Simulating pedestrian flow dynamics for evaluating the design of urban and architectural space

Arash Jalalian, Stephan K. Chalup and Michael J. Ostwald

The University of Newcastle, Callaghan, Australia

ABSTRACT: This paper proposes a new method for pedestrian behaviour analysis in simulated urban environments. Our proposed software system analyses pedestrian behaviour with a combined focus on movement trajectories, walking speed and the angle between the movement vector and gaze vector of individuals in large groups of simulated pedestrians. The system learns a statistical model characterising normal behaviour, based on sample observations of regular pedestrian movements without the impact of significant visual attractions in the environment. Sudden changes of the pedestrians’ behavioural characteristics, caused by the visual detection of “attractive” objects, are considered as abnormal behaviour. The simulated environment, which is at the core of the research can be automatically generated using scanned line drawings of two-dimensional street maps or public spaces. In the simulation model a variety of scenarios can be defined and modified by altering different parameters. Using the example of Wheeler Place in Newcastle (Australia) our pilot experiments demonstrate how pedestrian behaviour characteristics can depend on selected abstract features in urban space. The purpose of the system is to support architects and urban designers to better assess the impact of pedestrian behaviour on planned urban spaces and streetscapes.

Keywords: Human behaviour analysis, Design evaluation, Pedestrian behaviour modelling

INTRODUCTION

Analysing pedestrian flow dynamics in indoor and outdoor areas is an important facet of architectural and urban design. While a range of software programs have been developed in recent years to model idealised pedestrian flow between entry and exit points in a plan, such software typically neglects to consider the impact of ‘attractors’ and of the human gaze. In “public” places, including both external environments (streets and plazas) and internal spaces (malls and museums), ‘attractor’ objects, like billboards or display stands, distract pedestrians from following a direct path towards their destinations. While there are a range of possible names for these visual distractions, in the present paper they will be described as ‘attractive objects’. It can further be assumed that these objects have different levels of attraction; some will attract a pedestrian’s gaze, while others will completely interrupt their passage. An object with a low level of attraction, such as a piece of writing on the wall, would typically not attract pedestrians who walk fast. However, by placing objects with higher levels of attraction into the scene it is possible to reduce the speed of pedestrians, making them attractive to the objects with lower levels of attraction. The importance of this type of analysis is that it can be a useful predictive and analytical tool not only in architecture and urban design, but also in crowd management, transport facilities management, crime prevention, disaster planning, marketing, and epidemiology. Hence the ability to predict the response of a pedestrian in an urban area to his or her surroundings is important in estimating the effects of changes in the built environment.

The reality is that, contrary to most software simulations, pedestrians do not always follow a simple path along the line connecting origin to destination. Furthermore, in contrast to vehicular flows, which circulate along fixed corridors of the road environment and are subject to specific traffic rules, pedestrian flows are characterised by a significant degree of randomness, so that one could consider each individual’s trip is unique (Yannis and Golas 2009). Simulating and analysing such a big data-set of behaviours calls on an advanced intellectual method involving many ingredients such as navigation and orientation, evaluation and decision making, variation of personal behaviour, and crowding. Therefore, computational tools are crucial to map this randomness into a real-time model that simulates pedestrian behaviour. Regression models (Older 1968), gravity model formulations (Ness et al. 1969), doubly-constrained models (Hagishima et al. 1987), generic coupled differential equations (Gloor et al. 2003), and discrete choice models (Antonini et al. 2006) are all examples of applied analytical computational models in pedestrian behaviour simulations. In analytical models, changes in pedestrian behaviour are expressed as a mathematical function that controls the average pedestrian movement. Since the analytical models apply the same rules to all simulated individuals and perform a simulation based on average characteristics, they are restricted in simulating pedestrian behaviour that in reality would vary much more depending on different plans, personal behavioural characteristics, and social preferences.

