CALIBRATION OF A PEDESTRIANS' ROUTE CHOICE MODEL BASED IN FRICTION FORCES

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ABSTRACT

This paper presents a pedestrian route choice model and its calibration with real data. The model explicitly represents interaction between pedestrians as an impedance force influences pedestrians route choice. This model approach is inspired by friction forces equations, considering pedestrians avoid passing near other pedestrians with high relative velocity. Route choice process is a function of impedance force and route length. Social force model was used to model pedestrians walking behavior. Calibration was based on data acquired from a real experiment developed in a simplified network. Data collection was based on video analysis. The paper presents and discusses results from calibration processes. This model differs from others pedestrians' route choice model because it seamlessly incorporate pedestrians social force model into route choice decision process.

Keywords: route choice, model calibration, social force, pedestrian simulation, pedestrian behavior.

1. INTRODUCTION

Simulation of pedestrians is a complex task. In order to represent motion of pedestrians more realistically, models are required to simulate several processes, including sense and avoidance of obstacles, interaction with other pedestrians and route choice. Social force model has been successful in reproducing various observed phenomena on pedestrian simulation. Collective behaviors frequently emerge from interactions among individuals, such as shock waves in dense crowds, lanes of uniform walking directions in pedestrian counter flows, circulating flows at intersections or oscillating flows at bottlenecks [1][2][3]. This phenomenon, also called self-organization, is an emergent behavior arises from interactions between agents. Studies of self-organization in pedestrian crowds include pedestrian streams in corridors or alleys [4][5][6] and movement of pedestrians through a waiting crowd [5][7]. More complex studies consider escape of disoriented people from a room [8]. Understanding pedestrians´ behavior and how routes are chosen is essential for planning and designing public and private infrastructures.

Majority of pedestrians' models can be classified into two categories: (i) models where pedestrians/agents don't have imbedded route choice algorithms (route choice process can or cannot emerges from simulation) and; (ii) models where agents have imbedded route choice algorithms [9].

Selection of alternative routes in the first category happens as self-organization phenomena. This phenomenon is an emergent behavior arises from interaction between agents. These models are not suitable for wide-open spaces and complex urban networks.

Models from the second category present explicit route choice capabilities. Pedestrians adopt some sort of function to find routes to destination. These models can present static or dynamic route choice process. Static route choice models are built on the assumption pedestrians walk along shortest route, defined before the trip starts, and try to walk through this route while avoiding collisions. Dynamic route choice models differ from their static counterparts on the sense they represent route changes over time. They aim to provide a sounder representation of route choice process, emulating behavior of individual pedestrians while considering variations in the environment.

Several walking processes, such as route selection strategies, are based on subconscious decisions. Perception of distance and directness are the most common reasons for choosing a particular route [10]. Pedestrians frequently choose the shortest route, although they are not aware of this utility maximization process [11]. Most models presented in the literature are concerned only with the quickest or shortest route, like Kirik *et. al*. [12], Dressler *et. al*. [13] and Lämmel *et. al*. [14]. However, other factors play an important role in route choice behavior, such as: peoples' habits, number of crossings, pollution, noise levels, safety, shelter from poor weather conditions and stimulations of the environment [15].

Most relevant route choice models are concerned with pedestrians' evacuation. In Kretz *et. al.* [16], for example, pedestrians routes are chosen based on the minimal remaining travel time to the destination. Patil *et. al*. [17] propose an interactive algorithm to direct and control crowd simulations. Model presented by Treuille *et. al*. [18] unifies route planning and local collision avoidance by using a set of dynamic potential and velocity.

Teknomo [9] and Teknomo *et al*. [19] described an approach based on route choice self-organization to model the dynamics of mobile agents, such as pedestrians and cars on a simple network graph. This modeling approach is based on the route choice self-organization of multi agents. The agents decide, when reaching a vertex, which edge to enter next. This decision is based on a set of rules regarding the agent's observation of the local environment. The model simulates only one-directional movement from the origin to the destination vertex. In order to represent complex networks, such as urban scenarios, models need to include route choice capabilities.

Calibrating a pedestrian route choice model is a complex task mainly for two reasons: (i) Many factors interfere on pedestrians route choice, (ii) data collection is difficult. In real environments, pedestrians may change routes for many reasons not subject of this study, as pavement conditions, safety, the presence of stores, and others. [15]. Tracking pedestrians along real outdoor and indoor environments is difficult due to limited view of the modeled environment.

There are many different technologies regarding data collection of pedestrians. However, the manual data collection and the computer vision are the most common in the literature [20]. Some authors use video images of pedestrians recorded on a controlled environment [21][22][23]. This approach enables the study of a particular variable of interest without disturbs of other uncontrollable environment variables. In a controllable environment, the automatic detection and tracking of a pedestrian is easier due to facilities of positioning video cameras with a good view and the possibility to use colored markers for pedestrians' identification.

A pedestrian model calibration comprises several aspects. There are measurable variables as speeds, observable elements as avoidance of obstacles and other pedestrians and also behavioral aspects related to route choice preferences. The overall behavior and patterns of moving can be extracted by some measures as travel times, counting pedestrians and average speeds [24]. Schönauer *at al.* [25] represent the speed of pedestrians, bicycles and vehicles over a real environment using a color scale forming a heat map. The generated map characterizes the environment and allows comparisons between the collect data and simulation analysis.

