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Cellular automata microsimulation for modeling bi-directional pedestrian walkways

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Abstract

Pedestrian flow is inherently complex, more so than vehicular flow, and development of microscopic models of pedestrian flow has been a daunting task for researchers. This paper presents the use of Cellular automata (CA) microsimulation for modeling bi-directional pedestrian walkways. It is shown that a small rule set is capable of effectively capturing the behaviors of pedestrians at the micro-level while attaining realistic macro-level activity. The model provides for simulating three modes of bi-directional pedestrian flow: (a) flows in directionally separated lanes, (b) interspersed flow, and (c) dynamic multi-lane (DML) flow. The emergent behavior that arises from the model, termed CA-Ped, is consistent with well-established fundamental properties. © 2001 Elsevier Science Ltd. All rights reserved.

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1. Introduction

In recent years, Cellular automata (CA) microsimulation has emerged as an effective technique for modeling complex behavior. CA is characterized as an artificial life approach to simulation modeling (Levy, 1992) and is named after the principle of *automata* (entities) occupying *cells* according to localized neighborhood rules of occupancy. The CA local rules prescribe the

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behavior of each automaton creating an approximation of actual individual behavior. Emergent group behavior is an outgrowth of the interaction of the microsimulation rule set.

Unlike traditional simulation models that apply equations and not behavioral rules, CA behavior-based cellular changes of state determine the emergent results. This emergence happens at a more fundamental level than microscopic car-following models, for example, that use equations to determine inter-vehicular movements, since car following models are based on formulas of interaction. The attractiveness of using CA is that the interactions of the entities are based on intuitively understandable behavioral rules, rather than performance functions. They are easily implemented on digital computers, and compared to difference equation-based microsimulation models, run exceedingly fast. CA models function as discrete idealizations of the partial differential equations that describe fluid flows and allow simulation of flows and interactions that are otherwise intractable (Wolfram, 1994). Only the local rules and the sequencing of their use are coded, leaving the many autonomous interactions on the cell matrix to create the emergent macroscopic results. As a result it has been observed in CA simulations that very simple models are capable of capturing essential system features of extraordinary complexity (Bak, 1996).

CA microsimulation has been successfully applied to modeling vehicular flows and traffic networks. They have been proven to provide a good approximation of complex traffic flow patterns over a range of densities (Nagel and Rasmussen, 1994; Paczuski and Nagel, 1995; Nagel, 1996, 1998). Over the past several years, researchers have demonstrated the applicability of CA to model car-following and vehicular flows. This work includes traffic within a single-lane (Nagel and Schreckenberg, 1992), two-lane flow with passing (Rickert et al., 1995; Simon and Gutowitz, 1998), and network-level vehicle flows in the TRANSIMS model (Nagel et al., 1996). Nagel has shown how these CA or particle hopping models fit into the context of traffic flow theory (Nagel, 1996, 1998). The CA traffic model has also been used as a benchmark to identify capabilities and shortcomings of the kinetic vehicular modeling approach (Nelson and Raney, 1999).

While the field of vehicular flow modeling is well established, researchers have found the task of modeling pedestrian flows to be daunting. In several ways, pedestrian movements are more complex and chaotic than vehicle flows. Pedestrian corridors may have several openings and support movement in several directions. Pedestrian walkways are not as regulated as are roadways. For the most part pedestrian flows are not channeled; pedestrians are free to vary speed and occupy any part of a walkway. Unlike roadways where vehicle flow is separated by direction, bidirectional walkways are the norm rather than the exception. However, since safety and crash avoidance are less of a concern to pedestrians, slight bumping and nudging are often a part of walking through crowded corridors. Pedestrians are capable of changing speed more quickly when gaps arise and can accelerate to full speed from a standstill. In addition, it is not uncommon for pairs or groups of pedestrians to walk side-by-side, in clusters, or to form lanes dynamically.

Fruin (1971) did an extensive analysis of pedestrian flows and this work is reflected in the Highway Capacity Manual (Transportation Research Board, 1994) along with the work of others (see HCM for references). Over the years, researchers have developed several approaches to model pedestrian flows (see AlGhadi and Mahmassani, 1991; Lovas, 1994 for example). Gipps and Marksjo (1985) developed an approach that is not quite a CA model. This method focused on the use of reverse gravity-based rules to move pedestrians over a grid of cells. Pedestrians are repelled from each other as they seek their destinations in buildings. Their method used integer arithmetic to speed calculation, but used a sequential updating process. A social force model by Helbing and

Molnar (1995) moved bi-directional flows as social forces. The above models did not investigate fundamental flows of pedestrians, though each captures pedestrian movement in some measure.

One advantage of a CA or particle hopping approach is that CA models, generally, and CA models of vehicular traffic, in particular, have been undergoing rigorous study and examination (Nagel, 1996, 1998). CA models include the dynamic phenomena of fluid flow models and are easier to apply on realistic networks. CA models approximate the more complex models with a minimal set of simple rules. CA models run fast. They are microscopic models and can be designed to give individual properties to each traveler. They are intuitively understandable and in some sense the rule sets and individual properties make them behavioral models. The flow characteristics emerge from the application of the rule set to the individual travelers. Such emergence also occurs in actual travel from the interaction of the individual travelers without any outside control or orchestrating director. As stochastic simulators they can be used to yield a variety of outcomes as would be found in the many instances that occur in actual traffic systems.

The authors investigated unidirectional flow (Blue and Adler, 1998) and also demonstrated that for the case of a unidirectional flow walkway a two-regime macroscopic flow model emerged from the simulation experiments (Blue and Adler 1999a,b) that corresponds to the fundamental parameters described in the Highway Capacity Manual (1994). This paper presents the use of CA microsimulation for modeling bi-directional pedestrian flows, termed CA-Ped in this manuscript. This work advances three bi-directional modes: (a) separated directional flows; (b) interspersed directional flows, and (c) dynamic multi-lane (DML) flows as important cases that can be treated with the CA-Ped model. Simulation results are presented to demonstrate the CA method's ability to capture fundamental properties of pedestrian movements using a small set of fairly simple rules. A comparison with published empirical results follows. The paper then examines the importance of lane changing in pedestrian modeling. This is followed by a discussion of results and directions for future work.

2. Cellular automata microsimulation formulation

Though pedestrian flows are inherently more complex than vehicular flows, the success of using CA microsimulation to model vehicular flows on roadways provides impetus for exploring its suitability to modeling pedestrian flows. The objective is to develop an intuitively and empirically appealing CA microsimulation that employs an essential, minimal rule set. By incorporating a rule set that eliminates anything but critical behavioral factors, the microsimulation will facilitate a clear understanding of the underlying fundamental dynamics.