One of the useful ways of modelling pedestrian behaviour and overcome the shortcomings of the analytical models, is to develop an agent-based simulation. An agent-based simulation is a computational model for modelling the behaviour of autonomous agents. In agent-based modelling (ABM), a system is modelled as a collection of autonomous decision-making entities called agents (Bonabeau 2002). For an architectural or urban simulation to be
is a multi-agent simulation software (U. Wilensky 1999). Francesca Camillen (2009) has confirmed the usefulness of Castello Ursino in emergency situations. They modelled the environment in 2D using the NetLogo platform which is intended for use in graphical computer simulation. In agent-based pedestrian simulation, Marksjo (1985) have presented a macro-simulation cellular approach to model interactions between pedestrians and the effectiveness of agent-based simulations in the design and analysis of complex social systems. Such simulations are used to support more traditional strategies already available to the engineers. For example Gipps and Marksjo (1985) have presented a macro-simulation cellular approach to model interactions between pedestrians which is intended for use in graphical computer simulation. In agent-based pedestrian simulation, cellular automata and intelligent agents have had a huge growth in adoption in recent years (Burstedde et al. 2001; Francesca Camillen et al. 2009; Wang and Chen 2009). In another example the team of Kzuhiro Yamamoto (2007) have proposed the use of real coded cellular automata as a new numerical model for pedestrian dynamics. They have obtained the critical number of people below which the clogging appears at exits of rooms. In all cellular approaches, researchers have assumed that in each cell, only one agent can be placed. Cellular approaches ease the way for simulating pedestrians; however they also reduce the accuracy of pedestrian models in urban areas. While agent movements in cellular models are limited by cell sizes, in the real word pedestrians are not limited to follow cells and can choose their next step in any direction.

Virtual pedestrians placed in architectural space aid in analysing the effectiveness of the space and improving the design of the space. Thiele (2002) has discussed the importance of virtual architecture in design and using the computer world as a suitable medium by which designers can convey the human side of design. An outline of Cura, a virtual presenter, was presented by the author to demonstrate the idea of using simple intelligence (SI), instead of artificial intelligence (Al). Simulating the behaviour of pedestrians in ‘normal’ situations is also important in urban planning (Jiang 1999), land use (Parker et al. 2003), and traffic operations (Cetin et al. 2002). By analysing this behaviour in different spaces the usage of those spaces can be assessed. Behaviour normality analysis is an active research topic to increase the security of public places such as museums, parks, and cinemas. One of the most popular methods to detect abnormal behaviours is comparing the behavioural characteristics with the most frequently observed behaviours in the past. Utilising advanced technology increases our computational abilities to employ complex algorithms for comparing pedestrians’ behavioural characteristics. For instance, Suzuki et al. (2007) proposed a computational method to learn motion patterns and detect anomalies by human trajectory analysis. They employed HMMs (Hidden Markov Models) to model time-series features of human positions. Using a similarity matrix of HMM mutual distances and k-means clustering they acquired features of human motion patterns.

In the present paper we simulated a multi-agent system with the characteristic dynamics of a crowd of moving pedestrians in a section of an abstract urban 2-dimensional environment. A similar approach to 2D mapping of environments has previously been proposed (Leal et al. 2006) and it has also been used in robotics for the exploration of an office-like indoor environment using a multi robot team (Lau 2003). Our approach is based on artificially generated abstract point-like agents. In the proposed agent-based pedestrian behaviour simulation each agent individually assesses its current situation and makes decisions on the basis of its current state and a set of rules. In the simulation, agents may carry out various behaviours resembling real world pedestrian behaviour in an urban streetscape. The simulation generates a set of behavioural characteristics – for example walking, running, standing, getting attracted to an obstacle, and associated changes of the gaze direction. The developed analyser software evaluates the simulated behaviours in order to identify the impacts of different walking environments on pedestrian behaviours. The analyser uses a combination of machine learning classifiers and statistical algorithms to allow it to learn past normal behaviours and distinguish between normal and abnormal behaviours in future data.

To demonstrate the software developed by the authors, a simulation using the plan of an urban space called Wheeler Place is presented. This space, located between the two busiest streets in Newcastle (Australia) features a constellation of attractive objects offering an excellent test environment for analysing different pedestrian behaviours (Figure 2). The space is next to Newcastle’s Civic Theatre and City Council Chamber and these two busy buildings have made this area to one of the Newcastle’s most crowded public areas. There are also several places of different levels of attraction in this area itself including the City of Newcastle Information Centre and Climate Meter, Juicy Beans Restaurant and Internet Cafe, a big public art work, the Civic Theatre and Civic Theatre Restaurant. In combination these contribute to offer several destinations for pedestrians who can be differentiated in behavioural characteristics, physical characteristics, and personal preferences. As shown in Figure 2, the vicinity’s five entrances (black squares) and exits (red exit signs) are restricted to several distinguishable points and pedestrians mainly choose one of these points to enter and exit Wheeler Place.