This paper presents a dynamic route choice model based on a combination of distance and impedance generated by other pedestrians [26]. The calculation of the impedance is derived from friction concept proposed by Helbing and Johansson [1]. The impedance generated by friction equations involve variables related to pedestrian's profile like the desired speed and other pedestrians' velocity. We develop a real data collection experiment to calibrate the proposed model. The results show model soundly represents the pedestrians' route choice process.

2. THE MODEL

An agent-based model is proposed to address the pedestrian route choice problem. Agent-based models represent agents' decision-making ability based on agents' characteristics profile and perception over the environment. In the proposed model, pedestrians are agents able to choose and recalculate routes. Pedestrians are not assigned to predetermined routes.

In this model, a route is a set of coordinates followed by a pedestrian form origin to destination. The route choice process comprises distance and the interaction with other pedestrians. Route choice looks upon pedestrians' ability to avoid crowded areas and conflicting flows. The proposed approach allows the definition of several origins-destination pairs, reproducing real urban environments, like transportation stations, buildings, parks and others.

The aggregation of different levels of abstraction on a simulation model is a complex task. In most cases, each level of abstraction can be separately modeled on a multi-layer simulation approach [27][28][29]. The framework adopted to describe pedestrian behavior in this model (Figure 1) presents a three-layer structure, each layer representing:

(i) demand for travel: set of origin and destination;

(ii) structure of simulation environment: set of nodes composing the simulation graph;

(iii) pedestrians movement, sense and avoidance of obstacles: set of equations and agents behavior rules.

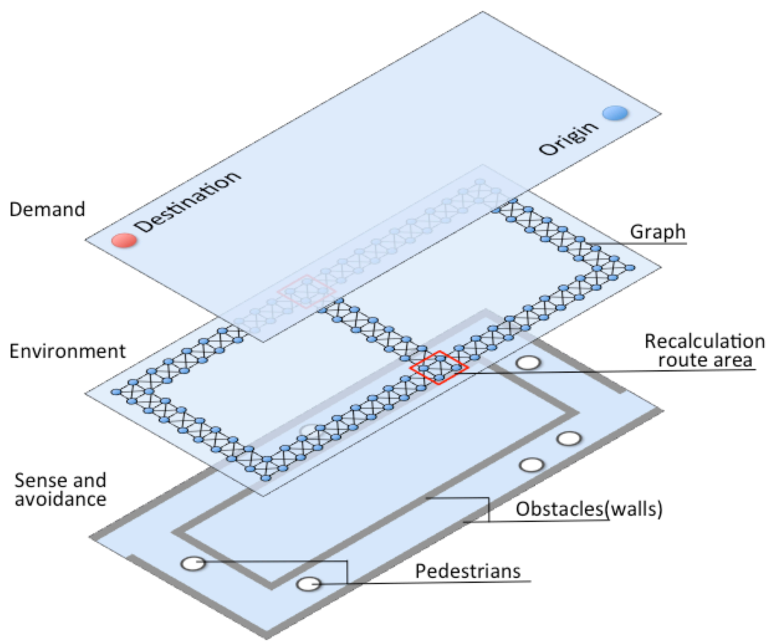

Figure 1 – Multi-layer model

2.1. Demand configuration

Each origin-destination pair is associated to a number of trips and a pedestrian generation rate. Origins and destinations are associated with the nearest nodes from the graph on the environment layer. A graph is a set of objects where some pairs of objects are connected by links. The interconnected objects are represented by mathematical abstractions called nodes. Nodes are defined as a pair of coordinates (*x,y*) in the simulation environment.

2.2. Environment configuration

The environment is described as a continuous space and is composed by geometric entities, such as rooms, doors, and other obstacles. The environment entities are linked by a graph-based structure. The graph provides a route to all entities. The graph generation process should guarantee no edge of the graph intersects any walls or obstacles.

This layer also contains route recalculation areas where a pedestrian can choose between alternative routes. The role of recalculation areas will be discussed later.

2.3. Pedestrian movement

The social force model [1] describes pedestrian walking behavior regarding the agents' low-level motion, collision avoidance and velocity adaptation. The social force model considers pedestrians' motion can be described as a superposition of several forces. Helbing and Molnár [6] assume these forces are a combination of psychological and physical forces. Pedestrians freely walk on the modeling environment seeking the next graph node of the designated route. Pedestrians' movements are ruled by the sense and avoidance model and are not restricted to a strict set of links.

A pedestrian α who wants to reach his destination $\vec{r}_\alpha^0$ takes the shortest possible route. The pedestrian's trip will usually have some intermediate destinations, $\vec{r}_\alpha^1 \ldots \vec{r}_\alpha^k$. Assuming $\vec{r}_\alpha^k$ is the next partial destination, the desired direction of motion $\vec{e}_\alpha(t)$, according Helbing and Molnár [1], will be:

$$\vec{e}_\alpha(t) = \frac{\vec{r}_\alpha^k - \vec{r}_\alpha(t)}{\|\vec{r}_\alpha^k - \vec{r}_\alpha(t)\|} \tag{1}$$

Where $\vec{r}_\alpha(t)$ denotes the pedestrian's α position at time t.

