Scene- and Activity-Aware Agent-based Model (SA^2-ABM): Overview, Design Concepts, and Details Document

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1. The Scene- and Activity-Aware Agent-based Model (SA^2-ABM)[1]

The purpose of *SA^2-ABM* is to enhance a basic ABM through a simple set of rules identified using the activity-driven models of as outlined in Section 3 of Crooks *et al.*, (accepted). This agent-based model is enhanced by simple behavioral rules that are presented below in order to produce more realistic patterns of pedestrian movement. These rules are informed by real pedestrian movement data and information about the physical environment through which the pedestrians are moving. We supplement this with other data from the literature of pedestrian movement where necessary. For example, it is well known that people walk at different speeds (e.g. Ando *et al.*, 1988; Fruin, 1971); from analyzing our particular scene information we found the maximum walking speed to be 1.5 meters per second and this is what we use in the model for the maximum walking speed of our agents. Nelson and Mowrer (2002) also note that humans have a psychological preference to avoid bodily contact, defined by Fruin (1971) as the 'body ellipse'. Within this model, we set for computational simplicity the agent size to be 37.5cm by 37.5cm (accounting for their anthropomorphic dimensions and body ellipse (Pheasant and Haslegrave, 2006)), as we are using an enclosure representation of a regular lattice which often treats all agents as having the same size. Alternate approaches employing continuous space representation would allow for varying sizes of pedestrian agents (e.g. to match the corresponding sizes extracted from the video feeds (D'Apuzzo, 2002)), but at substantial computational costs (Castle, 2007b). Such detailed representations of the size of the pedestrians without the transition to a continuous space would not impact the results considerably of the following ABM (this might be different if we were looking at bottlenecks or evacuation from confined spaces).

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[1] Please note this is a edited version of the model description which can be found in: Crooks, A.T., Croitoru, A., Lu, X., Wise, S., Irvine , J.M. and Stefanidis, A. (accepted), 'Walk this Way: Improving Pedestrian Agent-Based Models through Scene Activity Analysis', *ISPRS International Journal of Geo-Information*.

The SA^2-*ABM* is programmed in Java using and extending the MASON Simulation toolkit (Luke *et al.*, 2005). In Figure 1 we show the graphical user interface (GUI) of the model. Clockwise from the top left, the GUI features a map with the option to view or hide any layer of data, a graph that summarizes walking speeds over time, and the model controller. The model controller allows the user to initialize, pause, or stop the simulation, control which displays are hidden or shown, and view some basic model information along with running the different scenarios presented below. Such an interface allows for ease of use in understanding and debugging the model (Grimm, 2002).