There are three fundamental elements of pedestrian movements that a bi-directional microscopic model should account for: side stepping, forward movement, and conflict mitigation. Side stepping refers to the desire of a pedestrian to "switch-lanes" – move laterally to either enable increased velocity or avoid head-on conflicts. Forward movement must be adaptable to the desired speed of the pedestrian and the placement of other persons in the immediate neighborhood. Conflict mitigation refers to the manner in which pedestrians approaching each other from opposite directions manage to avoid a head-on deadlock. In a previous paper, we introduced the use of *place exchange* for mitigating head-on conflicts (Blue and Adler, 1999a). In this procedure, that is invoked when opposing pedestrians are within 1 cell of each other, the passing movement is modeled by swapping the positions of the opposing pedestrians with some random probability, denoted as p_{exchg}. This innovation extends the range of densities that the model can process.

The bi-directional CA rule set, stated in Table 1, extends the rule set for unidirectional pedestrian flows (Blue and Adler, 1998) and incorporates the three fundamental elements described above. The CA rule set is applied in each time step and consists of two parallel updates. First, lane assignment and, second, forward motions change the positions of all pedestrians in two parallel update stages according to local rules applied to each pedestrian. Parallel updates avoid succession interdependencies encountered in sequential updates. With sequential updates the order of each move becomes unrealistically important, since as each entity moves, the next entity repositions in relation to the previous entity. Thus, the first entity would affect the position of all entities over the whole lattice. However, parallel updates, as used here, avoid sequential updating succession problems by determining all the new positions before moving any entity. All the entities are then repositioned together. Only the pedestrians in the immediate neighborhood affect the movement of a pedestrian, which is much more realistic. This parallel procedure is derived from the procedures used for vehicles in Rickert et al. (1995) and is also used in Simon and Gutowitz (1998). Though applied on a serial computer the two updates function as if applied on a parallel

Table 1
CA-Ped Microsimulation rule set

Lane change (*parallel update* 1)
(1) Eliminate conflicts: two walkers that are laterally adjacent may not sidestep into one another
(a) an empty cell between two walkers is available to one of them with 50/50 random assignment
(2) Identify gaps: same lane or adjacent (left or right) lane is chosen that best advances forward movement up to v_{max} according to the gap computation subprocedure that follows the step forward update
(a) For dynamic multiple lanes (DML):
(i) step out of lane of a walker from opposite direction by assigning gap $=0$ if opposing pedestrian is within 8 cells
(ii) step behind a same direction walker when avoiding an opposite direction walker by choosing any available lane with $gap_{same,\ dir}=0$ when gap $=0$
(b) ties of equal maximum gaps ahead are resolved according to:
(i) Two-way tie between the adjacent lanes: 50/50 random assignment
(ii) Two-way tie between current lane and single adjacent lane: 80/20 random assignment for stay in lane/adjacent lane
(iii) Three-way tie: 80/10/10 assignment for stay in lane or either adjacent lane
(3) Move: each pedestrian p_n is moved 0, +1, or −1 lateral sidesteps after (1) and (2) are completed
Step forward (*parallel update* 2)
(1) Update velocity: Let $v(p_n)=$ gap, where gap is from gap computation subprocedure below
(2) Exchanges: IF gap $=0$ or 1 AND gap $=gap_{opp}$ (cell occupied by an opposing pedestrian) THEN with probability p_{exchg} $v(p_n)=$ gap $+1$ ELSE $v(p_n)=0$
(3) Move: each pedestrian p_n is moved $v(p_n)$ cells forward on the lattice after (1) and (2) are completed.
Subprocedure: Gap computation
(1) Same direction: Look ahead a max of 8 cells ($8 = 2 * \text{largest } v_{max}$) IF occupied cell found with same direction THEN set gap_{same} to number of cells between entities ELSE $gap_{same}=8$
(2) Opposite direction: IF occupied cell found with opposite direction THEN set gap_{opp} to INT ($0.5 *$ number of cells between entities) ELSE $gap_{opp}=4$
(3) Assign gap $=$ MIN (gap_{same}, gap_{opp}, v_{max})

computer just as a true CA would. That is, each pedestrian's movement is evaluated in turn (sequentially), but the move is made only after all pedestrians on the lattice have been visited and the allowed moves identified, creating a virtual parallel update.

In the first parallel update stage, a set of lane changing rules is applied to each pedestrian on a lattice of square cells to determine the next lane of each pedestrian based on current conditions. The lane that best promotes forward movement is chosen from the local decision neighborhood, consisting of the left, same, and right lanes. Only after all the pedestrians are examined, are they moved to the new cells. In the second parallel update, a set of forward movement rules is applied to each pedestrian. The allowable movement (and thus the speed) of each pedestrian is based on the pedestrian's desired speed and the available gap ahead as constrained by the pedestrian in its current position directly ahead. Finally, all the pedestrians "hop" forward to new cells or remain in place if in a jam.

The lane-changing behavior is captured with two basic steps. Pedestrians can change lanes only when an adjacent cell is available. The availability of the adjacent cells to the immediate right and left are determined. If an adjacent cell is available but the cell two lanes over is occupied, a random number is drawn to designate the lane as available to this pedestrian or to the pedestrian two cells away. If an adjacent lane is free, then lane change is determined by the maximum gap ahead determined by the subprocedure for gap computation. In addition, at this point in the lane-change parallel update, bi-directional DML flows will result by assigning a forward gap of zero if the pedestrian encounters an opposing entity when determining the gap ahead (Rule 2(a)(i)). Rule 2(a)(ii) encourages walkers to step behind a same direction walker. Rule 2(a)(ii) is a new addition to the rule sets presented in earlier work (Blue and Adler, 1999a,b). This behavioral adjustment tends to move the pedestrians into a same-direction flow lane.

If the maximum gap is common to two or more lanes, Rule 2(b) of the lane change parallel update breaks ties for making lane assignments. If all three lanes are equally desirable, an 80/10/10 split is used for all three lanes, since pedestrians generally stay in the current lane (80%) and drift out of it occasionally (10% to either side). When both adjacent lanes are equally the most desirable, a 50/50 split between the adjacent lanes is the most reasonable assumption. It should be noted that in bi-directional flow, if this adjacent-lane tie is resolved by moving to the right, the opposing flows separate over time into two opposing lanes. For a tie between the current lane and an adjacent lane, we assume pedestrians in some cases wish to step away from a person in the adjacent lane that is not available, so 20% are assigned to the available adjacent lane. These probabilities worked well for the simulation, though other tie-breaking splits are under examination.

The second parallel update stage determines the forward movement of the pedestrians. The gap ahead is determined first from the subprocedure for gap computation. If there are opposing pedestrians, step forward Rule 2 guards against deadlocks by emulating what people actually do. Under constrained conditions temporary standoffs occur leaving opposing pedestrians to guess which way to step past one another, effectively exchanging places. Thus, the simulation contains a probability of a temporary standoff between closely opposing walkers. With probability p_{exchg}, closely opposing pedestrians exchange places in the time step. The opposing entities each move the same number of cells, based on a gap that is 0, 1, or 2 cells. In the last step the pedestrians go forward based on the gaps determined for all the pedestrians.