2. PEDESTRIAN MODEL

Figure 1 demonstrates our agent model in the proposed multi-agent-based pedestrian simulation. In the real world individuals have several characteristics representing their spatial behaviours in an urban streetscape such as speed of movement, head direction, and location. Table 1 describes the parameters we used for modelling a pedestrian’s behaviour.

At the start of the simulation each agent is initialised using the described parameters. Some parameters are generated randomly and others are calculated based on those randomly generated. In the initialisation step...
end_{x,y} and start_{x,y} are generated based on random values, and one start-point and one end-point are selected among the defined start-points and end-points in our urban model. In the urban model we have different categories of behaviours which are defined by the $S_{cat}$ and $V_{cat}$. In each category we have varieties of behaviours defined by a random function. To separate the behaviour of each category from others, in each category the range of randomness is restricted by defined maximum and minimum values. After initialising $S_{cat}$ and $V_{cat}$ for each agent, $V$ and $||s||$ are calculated based on $V_{cat}$ and $S_{cat}$ respectively.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit, symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>Location of an agent in the urban plan at time $t$.</td>
<td>pixel, $(x_t, y_t)$</td>
</tr>
<tr>
<td>Speed</td>
<td>Speed of an agent at time $t$, determined by speed category and location of the agent relative to its surroundings.</td>
<td>pixel, $\left(\frac{dx}{dt}, \frac{dy}{dt}\right)$ OR $(\beta,</td>
</tr>
<tr>
<td>Angle</td>
<td>The angle between the head direction and speed vector at time $t$.</td>
<td>degree, $\alpha$</td>
</tr>
<tr>
<td>Field of view</td>
<td>Standard pedestrian’s functional or useful field of view (UFOV) which is assumed to be 95°(Ball and Owsley, 1991).</td>
<td>degree, UFOV</td>
</tr>
<tr>
<td>Sight</td>
<td>Random number that represents an agent’s visual ability. It is associated with the agent’s sight category.</td>
<td>pixel, $V$</td>
</tr>
<tr>
<td>Starting point</td>
<td>The first location of the agent in the plan.</td>
<td>pixel, $start_{i,y}$</td>
</tr>
<tr>
<td>Destination</td>
<td>Final destination where the agent is going to leave the urban area.</td>
<td>pixel, $end_{i,y}$</td>
</tr>
<tr>
<td>Speed category</td>
<td>5 different speed categories to model different pedestrian behaviours subject to speed.</td>
<td>$S_{cat}$</td>
</tr>
<tr>
<td>Sight category</td>
<td>5 different sight categories to model different pedestrian behaviours subject to vision capability.</td>
<td>$V_{cat}$</td>
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</table>

In the simulation when there are no stimuli to attract pedestrians’ attention in urban space the angle $\alpha$, controlling the gaze direction, remains a small random value. This is because under normal conditions, pedestrians would typically look straight ahead such that the gaze vector can be assumed to be almost parallel to the speed vector. In all other conditions, $\alpha$ will be changed accordingly. The aim of each agent is to reach $end_{x,y}$, and therefore the direction of movement, $\beta$, is determined by a random value and the direction of an imaginary line passing through $end_{x,y}$ and $start_{x,y}$.

### 3. URBAN MODEL

In our simulation the urban model was obtained by using a scan of a plan of Wheeler Place. As shown in Figure 2 the considered area has five entrances and exits ($start_{i,y}, end_{i,y}$: $i, j = 1 \ldots 5$). Each attractive object is surrounded by a circle that indicates its assumed level of attraction. The radius corresponds to the attraction level. In the reported simulation experiments we have selected five positions (Pos#1, Pos#2, ..., Pos#5) where attractive objects can be placed (see Figure 2). During simulation, once an agent’s UFOV overlaps with the attraction area of an object the agent will move towards the object with the maximum allowed speed in its speed category $S_{cat}$. Therefore objects with higher levels of attraction can attract agents with the same $V_{cat}$ further distances. On the other hand agents with bigger $V$ can be attracted by further objects with the same level of attraction.

In the urban model the following terms are used: image plan which is an aerial one-point perspective plan of the area; start points, the locations of the entrances and end points, the locations of the exit points. There is also object location, the location of the attractive object on the image plan ($obj_{i,y}$); object visit counter, which shows the number of agents that have been attracted to the object and finally object attraction level, which defines the level of attraction for an attractive object. We have also assumed that boundaries of pathways and other obstacles such as trees are impermeable.