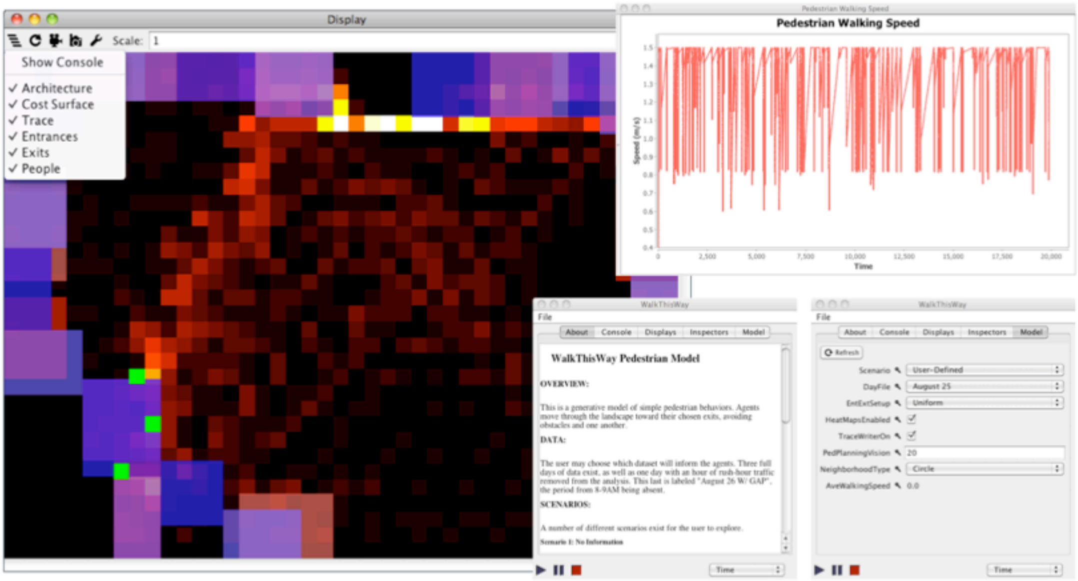

Figure 1. Graphical user interface of the SA^2-*ABM* model.

Rather than taking a forced-based modeling approach (e.g. Helbing and Molnár, 1995), which often treats people as responding to “forces” exerted by others and the environment which some would argue creates an ecological fallacy in assuming pedestrians have no internal decisions making capabilities (Castle, 2007b; Torrens, 2012), here we focus on the actions of individual entities (i.e. a rule-based approach, see Schadschneider *et al.* (2009) for a discussion of the differences) in a cell-based environment (similar to the work of Batty *et al.* (2003)). Route-choice is a critical component of any pedestrian model, as it describes the dynamic process through which people move through a scene, making and reassessing decisions as time progresses and scene traffic changes with it. Route choice is an active area of research which spans multiple disciplines such as psychology (Caduff and Timpf, 2008; Chan *et al.*, 2012), geography (Torrens, 2012), engineering (Hoogendoorn and Bovy, 2004; Wagoum *et al.*, 2012), computer graphics (Gayle *et al.*, 2009; Patil *et al.*, 2011), to name but a few. Computationally, this is a challenging issue, both in terms of theoretical and practical problems associated with describing pedestrian behavior. Two common approaches for route-choice are *shortest path* and *following signage* (Hoogendoorn and Bovy, 2004). The shortest path approach is based on the notion that individuals wish to minimize the distance they have to walk, and this is not necessarily the route indicated by signage. However, it needs to be noted that the shortest path might not be the quickest path, for example if there are many pedestrians along the shortest path, this will slow down the agents. To calculate the quickest path one needs consider dynamic routing (Wagoum *et al.*, 2012).

Both the shortest path and following signage approaches relate to the pedestrians enclosure perspective, which varies when they know or do not know their environment. People familiar with the building would have intrinsic broader knowledge of it (i.e. they are able to calculate the shortest path), whereas visitors with limited knowledge of building layout are more likely to follow emergency signage (Castle, 2007a; Wagoum *et al.*, 2012). Here we choose the simplest option where pedestrians initially follow the shortest path between entrance and exit but as they have a line of sight and carry out dynamic route-planning to avoid obstacles and other agents (see Section 1.3.4.2) they in essence find the quickest route. This is also consistent with the size of the area under consideration, where intrinsic knowledge of the environment does not greatly affect routing decisions, which are driven instead by the visual identification of entrances and exits. Work by Hillier *et al*. (1993) reinforces this idea, in the sense that they demonstrated that the majority of human movement occurs along lines of sight Also, as is common in many ABMs of pedestrian movement, we have preplanned entrance and exit locations (see Section 1.3.1) based on information from the scene itself (as discussed in Crooks *et al.*, accepted) but the choice of route is determined at run time. The remainder of this document describes in detail the ABM following the overview, design concepts, and details (ODD) protocol advocated by Grimm *et al*. (2006) amongst others.

