behavior of the normal distribution is given by the standard deviation. If we assume that our interval ΔD_i includes about 95 percent of all possible values, we can determine the standard deviation as $\sigma = \frac{1}{4}(\Delta t_{max} - \Delta t_{min})$. In the next step, we determine the probability that the arrival time τ_k of public transport service is chosen as the starting time of pedestrian p_i at the station:

$$\Psi_{i,k} = \frac{\psi_i(\tau_k)}{\sum_j \psi_i(\tau_j)} \tag{4}$$

Parameter τ_j with $j = 1 \ldots J$ corresponds to all possible arrival times of public transport services at the station relating to their timetable. If multiple starting times τ_i are possible, one starting time $\tau_i = \tau_k$ is chosen randomly relating to its probability $\Psi_{i,k}$.

3 Allocation of routes from station to the event site

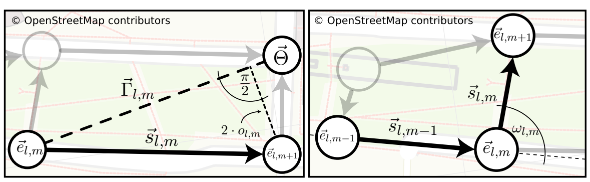

Fig. 2 Scoring calculation for the preference of bee-lines (left) and few direction changes (right)

In the next step, we determine the most likely route a pedestrian has chosen from the station to the event site. Thus, we introduce a rating system which is based on the physical boundary conditions of the scenario and on the cognitive routing behavior of humans. The time a visitor p_i needed to walk from the station to the event site equals $\Delta\tau_{i,k} = t_i - \tau_k$. This corresponds to an estimated walking distance of $d_i = v_i \cdot \Delta\tau_{i,k}$. The smaller the difference between d_i and the total length d_l of a route λ_l, the higher the probability that this route was chosen by pedestrian p_i. Thus, we introduce a rating system Ξ to rate all possible routes for a visitor p_i. The route with the highest score will be assumed as the route the pedestrian has chosen:

$$\Xi(p_i, \lambda_l) = \begin{cases} \xi(p_i, \lambda_l) & v_{min} \cdot \Delta\tau_{i,k} \leq d_l \leq v_{max} \cdot \Delta\tau_{i,k} \\ 0 & \text{else} \end{cases} \tag{5}$$

In a first step, the score depends only on the difference between the estimated walking distance d_i and the total length d_l of a route λ_l. According to the potential time interval ΔD_i of a visitor, a walking distance d_i must be between $v_{min} \cdot \Delta\tau_{i,k}$ and $v_{max} \cdot \Delta\tau_{i,k}$. Thus, we can normalize the distance between d_i and d_l by:

$$\alpha(d_i) = 1 - \frac{|d_l - d_i|}{(v_{max} - v_{min}) \cdot \Delta\tau_{i,k}} \tag{6}$$

Unfortunately, the matching of walking distance d_i and total route length d_l is not sufficient, since the assumed velocities v_i are only approximations. Cognitive sciences suggest, that the navigation behavior of humans is a complex process [11]. Some routes are more likely to be used even if the lengths between the predicted walking distance and the existing routes to the event site match not perfectly. Thus, we correct the rating $\xi(p_i, \lambda_l)$ of routes λ_l according to their attractiveness for the human navigation process. For example, pedestrians prefer routes which run close along the beeline from their position to their target $\boldsymbol{\Theta}$ [9]. Based on these scientific findings, we extend the rating $\Xi(p_i, \lambda_l)$ by a factor $\beta(o_l)$ to describe the preference of beeline-oriented routes. We calculate the mean derivation $o_{l,m}$ from the beeline for each section $\mathbf{s}_{l,m}$. The beeline from a certain intersection to the target is given by $\boldsymbol{\Gamma}_{l,m} = \boldsymbol{\Theta} - \mathbf{e}_{l,m}$. Since the intersection $\mathbf{e}_{l,m}$ is located at the beginning of section $\mathbf{s}_{l,m}$, we can calculate the mean derivation of this section as (see Figure 2):

$$o_{l,m} = \frac{1}{2} \left| \mathbf{e}_{l,m} + \frac{(\mathbf{e}_{l,m+1} - \mathbf{e}_{l,m}) \circ \boldsymbol{\Gamma}_{l,m}}{\boldsymbol{\Gamma}_{l,m} \circ \boldsymbol{\Gamma}_{l,m}} \cdot \boldsymbol{\Gamma}_{l,m} - \mathbf{e}_{l,m+1} \right| \tag{7}$$