Any pedestrian α presents a desired speed v_α^0 and a desired direction $\vec{e}_\alpha$. The desired velocity is, therefore, $\vec{v}_\alpha^0(t) = v_\alpha^0 \vec{e}_\alpha(t)$.

In case of deviations from the desired velocity, the pedestrian assume a current velocity $\vec{v}_\alpha(t)$. The pedestrian α tends to restore $\vec{v}_\alpha(t)$ within a certain relaxation time τ_α. Helbing and Molnár [1] describe this adaptation by the acceleration term $\vec{F}_\alpha^0$:

$$\vec{F}_\alpha^0(\vec{v}_\alpha, v_\alpha^0 \vec{e}_\alpha) = \frac{1}{\tau_\alpha}(v_\alpha^0 \vec{e}_\alpha - \vec{v}_\alpha) \tag{2}$$

Pedestrians feel uncomfortable close to other pedestrians and walls; therefore, the presence of pedestrian β will result in a repulsive force affecting the motion of pedestrian α. Helbing and Molnár [1] represent this effect by $\vec{f}_{\alpha\beta}$:

$$\vec{f}_{\alpha\beta}(\vec{r}^{\alpha\beta}) = -\nabla_{\vec{r}_{\alpha\beta}} V_{\alpha\beta}[b(\vec{r}_{\alpha\beta})] \tag{3}$$

Where $V_{\alpha\beta}$ is the repulsive potential, represented by a monotonic decreasing function with equipotential elliptical lines. The elliptical shape reproduces the pedestrian's need for more space in the direction of motion. b is the semi-minor axis of the pedestrian ellipse defined by $\vec{r}_{\alpha\beta}$ ($\vec{r}_{\alpha\beta} = \vec{r}_\alpha - \vec{r}_\beta$). The resultant force exerted over a pedestrian is a superposition of three forces:

the force to adapt the current velocity to the desired velocity ($\vec{F}_{\alpha}^{0}$), the forces exerted by other pedestrians ($\vec{f}_{\alpha\beta}$), and the forces exerted by walls and other obstacles.

3. ROUTE CHOICE PROCESS

In this model, the cost of each route is calculated as a function of two factors: route length and the impedance generated by other pedestrians. The impedance generated by the friction between pedestrians is assumed to exist even before physical contact, due to the psychological tendency to avoid passing close to individuals with high relative velocity [1]. Pedestrians seek minimal route length and minimal friction with other pedestrians.

The pedestrian starts the route choice process as soon as he starts the trip. In order to choose the route, the pedestrian takes into account the distance between nodes and also the impedance generated by other pedestrians. Once a route is defined, the pedestrian walks trough this route until he reaches an area of route recalculation or the final destination. An area of route recalculation is any location where pedestrians can choose between two or more alternatives routes.

Dijkistra algorithm [30] is adopted to generate valid routes for any origin/destination pair in the graph. In this formulation, cost is a combination of distance and impedance exerted by other pedestrians in the simulation. The impedance is calculated by the procedure described bellow.

Figure 2 describes a pedestrian α who wants to find a route between nodes O and D on the graph. The algorithm traverses the graph assigning the cost for each link between the nodes. Figure 2 shows the parameters involved in the calculation of impedance cost between nodes u and n for pedestrian α. The impedance calculation process generates a fictitious pedestrian α' positioned on node u and has the desired direction motion, $\vec{e}_{\alpha'}$, oriented to the direction of node n. The fictitious pedestrian has the same attributes of pedestrian α ($\vec{v}_{\alpha'}^{0} = v_{\alpha}^{0}$).

