PEDESTRAIN CELLULAR AUTOMATA AND INDUSTRIAL PROCESS SIMULATION

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ABSTRACT
Individuals base decisions on their surroundings and change their minds based on the action of others and interactions with the environment. Current Cellular Automata techniques for modeling pedestrian movement predetermine the individual's goals and do not change them throughout the execution of the simulation. To allow the individuals to make decisions as the simulation progresses a technique has been developed to separate the decision making process of environmental factors and the static environmental effects. Any individual can modify where they are going, based on the locations of other individuals, their capabilities of movement, current velocity and relationships to the environment. This technique will allow individuals to pick the best paths based on what is actually happening during the simulation. This technique can be used to optimize work flow strategies and seek the best way to deal with work stoppages and other problems which may arise.

Keywords: crowd simulation, cellular automata, walking worker production design

1. INTRODUCTION

The purpose of this paper is to provide a 'proof-of-concept' that a cellular automata (CA) model of pedestrian motion can be integrated into manufacturing job shop production simulations. The outline of this paper is first an introduction to models of pedestrian motion, second a description of the CA model that is used during this research, and third an argument for models of pedestrian motion in job shop production models. Next a brief overview of the modifications we have made to the original CA model which allows the model to be applied to a broad range of pedestrian modeling problems. Finally, we present a simple example of a combined pedestrian-job shop simulation.

2. PEDESTRIAN MODELS

Recently, a considerable amount of research has been done on simulating collective behavior of pedestrians in the street or people finding their way inside a building or a room. Models of crowd behavior attempt to describe collective pedestrian behaviors that result from complex interactions among the individuals composing a crowd and between these individuals and their physical environment. Reviews of the state of the art can be found in a volume containing Schadschneider (2002) and Kessel, Klüpfel, Wahle, and Schreckenberg (2002).

Existing models can be broadly separated into the following two categories: (1) discrete-space models and (2) continuous-space ones. Discrete-space, or cellular automata-based models allow pedestrians to be located at nodes of a fixed or adaptive grid, and pedestrian coordinates are updated at discrete time intervals. Particular models of this category are described in Schadschneider (2002); Blue and Adler (2002); Dijkstra, Jesurun, and Timmermans (2002); Kessel, Klüpfel, Wahle, and Schreckenberg (2002); and Batty, DeSyllas, and Duxbury (2002). The models of the second category allow pedestrians to move continuously in a part of the 2-D surface representing a street, a room, and so forth.

The continuous space models can further be subdivided. Some models, such as the ones considered in Helbing, Farkas, and Vicsek, (2000) and AlGadhi, Mahmassani, and Herman (2002), are based on a similarity between the dynamics of a crowd and that of a fluid or gas. Other models of the second category allow pedestrians to choose their paths by optimizing a certain cost function (Hoogendoorn, Bovy, and Daamen 2002). An interesting model combining the fluid dynamics approach with that of a cost function is considered in Hughes (2002); there the role of the cost function is played by the pedestrian's estimated travel time. Finally, the model considered in other sources (Helbing and Molar 1995, Helbing, Farkas, and Vicsek 2000) introduces social and physical forces among pedestrians and then treats each pedestrian as a particle abiding the laws of Newtonian mechanics.

Generally all the models mentioned above are microscopic and rooted in the 'generalized behavior concept' that is, for a model of crowd movement to be reliable it need not model any certain individual correctly - just the average behavior of a group of individuals responding to certain situations. It is assumed that since pedestrians face similar movement and route choices everyday their response become in effect automatic and can therefore be predicted. In order to mathematically model pedestrian movement one must suppose that an individual's behavior will exhibit certain regularities. With the acceptance of the premise that pedestrians exhibit regular behaviors general mathematical models of crowd dynamics can be formed.

2.1. Cellular Automata and Pedestrian Simulation

This paper focuses on modification to the implementation of Schadschneider's (Schadschneider 2002) cellular automata model of pedestrian dynamics. Cellular Automata (CA) models use logical rules and stochastic processes to define pedestrian motion. CA models divide a pedestrian's movement space into a defined number of identically sized cells, usually in a rectangular grid. Each grid cell has a finite number of states; with pedestrian models this is generally occupied or unoccupied. At a specified time step (generation) the state of the each cell is determined by some function using inputs from a neighborhood of surrounding cells.