The available gap ahead depends on the direction of flow of the next vehicle downstream. From the gap calculation, if the pedestrian ahead is going in the same direction, the new velocity of the follower is the minimum of the desired velocity (v_{max}) and the available gap ahead. If the pedestrian immediately ahead is going in the opposite direction and within the local neighborhood that both pedestrians could move at maximum speed (i.e., 8 cells is the maximum – 4 in each direction), then the updated velocity is the minimum of v_{max} and moving halfway forward. Moving halfway forward guards against collisions and hopping over one another.

3. Simulation experiments

The model was tested through rigorous simulation. As in previously documented experiments (Blue and Adler, 1998, 1999a,b), a circular lattice of size 1000×10 with square cells at 0.457 m per side is used (occupying a minimum area of 0.21 m^2). To generate fundamental parameters of pedestrian flow, experiments are conducted at 19 different densities ranging from 5% to 95% lattice occupancy in intervals of 5%. Density, *d*, as the proportion of occupied cells is used to aid the discussion rather than pedestrians/m^2, which can easily be converted from $d/(0.21\ m^2)$. The walking speed of entities assigned to the lattice are randomly distributed (5% fast – 4 cells/time step, 90% standard – 3 cells/time step, 5% slow – 2 cells/time step). This speed distribution of walkers implies some variety in lane changing aggressiveness, since faster walkers also will tend to change lanes more often. For the bi-directional walkway, pedestrians are also assigned a direction. Six different directional splits, specified in 10% increments from 100–0 (unidirectional flow) to 50–50 (balanced flow) were used.

Simulations are performed for 11 000 one-second time-steps; the first 1000 are used to start the run and are then discarded. For statistical accuracy, 20 replications at each density level were run and the fundamental parameters were computed as the average over these replications. The emergent fundamental profile of the model is generated from the averaged parameters over the range of densities for specific directional splits. In the circular lattice, space is the reciprocal of density and is constant for each run. Flow rate is computed as the total number of revolutions made by each pedestrian over the duration of the simulation. Speed is computed as number of total steps divided by the time duration. Also, other measures, such as sidesteps, place exchanges, and computation time, are also gathered to gain insight into the model's capabilities and performance.

3.1. Three cases of bi-directional flow

There are three distinct cases of bi-directional flow of interest: separated flow, interspersed flow, and DML flow.

Separated flow: According to Chapter 13 of the Highway Capacity Manual (1994), when bi-directional flows exist, it is generally assumed that the directional flows segregate and occupy proportional shares of the walkway. For example, if a walkway is randomly filled with interspersed pedestrians, over time, the flows will tend to migrate to one side (e.g., toward the right) forming two sets of contiguous directional lanes.

Interspersed flow: In this case pedestrians pick their way through a crowd without forming distinct directional flow lanes. This is usually a short-lived (i.e., transient) group behavior. This phenomenon is witnessed at busy crosswalks, in crowded subway stations, and in emergency situations, among others. Historically, interspersed bi-directional flow has not been well examined, documented, or modeled. As a result this case is not thoroughly understood. Interspersed flow could be considered the far extreme from separated flow and the lower limit of movement efficiency. It is examined here to assess the model's capability to capture such group behavior and to better understand the flow effects of such conditions.

DML flow: The third mode of pedestrian flow is observed where the pedestrians dynamically form groupings of directional lanes by avoiding persons coming from the opposite direction and by following a person going in the same direction. These lanes are not generally well defined or stable. This case has been videotaped by one of the authors at a busy pedestrian corridor in Grand Central Station, New York City and also observed in busy corridors and at traffic crosswalks. Helbing and Molnar (1995) examined this case in their treatment of bi-directional flows as social forces. It is an important instance of bi-directional flow that is a transition state between interspersed and separated flows.

An extensive presentation follows to represent and interpret the effects of (a) directional splits and (b) exchange probabilities under each of the three flow conditions. This analysis aims to provide a more complete representation and a better understanding of the capability of this CA methodology to capture the complex behaviors of pedestrians. Directional splits of the pedestrian volume were studied and, as prescribed in Rule 2 of the step forward parallel update, different probabilities of exchange (p_{exchg}) were also studied.

To the authors' knowledge, the characteristics of place exchange have not been examined in any field study of pedestrian activity, though it is well known that pedestrians will bypass, bump, slip past, and otherwise exchange places with one another when necessary. This model allows for such activity, specifically, in the form given in Rule 2 of the step forward parallel update. Given that the model correctly approximates speed–volume–density relationships for the single and lane-based bi-directional cases, we set out to examine what the model would predict for fundamental diagrams at different exchange rates. In the absence of explicit empirical data (see also Section 4), these findings are considered preliminary, though they are quite instructive regarding the capabilities of the model and, to a lesser extent, actual crowd behavior in the random bi-directional setting. We examined exchange rates of 100%, 75%, 50%, 25%, and 0% for the various directional splits. 0% is the base case where pedestrians cannot move if an opposing pedestrian creates a direct conflict.

3.2. Separated flow

Fig. 1 depicts results of microsimulation experiments conducted for separated lanes over a range of directional splits in 10% increments from 100–0 (unidirectional flow) to 50–50 (balanced flow). As expected, it was found that the emergent flow–density curves were virtually identical to the results of the unidirectional case (see also Blue and Adler, 1998). In addition, very little variation in the resulting behaviors between splits was found. Exchange probabilities do not factor into the case of separated flows and so were not examined.

3.3. Interspersed flow

Figs. 2–4 illustrate the simulation results over different directional splits and levels of exchange probabilities for interspersed flow. The speed–density curves based on exchange probabilities of

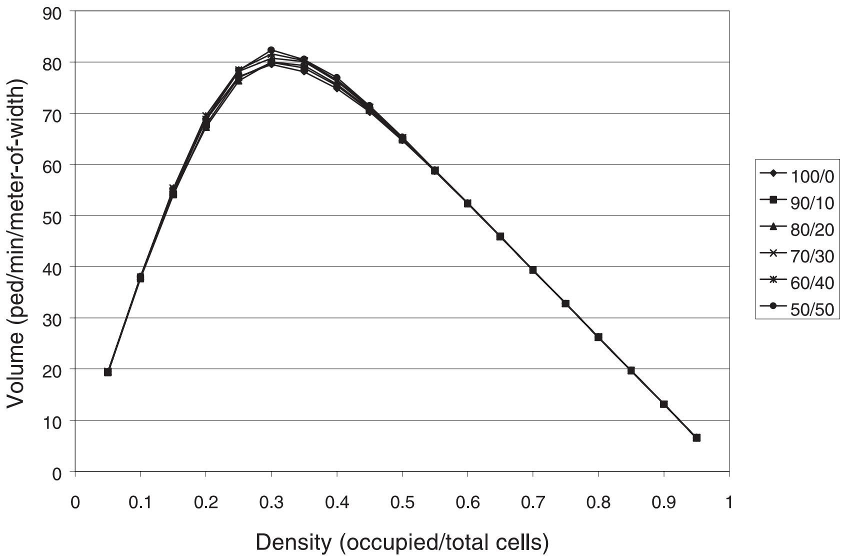

Fig. 1. Volume–density curves for bi-directional walkway and varied splits.