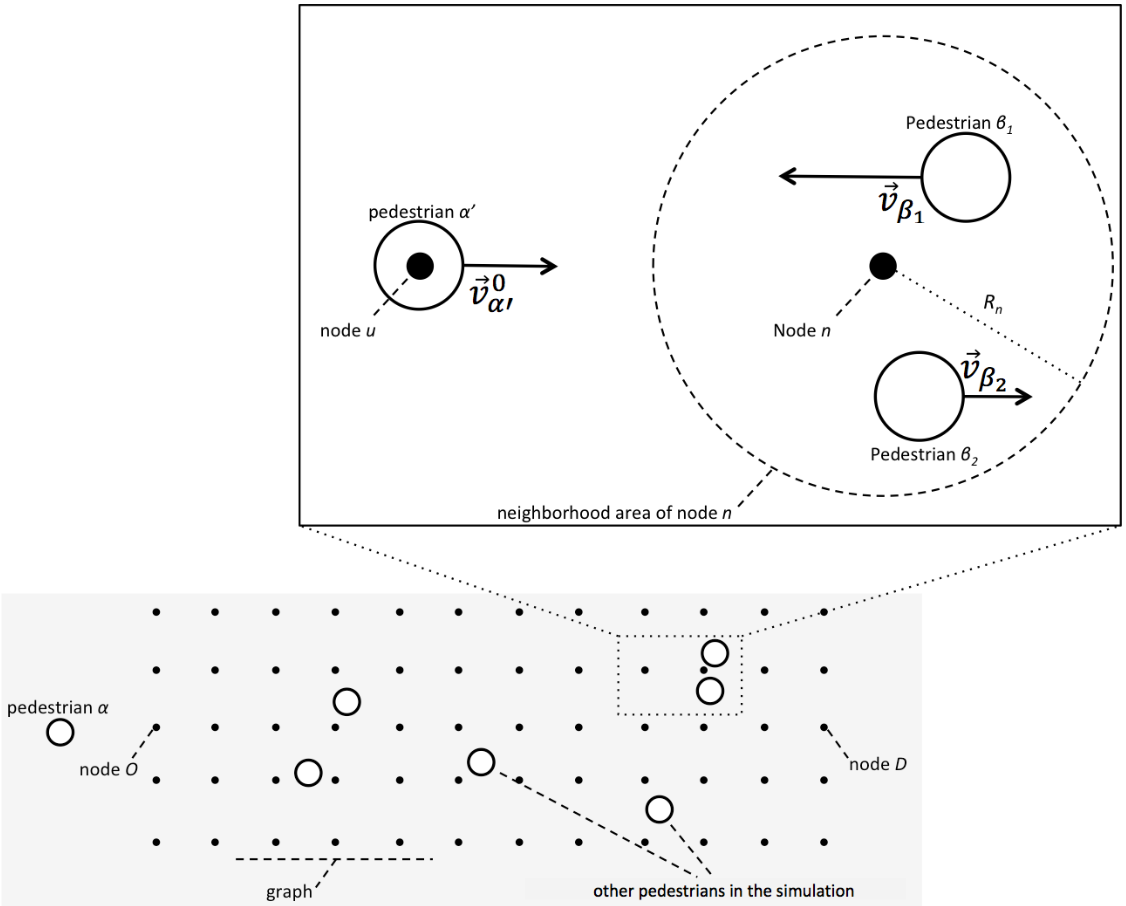

Figure 2 - The route choice model

To estimate the impedance exerted over the pedestrian α' it is necessary to know the pedestrian desired velocity, $\vec{v}^0_{\alpha'}$,when he is trying to walk from $\vec{r}_u$ to $\vec{r}_n$

$$\vec{v}^0_{\alpha'} = \frac{\vec{r}_n - \vec{r}_u}{\|\vec{r}_n - \vec{r}_u\|} . v^0_{\alpha} \tag{4}$$

In order to calculate the impedance exerted by other pedestrians over α', it is defined a neighborhood area around the graph nodes, with a radius R_n. The impedance is evaluated by the difference between $\vec{v}^0_{\alpha'}$ and the current velocity of other pedestrians β, $\vec{v}_\beta$, walking in neighborhood area. Only pedestrians within the neighborhood area of the node n are considered in the impedance estimation.

Considering each pedestrian β currently in the neighborhood area of the node n, the absolute impedance perceived by the pedestrian α' to walk from u to n, $I_{\alpha'}$ is:

$$I_{\alpha'} = \sum_{\beta} \|\vec{v}_\beta - \vec{v}^0_{\alpha'}\| \tag{5}$$

The value of I_{α}, is normalized over a settable parameter I_{max}. The cost perceived by the pedestrian α to walk from node u to n, $W_{\alpha}^{u,n}$, is a balance between distance and the impedance exerted by other pedestrians:

$$W_{\alpha}^{u,n} = \|\vec{r}_n - \vec{r}_u\|.(1 + I_{\alpha}, /I_{max}) \qquad (6)$$

The described procedure is repeated until all possible routes costs are defined. Pedestrian α chooses the route with the lowest cost. The algorithm adopted to calculate the motion cost for pedestrian α' from node u to n is presented below:

```
Double Cost_from_node_u_to_n(Node u, Node n, Pedestrian A)
{
 Double Absolute_Impedance = 0;
 Vector vA = Normalize(n.position - u.position) * A.DesiredVelocity;
 Q = List with all Pedestrians in the simulation;

 foreach Pedestrian B in Q
    if(DistanceBetween(B, n) < n.NeighborhoodRadius)
        Absolute_Impedance += Module(B.currentVelocity - vA);
    end if;
 endforeach;

 return Module(n.position - u.position) * (1 + Absolute_Impedance/ Max_Impedance);
}
```

One important aspect of model configuration is the distance between the graph nodes. The radius of neighborhood areas (R_n) is defined as half distance between nodes. Impedance measures associated to nodes neighborhood areas emulate pedestrians' sensors. Distance between nodes must be defined in order to reduce missing pedestrians. If distance between nodes is too large the impedance estimation could not capture real pedestrians' organization. On the other hand, if a graph is too dense, models performance can be jeopardized due to computation costs.

I_{max} (Equation 6) is a key parameter in the calculation of the cost perceived by pedestrians (W). This parameter acts as weighting factor between travel distance and the perceived impedance. The higher the value of Imax, the lower the willingness of pedestrians to choose an alternative longer route. The I_{max} is a calibration parameter adjusted to reflect the willingness of pedestrians to trade for longer routes, depending on pedestrian's density on the shortest route. More details about the calibration process are presented in Section 6.