1.1. Overview

1.1.1. State Variables and Scales

Our simulation is addressing pedestrian agents. Pedestrian objects have a physical presence, in that they uniquely occupy a location in the environment, as well as an eventual destination point through which they intend to exit the simulation. The goal of these agents is to move towards their exit locations as quickly as possible. They do so via the shortest path, however, this path can change if obstacles (such as other pedestrians) are encountered along the way (see Section 1.3.2.2). They are constrained in reaching this goal by the presence of other agents or obstacles in the simulation and their maximal walking speed; their ability to plan their future paths is limited by their 'vision' which in this case is 7.5m (the extent of the area being modeled)[2], or the distance in front of themselves they can look when planning their course. Agents are situated within an environment that contains immobile obstacles (staircases, information booths, fountains, etc.) as well as mobile obstacles (other pedestrians). Pedestrians are also aware of less tangible aspects of the situation: they know how frequently other pedestrians in the past have passed through various locations in moving from a given entrance to a given exit. Heat maps derived through scene activity can provide this information. This is akin to the notion of the emergence of a trail system whereby paths are manifested without planning or communication from users Helbing *et al*. (1997), in the sense that paths through a grassy field develop even when the field offers no substantial obstacle and a more direct but less-trodden path may be provably shorter. Agents' choices to move in accordance with the heat map have several natural analogs in the real-world, including the way individuals copy the behavior of others who are walking ahead of them or the way that patterns of movement can eventually trace out a footpath or other

[2] We have explored a range of vision parameters from 1 cell ahead to the whole scene. Setting the vision to a low value resulted in unrealistic walking patterns and as this is a flat and relatively small open scene we thought it was appropriate to give the agents the full visual range of the area.

physical indication of the passage of others, signaling where to walk. This does not necessarily mean that pedestrians seek crowded places, but rather that they tend to follow prior trails. This information is combined with the explicit distance between a given location and the goal point to form a gradient, down which the agent moves toward its goal. Part of the research done here focuses on how the construction of such gradients (Section 1.3.2.1) influences the emergent macro-scale patterns of movement over the course of the simulation, and which gradients result in realistic patterns of movement.

As the goal of the model is to connect low-level, simple decision making with macroscopic patterns, both a heat map measuring the degree to which different locations were used in transit and a full record of each agent's movement are saved out at the end of the simulation. This information can then be used to gauge the success of our model in recreating realistic patterns of movement. The results from the *SA^2-ABM* can then be compared to the real-world data (as shown in Crooks *et al.*, accepted).

1.1.2. Process Overview and Scheduling

The simulation is measured in discrete time, with each tick representing one second of time. There are two processes that are handled by the scheduler, namely agent movement and the addition of new agents to the simulation. The former happens every step of the simulation, as each agent selects a new location and updates its position accordingly. Agents update their locations one by one, in order of increasing distance from the individual's goal point. The addition of new agents into the simulation happens randomly, with each new agent addition being scheduled n time steps after the previous addition, n being uniformly distributed over the integers and having an expected value of the average time between real-world additions. The addition of a pedestrian may happen at any point during the time step. If the user chooses, instead of randomly generating pedestrians the system can read in a record of the true times at which pedestrians entered the system and initialize a series of agents based on this real-world data. This allows the researcher to explicitly compare the generated paths arising from the counterfactual world of the simulation with the real path information.

1.2. Design Concepts

The model incorporates a number of important design concepts. Primary among these are prediction, sensing, interaction, and stochasticity. The goal of the model is to see the emergence of realistic patterns in the use of space.

- **Prediction** features in the simulation in terms of agent path planning. Agents look ahead and steer towards an unoccupied space, and will not move into an occupied space. They do not track other agents to predict where they will be in the future (i.e. we don’t model collision avoidance (such as Guy *et al.*, 2009; Torrens, 2012), as this is computationally expensive), in order to plan around these future trajectories, but they do move around other agents and reroute dynamically.
- **Sensing:** There are two aspects of the environment that agents can sense, namely the presence of other agents or the presence of immobile, more permanent obstacles. Agents do not distinguish between these two kinds of impediments to movement in planning their own paths.