Pedestrian movement over the grid is represented by either by sizing the lattice to allow for only one individual per cell or by tracking cell density. Movement between cells is based on a matrix of preferences (transition rules) that determines the state of individual grid cells at each generation. The matrix of preferences and neighborhood of cells are processed by a global transition function that defines cell state, the same function applies to all cells in the lattice. CA models have the advantage of being able to simulate the dynamics of large crowds in less than real time due to their discrete nature.

2.2. Floor Field Approach to CA

Schadschneider (2002) proposed a CA floor field approach that models pedestrians as elementary particles, fermions. They react to their immediate neighborhood with long-range interactions modeled through the use of mediating particles called bosons. In particle physics all elementary particles are composed of either bosons or fermions - fermions (pedestrians) resist being placed near each other and bosons (virtual traces) do not. Pedestrians are fermions thus unable to occupy the same cell (hard-core exclusion principle) and bosons model the virtual traces left behind by the pedestrians as they move over the grid. More than one boson is able to occupy the same cell, so the virtual trace and pedestrians are handled separately.

Pedestrian 'intelligence', by which we mean their choice of movement direction, is modeled through the use of floor fields. Each grid cell has attributes associated with either a dynamic or static floor field. The dynamic floor field changes with each time step as a function of the density and diffusion of bosons. The static floor field remains constant and represents and defines the attraction to exits and the location of obstacles.

The general formula for this CA model is

$$p_{ij} = NM_{ij} \exp(k_d D_{ij}) \exp(k_s S_{ij})(1 - n_{ij}) \tag{1}$$

In this formula

1. p_{ij} is the probability the pedestrian will move to a neighboring cell.
2. N is a normalization factor ensuring that $\sum p_{ij} = 1$.
3. M_{ij} is the pedestrian's matrix of preferences.
4. D_{ij} is the dynamic floor field value.
5. S_{ij} is the static floor field value.
6. $n_{ij} = 1$ if the cell is occupied.
7. k_s and k_d are coupling factors for the floor field.

The sequence of updates for this model is as follows:

1. Update the dynamic floor field based on diffusion and decay rules.
2. Calculate transitional probabilities (p_{ij}) for each pedestrian.
3. Choose pedestrian's target cell.
4. Resolve conflicts if two pedestrians target the same cell.
5. Execute pedestrian movement.
6. Alter dynamic floor field based on rules (i.e. dropping bosons).

3. CURRENT RESEARCH

Though designed to simulate crowd dynamics we believe models of pedestrian motion can be applied as valuable additions to simulations of other processes. In particular we feel that inclusion of explicit models of pedestrian motion may be beneficial in simulations of manufacturing processes such as walking worker production lines. Simulating worker movement may result in more realistic production output estimates and provide greater insights into human factors that affect the production process.

3.1. Need for Pedestrian Modeling in Industrial Manufacturing

Simulations for job shop performance and layout have traditionally been solved mathematically as 'static' problems. This allows for optimization techniques to be applied to production scheduling and job shop layout problems. In reality job shops operate as dynamic systems with complex interactions between workers and machines (MacCarthy 2001). Patterns of worker movement, the impact of shop-floor layout (local and global configurations) and presence of other workers in the manufacturing process have rarely been explored in job shop simulations.

Walking worker production designs may potentially benefit from explicit simulation of worker (pedestrian) movement. Under this method workers build a product completely from start to end. Walking workers production designs provide flexibility in capacity as workers may be added or removed from the production line in response to the output demand. Two common types of walking worker production lines are: 1) liner production lines where assembly operators travel along the line carrying out each assembly task at each workstation, and 2) fixed-position assembly lines where products are placed at fixed position workstations and assembly operators move between workstations.

Past simulations of walking worker production lines have assumed equal worker efficiency and movement times (Wang 2005). Celano, Costa, Fichera, and Perrone (2004) used the critical worker concept and parameterized walking speeds to obtain more realistic simulation results for linear walking worker production line scenarios. A critical worker is one who does not have enough space or time to complete their task within a workstation thus bringing production to a halt (Celano, Costa, Fichera, and Perrone, 2004). Workers nearby who have free time and the correct skills are able to help critical workers and reduce stoppage times; however, simulation of this requires knowledge of worker location and thus the explicit modeling of worker positions. The worker's position and walking speed within their workstation influences the possibility of their intervention to help a critical operator during a stoppage.

Position, movement, and route choices of the assembly operators also play a major role in the simulation of fixed workstation production lines. Figure 1 shows a process diagram for fixed workstation walking worker models.