3.1 Pedestrians level of knowledge about the environment

The pedestrian's level of knowledge about the state of the environment in an important element in the route choice process. Pedestrian knowledge concerns his awareness about the number, position and velocity of other pedestrians in the network. In this study, was considered pedestrians have partial knowledge of the network conditions and memory of past experiences. During a simulation period, pedestrians keep in memory the past conditions of the links already traveled. The memory is available for one simulation only. When another simulation is started, the pedestrians have their memory reset. Werberich et al. [31] describe the memory process in more details.

4. EXPERIMENT

In order to obtain data to calibrate the model a route choice experiment on a simplified network was developed. The experiment was set up inside the university campus. The network built for the experiment had 2-meter-high walls and two opposite entrances. Figure 3 shown the scenario layout presenting detailed measurements and corners numbers from 1 to 8. The main goal of this experiment is to collect data related to the pedestrians' route choice behavior in a congested network. For this analysis, volunteer students walked inside the scenario as if they were in a real environment.

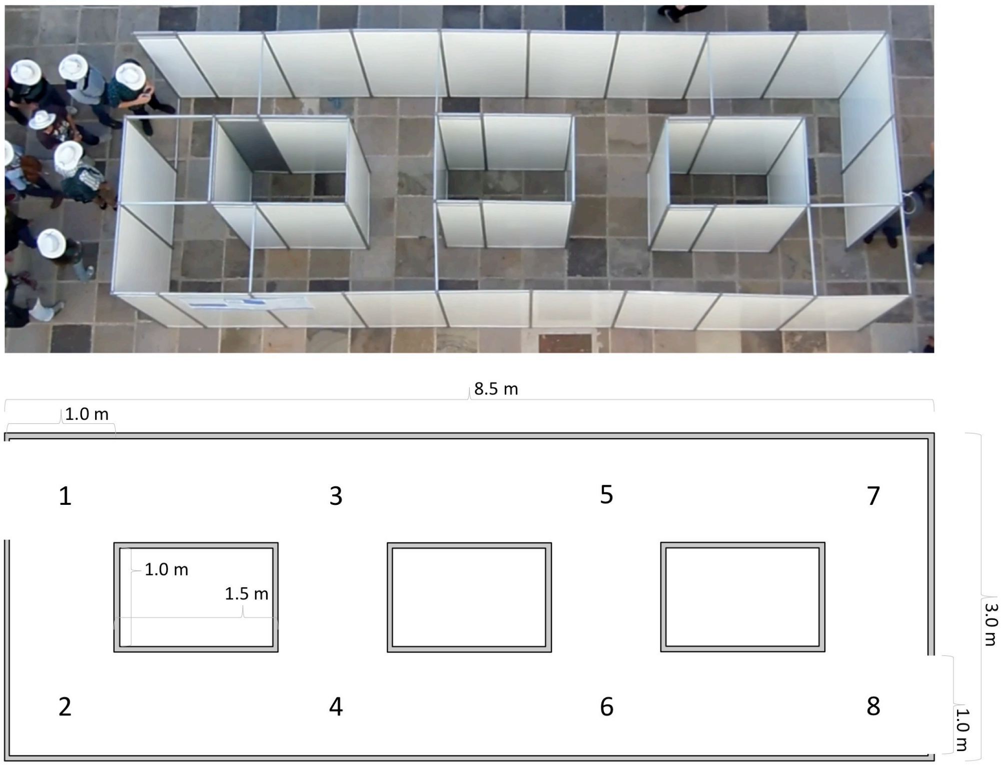

Figure 3 –Experiment layout

Forty pedestrians were split into two groups of twenty pedestrians to perform the data collection. The first group walked from the entrance in corner 1 to the exit at corner 8. The other group walked into the opposite direction (corner 8 to 1). The first group was instructed to follow a fixed route. The fixed route was defined by corners {1 – 3 – 4 – 6 – 8}. The other group had no specific orientation about routes. They were free to choose any route from entrance to exit. We call these two groups by the fixed route group and the free route group, respectively. Figure 4 shows images of the experiment. White hats identify the fixed route group and black hats the free route group.

Data was collected by video recording. The camera was set at approximately 15m high with a top view to capture the video images.