The total derivation o_l equals the sum $o_l = \sum_m o_{l,m}$ of all sections of route λ_l. For the rating, we scale $o_{m,l}$ by the average beeline derivation $o_\varnothing = \frac{1}{L}\sum_{l=1}^{L} o_l$ of all routes:

$$\beta_l(o_l) = \begin{cases} 1 - \Delta p & o_\varnothing / o_l < 1 - \Delta p \\ o_\varnothing / o_l & 1 - \Delta p \leq o_\varnothing / o_l \leq 1 + \Delta p \\ 1 + \Delta p & o_\varnothing / o_l > 1 + \Delta p \end{cases} \tag{8}$$

According to a field experiment from Kneidl [10], 71.2% of all routes chosen by the participants were beeline-oriented and 28.1% were not [9]. Thus, we limited the influence of the rating to $\Delta p = \pm 0.5 \cdot (71.2 - 28.1)\% = \pm 21.6\%$. Another important aspect is the preference of humans to choose routes with a small number of direction changes [10]. A direction change occurs if the angle $\omega_{l,m}$ between two sections $\mathbf{s}_{l,m-1}$ and $\mathbf{s}_{l,m}$ differs by more than $\omega_0 = \frac{\pi}{18}$ [9]. The angle $\omega_{l,m}$ can be calculated by the scalar product of the neighboring edges (see Figure 2). The total number of direction changes h_l for a route λ_l can be calculated by the Heaviside-function:

$$h_l = \sum_m \mathscr{H}\left(\omega_{l,m} - \omega_0\right) \tag{9}$$

The rating $\gamma(h_l)$ is analogue to the calculation of the beeline factor $\beta(o_l)$ with $h_\varnothing$ as the average number of direction changes per route:

$$\gamma(h_l) = \begin{cases} 1-\Delta q & h_\varnothing/h_l < 1-\Delta q \\ h_\varnothing/h_l & 1-\Delta q \leq h_\varnothing/h_l \leq 1+\Delta q \\ 1+\Delta q & h_\varnothing/h_l > 1+\Delta q \end{cases} \quad (10)$$

Rating parameter Δq is based on Kneidl's experiment [10]. 73.2% of all routes selected by the participants had few direction changes, where as 26.8% had many direction changes. Therefore, the influence of the number of direction changes was limited to $\Delta q = \pm 0.5 \cdot (73.2 - 26.8)\% = \pm 23.2\%$. Additionally, the navigation of humans is influenced by the surrounding density of pedestrians. Persons with low local knowledge often use the route choice of other people to navigate. A sufficient description of this behavior was described by Schadschneider et al. [12], who applied the established ant-algorithm from Dorigo et al. [6] to pedestrian dynamics. At this, the influence of other humans on the route choice is valid only if these people are visible for the pedestrian p_i. Additionally, other people can decrease the attractiveness of a route: a too crowded street ($\rho \geq 0.5\,\mathrm{Ped/m^2}$) affects the operational behavior of pedestrians [13]. Thus, people will avoid such sections. A density depending algorithm can model both contrary aspects. Since each unique section $\mathbf{s}_{l,m}$ runs linear between $\mathbf{e}_{l,m}$ and $\mathbf{e}_{l,m+1}$, we can assume that each pedestrian on a section $\mathbf{s}_{l,m}$ is visible to any other pedestrian on this section. This means, that a pedestrian p_j is visible on $\mathbf{s}_{l,m}$ for a time period $[T^-_{l,m,j}, T^+_{l,m,j}]$ with the starting time $T^-_{l,m,j} = \tau_j + \sum_{k=1}^{m-1} |\mathbf{s}_{l,k}|/v_j$ and the ending time $T^+_{l,m,i} = \tau_i + \sum_{k=1}^{m} |\mathbf{s}_{l,k}|/v_j$. The sum of all visible pedestrians determines the density of this section for a pedestrian p_i:

$$\rho_{l,m,i} = \frac{N_{l,m,i}}{|\mathbf{s}_{l,m}| \cdot b_{l,m}} \quad (11)$$

The parameter $b_{l,m}$ describes the width of a section $\mathbf{s}_{l,m}$. The number of all pedestrians p_j, which are visible for a pedestrian p_i at a section $\mathbf{s}_{l,m}$ are given by:

$$N_{l,m,i} = \sum_j \mathscr{H}\left(t_{l,m,i} - T^-_{l,m,j}\right) \cdot \mathscr{H}\left(T^+_{l,m,j} - t_{l,m,i}\right) \quad (12)$$