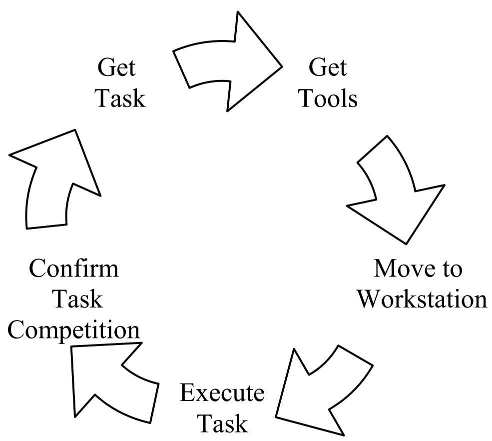

Figure 1 – Process Diagram for Assembly Operators

At a minimum two of the process tasks (get tools, move to workstation) are significantly impacted by human factors of movement and are highly dynamic. Inclusion of pedestrian movement models may also help identify bottlenecks caused by human factors association with position and movement, test the robustness of the production line design to handle the addition and subtraction of workers, and assist in the design of the production line, for example moving workstations that are likely to have critical worker stoppages to highly trafficked areas.

3.2. Modifications to Pedestrian Model

Our implementation of Schadschneider's (2002) floor field CA model modifies the static floor field by splitting it into two fields: 1) one static field for obstacles and static environmental attraction and repulsion forces and 2) a second dynamic field which determines individual's attraction towards a goal or point of interest for the individual. Additionally we deviate from their homogeneous approach by allowing each agent to store its own representation of the dynamic field. This allows each individual pedestrian to change desired destinations based on the evolving environmental conditions.

Through this implementation individuals can be seen to adjust their movement and choose a new exit when conditions such as their inability to move forward, or the density at an exit becoming too large. Modifications of our technique to allow individuals to dynamically select exits based on environmental conditions allows for production line workers to shift between tasks and workstations as well as to go to workstations which need the most assistance.

Cellular automata models as discrete models are well suited for the inclusion of hierarchal rules sets that provide 'intelligence' to the simulated agents. Using multiple static floor fields to describe the job-shop environment and use of hierarchal rule sets to determine agent (worker) objectives, we demonstrate a 'proof-of-concept' that models of pedestrian motion can be integrated into production process simulations. We do this by example using standard linear and fixed position job shop layouts for walking worker production lines. Our production line simulations are implemented in the UCF Crowd Simulation framework (available at http://www.simmbios.ist.ucf.edu/Research/DynamicHumanBehaviors/Repository.aspx) built using the MASON library (Luke, Cioffi-Revilla, Panait, Sullivan and Balan, 2005).

4. PRELIMANRY RESEARCH

4.1. Comparison Job Shop Model

The manufacturing system design used in this research was presented as an example of a Job Shop model in Law and Kelton (2000). The job shop is modeled as a network of five-multiserver queues. The system has five workstations with 3,2,4,3 and 1 identical machine(s) respectively. Job inter-arrival times are identically individually distributed (IID) exponential random variables with a mean of 0.25 hour. There are three job types that arrive with probability 0.3, 0.5, and 0.2. The jobs must be completed in a certain route order. Table 1 shows the number of tasks and routing for each job type.

Table 1: Job tasks

Job Type	Workstation routing
1	3,1,2,5
2	4,1,3
3	2,5,1,4,3

If a job arrives at a workstation and all machines are in use the job joins the first-in-first-out queue for that workstation. The time to perform the individual tasks that make up the overall job is an independent 2-erlang random variable with a mean based on job type and station. Table 2 two defines the mean service times for tasks by workstation.

Table 2: Task Service Times (Hours)

Job Type	Mean service times for tasks
1	0.50, 0.60, 0.85, 0.50
2	1.10, 0.80, 0.75
3	1.20, 0.25, 0.70, 0.90, 1.00

Law and Kelton (2000) used discrete-event simulation to model the system with arrival, departure, and end of simulation comprising the three possible event types. The code to run this model was copied from Law and Kelton (2000) and is written in C. A significant feature of their implementation is that once a workstation task is completed the job is instantaneously transmitted to the next workstation to begin work or be added to that workstations queue.

4.2. Pedestrian inclusion in Job Shop Model

Law and Kelton's (2000) job shop model was implemented in our crowd simulation framework so that we may explicitly model a walking workers movement as part of the job shops manufacturing process. A simplified version of Schadschneider's (Schadschneider 2002) floor field model for pedestrian motion (described in section 2.2) was used to control worker motion. The matrix of preference and dynamic floor field were excluded.