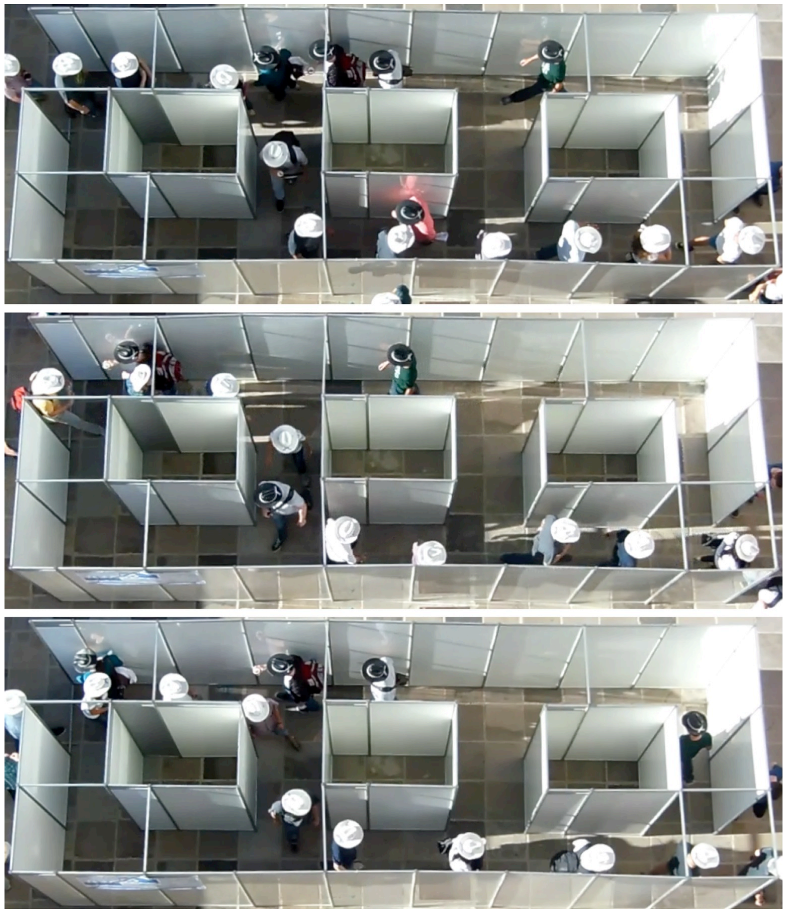

Figure 4 – Running the Experiment

The average entrance rate for the fixed route pedestrians is 2 seconds, for free route pedestrians 5 seconds. The large interval time for the free route pedestrians' entrance ensures they make their decisions observing the environment, not simply following the previous pedestrian.

The video analysis was made with the aid of software called Tracker [32]. Its main features include object tracking with position, velocity and acceleration, special effect filters, multiple reference frames and calibration points. The data collection was a semi-automatic process for video analyses. The data were collected independently for each pedestrian in the experiment. The software collected a position (x, y) for a pedestrian at each video frame; the video was recorded with 30 fps. Figure 5 shows the route for all pedestrian in the free route group. The black dashed line represents the fixed route. In the density colored map of pedestrians (figure 5) the blue color represent areas with no pedestrians and red colors represent areas with higher presence of pedestrians. The same color map was used in the calibration process for a visual feedback.

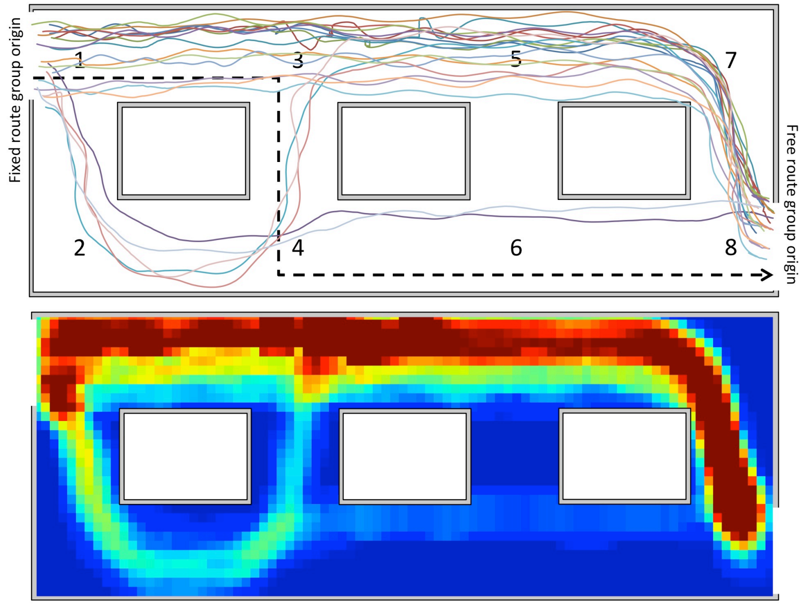

Figure 5 – Collected Data

The average travel time for the free route group in the experiment was 12.8 seconds with a standard deviation of 3.6 seconds. The average distance traveled was 10.6 meters with standard deviation of 0.89 meters.

5. SIMULATIONS

The following session presents the results of simulations derived from the implementation of the model described above.

The experiment layout and graph granularity adopted in the simulation network is presented in Figure 6. The distance between nodes is 1.0m and the R_n value is 0.5m.

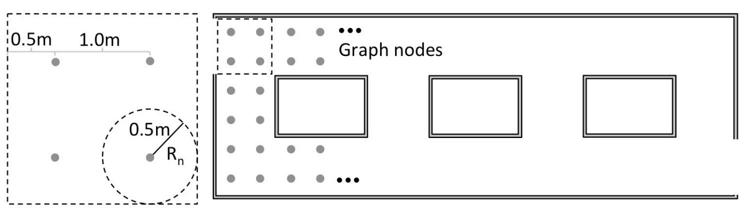

Figure 6 – Simulation Graph

Pedestrians were generated with variable desired speed with average value of 1.0 m/s and standard deviation of 0.1 m/s. Similarly to the experiment, the simulations included two classes of pedestrians: pedestrians with fixed route and free route pedestrians. Pedestrians generation rate of the fixed route group was 1 pedestrian at each 2 seconds. The generation rate of the free route group was 1 pedestrian at each 5 seconds.

5.1. Calibration

The first step of the calibration process was the adjustment of the social force model parameters. The calibration of the social force model allows the correct representation of the repulsive forces from obstacles and pedestrians. The parameters of the social force model used in this experiment were similar to those presented in Helbing and Molnár [1].