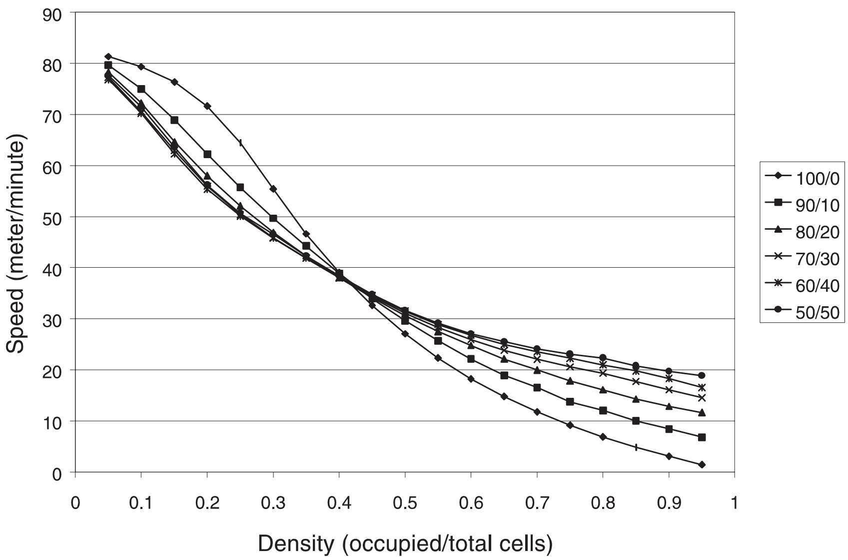

Fig. 2. Speed–density curves for bi-directional walkway, interspersed flow, and varied splits for 1.0 exchange probability.

100% success (Fig. 2) show a pattern emerging that is orderly and understandable. At a density below 0.45, speeds reduce from unidirectional flow according to the directional split. Above a density of 0.45, the high degree of exchange rate allows higher speeds, as splits become more even. This is because, by exchanging places, pedestrians are not as often held back by opposing persons

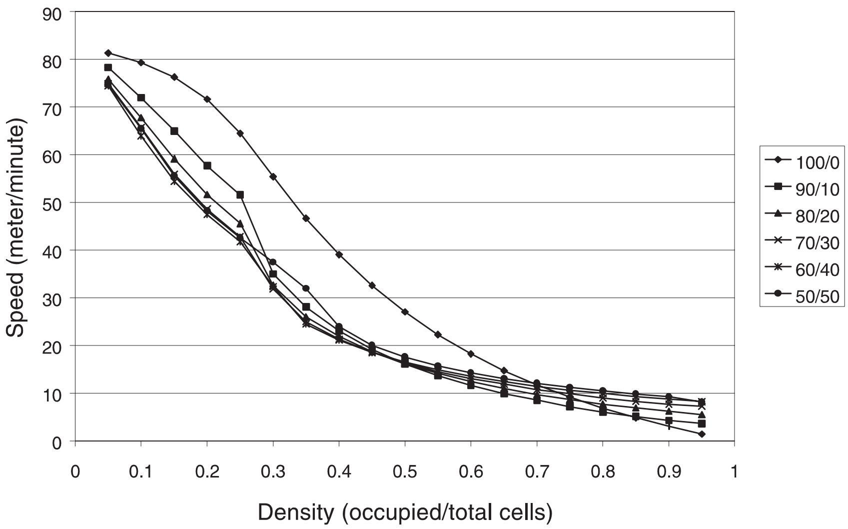

Fig. 3. Speed–density curves for bi-directional walkway, interspersed flow, and varied splits for 0.5 exchange probability.

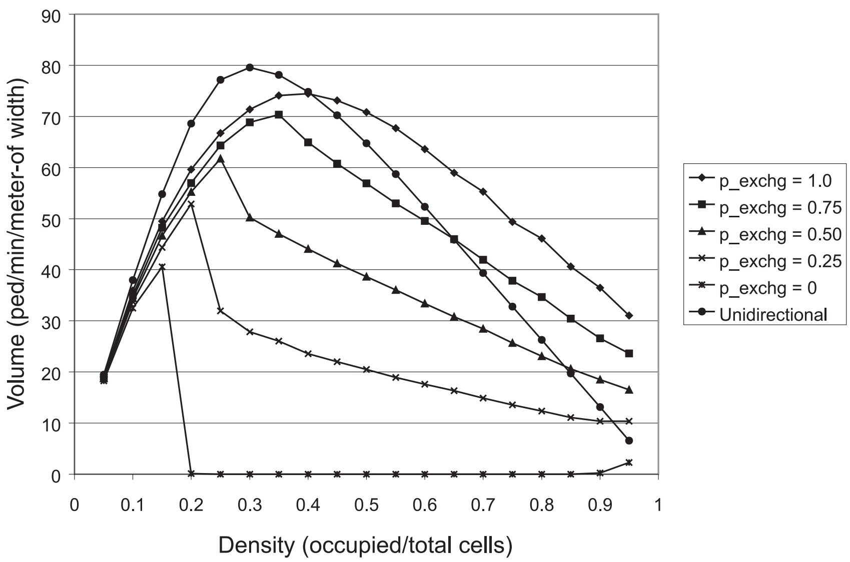

Fig. 4. Volume–density curves for bi-directional walkway, interspersed flow, and 90:10 volume split.

ahead and because more balanced directional flow provides more opportunities for face-to-face conflicts and smooth exchanges of position. This may seem counterintuitive at first, but is easily explained. In unidirectional flow at densities above 0.45, slow moving persons ahead cannot exchange places but rather create jams readily. The bi-directional exchanges enhance forward movement. More face-to-face exchanges mean opportunities for forward exchanges to advance people. These occur only in bi-directional flow and more often with more balanced flows (toward 50–50 directional splits).

