Modelling Impact of Morphological Urban Structure and Cognitive Behaviour on Pedestrian Flows

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Abstract. A novel, discrete space-time model of pedestrian behaviour in real urban networks is presented. An agent-based approach is used to define characteristics of individual pedestrians, based on spatial awareness and cognition theories, combined with preferential choices of different social groups. Behaviour patterns are considered incorporating rules of movement along pedestrian routes and for intermediate decision and conflict points. The model utilises dynamic volunteered geographic information system data allowing analysis of arbitrary city networks and comparison of the effect of grid structure and amenity distribution. As an example, two distinctive social groups are considered, namely 'directed' and 'leisure', and their interaction, together with the way in which flow congestion and changes in network morphology affect route choice in central London areas. The resulting stress and flow characteristics of the urban network simulations as well as the impact on individual agent paths and travel times, are discussed.

Keywords: GIS, agent-based modelling, urban spatial-temporal modelling, pedestrian behaviour, geovisualisation.

1 Introduction

As urban environments expand, routine travel to work or other destination becomes more complex causing increase in commuter stress. From the pedestrian viewpoint, familiarity with and ease of navigation on the urban grid can facilitate rapid transit to daily destinations, such as schools, offices, parks and entertainment venues. This in turn can influence lifestyle choice by making walking or cycling both more attractive and efficient than driving.

Although pedestrian behaviour has been studied for more than several decades [1,2], the research has intensified since the early nineties due to improved computational models and increased availability of computing power. Pedestrian dynamic studies have mostly focused on self-organisation and interaction of pedestrian flows [3,27]. A typical application of such models is the prediction of evacuation patterns from enclosed spaces, such as buildings, underground stations and public venues [4,5,6]. Additionally, models were developed to address

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large-scale problems, notably evacuation in the context of naturally-occurring and man-made disasters, such as hurricanes and terrorist attacks, [7,8].

Notably, following early use of discrete methods (such as cellular automata), agent-based modelling (ABM) has gained considerable popularity for representation of individual interactions. The approach has several key advantages, the most important being the expressive and intuitive nature of the modelling language, its suitability to high-performance execution environments, adaptability to inclusion of heterogeneous behaviour and incorporation of stochasticity [9,10]. The origins of application of ABM to pedestrian modelling lie in simulations of social behaviour and decision-making, [12], introduced in detail in [13]. From early models, where agents of two distinct types populated a simple grid, [11], use has expanded to representation of complex real-world situations and social behaviour involving millions of entities (TRANSIMS, [14]).

In simulating crowd and group dynamics, ABM enables exploration of force effects at different crowd densities by using discrete grid cells with assigned force vectors, [15], and demonstration of local patterns for random pedestrian walks, emphasising the importance of both micro- and macro-simulations, [17]. In addition, ABM can be linked to geographic information systems (GIS), combining spatial and temporal aspects in an effective geo-simulation tool to enable interpretation of urban environments, [18,16]. Nevertheless, models using both separate crowdsourced GIS and ABM are relatively unexplored [19] and, in order to link these, investigation of social behaviour patterns is required, [20]. Studies report that, rather than individual movement, interactions inside and between groups lead to formation of typical walking patterns [21]. Visual perception and route choice is shown to depend on the configuration of the urban street network with focus on cognitive understanding of spatial complexity, and the way in which directional change, rather than distance, impacts the route choice [22,23].

While motorised (and non-motorised) road-using vehicles are constrained by traffic rules, signalisation and street orientation, pedestrian flows are subject to fewer rules and exhibit more flexibility and randomness of choice at every time point [30,24]. Depending on real-time assessment of congestion, route choice can be readily adapted. Further, pedestrian behaviour is much more diverse with each individual permitted flexible options for movement through crowds or definition of 'optimal' route.

These properties motivate the need for bottom-up modelling of pedestrian movement, with the agent basis providing a flexible tool for analysis of complex social behaviour [25]. In this context, the ABM paradigm allows simulation of individual actions by representing pedestrians as agents with active awareness of their environment (traffic, neighbouring pedestrians and the street network).

