Project Checkpoint: CSE 6730 Project 1

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February 2016

1 Problem Statement

The efficient evacuation of physical structures is an important problem with a long history of multi-disciplinary study [14]. For this study, we focus specifically on the problem of efficiently evacuating the area around Bobby Dodd Stadium in Atlanta, GA. Bobby Dodd Stadium, the home of the the NCAA Division-I Georgia Tech Yellow Jackets football team, has a seating capacity of 55,000 individuals.

Figure 1: Bobby Stadium Stadium seating chart.

Our primary objective in this study is to minimize the pedestrian evacuation time of the stadium and its surrounding area as attendees leave the area following a home football game. We do this by taking a parametric approach, in which we explore the effects of road closures, strategically placed guidance symbols (i.e., signs), and the "takeover" of certain intersections by law enforcement in promoting an optimal result.

For purposes of this study, we define the system under investigation (SUI) as a rectangular polygon (Fig. 2) surrounding the stadium. To be clear, the SUI is defined as the area inside the polygon but outside the stadium. As pedestrians exit the stadium, they enter the SUI, and as the cross the boundary of the polygon, they exit it.

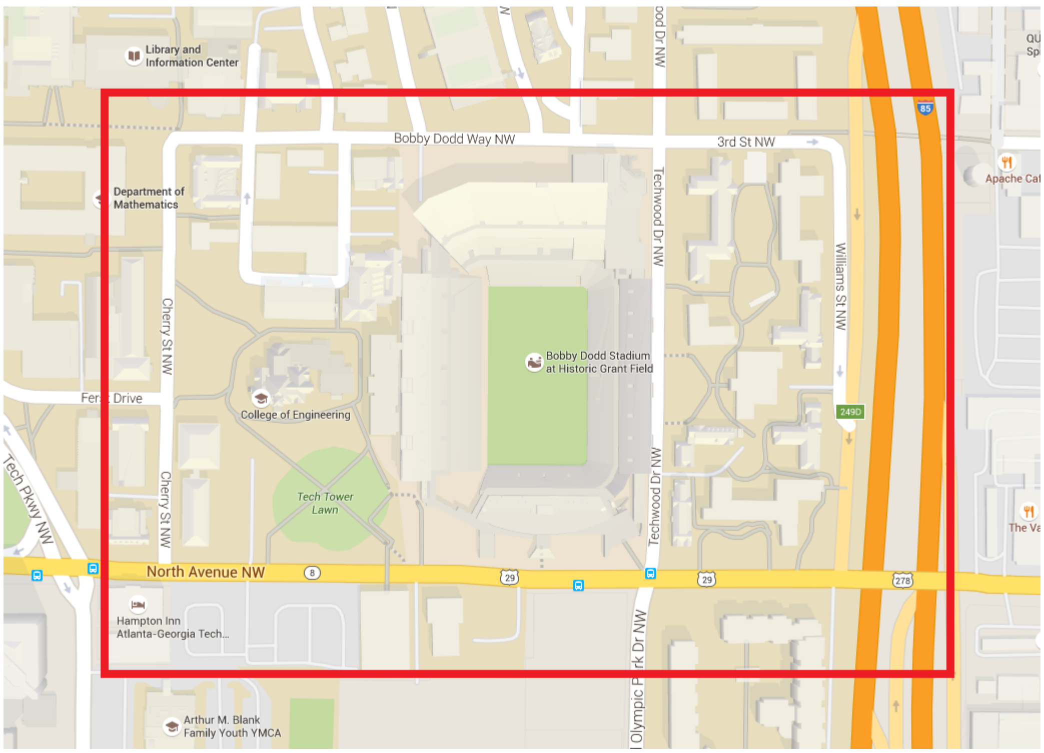

Figure 2: The system under investigation.

The stadium has 10 "gates," which serve as ingress (pre-game) and egress (post-game) sites. These serve as the entry points to our simulation. As pedestrians enter the SUI, they are assigned a destination and then proceed to their destination by way of pedestrian walking paths (i.e., sidewalks).