- **Interaction:** Agents define the environment in which other agents move because they are themselves obstacles. As a result, the set of 'obstructed' locations changes every step of the simulation. The interaction among agents is therefore exclusively accomplished through their impact on the landscape.
- **Stochasticity** enters the model as a function of the addition of agents to the simulation. When a new pedestrian is randomly generated, it selects an entrance through which to enter the simulation based on the distribution of entrances. Having selected that entrance, it then selects the exit it wants to reach from the distribution of exit destinations given its entrance. These distributions can be drawn from the data, but are still a source of randomness in the simulation. The timescale on which agents are added to the simulation is also subject to stochasticity, as described above.

1.3. Details

Within the following section greater details are provided about the intricacies of the model, specifically how the model is initialized and what the model takes as inputs (Section 1.3.1) before a discussion sub-models for gradient production and movement planning (Section 1.3.2).

1.3.1. Initialization of the Model

The simulation is initialized using geometrical and behavioral properties as they are presented in Section 3 of Crooks *et al.* (accepted). The distributions of entrance usage probabilities and the entrance-conditional exit selection probabilities were harvested from actual scene tracking data; their values are shown in Tables 1 and 2[3]. Figure 2 shows the locations of these entrances and exits. For example, Entrance 14 is the one used most often on the 25th August when pedestrians are entering the scene as shown in Table 1. Once agents have entered via this entrance they have a specific probability to leave the scene via any exit - for example, 46% of all pedestrians entering via Entrance 14 are leaving via Exit 6 as shown in Table 2. These distributions are read into the simulation, as are the locations of any obstacles in the landscape based on harvesting scene activity. The gradients associated with every entrance-exit pair are also read into the simulation for use by agents. Additional data input to the model includes obstacle locations. A single agent is added to the simulation initially, and the simulation is then started.

This raw tracking data used in this experiment was taken from the Edinburgh Informatics Forum Pedestrian Database (2010) based on a particular date (the 25th August 2009) and processed to provide the scene activity information as discussed in Section 3 of Crooks *et al*. (accepted). Tracking data were derived from video feeds at a resolution of 640 by 480 pixels, where each pixel had a spatial footprint of 24.7 by 24.7 mm. Processing of the video data resulted in tracking accuracy of approximately 9 cm (Majecka, 2009), while this is a larger error compared to say the work of Boltes *et al*., 2010[4] whose a

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[3] From the analysis of the trajectory data, more exits than entrances were identified. Specific entrances were not used on 25th August but were used on other days therefore they are used within the simulation for completeness.

[4] Readers wishing to use a tool to automatically extract pedestrian trajectories from video recordings should see http://www.fz-juelich.de/jsc/petrack/.

max error was 5.1cm, it is considered good enough for our application, in the sense we are interested in the general movement of pedestrians through a scene, not their precise movement. Especially as we resample the scene information to account for the anthropomorphic dimensions of pedestrians (as discussed below). For our simulations a scene tessellation of 43 by 32 cells (making a total of 1376 cells, of which 1231 are walkable due to existing obstacles), each having a spatial footprint of 37.5 by 37.5 cm, to better reflect the anthropomorphic dimensions of the pedestrians (as discussed above). We chose to use a regular lattice representation of space as it allows us to have the internal geometry represented as well as representing individual pedestrians but also is relatively computational inexpensive compared to a continuous space representation (Castle, 2007b) however, this restricts our ability to represent different sizes of pedestrians such as those seen in Torrens (2012).