In this paper, we introduce a discrete, behaviour-driven space-time framework, allowing pedestrian movement to be modelled on a real urban network. The main focus here is on exploring the potential of the approach through example scenarios and investigation of simple hypotheses of pattern evolution as a foundation for later extension. We consider pedestrian movement originating from three main 'cognitive features' [28,23]: (i) walking strategy, (ii) spatial awareness and (iii) knowledge of the urban grid.

The paper is organised as follows: in Section 2 we present the core behavioural model by defining the agent state machine and types of pedestrian behaviour. We also describe the GIS from which the data is sourced for the models. In Section 3 we describe several different behavioural scenarios with respect to different city locations and analyse the key movement patterns observed. Finally, in Section 4 we summarise findings and possible future questions of interest.

2 Model

2.1 Agent State Machine

In order to create direct mapping between pedestrian behaviour in a particular simulation scenario and the urban network through which an individual will move, we decompose pedestrian movement into three basic states (Figure 1). Each of these corresponds to a 'mode of thinking' of an idealised pedestrian:

– *Decision state.* This state describes the options open to an individual agent, positioned at an intersection (node) between two or more streets (edges). Each agent, depending on its behavioural type, can choose to move in one of several directions (towards the next decision point or intersection). This decision is made based on a number of factors (see Section 2.2), distinguished mainly by the individual's knowledge of the 'optimal' route. An agent, having made a choice, is then in *Transition.*
– *Transition state.* In this state, the agent attempts to move from the origin intersection in the direction chosen. The agent will move in discrete steps (one per iteration) along the connecting edge, with speed (number of iterations) determined by its behavioural type. Before each step, a search is made for any agents occupying the next 'point' (space) on the connecting edge in the direction chosen. Movement is then evaluated, based on the average throughput of street type and the number of street spaces occupied by other agents. Depending on the outcome, the agent can make one of two state transitions: if there is adequate space, the agent moves forward one step, and stays in *Transition* state, or, if the road ahead is blocked, the agent pauses and enters the *Waiting* state for one time step. If the next step requires a further decision, e.g. direction choice at an intersection, the agent enters a new *Decision* state.
– *Waiting state.* If the agent movement is blocked due to congestion, it is assigned a 'wait counter' representing the maximum number of iterations it is 'patient' enough to wait. The agent attempts to move until the counter expires, at which point it 'recalculates' the decision to proceed by the current route. Effectively, it removes the congested edge from its decision tree and enter a new *Decision* state.

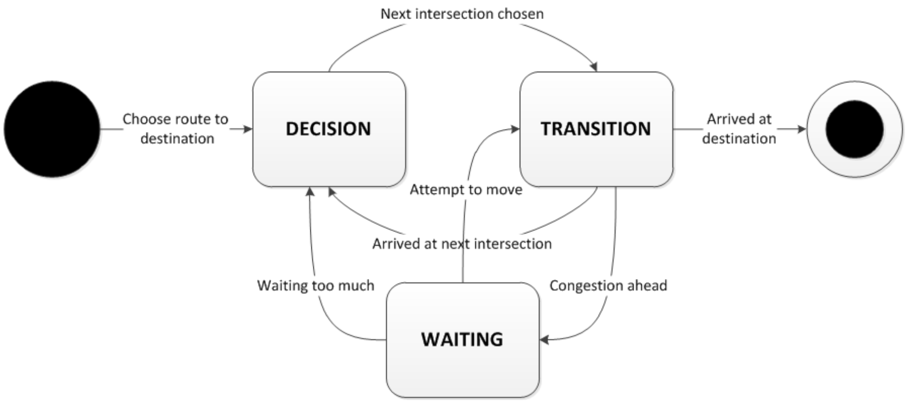

Fig. 1. Behavioural state machine representing transitions between three possible pedestrian states - decision, transition and waiting

2.2 Types of Pedestrian Behaviour

The *Destination* state of the core state machine presented above allows for arbitrary pedestrian cognitive behaviour to be incorporated into the model, on the basis that the next point along the pedestrian path to the ultimate destination is the outcome of such behaviour. We note here that, at present, we consider only path selection behaviour. Another important category, 'crossing' behaviours [24] has not been considered. Given current model scale and the fact that purposeful choice is constrained by road usage in urban environments, paths between intersections tend to be the rational choice and random crossovers are limited. Inclusion of crossings may lead to some impact on pedestrian congestion at intersections.