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4. BEHAVIOUR SIMULATION

In the simulation each agent assesses its behaviour according to several decision making rules defined by the pedestrian model and the urban model. We defined two major types of agents; attracted agents and normal agents. While the former is attracted to an attractive object, the latter has not seen any attractive object and just moves along the normal direction of movement towards its destination. Normal directions of movement are defined by the lines between start points and destinations. Each agent has selected one normal direction in the initialisation stage.

Agents may carry out various behaviours roughly resembling real world pedestrian behaviour in an urban streetscape such as walking, running, standing, or attracting to an obstacle. Regarding to pedestrian’s reaction to the attractive objects in an urban area, pedestrians may have four different spatial behaviours: becoming attracted (when they see the object for the first time, and they believe the object is attractive for them), not becoming attracted (when they can see the object for the first time, and they believe the object is not interesting enough for them to attract them), visiting (stopping while they are studying the object) and normal (while they cannot see any attractive object). In the simulation various behaviours are defined by changing an agent’s characteristic parameters. To obtain the next location for each agent we first calculate the direction of movement, $\beta_{t+1}$, as follows:

$$\begin{align*}
\beta_{t+1} &= \begin{cases} 
\tan^{-1}\left( \frac{end_y-x_t}{end_x-y_t} \right) + \text{rnd} \cdot \beta_{osc} & : \text{normal/not becoming attracted} \\
\tan^{-1}\left( \frac{\text{obj}_y-x_t}{\text{obj}_x-y_t} \right) + \text{rnd} \cdot \beta_{osc} & : \text{visiting} \\
\beta_t & : \text{becoming attracted}
\end{cases}
\end{align*}$$

Here $\text{rnd}$ is a random value in $[0,1]$. Since pedestrians do not walk exactly on a straight line, we simulated this behaviour by using $\beta_{osc} = 20^\circ$ which indicates the oscillation range for $\beta$. When the UFHOV for an agent overlaps with the circle indicating an object’s level of attraction, the simulated agent will be notified of the attractive object. In this case, the agent uses the “becoming attracted” equation to calculate $\beta_{t+1}$. By using this equation the agent moves towards the object instead of the end point. When the agent comes close enough to the object, it will spend some time standing at the object and studying it. During this period (“visiting”), the direction of movement remains constant. In all other times the agent shows normal spatial behaviour and uses the “normal” equation to calculate $\beta_{t+1}$. In a real world scenario, while pedestrians are moving, they do not always look straight ahead. To simulate this behaviour we defined $\alpha_{osc}$ as the oscillation range for the relative gaze angle $\alpha$, in normal behaviour, which is calculated as follows:

$$\alpha_t = (\text{rnd} \times 2 \times \alpha_{osc}) - \alpha_{osc}$$

In ‘not becoming’ and ‘becoming attracted’ behaviours the agent’s gaze vector points to the attractive object.

To obtain the next location for each agent we also need to calculate speed of movement, $||\dot{s}||$. In the simulation we used five different speed categories for each agent. Each category has a maximum speed and a minimum speed.
Agents choose their speed category when they are initialised and this category remains constant during the agent’s lifespan. $\|s\|$ is obtained as follows:

$$\|s\| = \begin{cases} 
\frac{1}{2} s_{\text{max}}(\text{rand} + s_{\text{cat}} - 1) & : \text{normal/not becoming attracted} \\
0 & : \text{visiting} \\
\frac{1}{2} \text{rand}(s_{\text{max}}s_{\text{cat}}) & : \text{becoming attracted}
\end{cases}$$

Where $s_{\text{max}}$ is the maximum possible speed, and rand is a random value in [0,1]. By applying $\beta_{+1}$, $\|s\|$ and $(x, y)$ in the following equations and solving them for $(x_{t+1}, y_{t+1})$, we obtain the next location for each agent:

$$\begin{align*}
\|s\|^2 &= (x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2 \\
\beta_{+1} &= \tan^{-1} \left( \frac{x_{t+1} - x_t}{y_{t+1} - y_t} \right)
\end{align*}$$

Since we assumed boundaries of pathways and other obstacles such as trees to be impermeable, we developed an algorithm to extract the boundaries and the obstacles from the image plan using image processing techniques. We applied Otsu’s method, which chooses the threshold to minimize the intraclass variance of the black and white pixels, to extract objects from the image plan (Otsu, 1979). The extracted boundaries and obstacle information are then used to validate the obtained next location for each agent $(x_{t+1}, y_{t+1})$.