The matrix of preference is unnecessary as our crowd simulation framework recalculates the static floor field as waypoints change and the worker's preference is always to go towards the waypoint. The matrix of preference is generally used to override the static and dynamic floor fields when, for example, individuals 'get-stuck' during evacuation simulations. The dynamic floor field is used to model the tendency of individuals to follow one another and allows for the characteristic lane formation seen in crowd dynamics. For this application we felt this tendency to follow your predecessor's footsteps was not needed. The individuals are primarily driven by the location of the next workstation (waypoint). Equation 2 shows the general formula for the equation of motion used in the pedestrian job shop model.

$$p_{ij} = N \exp(k_s S_{ij})(1 - n_{ij}) \quad (2)$$

We assume that there are always enough workers to associate with arriving jobs and the distributions and means for job inter-arrival time and task service time are the same as those given in the Law and Kelton model (2000).

The workflow for our JAVA implementation of the model for individuals is shown in Figure 2.

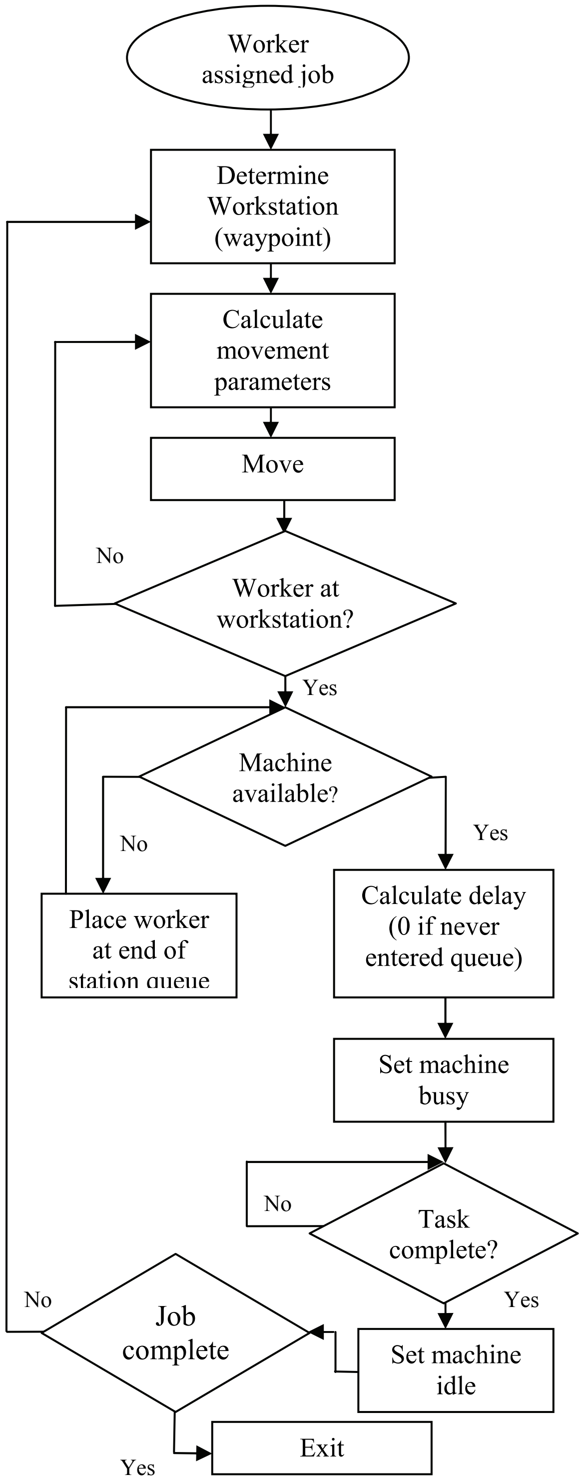

Figure 2: Flowchart for Worker Process

We do not queue workers by having them stand in line. Getting agents to self organize and maintain a formation is a problem not currently addressed in our crowd simulation framework. Workers entering the queue are relocated to a cell just below the workstation (the queues are labeled in Fig. 3). This is the only time that more than one individual is able to share the same cell. When a worker is removed from the queue they are placed at the original location they occupied before entering the queue. Figure 3 shows workers moving between workstations. The workers that are touching workstations are engaged in the task.