The model implements a number of core cognitive behaviours, divided into two broad groups:

Pedestrians with Partial or no Knowledge of the Urban Network. This first group represents 'leisure' pedestrians, mostly tourists or casual walkers, with a vague, or even no, knowledge of the configuration of streets between their current location and the intended destination. In [33] authors have emphasised the importance of this group to overall pedestrian traffic in urban environments. These pedestrians can be represented by agents, whose node choice behaviour is driven by minimisation of the following function:

$$f(n) = \delta \cdot d + \omega \cdot o \tag{1}$$

where n represents the node descriptor, d - the straight line distance between the node and the pedestrian's destination (the measure of perceived proximity) and o - current occupancy of the node (the measure of perceived crowding); δ and ω are variable weight factors which reflect the particular pedestrian preference when it comes to route selection. Certain behavioural types will ignore crowding and attempt strictly to approach the destination as directly as possible. However, more cautious individuals will select what they perceive to be a sub-optimal route, if it means that congestion can be avoided and time minimised, even if distance is slightly longer.

Based on the possible options for minimisation of Equation 1, we define three fundamental types of 'leisure' agents in our model:

- **Aggressive** - This type of agent has high δ factor, and low ω factor, and aims consistently to transition to the perceived nearest node;
- **Cautious** - This type of agents has high ω factor, and tends to avoid crowds. However the δ factor value is still high, with node proximity always an important driver of the agent behaviour;
- **Random** - A certain proportion of pedestrians will have few or no route preferences, but are content to wander randomly about the urban grid. This category is useful for simulating urban areas of high attraction to tourists where a single destination is not dominant (or even apparent), or for simulating the effect of spontaneous reaction of other pedestrian types to 'background noise' present in a given street layout.

Pedestrians with Full Knowledge of the Urban Network. Unlike the previous major group, which makes decisions based on 'local' knowledge i.e. the next node only, pedestrians who are completely familiar with the street layout (e.g. local residents or daily office workers) generally attempt to follow a well-known, predetermined route, which they take every day from origin to destination. The behaviour of these agents is based on the previous work [23], which relates route choice to spatial awareness of the street layout. Before embarking on a trip, each agent computes a desired path (a series of nodes connected via street edges) using Dijkstra's algorithm, where edge 'cost' can take one of the following three forms:

- **Least cumulative angle change between the streets**. In this mode, an agent computes Dijkstra's shortest path that considers edge cost as the angle formed by edges connecting at the next node, Figure 2-II. The agent attempts to find the minimum of the following sum:

$$d(p) = \sum_{k} \alpha_k, \alpha_k = \pi - \delta_k \tag{2}$$

  where d is the total perceived distance of a subset of nodes $p = \{n_1, n_2, ...n_n\}$ along the determined path, with $alpha_k$ representing the cost of travelling between the two edges and δ_k being the lesser of two angles between the lines constructed by geometric coordinates of the nodes n_{k-1}, n_k and n_{k+1}, respectively, with $\alpha_0 = \alpha_n = 0$.
- **Least cumulative number of turns between the source and destination**. In this mode, an agent computes Dijkstra's shortest path such that edge costs depend on the number of turns (direction changes) between

origin and destination nodes, (Figure 2-III), making this a binary form of Equation 4:

$$d(p) = \sum_k A_k, A_k = \begin{cases} 1, & \text{if } \alpha_k \neq 0 \\ 0, & \text{if } \alpha_k = 0 \end{cases} \tag{3}$$

where A_k represents the binary metric of turn or no turn with boundary values $A_0 = A_n = 0$.

– **Shortest distance between source and destination.** Finally, a certain number of pedestrians will know the shortest metric distance (the geographical distance) to their destination, even though it might not be the most obvious route, Figure 2-I:

$$d(p) = \sum_k d_k, d_k = |\mathbf{x}_k - \mathbf{x}_{k-1}| \tag{4}$$

where $\mathbf{x}_k$ is the vector containing the geographical coordinates of node n_k, and $d_0 = 0$.