At $p_{exchg} = 1.0$ speeds appear to do unreasonably well at very high density, allowing directionally split flows to increase above what single-direction flow would allow. Thirty or more exchanges per pedestrian per minute occur, a number that appears unlikely in practice. Primarily because of this result, the perfect exchange concept appears more useful as a benchmark of maximum flow. Actual levels of exchange are likely to be hampered by occasional wrong-steps, as would be modeled with an impedance factor in an equation-based model. Fig. 3 shows the speed–density curve at $p_{exchg} = 0.5$. The result is a drop in speed and a closer agreement with the uni-directional curve at very high density.

In examining the effect of reduced exchange rates on flow, a pattern emerges. There is an inverse relationship between exchange rate and peak lane changing, generally. As p_{exchg} decreases there are proportionate decreases in speed, flow, and exchange rate, and some increase in the peak rate of lane changing. This is easily understandable at low density, since as exchange rate goes down, more lane changing opportunities present themselves. Smooth exchanges would mean lane changing is less essential to flow. Lane changing is more thoroughly discussed in a separate section below.

As Fig. 4 illustrates, at very low values of p_{exchg} there are catastrophic changes in performance at low densities (around 0.15–0.20). Speeds fall off quickly and remain low, reflecting jam conditions. Sidesteps fall off dramatically and exchanges become asymptotic at density of about 0.25 and at low values. This should be expected as the system is locked due to the inability of entities to advance. According to the HCM (1994), a 15% reduction in capacity should be witnessed in cases of bi-directional flow where lane formation does not occur. Fig. 4 indicates that the CA-Ped model is consistent with the HCM (1994), as there is a proportionate reduction in capacity that varies with p_{exchg}.

3.4. DML flow

A more enduring mode of flow than interspersed flow, DML flow falls between the extreme cases of separated and interspersed flows. Lanes emerge from the interaction of autonomous entities (the lanes are not hard coded into the model) and change dynamically as walkers try to avoid oncoming walkers and fall in line with others moving in the same direction. Over a 10 lane wide walkway, lanes form and reform as the interactions of oncoming pedestrians cause lane adjustments. For example, at a given moment where flows move to the left and right on the 10-lane wide grid, 3 lanes may be going to the left, then 2 to the right, another 2 to the left, and then another 3 to the right. However, the lanes are not directionally well defined and so over time, dynamically, they slowly change, and are always in the process of reformation. It is possible, though unlikely, that permanent lanes become locked into place.

In Figs. 5 and 6 can be seen the difference in speed–density that results from the quasi-lane formation of this scenario. Speeds improve over interspersed flow and fall closer to the unidirectional curve. This is expected from the nature of the improvement in lane formation. This is a desirable and reasonable result. In the case of $p_{exchg} = 1.0$, the speed–density curves become nearly linear except at very high density where lane formation breaks down. When $p_{exchg} = 0.5$, the speed–density curves resemble the unidirectional curve, somewhat shifted down, but look more like a

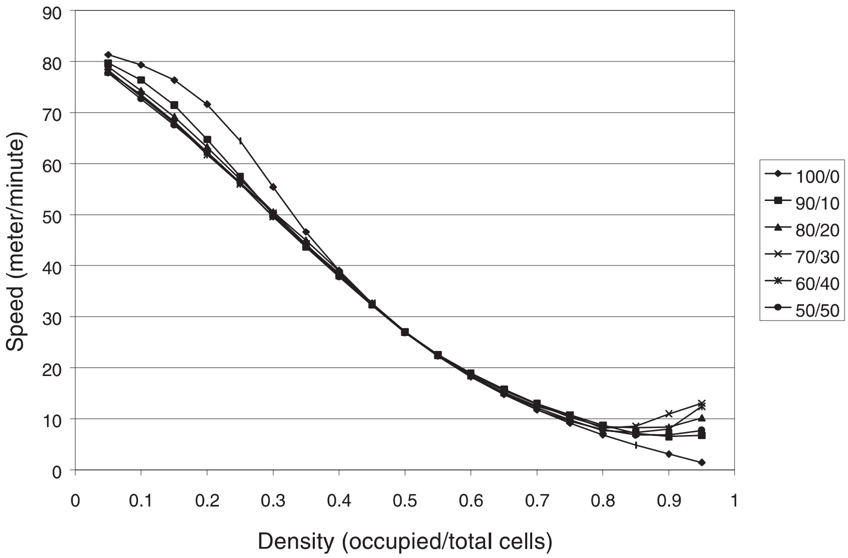

Fig. 5. Speed–density curves for bi-directional walkway, DML flow, and varied splits for 1.0 exchange probability.

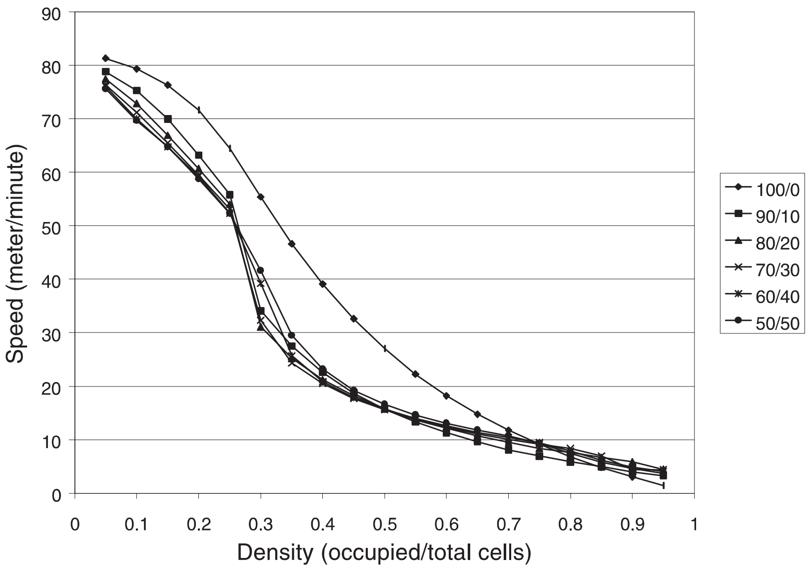

Fig. 6. Speed–density curves for bi-directional walkway, DML flow, and varied splits for 0.5 exchange probability.

two-regime model, linear (Greenshields model) at low density (0.25 or below) and negative exponential (Underwood model) above 0.25 density. The increased speeds at low density and lower speeds at high density over earlier results (Blue and Adler, 1999a,b) stem from adding same direction alignment in lane change Rule 2(a)(ii) (see Table 1). At high density Fig. 5 especially appears more reasonable with the addition of Rule 2(a)(ii) with respect to earlier results that resembled more closely interspersed flow results in Fig. 2.