Table 1. Entrance probabilities for each entrance derived from scene activities

Entrance Probabilities for August 25th	
Entrance	**Probability**
1	0.002
2	0
3	0.002
4	0.008
5	0.141
6	0.032
7	0.114
8	0
9	0.006
10	0.004
11	0.076
12	0.013
13	0.068
14	0.454
15	0.0253
16	0.0359

Table 2. Entrance and exit probabilities for each entrance and exit pair derived from scene activities

		Entrance															
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Exit	**1**	0	0	1	0.25	0	0	0.019	0	0	0	0	0	0	0	0.083	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0.067	0	0	0	0	0	0	0	0	0	0
	5	0	0	0	0	0	0	0	0	0	0	0	0	0.031	0.014	0	0
	6	0	0	0	0	0	0.4	0.093	0	0	0	0.361	0.167	0.469	0.46	0.083	0.588
	7	0	0	0	0	0	0	0.037	0	0	0	0	0	0	0	0	0
	8	0	0	0	0	0.075	0	0.037	0	0	0	0.028	0.167	0.063	0.005	0	0.118
	9	0	0	0	0	0.03	0.133	0.037	0	1	1	0.167	0	0	0.098	0.25	0.118
	10	0	0	0	0	0	0	0.037	0	0	0	0	0	0	0	0.083	0
	11	0	0	0	0	0	0	0.037	0	0	0	0	0	0	0	0	0
	12	0	0	0	0.5	0.194	0	0.204	0	0	0	0.028	0	0.375	0.163	0.25	0
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0.07	0	0
	14	0	0	0	0	0.209	0.067	0.037	0	0	0	0.028	0	0	0.181	0.25	0.059
	15	0	0	0	0	0.015	0	0	0	0	0	0.028	0	0	0	0	0
	16	0	0	0	0.25	0.448	0.2	0.148	0	0	0	0.333	0.5	0	0.009	0	0.118
	17	0	0	0	0	0.015	0	0.167	0	0	0	0.028	0.167	0.063	0	0	0
	18	0	0	0	0	0.015	0.133	0.148	0	0	0	0	0	0	0	0	0

1.3.2. Sub-Models

There are two specific sub-models that warrant discussion, specifically the way in which gradients are generated based on the source data (Section 1.3.2.1) and the way in which agents plan and accomplish their movement (Section 1.3.2.2).

1.3.2.1. Gradient Production

In the context of this paper, we refer to a gradient as representing a cost in some sense, associated with each entrance-exit pair. We chose to consider entrance-exit pairs instead of just exits as entrances contribute a certain scene semantic meaning. For example, a person entering the scene from door 1 and another entering from neighboring door 2 (Figure 2), may be arriving from different parts of the building, and as such they may have different intents and therefore select different exits, even though they me be temporarily spatially proximal. Two kinds of gradients were experimented within this research, specifically one that was calculated solely on Euclidian distances derived from entrance and exit locations (distance-based gradients), and second that was derived from scene activity (activity-based gradients), as shown in Figure 3. For both gradient types, the Moore neighborhood relationship was used in the calculations. For the distance-based gradients, the exit points are assigned a cost of zero, with any locations neighboring the exit points having a distance of zero plus one. Fanning out from these originally tagged locations, further neighboring cells are also associated with the cost of the tagged cell they border plus the cost of moving from that cell to the neighboring cell. In these calculations the transition from one cell to a neighboring cell is assigned to equal one[5]. The distance based gradients also incorporate information about the presence of obstacles, as obstacles are assigned an infinite cost (e.g. a large value), making these cells effectively impassible.