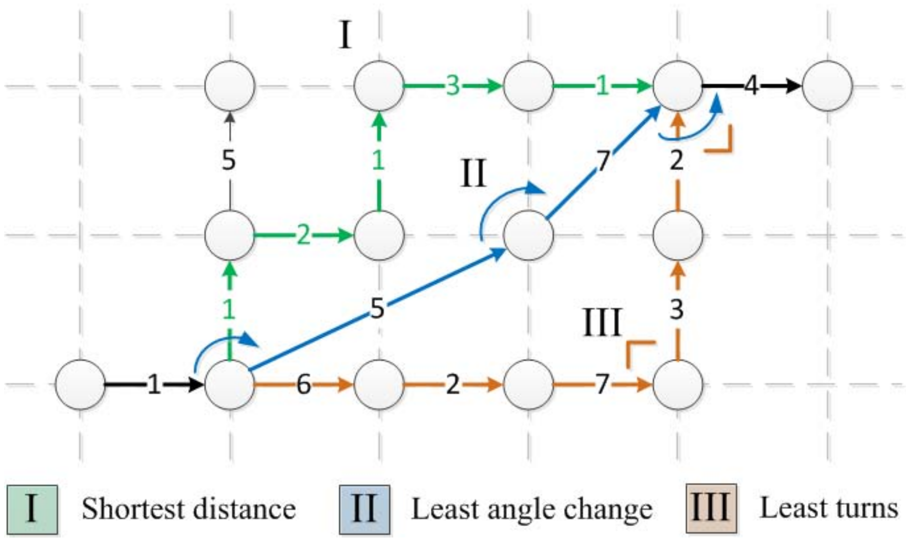

Fig. 2. Shortest path algorithm examples. The nodes represent intersections, and the numbers a distance metric representing cost. Three possible route choices based on the type of edge costs are shown.

The appropriate distance function is recalculated each time congestion occurs, by removing the congested path from an agent's network view, and permitting it to re-compute its route.

2.3 Modelling Workflow

In order to analyse and evaluate assumptions of the model proposed with respect to real urban environments, (including both street network layout and the location of main transportation, business and leisure zones of interest), we have built a framework that sources urban map data on demand from a suitable, external GIS. A rise in popularity of volunteered geographic information (VGI) has recently been observed [19]. The data, obtained from such systems, provide several advantages for macroscopic pedestrian modelling:

- Open data format, allowing for easier consumption and exchange of data between applications
- Street layout details, which compare favourably with commercial solutions, including street types and venue information
- Ability to make local edits of the layout data, allowing experimentation and flexibility with respect to infrastructure changes.

The framework sources data from OSM datasets, readily available from the OpenStreetMap APIs, for the coordinates provided. Once the dataset, along with the main pedestrian source and destination locations is loaded into our framework, the street network is automatically extracted and converted to graph representation. The resulting grid is populated with pedestrians of the various behaviour types. During simulation, the framework enables visualisation of individual pedestrian movement and keeps tracks of the paths used toghether with flow and density information. As well as the grid-level visualisation, the framework outputs detailed density maps, flow graphs and average time information that can be used for further analysis, (Figure 3). The sparsity of data, inherent in early versions of crowdsourced systems, has been alleviated in recent years [34] with a surge in the number of contributors to the GIS dataset. Super-urban areas, such as London, attract a very high level of detail, adequate for modelling applications and readily combined with available census data.