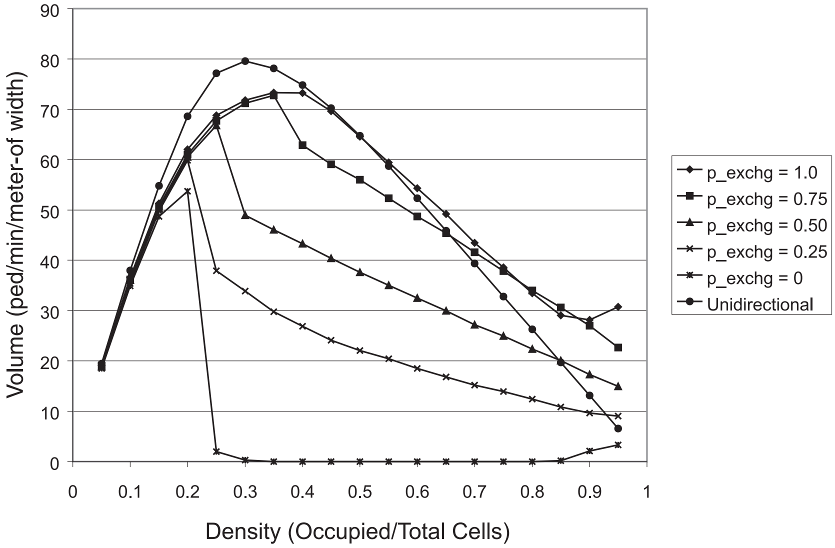

Fig. 7. Volume–density curves for bi-directional walkway, DML flow, and 90:10 volume split.

Because the 90–10 split allows for some lane development, the volumes shown in Fig. 4 for interspersed flow increase somewhat for DML flows as shown in Fig. 7. The falloff of 15% in capacity is also effective for DML flows for a larger range of values of p_{exchg} and is, thus, consistent with the HCM (1994).

4. Comparison with empirical data

The results clearly show a family of curves that depend on the type of flow and values of parameters associated with those flows. It has been shown in earlier papers (Blue and Adler, 1999a,b) that the unidirectional and separated bi-directional flow S-curves of speed–density fit well to a two-regime Bell curve at mid-to-low density and a linear curve at higher density. Based on empirical studies of pedestrians, the HCM (1994) presents a Greenshields model that is a linear model of speed–density. A linear Greenshields model aligned with the beginning and end points of the CA-Ped-based unidirectional curve divides the two halves of the S-curve into two arcs positioned on either side of the Greenshields line. There is, thus, in unidirectional and separated flow some agreement with the Greenshields model. The S-curve also corresponds well to traffic flow theory that holds that at low density free flow would be unimpeded and then would fall off gradually, creating an S-curve (Prigogine and Herman, 1971; May, 1990). An empirical study of unidirectional pedestrian flow showed that a Bell curve gave the best representation of unidirectional flow (Virkler and Elayadeth, 1994).

The CA-Ped interspersed flow and DML bi-directional curves differ from the unidirectional and bi-directional separated flow S-curve. Both the interspersed flow and DML cases where $p_{\mathrm{exchg}} = 1.0$ show a movement toward a more linear (Greenshields) model. The interspersed flow case where $p_{\mathrm{exchg}} = 0.5$ shows a more negative exponential curve, corresponding to an Underwood model (see May, 1990). The DML case where $p_{exchg} = 0.5$ shows an S-curve with a sharp drop in speed at mid-density, corresponding, at least visually, to a two-regime model, linear at low density and Underwood at density above 0.25.

The fact that a family of curves emerges from the CA-Ped model gives an explanation to the various empirical curves described in the literature. A study of pedestrians in Hong Kong (Lam et al., 1994) showed that Greenshields, Underwood, and Bell curves described pedestrian flows over various walkways. However, no explanation was given for the differences. In that paper the amount and type of bi-directional flow is not given. The CA model presented here offers a set of curves and an explanation based on the amount and type of bi-directional flow. Given the degree of inaccuracy in measuring speed and density in the field and the relative scarcity of data points, the empirical curves and the curves found with the CA-Ped model may very well correspond to common patterns. The CA-Ped model gives insight into those factors that contribute to the different curves found with field data.

In those cases where a negative exponential curve, or Underwood model, appears to fit the data, the CA-Ped model yields an explanation. This case appears with bi-directional flow with $p_{exchg} = 0.5$. The major change from the S-curve and linear model is that speed falls off quickly in the negative exponential curve at low density. This could be due to two factors, primarily. The first could be from a high variance in desired walking speed. As the percentage of slow walkers increases, all walkers are slowed considerably, since the slow walkers set the pace for the group. The second reason, applicable to these simulation experiments, is due to opposing pedestrians mixed into the stream that cause a similar slowdown at low density for the group. In short, the macroscopic curve depends on characteristics that have to do with the population of pedestrians, the presence of slow walkers or at least some bi-directional walkers.

Discussions about which curves correctly describe empirical data seem problematic. The empirical data samples are small, the dynamics occurring at any time so varied, and the characteristics of the pedestrian population can be so diverse that any of a number of curves may suffice during any sampling period. The CA-Ped model makes possible investigations into the population dynamics at work and creation of the curves that may describe those flows under known conditions of population characteristics and density with precise data collection. However, it seems that understanding of flows for design of walkways has more to do with the exceptional cases that may arise than with short or even longer-term averages. Based on studies of vehicular dynamics (e.g., Nelson and Raney, 1999) the CA-Ped model would be capable of capturing important aspects of pedestrian dynamics that go unstudied with macroscopic curves that describe fundamental flows.

5. Lane changing behavior

Understandably, most of the historical effort that has gone into capturing pedestrian flow characteristics has been directed toward their forward movement. However, an important factor in understanding pedestrian flow is lane changing. Lane changing has been modeled using CA for vehicular traffic (see Rickert et al., 1995; Ben-Akiva et al., 1995 for example). Since extensive data gathering and modeling of pedestrian lane changes has not been previously studied, the effort here has been to perceive the activity of pedestrian lane changing from experience and empirically capture the forward movement with reasonable rules. The rule set in use allows for ample lane changing since ties are broken by randomly assigning lane changes. Since in these rules a pedestrian changes lanes 20% of the time when there is a tie involving the current lane, the sidestep rates, especially at low density, may be nearer the high-end of lane changing proclivity, but have the desirable effect of reducing mode locking.

Attention to modeling of lane changing is needed to avoid excessive mode locking of pedestrians, or a marching effect, which may emerge in some instances. Mode locking, or synchronization of motions, occurs in many physical processes (Schroeder, 1991). In this case pedestrian self-organization affects the ability to synchronize movement. Mode locking is almost certain to emerge at about a density of 0.25 if all the entities are of the same user class and walk at the same speed. If rigid mode locking occurs, slowdowns and small jams do not occur and average speed may be unreasonably high. Even with substantial opportunity to pass in the model, the pedestrians achieve flexible self-organization. Self-organization arises naturally in the model, but the lane changing rules should avoid rigid locking into step, or the forward flow characteristics will not emerge correctly.