The key parameter for the calibration of the route choice process is I_{max} (Equation 6). This parameter is a weighting factor between travel distance and the perceived impedance. The higher the value of I_{max}, the lower the willingness of pedestrians to choose an alternative longer route. For the goals of this paper, the main calibration method was similar to Johansson et al. [33] where a microscopic simulation model was applied and calibrated by using pedestrian route data. Figure 7 shows the results of five simulations with different I_{max}values $\{0.3, 0.6, 0.9, 1.2, 1.5\}$. The increment of 0.3 in I_{max} value was chosen as the minimal value showed a significant influence in the simulation outcomes. Density color map, average travel time and average distance traveled were adopted as calibration references to identify the best fit for the experiment data. Figure 6 shows the density color map, average distance traveled and average travel time for each I_{max} value, for free route pedestrians.

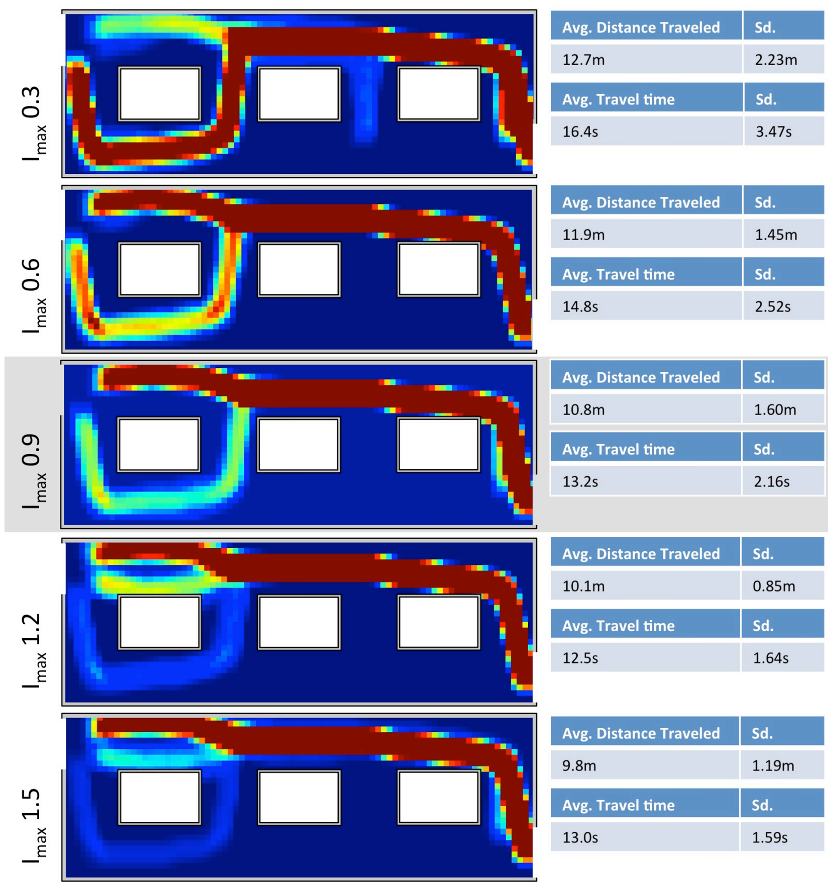

Figure 7 – Calibration Process

5.2. Results

In this case study, $I_{max} = 0.9$ was defined as the best fit to calibrate the model. The average travel time of free route pedestrians in the experiment was 12.8 seconds with a standard deviation of 3.6 seconds. The average distance traveled of the pedestrians at the experiment was 10.6 meters with standard deviation of 0.89 meters. The difference between the real average travel time and the simulation was 3.1% and for the average distance traveled was 1.8%.

I_{max} value variability has influence on the route distances and travel time. As I_{max} increases the route distance tends to decrease. However, for higher values of I_{max} the travel time tends to be extremely higher due to excessive congestion on shorter routes. Figure 8 shown the variability of travel times and distance for different values of I_{max}.