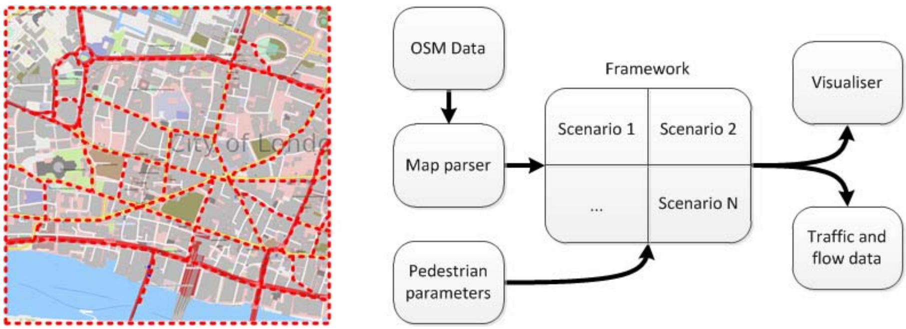

Fig. 3. Example transport graph parsing and model workflow schematics

3 Simulation and Results

3.1 Model Outputs

In order to evaluate the pedestrian traffic patterns resulting from our model, we focus on: (a) sections of the urban grid with good connectivity and presence of alternative routes between the nodes which, according to [23] are expected to show similar performance for non-congested and congested scenarios, and (b) sections where few alternative routes exist, which are expected to lead to significant bottlenecks as the traffic increases.

As density of pedestrian traffic along a given street varies with time of the simulation [13], peaking for high congestion periods, such as the morning rush, and mimicked by the simulation, we estimate the average density of pedestrians at a given geolocation by making use of the bivariate normal *kernel density function* and plot the mean of the density against the map:

$$f_h(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} K_H(\mathbf{x} - \mathbf{x}_i) \tag{5}$$

here, $\mathbf{x}$ and $\mathbf{x}_i$ are vectors of agent positions, $\mathbf{K}_H$ is the smoothing bandwidth function applied to a standard bi-variate normal distribution curve and n is the number of agents passing through the given measurement point.

To measure the velocity of pedestrians along the grid, we also calculate the flow through the map by measuring the number of pedestrians passing a given intersection over time [26]:

$$J = \frac{1}{\langle \Delta t \rangle}, \langle \Delta t \rangle = \frac{1}{N}\sum_{i=1}^{N}(t_{i+1} - t_i) = \frac{t_{N+1} - t_1}{N} \tag{6}$$

where J denotes flow, and $\langle \Delta t \rangle$ the average of time taken for two consecutive pedestrians to pass through the intersection. N denotes the total number of measurements (total number of pedestrians passing through).

Finally, we observe and chart the paths taken and the average travel distances and times between source and destination nodes, and compute the average speed of pedestrians of given type within the context of the total urban network load.

3.2 Scenario Matrix

In order to perform robust *sensitivity analysis* of the relationships between model inputs and outputs, several behaviour scenarios were simulated for two different urban environments within London. For one location, we chose the area of the inner financial district within the city of London, with the pedestrian traffic of interest being prevailingly directional (office workers and daily commuters). For the other, we chose London's West End, where the pedestrian groups mainly consist of tourists and people attending leisure venues, such as theatres, restaurants or pubs.

Table 1. Direct/leisure pedestrian distribution for different simulation runs

Scenario	Agent numbers	Leisure	Direct
1	1000	0%	100%
2	2000	50%	50%
3	3000	66%	33%
4	7000	70%	30%
5	10000	50%	50%
6	15000	33%	66%

For directional traffic, public transport, specifically underground stations, were taken as points of origin, and a central location as the destination, while leisure traffic destinations were taken to be equally likely all entertainment venues present in the given map segment. Points of origin of leisure traffic varied between public transport points to start points at random positions on the map.

For each location, we simulated scenarios for the relationship between the size of the agent population (from 1000 to 15000 pedestrians) and the behavioural profile of different groups. In terms of output, we monitored the flow and density effects as well as average transit times for each group. Table 3 presents the matrix of explored scenarios.

Table 2. Scenario list

#	Area	Direct behaviours	Leisure behaviours
1	Financial district	Distance, turn or angle	Random
2	Financial district	Distance, turn or angle	Cautious
3	Financial district	Distance, turn or angle	Aggressive
4	West End	Distance, turn or angle	Random
5	West End	Distance, turn or angle	Cautious
6	West End	Distance, turn or angle	Aggressive

Physical dimensions of each agent were taken to be 50cm width and 30cm breadth [31], with the maximum throughput of street sidewalks averaged using estimates on street size from OSM data. Base speed of an individual agent was taken to be 1.5 m/s [28]. Street sizes used are outlined in Table 3, with data on standard sidewalk sizes in urban London sourced from [32]. The number indicates the maximum number of people standing abreast on the sidewalk, at either side of the street. Non-pedestrian transport routes (such as railways, metro lines and river transport routes) were removed from the map for the current exploratory work, although these form obvious designated points of origin of pedestrian traffic for the future extensions of the framework. Also, local pedestrian to road traffic interactions (including cross-walks and traffic lights) were omitted from consideration in order to focus on the primary effects of the global street layout. This can be additionally incorporated at later stages. Each simulation was run for 3000 iterations, representing 50 minutes of real time.