2 Related Work

A variety of techniques have been used to model pedestrian movement. Cellular automata, lattice gas, social force, fluid-dynamic, agent-based, game-theoretic, and animal experimention-based approaches have been used [14]. As noted by Zheng, Zhong, and Liu [14], models often encounter or attempt to model several common phenomenoma: clogging, side-stepping, lane formation, and herding behavior, among them.

These phenomena manifest themselves in different ways and at different magnitudes depending on the system being modeled. In one of the early explorations of 2D cellular automata for simulating traffic flow in the related domain of vehicular traffic simulation, Biham and Middleton [1] note the presence of a sharp *jamming transition* in which all cars in the simulation transition from moving at maximal speed to being stuck. Similar effects were noted in simulations of bi-directional pedestrian movement, with Weifeng, Lizhong, and Weicheng [12] finding that as total pedestrian density increases, a critical value is reached at which the system transitions into a jammed state where only a few pedestrians are able to proceed.

In a slightly different take on the problem, Okazaki and Matsushita [11] modeled pedestrian evacuation using Coulomb's Law, with actors magnetically moving toward their goals and away from obstacles that would lead to collisions. In another application of equations of natural phenomena, Helbing [6] derived fluid dynamic equations for explaining the movement of pedestrian crowds, observing phenomena such as the development of lanes, jamming, and crossing. Helbing [8] further notes an explicit "faster-is-slower" effect, in which attempting to move faster results in a smaller average speed of leaving at high pedestrian density in evacuation scenarios.

In a more recent study, Helbing et al. [7] use a "social force" model, which states that pedestrians operate in some sense automatically when reacting to obstacles and other pedestrians, applying strategies that have been learned to be most effective over time. Several suggestions are made to alleviate the three most common problems in pedestrian crowds: counterflows, bottlenecks, and intersecting flows. The presence of strategically placed obstacles are found to actually reduce these negative phenomena, leading to improved flow.

Building on previous cellular automata-based models, Burstedde et al. [3] introduce a *floor field*, a secondary grid of cells which underlies the main grid and acts as a substitute for pedestrian intelligence. These fields can be either static or dynamic, and are capable of promoting the avoidance of jams, as well as simulating attractive effects, in which pedestrians are more likely to follow in the paths of pedestrians ahead of them.

Taking a more algorithmic approach, Fang et al. [5] have designed a modified ant colony optimization (ACO) algorithm for optimizing pedestrian evacuation, seeking to minimize evacuation time, evacuation distance, and congestion. Kemloh Wagoum, Seyfried, and Holl [9] utilize an observation principle approach in modeling pedestrian evacuation, in which pedestrians first observe their environment and then make a final decision on strategy based on obtained data.

There are several takeaways from the literature described above that have potential applicability to the model at hand. First, on the topic of modeling pedestrian walkways, several papers focused on either a single passageway, enclosed areas with obstacles (walls, pillars, etc.), or evacuation from a room with a single doorway. However, modeling walkways as a directed graph [5] seems feasible given the problem at hand, where there are multiple pathways one can take to get to a single destination. In papers where cellular automata was utilized, the median size of each cell on the walkway was 0.4m^2 [2,3,12].

Second, on the topic of pedestrian modeling, multiple walking speed techniques were used, ranging from a constant speed of 1 m/s [12] or 1.3 m/s [3], to using a distribution resembling a step function [2] or a Normal distribution [10]. In either distribution, the median walking speed was also approximately 1.3 m/s. For reaction to stimuli, 0.3 seconds was utilized [3], which was one time step in that particular simulation. Incorporation of opportunistic side-stepping was done [2], in addition to using least-cost algorithms for establishing the path a pedestrian would like to take [5]. In the context of cellular automata, analyzing a given pedestrian's cell's neighbors in either a 4-connected [12] or 8-connected fashion [3] to decide in which direction the pedestrian would like to walk for the next time step was utilized. This, coupled with a dynamic floor field [3] to factor in long-distance forces, could be utilized.

Finally, simulation execution practices were also gleaned. Care must be taken to do parallel-based updating to avoid sequential updating from interfering with underlying model execution [2]. The practice of using a deterministic model running with randomized initial conditions has precedent [1]. Finally, to achieve statistical significance, 20 runs per configuration has been used [2].