Parameter $t_{l,m,i}$ is the moment a pedestrian p_i would enter the intersection $\mathbf{e}_{l,m}$. At this time, the pedestrian p_i has to decide which section they choose next. Therefore, the local density at this moment would influence the decision making process. This point in time can be calculated by $t_{l,m,i} = \tau_i + \sum_{k=1}^{m-1} |\mathbf{s}_{l,k}|/v_i$. We use the established parabolic relation from Greenshield [7] to model this density depending behavior. It is based on the fundamental relation of traffic sciences and describes the density dependency of traffic flow. Our scoring system is based on this approach to model the contrary density behavior of pedestrians:

$$\zeta_{l,i} = \sum_{m=1}^{M} \frac{\rho_{l,m,i}}{\rho_{max}} \left(1 - \frac{\rho_{l,m,i}}{\rho_{max}}\right) \quad (13)$$

The parameter $\rho_{max} = 5.4\,\mathrm{Ped/m^2}$ describes the amount of density, at which crowd flow stops [13]. The rating of each route is compared to the average value $\zeta_\varnothing$:

$$\delta(\rho_{l,i}) = \begin{cases} 1-c & \zeta_{l,i}/\zeta_{\varnothing} < 1-c \\ \zeta_{l,i}/\zeta_{\varnothing} & 1-c \leq \zeta_{l,i}/\zeta_{\varnothing} \leq 1+c \\ 1+c & \zeta_{l,i}/\zeta_{\varnothing} > 1+c \end{cases} \tag{14}$$

The factor $c = 0.01$ determines the influence of the density dependencies and is based on our experimental observations. Finally, we can calculate the total score of a route λ_l. The route with the highest score is assigned to pedestrian p_i.

$$\xi(p_i, \lambda_l) = \xi(d_i, o_l, h_l, \rho_{l,i}) = \alpha(d_i) \cdot \beta(o_l) \cdot \gamma(h_l) \cdot \delta(\rho_{l,i}) \tag{15}$$

4 Field Study and Outlook

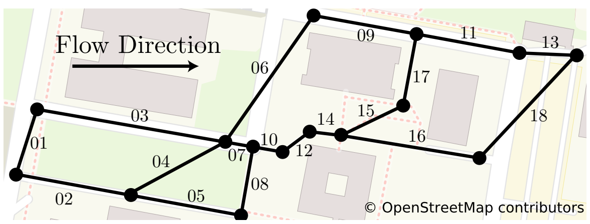

Fig. 3 Layout of the researched field study with section-wise identification numbers for Table 1

The Oppilatio method was implemented and afterwards tested on a local music festival with 5000 visitors. We tracked 700 visitors on their way from the subway station to the actual event site to verify the routing suggestions. The field study was executed by student assistants, who followed visitor groups to record their trajectories with GPS devices. Based on this data, we determined the probability that visitors use a specific section $\mathbf{s}_{l,m}$ on their way to the event site. These probabilities were compared with the probabilities calculated by Oppilatio. The results (see Figure 3 and Table 1) were averaged over 30 calculation runs and corresponded quite good to the data. Larger differences to the experiment exist in section sequence 02-04 (see Figure 3). The reason is mainly due to problems with the data acquisition. During the field study, about ten student assistants tracked the visitors from the station to the event site. At the peak hours, as most of the visitors arrived, the number of student assistants was too small to record a proportional share of visitors. Thus, the route choices of these visitors are underrepresented in the experimental data. Due to herding behavior, nearly all of them walked along the section sequence 01-03-06-09-11-13. Thus, our experiment has most likely underestimated the total number of pedestrians on this section sequence. In further research, various extensions are planned for Oppilatio. One main issue concerns the layout input: at the current state, event organizers have to set possible routes from station to event site on their own. We will couple the Oppilatio method with an network design approach, which calculates optimal route networks based on information from open geodatabases.

Table 1 Experimental pedestrian distributions compared with the results from Oppilatio

Section	01	02	03	04	05	06	07	08	09
Study	82.5%	17.5%	82.5%	12.2%	5.3%	74.9%	19.8%	5.3%	74,9%
Oppilatio	98.2%	1.9%	98.2%	1.1%	0.9%	83.8%	15.5%	0.9%	83.8%
Section	10	11	12	13	14	15	16	17	18
Study	25.1%	74,9%	25.1%	74.9%	25.1%	2.1%	22.9%	2.1%	22.9%
Oppilatio	16.3%	84.6%	16.3%	84.6%	16.3%	0.9%	15.5%	0.9%	15.5%

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