Table 3. Pedestrian throughput of different street profiles

Type	Throughput
Footways and walkways	3
Steps and stairways	2
Residential area streets	4
Pedestrian paths in parks and green areas	6
Major thoroughfares (highways, embankments)	12
Main streets (primary roads)	8
Side streets (secondary and tertiary roads)	6

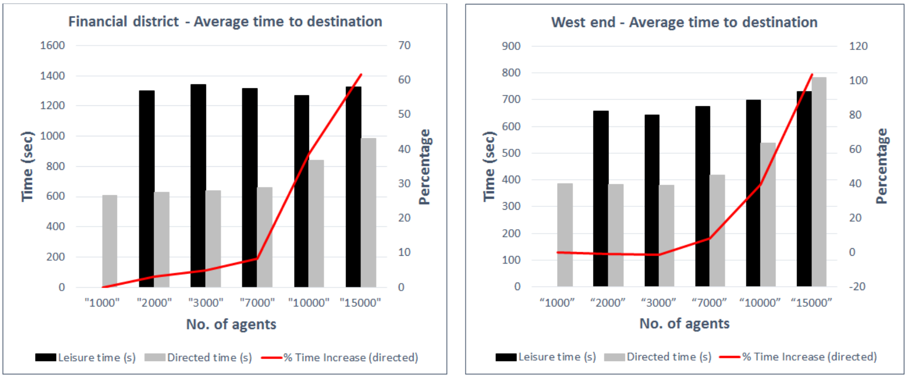

Fig. 4. Average walking times for various pedestrian ratios (directed vs. leisure). The red line indicates relative change in travel time of directed agents, with the inflection point marking the point where the network starts experiencing significant congestion.

3.3 Results

Figures 5 and 6 represent the density and flow of the two major pedestrian categories for scenarios 1 - 6 from Table 2. The results help gauge the ability of the inner city network to accommodate pedestrian traffic densities. For public transports origin points in both areas, we have used the nearby London Underground stations.

From the graphs and model visualisations several marked phenomena can be observed:

- **Lane formation.** As an individual agent's waiting period typically allows the agent in front to move one step, pedestrians naturally form lanes of traffic going from origin to destination. Only at intersections where multiple flows merge, does an agent wait long enough to consider taking an alternate route. For directed flows, lanes are mostly formed closer to origin point, while for leisure traffic these tend to occur at intersections where multiple flows meet. For single origin traffic (e.g. pedestrians originating from a single underground station), the fan out degree (number of distinct lanes) of lane formation is fairly small, with primary roads having highest flow. Side streets are much less used as alternative means of navigating to the destination.