3 Conceptual Model

For our simulation, we utilize a 2-dimensional cellular automata (CA)-based approach. We construct a discrete time-stepped model, in which the simulation clock advances by a fixed interval every time step. We utilize a stochastic (probabilistic) approach, in which the output of each individual simulation run is a random variable. Thus, multiple simulation runs will be performed and statistical analysis will be used to provide confidence levels in our results.

3.1 Inputs

The primary input to our simulation model is a stream of football game attendees (i.e., pedestrians) exiting Bobby Dodd Stadium following a home football game. For purposes of modeling this input stream, we assume pedestrian interarrival time at the stadium gate boundary is a homogenous stochastic process that follows a *TODO: insert* distribution. As pedestrians arrive at the gate boundary, they enter the SUI.

In addition, we select each pedestrian's target destination and walking speed at random. For selecting a target destination, we utilize *TODO: Allen?* For determining a walking speed for each pedestrian, we sample from a distribution previously referenced in the literature by Blue and Adler [2] (5% fast walkers (4 cells/time step), 90% standard (3 cells/time step), 5% slow (2 cells/time step)).

Pedestrians in our model can be considered a consumer entity class *Pedestrian* with attributes which will be set and updated during the course of our simulation. Table 1 provides an overview of the attributes of the *Pedestrian* class.

New instances of the *Pedestrian* class are created and initialized as pedestrians exit the stadium.

3.2 Output

For each simulation run, when all pedestrians were evacuated from the SUI we determined the simulation to be complete. As this is a stochastic simulation, the output results must be interpreted as samples from a random process.

At the conclusion of a series of simulation runs for a given set of parameters, we compute an average of the total egress duration across all runs from that series. More formally, the average egress time E_{avg} for n simulation runs can be represented as:

$$E_{avg} = \frac{1}{n} \sum_{i=1}^{n} d_i \tag{1}$$

where d_i is the total egress duration of the ith simulation run. This output can be considered a derived scalar output variable (DSOV). We then define the optimal parameter strategy to be the set of parameters P that give the the minimum value of E_{avg}.

3.3 Content

3.3.1 Approach

Pedestrians exit the stadium from one of four potential exits. To build the simulation space, we overlay a 2-dimensional cellular automata grid on a map of the SUI. We model this space as a directed graph, a type of graph in which each graph edge is replaced by a directed graph edge [13].

As pedestrians exit the stadium, they are probabilistically assigned a destination node, which can be formulated as a unique node identifier in the graph. Destinations take one of three possible classes: on-campus housing (dormitories), parking lots, or the North Avenue Metropolitan Atlanta Rapid

Attribute	Description
DestinationID	NodeID of the final destination of the pedestrian.
Speed	Walking speed, formulated in grid cells traversed per time step.
NodeID	Location of the pedestrian in the simulation, specified by a unique node identifier (NodeID).
EgressComplete	A binary value. This value is 0 when the pedestrian has not yet egressed, and 1 when egress is complete.

Table 1: Attributes of the *Pedestrian* entity class.

Transit Authority (MARTA) station.

For each node in the graph, we precompute the least-cost path to every possible desination node. We represent each node as member of a *Node* class, which has attributes as shown in Table 2.

Attribute	Description
NodeID	Unique identifier for the node.
XCoordinate	TODO
YCoordinate	TODO
Paths	A dictionary (hash map) relating each possible destination to the NodeID of the next node in the shortest path as determined by Dijkstra's algorithm.

Table 2: Attributes of the *Node* class.

At each time step, the shortest path approach is selected for every pedestrian in the path towards their destination. We compute the shortest path between any source node N_s and destination node N_d using Dijkstra's well-known algorithm [4].

3.3.2 Parameters

3.3.3 Random Numbers

To model the egress of the stadium, we take a stochastic (probabilistic) approach. In the context of a computer simulation, this necessitates the use of a pseudorandom number generator. For this study, we use the simple linear congruential approach. This generator is given a *seed* value, and then produces a uniformly distributed pseudorandom number. This value is then used to sample from a given probability distribution.

3.4 Assumptions and Simplifications

Our simulation is simplified by focusing only on *pedestrian* traffic, avoiding the inclusion of vehicular traffic. In future studies, this could be included as an enhancement.

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