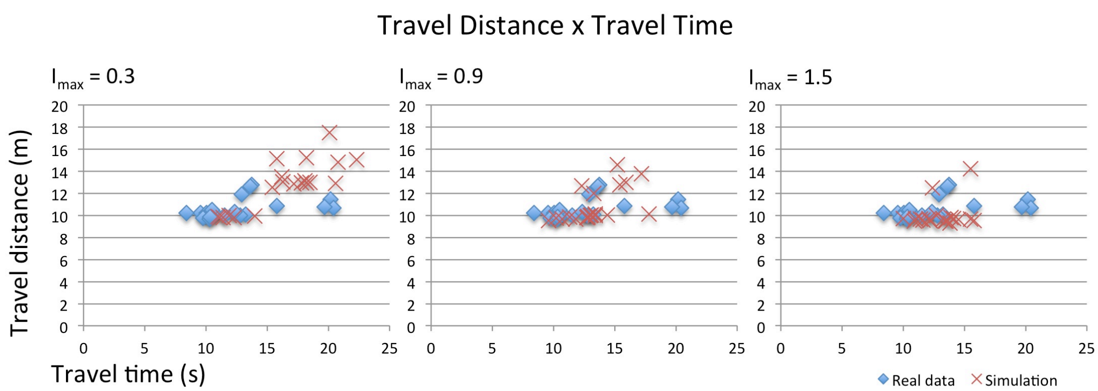

Figure 8 – Traveled distances

The network in this experiment has four minimal routes {8-7-5-3-1}, {8-6-5-3-1}, {8-6-4-3-1}, {8-6-4-2-1}. A minimal route choice model would assign pedestrians to any of these routes. However, in real circumstances pedestrians do not chose routes based only on distances. Pedestrians tend to avoid congested routes. This behavior was evident in experiment, as showed in color map (Figure 5). Through adjustment of I_{max}, calibrated model was able to realistically represent pedestrians' decisions to avoid links congested by fixed route pedestrians. These results show impedance equations ability to model route choice under congested conditions.

6.0. Validation

Model validation is needed to assess model representativeness in different situations. Validation data were collected on the same network previously presented. The configuration of fixed route pedestrians and free route pedestrians remains, but now the number of pedestrians on fixed group was reduced to a half, remaining only 10 pedestrians. Reducing the number of pedestrians on fixed route reduce the flow generating gaps between pedestrians. Free route pedestrians are now expected to be more spread out on network comparing to previous experiment.

Figure 9 shows two datasets collected from video analysis (Experiment run 1 and 2). For each run, volunteer's group performing free route pedestrians was completely changed. The heat maps were generated considering the traversed route for 20 free route pedestrians.

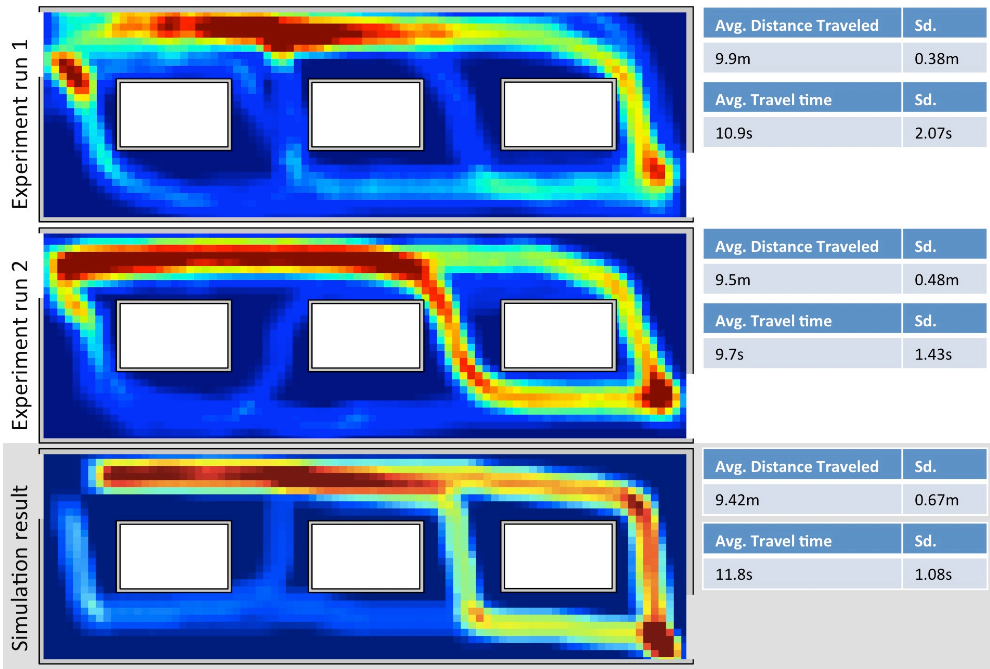

Figure 9 – Validation data

As expected, free route pedestrians are now far most overspread in network compared with previous experiment. The simulation result (Figure 9) was run for this new scenery with previously calibrated value of Imax. (Imax = 0.9). Simulation heat map is quite similar to data collected. The effect of weaker flow of fixed route pedestrians can be observed on both collected and simulated heat maps. Free route pedestrians are still avoiding the fixed route pedestrians, but now, in a more subtly way. In the previous experiment, almost all free route pedestrians diverted from the fixed route immediately upon entering the scenario, choosing the link between the corners {8 - 7}. This avoiding behavior is now split into other links. Higher congested links are now between corners {5 - 3 - 1}. These similarities between collected and simulated data show the model could be used to represent real pedestrians' behavior.

6. CONCLUSIONS

Route choice is a complex process to model since most route selection strategies are based on subconscious decisions. Perception of distance and directness are most common reasons for choosing a particular route, however, other factors may also play an important role in this decision, such as density of people and people walking in the opposite direction. This model assumes cost of a route as a function of route length and impedance generated by other pedestrians. The impedance generated by friction between pedestrians is generated even before physical contact, representing the psychological tendency to avoid passing close to individuals with high relative velocity. This modeling approach provides a sound representation of pedestrian route choice dynamics. Simulations results were calibrated with real data and indicate this model provides a promising approach for real case applications. Balance between impedance and distance could be easily calibrated with a single parameter. The model approach seamlessly incorporates pedestrians social force model into route choice decision process, and emerges as a promising approach for pedestrian route choice simulation.

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