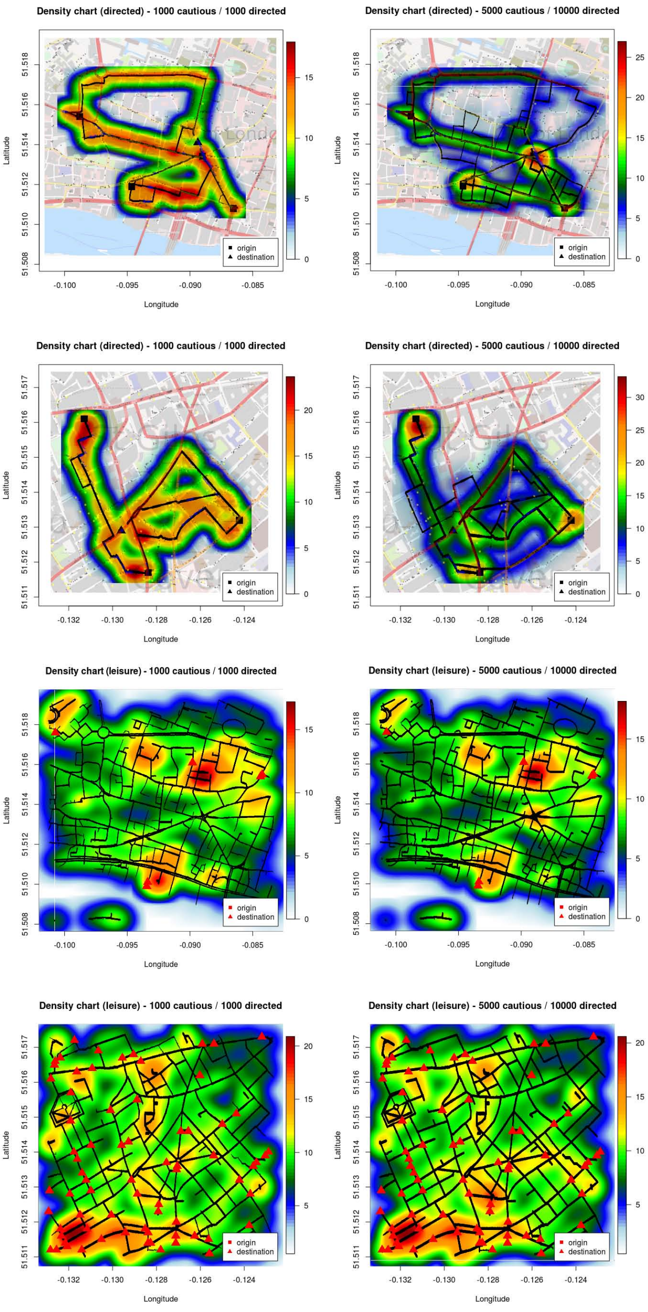

Fig. 5. Density diagrams comparing low and high congestion scenarios for directed (top two rows) and leisure traffic (bottom two rows) in London city vs. West End. The colours indicate approximate density per $9m^2$ (a single step, unit time interval of 1 second, in any direction from the agent's current location).