5. PEDESTRIAN BEHAVIOUR ANALYSER

In order to analyse a pedestrian behaviour, we have previously proposed and applied a new approach for outlier detection (Jalalian et al. 2010). This approach utilises a combination of one-class support vector machines and dynamic time warping to identify pedestrians who show abnormal changes in their direction of movement, in their gaze direction or their walking speed. Our system analyses pedestrian behaviour with a combined focus on $(x, y)$, $\beta$, $\|s\|$, $\alpha$, and $\alpha/\text{dt}$ of individuals in large groups of simulated pedestrians. The system learns a statistical model characterising normal behaviour, based on sample observations of regular pedestrian movements without the impact of significant visual attractions in the environment. Irregular pedestrian behavioural characteristics, mainly caused by detection of visually attractive objects, are considered as abnormal behaviour.

We employed one-class support vector machines (SVMs) combined with Dynamic Time Warping (DTW) to separate agents into two classes; attracted agents and normal agents. One-class SVMs are able to differentiate one class of data from the rest of the data in the input space based on similarities (Vapnik, 1998). They are useful when we have either only positive or only negative data because they are trained on one group of data only. Since in the simulation attracted agents may show unpredictable behaviours, it would be impractical to train the classifiers with their behavioural data. Therefore to detect outliers and distinguish between normal samples and attracted samples we fed normal data to the classifiers. Our implementation uses SVMs with Gaussian Kernel Function as provided by the LIBSVM toolbox (Chang and Lin 2009).

Classification of noisy features can be a serious challenge. To keep the false detection rate as low as possible, we applied dynamic time warping (DTW) combined with SVMs. DTW is a popular method that has been used for comparing two different sound spectrums with different lengths (Sakoe and Chiba 1978; Keogh and Pazzani 2001). The ability of DTW to compare two different signals and calculate the distance between them makes it a suitable tool for comparing the complete sequences of locations, speeds, angles and their derivations.

6. EXPERIMENTAL RESULTS AND DISCUSSION

Although human walking speed can vary greatly depending on factors such as height, weight, age, terrain, surface, load, culture, effort, gender and fitness, it can be categorized into five distinguishable ranges in urban areas (Burnfield and Powers 2006). Figure 4 shows five different speed categories and their typical random characteristics for five agents in our simulation. As shown in this figure, there is a considerable difference in $\|s\|$ among different speed categories. Each agent moves with a random speed within the boundaries of its speed category. Using different categories of speed and sight, simulates different spatial behavioural characteristics.

The experiment shown in Figure 3 displays the simulated agents’ trajectories. In this example we used the five speed categories and distinguished them by colour-coding in the Hue Saturation Value (HSV) colour system. From left to right the colour bar at the bottom of the Figure 3 represents speed categories with higher speed. In this figure each circle represents an attractive object. The number of agents attracted to each object is shown in the centre of the circles. The number of agents that have been attracted to an object depends on many factors such as level of attraction for the object, and location of the object relative to the start points, end points and other objects.

We have developed the simulation software, the analyser and their Graphical User Interface (GUI) in the MATLAB R2010a environment. Our GUI provides several tools to change different parameters of simulation. This includes changes in maximum number of agents in the scene, methods of training the classifiers, image plan, start points, end points, number of speed categories, number of sight categories, levels of attraction for attractive objects, animation settings and visualization settings. The interface also provides the ability to save a running simulation and load it in the future. This helps designers to change a variety of settings and examine the impacts of those settings on the same design. Employing MATLAB and developing the simulation software from scratch, enables us to store the
simulation results in any desired data format. This provides enough flexibility for other software developers to use our simulation results in other software and programming platforms.

Figure 3: Colour-coded speed representation in scenario 2

Figure 4: Five agents with five different speed categories.