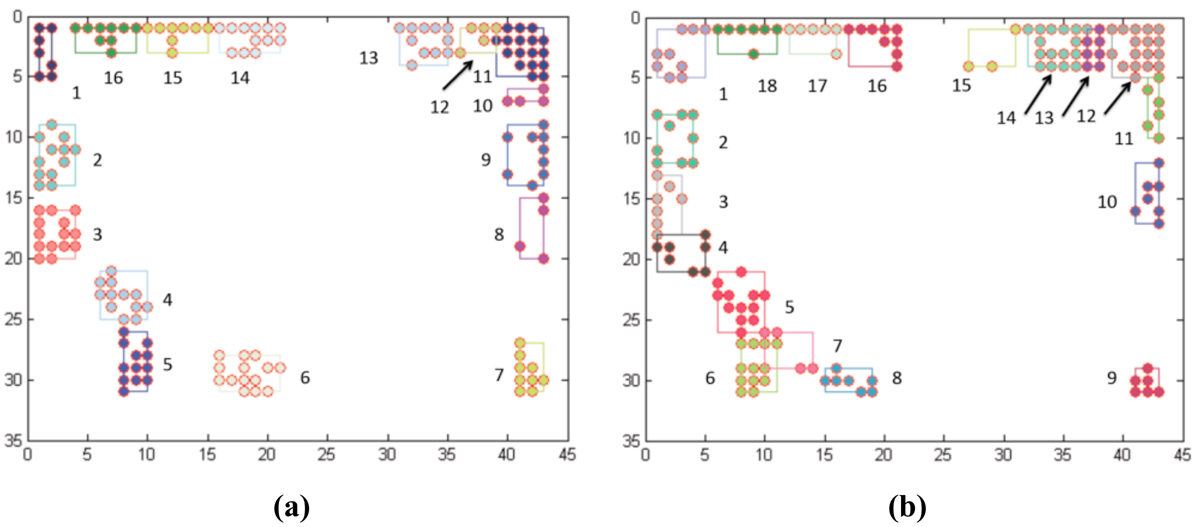

Figure 2. (**a**) Location of Entrances; (**b**) and Exits. Entrance and exit locations are identified from trajectory data and their numbers start at top left and move counter clockwise.

[5] One can consider this a simple shortest route path that can be computed with Dijkstra's algorithm.

The activity-based gradients are generated in a similar fashion, with the critical difference that the cost of moving between cells is associated with the corresponding heat map values, as drawn from the CCTV data. The heat map is generated by taking only the paths of agents traveling between the given entrance and exit, and counting the number of times each location is traversed in the data. Based on the resulting heat map, the activity-based gradients are calculated as follows. For each entrance and exit pair, the maximum heat map cell value is found and is used to calculate a difference from all other heat map cells. That value is then assigned as the activity-based gradient for the corresponding cell. One could consider this as an extension of the emergence of trails concept, introduced above but it also relates to work of Golledge and Stimson (1997) that showed that via experience of a particular space, people build up a repository of origins and destinations and paths connecting them which don't have to be the shortest path (Golledge, 1995).

These two approaches are shown in Figure 3, in which the top row illustrates process of calculating distance-based gradients and the bottom row shows the process of generating activity-based gradients. In this figure we show four steps in the calculation process, from step A (initialization) to step D (final gradient). In the top row (distance-based gradients), we see the room setup with the exit points marked with cost 0 and the obstacles in the room indicated (step A). In step B, we investigate the points neighboring exit points. In step C, starting from the exit points, we consider the cost of moving from the exit point to the neighbor point. This process of exploring neighboring cells continues, and step D shows the final gradient. In the bottom row, the discovery process is the same, except that the cost of movement between locations is drawn from the heat map shown in the lower row of step B.