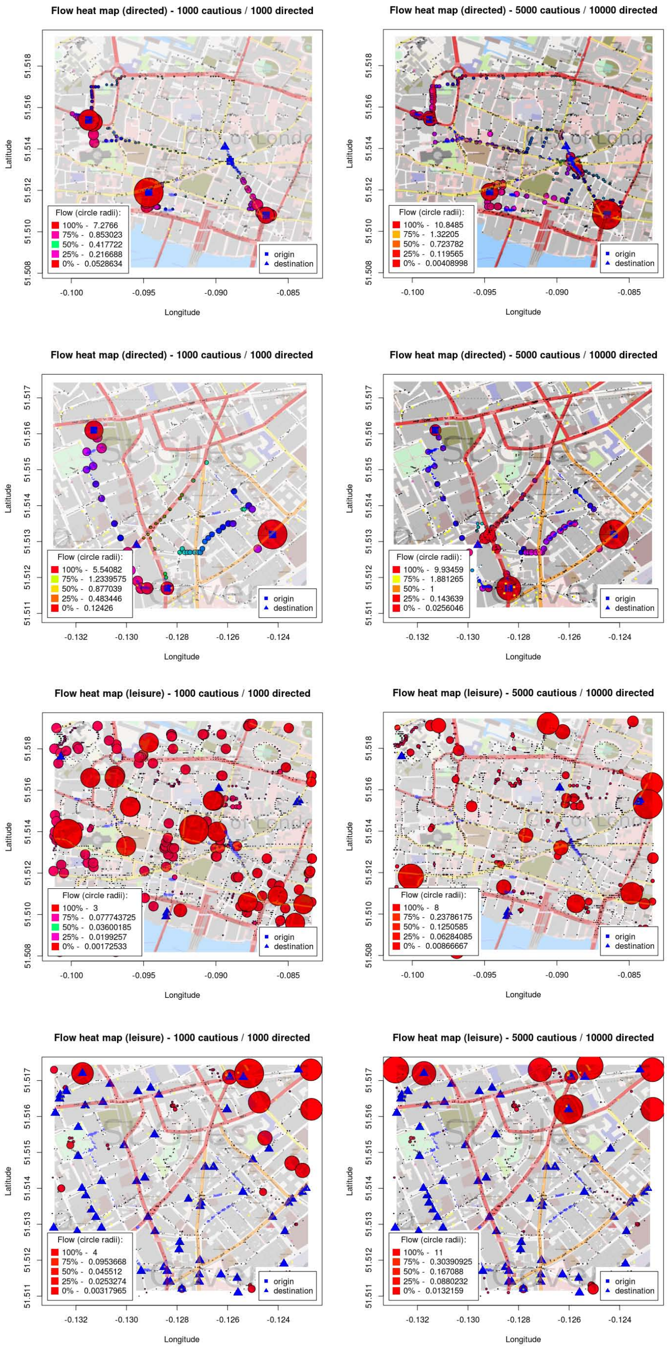

Fig. 6. Flow diagrams comparing low and high congestion scenarios for directed (top two rows) and leisure (bottom two rows) traffic in London city vs. West End. The circle size indicates flow rate of pedestrians per unit time.

- **Jamming.** In situations where the destination node has a limited number of approaches (Figure 5 top row), traffic merging on a given approach will cause local congestion, with agents attempting to re-route to a second approach but being blocked by traffic streaming in that direction. A given number of agents will take a sub-optimal (longer) route to avoid this block (Figure 5 top row, right.), but the majority stays at the intersection until the flow of traffic subsides as preceding agents reach the destination.
- **Local congestion avoidance.** As shown by the pedestrian path traces in Figure 5, pedestrians of both behaviour types (having both local and extensive knowledge) exhibit only localised congestion avoidance by preferring shortest routes around the congestion point instead of seeking alternative approaches *ab initio* to destination (i.e. these are reactive rather than planned). In this scenario the utilisation of side streets becomes significant. In extreme cases, this local congestion avoidance will be repeated as congestion occurs at every proximate side street intersection causing the network of side streets to become crowded in turn. Layouts, such as the one of Figure 5 second row, where central intersections have large interconnection degree and better side street connectivity, allow agents to switch from one major road to another by traversing side streets and generally give rise to lower travel times.
- **Venue dispersion effect.** Venue grouping has a *significant effect*, both on travel time and total network congestion. In the financial district layout, available leisure venues were grouped in several distinct places on the map, requiring lengthy paths from any given point on the grid. This extends the time interval for which pedestrians are present on the network, increasing congestion pressure. Layouts where the distribution of venues is more uniform across the map exhibit lower congestion, and consequently, shorter travel times, (note here, of course, that pedestrians rarely choose the 'nearest' map venue as their destination, instead picking distant ones causing paths to intersect across the network).
- **Network inflection points.** As shown in Figure 4, and in flow graphs in Figure 6, both urban networks are large enough to contain the the total number of pedestrians in the simulations. However, each network grid exhibits an 'inflection point' at which traffic levels start to exponentially impact on directed traffic, which is unable to find routes allowing free flow, thus leading to jamming behaviour. Again, networks with smaller interconnection rates exhibited inflection points for lower pedestrian traffic numbers.

4 Conclusions and Future Work

In this paper we have shown the potential for modelling macroscopic pedestrian flows using the agent based paradigm, combined with cognitive behaviour characteristics of different pedestrian groups. The main objective was to build an initial, general framework enabling adaptable combinations of elementary behaviours giving rise to more complex scenarios. We have demonstrated the ability of the framework to mimic important flow phenomena and to facilitate comparison of the effect of different urban grid structures. By using dynamically sourced map data, we were able to compare arbitrarily chosen city layouts. Of future interest is the expansion both in number of points of origin as well as behavioural features, to include addition of connected groups (such as families with children) rather than individual pedestrians. Additionally, network characteristics, such as "closeness" and "betweenness" metrics of nodes [23], and their correlation with traffic flows could be investigated, in order to provide a fuller picture of morphological effects. Validation against experimental observations of pedestrian traffic behaviour is obviously crucial, but dependent on detailed publicly available sources with social media recording (typically) only endpoints. Utilisation of census data is however a realistic objective for refinement of pedestrian group profiles.

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