Figure 5 (left and right) illustrates typical simulated behavioural characteristics for an agent. As shown in this figure, although the agent could see two objects, it was attracted to the first one and did not like the second one. The period that the agent was attracted by an attractive object is called the visiting period (dark grey areas in the figures). During this period, the agent was not moving and most of the behavioural characteristics remain constant. Just before the visiting period there is the “becoming attracted” period. In this period, the agent moves towards the object with highest allowed speed defined in its speed category (Figure 5). The $\beta$ and $\alpha$ curves also show a significant change during this period which represent change in direction of movement and the angle between the head direction and speed vector respectively. Figure 6 highlights trajectories for normal and attracted agents in scenario 10. The type of each track is identified by the analyser using simulated value for $( (x_t, y_t), \beta_t, s||, \alpha_t$ and $da_t/\text{dt})$. Applied classifiers in previous approaches analysed pedestrian spatial behaviour using normal and abnormal data sets. This increases the error rates when we can only observe a small proportion of all possible abnormal behaviours. Using normal data with one-class SVMs increases the accuracy of the analyser to 93%.

While the actual level of attractiveness of an object to any given person, cannot be predicted with any accuracy, we can make several informed assumption about object attractiveness to support the early stages of the simulation testing. For example, as discussed in the introduction, At Wheeler Place there are five obvious locations that can represent attractive objects including the art work and the Civic Theatre, which can be regarded as highly attractive and the rest as less attractive. In Figure 2 we have indicated five positions in the plan to put five attractive objects. We assume there are two levels of attraction; ‘high’ and ‘low’. Table 2 lists 10 possible scenarios that were considered in our simulation experiments of Wheeler Place. Because we have 5 positions to put 5 objects, two of which have a low level of attraction and three with a high level of attraction, the number of permutations for placing objects in positions without repetition is $5!/(3! \times 2!) = 10$.  

Figure 5: Simulated behavioural parameters for an agent; visiting period (dark grey area), becoming attracted period (light grey area), not becoming attracted period (patterned area) normal behaviour (white area)
Figure 7 shows the probability of attraction for different positions in all possible scenarios with respect to the number of simulated agents. The results shown in this figure were obtained from simulating 5000 pedestrians for each scenario. As shown, the 4th position has the highest probability of attracting agents in all scenarios. Placing a highly attractive object in this position and a less attractive object in 5th position (as in scenario 2) will balance the attracted crowds on both sides of Wheeler Place. The last column of Figure 7 shows the probability of attracting a pedestrian to an attractive object in Wheeler Place. These simulations demonstrate that arranging the objects based on scenario 2 will result in the highest number of attractions compared to the other scenarios.

Pedestrian spatial behaviours depend on different plans, personal behavioural characteristics, and social preferences. Using analytical models (Gloor et al. 2003) to simulate these behaviours based on average characteristics, leaves a considerable proportion of behaviour categories unexplained. Using multi-agent-based cellular models, on the other hand, to overcome this problem has its own difficulties. In the real world, pedestrian movements include a great variety of speeds and directions. Using cellular approaches (Burstedde et al. 2001; Francesca Camillen et al. 2009; Wang and Chen 2009) to model pedestrian spatial behaviours restricts this variation to several available cells for each agent. The cellular approaches not only restrict freedom of choice in direction at each step but also, the agents’ speed can only be generated based on the cell sizes. In contrast in our approach, agents can be designed with a high degree of freedom. They can have a wide variety of speeds and directions at each time step (as shown in Figure 5 and Figure 3).

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<tr>
<th>Scenario</th>
<th>Pos#1</th>
<th>Pos#2</th>
<th>Pos#3</th>
<th>Pos#4</th>
<th>Pos#5</th>
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**CONCLUSION**

This paper records the development and testing of a new multi-agent-based software simulation for pedestrian spatial behavioural analysis in urban space. The simulation adds two unique features to the conventional model: gaze vector and attractor objects. The benefits of this new approach become especially clear in cases of complex spatial arrangements where changing the configuration of walking environments (and thus adapting designs) is possible. A software system and its GUI were developed by the authors to read plans, extract boundaries and obstacles from them, run the simulation and then analyse behavioural characteristics of simulated agents. The GUI offers a user-friendly environment for architects who may not be familiar with complex computer programming problems. The simulation was run for a real-world space, Wheeler Place in Newcastle. Different scenarios, with different configurations and their impacts on pedestrian behaviour were presented and discussed. The experiments show that an approximate behavioural model has been produced to evaluate the authors’ behavioural analysis system. The system can be used to demonstrate that changes in the configuration of the physical/visual built environment can be reflected by measurable changes in agent behaviour. Finally, the authors are planning to employ the analyser system described in this paper for examining real world video data collected by a pedestrian detection and tracking system.
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