There are some spatial configurations of entities that promote lane changing and others that impede it. Thus, spatial efficiencies and self-organization are subjects of some interest to pedestrian forward motion. Consider the following illustration that may occasionally occur in simulation and makes the flow characteristics advantageous. In unidirectional flow, if every other cell in a row is occupied and there is an empty row between the next row of walkers who are similarly arranged, then the density of 100×10 Lattice is 0.25 (5 out of 20 cells occupied). If the occupied columns are staggered, so that an unrestrained step is encountered ahead, the propensity for lane changing to make more forward progress is minimized (effectively 0). This is because the same-lane forward movement is assured (3 cells) and sidestepping is less attractive (only one cell forward would be allowed). The entities are then locked into a self-organized march around the loop, making the forward speed unrealistically high. Such simple synchronization may occur at densities if 1/6, 1/4, and 1/2 when the number of lanes is even. Mode-locked marching is efficient, improving average speeds, though can be unstable, breaking apart easily, especially when speeds vary and random use of the space between two pedestrians is allowed. More complex self-organization and short-term mode locking effects are common at all densities to some extent, even in populations where walkers have a variety of speeds and ties can be broken by stochastic lane choices. The fundamental diagram of flow is a reflection of the spatial distributions that tend to occur at every density, and that is influenced by the lapsing of pedestrians into synchronized stepping.

In Fig. 8 as the 100/0 density increases above 0.25, the spatial efficiency for forward movement decreases and lane changing increases as entities tend to self-organize into the available space, breaking up the even spacing and making forward movement more difficult. It is suggested that this lowered spatial ability to self-organize in favor of forward movement accounts for the fast drop and S-shape of the speed–density curve in the vicinity above a density of 0.25.

The interspersed bi-directional case is considered next. Figs. 8 and 9 illustrate the relationship between sidesteps and density at 1.0 and 0.5 exchange probabilities over a range of directional splits. As can be seen from the figures, the spatial advantages of mode locking are entirely lost and the opposite effect even occurs. In fact, the spatial advantage of unidirectional mode locking at 0.25 density becomes a disadvantage with opposing flows and increases as flows become more

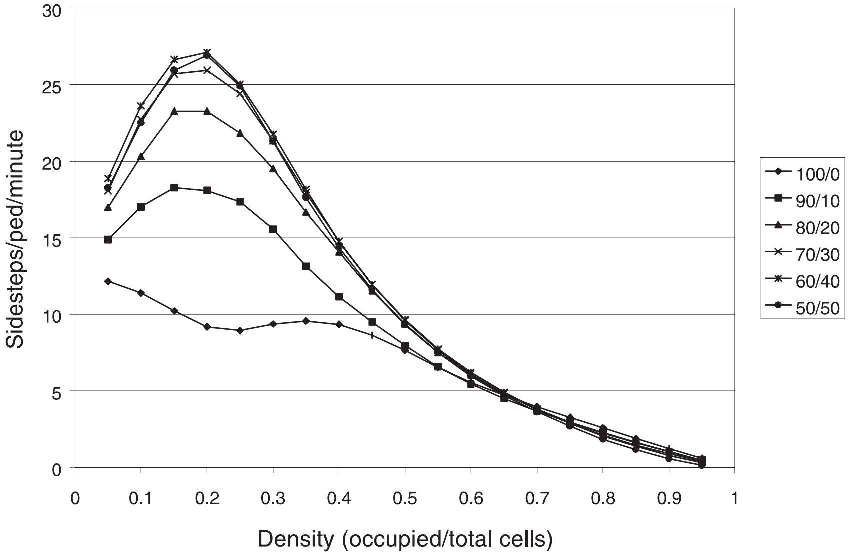

Fig. 8. Sidestep–density curves for bi-directional walkway, interspersed flow, and varied splits for 1.0 exchange probability.

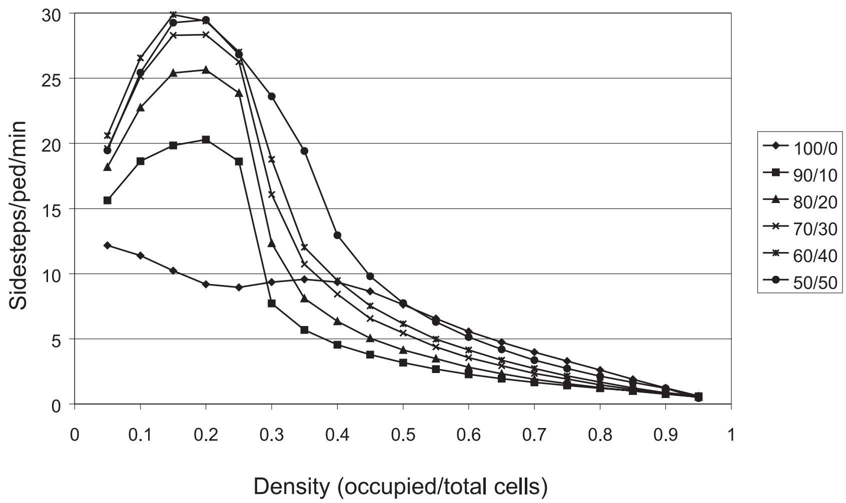

Fig. 9. Sidestep–density curves for bi-directional walkway, interspersed flow, and varied splits for 0.5 exchange probability.

evenly divided. Avoiding entities coming from the opposite direction is most effective for reasons similar to why mode locking is so effective in unidirectional flow.

In comparing Figs. 8 and 9, at an exchange probability of 0.50, it is clear that more lane changes occur at the peak, though the frequency of lane changing drops very quickly after a density of 0.25. With a lower exchange probability, more opportunities for lane changing arise at densities where deadlocks do not occur frequently. At higher densities more deadlocks occur. The need for lane changes to be useful is greater, but the reason the exchange is necessary in the first place, has not been eliminated. When exchanges occur freely, the lane changing is not as impeded. This is not an intuitively obvious result, and the ability of the CA-Ped model to produce such phenomena at particular densities is a testament to its ability to extend the range of understanding of pedestrian behavior and aggregate performance.

Figs. 10 and 11 show sidestep performance for the DML case at 1.0 and 0.5 exchange probabilities over a range of directional splits. Most notably the rate of sidestepping falls considerably from the interspersed case at low volume, to nearly half that of the unidirectional curve, since more are in lanes and need to sidestep less often. The same pattern follows as with the interspersed case in that 0.5 exchange probability sidesteps occur more frequently and the fate falls more quickly than at 1.0 exchange probability. It is interesting to note that with DML at 0.5 exchange probability at density 0.3 all the directional splits have about the same rate of sidestepping, though it is not intuitively clear why this should be so.