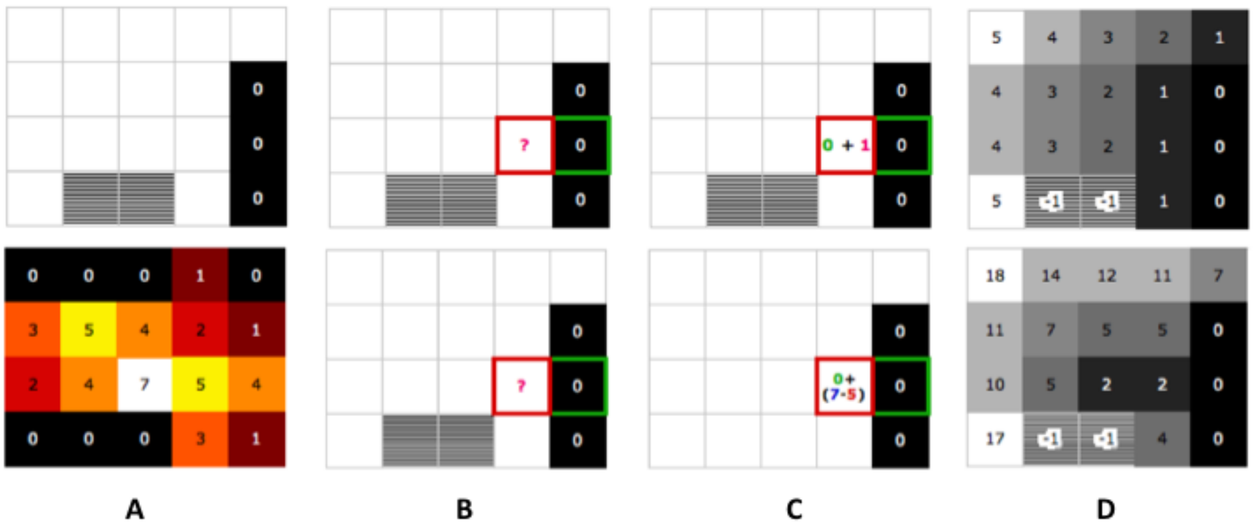

Figure 3. Constructing the gradient for the distance-based (top) and the activity-based heat map (bottom) informed spaces.

1.3.2.2. Planning Movement

While many navigation methods are possible, including visibility graphs and adaptive roadmaps (see Torrens, 2012; Wagoum *et al.*, 2012 for reviews), we are attempting to create the simplest model possible that can produce realistic patterns of pedestrian movement. In order to do so, every time an agent is called upon to move, it performs a number of checks, potentially selects a new intermediate target from among the set of cells it could theoretically reach within the time step, and then moves toward that intermediate target at the maximum possible speed. The checks which can prompt a reassessment of the agent's intermediate target include whether the agent has reached its current intermediate target point, whether the point is both near and currently occupied, whether the agent is technically moving up the gradient in approaching the point, or whether the agent lacks a clear line of sight to the point. Figure 4 sketches out this process. If any of these are the case, the agent searches to the extent of its vision for the minimum unoccupied gradient point, discarding points that do not have line of sight. This point is taken as the new intermediate target point. Given an intermediate target point, the agent determines its ideal heading. The agent moves to the available cell with the greatest dot product with the heading, selecting the cell with the lowest gradient value in the event that multiple such locations exist.

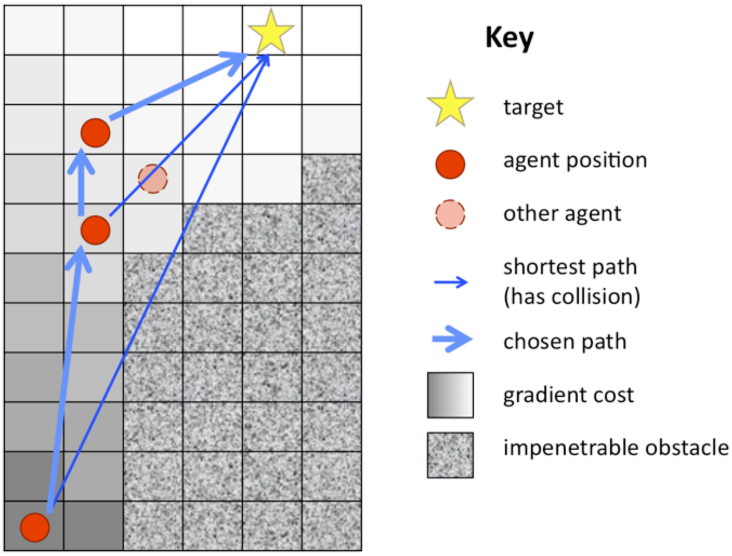

Figure 4. Diagram of the route-planning algorithm.

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