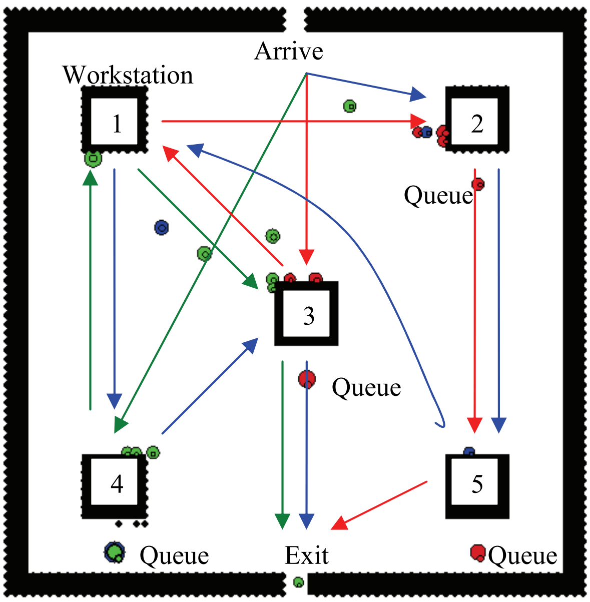

Figure 3: - Simulation Layout: Color Represents Job Type, Circles are Workers, Arrows are Routes

SIMULATION RESULTS

Law and Kelton's discrete-event simulation and our Java based simulation were both run for 98 continuous hours. Tables 3 and 4 show the summary results for Law and Kelton's discrete-event simulation code using the parameter values given in section 4.1.

Table 3: Law and Kelton: By Job Type (hours)

Job Type	Average total delay in queue
1	10.41
2	7.79
3	11.04
Overall average job total delay = 9.23	

Table 4: Law and Kelton: By Workstation

Work station	Ave. # in queue	Average utilization	Ave. delay# in queue (hr)
1	21.11	0.96	5.23
2	8.4	0.96	4.04
3	0.492	0.68	0.13
4	6.56	0.92	2.43
5	0.909	0.75	0.46

Tables 5 and 6 show the summary results for our pedestrian and job shop model. A total of 1397 workers completed their jobs during the 98 hour simulation.

Table 5: Simulation 1: Job Type (hours)

Job Type	Average total delay in queue
1	1.07
2	1.75
3	1.09
Overall average job total delay = 1.27	

Table 6: Simulation 1: By Workstation

Work station	Ave. # in queue	Average utilization	Ave. delay# in queue (hr)
1	6.41	0.91	1.54
2	16.42	0.96	1.05
3	12.81	0.98	1.18
4	7.49	0.94	2.48
5	0.11	0.42	0.06

5. ANALYSIS

The results of the two simulations differ, our pedestrian and job shop simulations have lower overall job and workstation queuing delays. The average numbers of individuals in the queues are within the same range but are ordered differently within the workstations. While one simulation run cannot provide conclusive results the difference may be explained by two factors. First the variability in inter-arrival times and task service times due to the distributions used to obtain there values. Second the inclusion of the explicit worker movement.

The time it takes workers to move between workstations and find an open space so they may be next to the workstation (they only attach to workstation if they occupy a neighboring cell) is not included in their time in queue. Their delay in queue is only calculated as the time workers actually enter the queue until the time they leave the queue. Movement between workstations in Law and Kelton's model is instantaneous thus it should be expected that queue delay times in their simulation would be somewhat higher.

Table 6 gives the minimum distances workers would have to travel along the different job routes. The movement model is probabilistic so workers would rarely if ever take the most direct route. Avoidance maneuvers (avoiding other people and obstacles) also increase the actual traveling distances and times for workers, who move at a velocity of 1.2m/s.

Table 6: Travel Distance by Job (meters)

Job Type	Center to Center Distance
1	59.02
2	51.87
3	81.6

6. SUMMARY

Our pedestrian motion model allows individuals to choose different paths on the fly. This allows for a much greater application base wherein the CA models of pedestrian motion can be used. Dynamic destination choice allows for implementation of greater agent intelligence, giving them the ability to address resource needs and modifying movement to optimize workflows. Job shop workflow models previously done by discrete event simulations did not consider the dynamics of the assembly operator's movements. This technique would allow workflow analysis to be done by not only considering the machinery processes being used, but the environment, the individual to individual interactions, and individual to workstation interactions which take place throughout the process.

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