One finding from this analysis is that lane changing is sometimes helpful and other times not very helpful in promoting flows. The effect depends on the density, or structural packing of the lattice. As density increases, speed declines in spite of the increase in lane changing at 0.35 density. Especially as density increases, when a pedestrian changes lanes to pass, another pedestrian can change lanes and block the first pedestrian's movement. Pedestrians make their decisions independently and are myopic to the movements others may take. In actual pedestrian traffic pedestrians can "read" the body movements of others to a certain degree, but this can also be deceptive and even oncoming pedestrians may still wind up in a face off. In road traffic lane changing, a phenomenon, referred by some as "snaking", can be observed (Resnick, 1994). In congested traffic if an adjacent lane moves faster, drivers switch lanes and congest the formerly

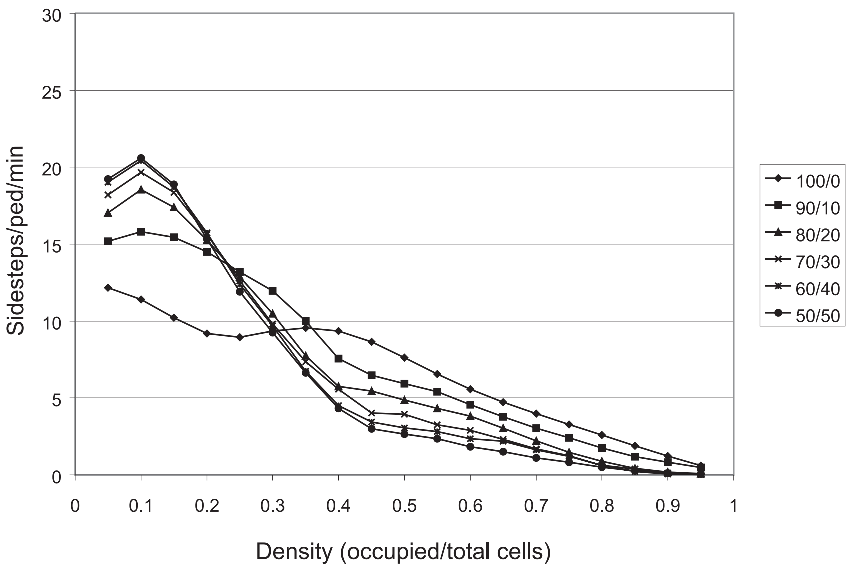

Fig. 10. Sidestep–density curves for bi-directional walkway, DML flow, and varied splits for 1.0 exchange probability.

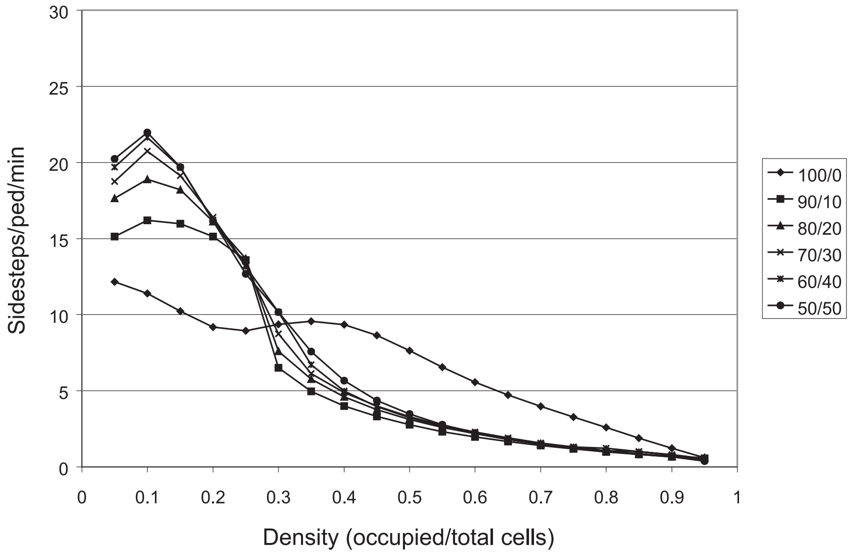

Fig. 11. Sidestep–density curves for bi-directional walkway, DML flow, and varied splits for 0.5 exchange probability.

moving lane. Then, the formerly stopped lane begins to move. The traffic moves like a snake, alternating the lane that is in freer flow. The fact that lane changing can be counterproductive or non-productive for forward flow does not stop lane changing from happening. Pedestrians can be as myopic as drivers, as can be observed, when at multiple queues, queue hopping occurs to the seeming eternal frustration of the person who always seems to switch to the wrong queue.

It is noteworthy that the CA model has a significant capability in capturing lane changing to the degree needed for what appears to be universal application. Though all the possible important rule sets are far from exhausted, sidestepping is clearly important to pedestrian modeling. Sidestepping offers some insight into the shape of the S-curve for speed–density; and, at the very least, lane change rules in CA models must prevent excessive mode locking from occurring while permitting reasonable amounts of self-organization of the pedestrians.

6. Discussion and conclusions

From a few simple rules the model produces reasonable emergent fundamental parameters of speed, flow, and density. These emergent group behaviors correspond well to published field data in the HCM (1994) and accepted norms for the unidirectional case (see also Blue and Adler, 1998, 1999a) and, to the extent that data has been examined, for the bi-directional case. The basic pedestrian behaviors have been approximated with a minimal rule set that effectively captures the essential pedestrian dynamics for the single and bi-directional case. The rule set and scaling can be adjusted to situations and conditions that correspond, in some measure, to actual behaviors. The correspondence of the rules to actual behaviors need not be exact. The essential rules are simple enough to program and modify without imposing unnecessary detail, and yet capture complex phenomena. The bi-directional case where lanes are dedicated by directional split appears sufficiently validated in that those flows are not significantly different from single-direction flows. The bi-directional 90–10 interspersed and DML capacities correspond reasonably well with the 15% reduction in capacity noted in the HCM (1994) when separate lanes do not form.

Using CA microsimulation allows for examination of conditions that are complex and difficult to model. Modeling the bi-directional cases with long simulation runs creates data that can be cautiously applied to analysis. Though the CA model is useful in itself for many purposes, the output curves fit to the simulation results make data available for macroscopic models or back-of the envelope calculations. The family of curves found with the model, in some measure, explain the presence of different macroscopic curves in the literature, such a Bell, Greenshields, and Underwood models (HCM, 1994; Lam et al., 1994; Virkler and Elayadeth, 1994). These different curves represent the flow characteristics of a population of walkers and can range significantly, based on the presence of slow walkers and bi-directional walkers that do not form separated lanes.

If computation speed is considered, the CA-Ped model calculations involve only integer arithmetic, using simple counting procedures for gap calculations. At a mid-range density of 0.5 at a 90–10 split and exchange probability of 0.75, the model did about 80 000 updates per second on a 150 MHz Pentium PC. The rate is slowed to 50 000 updates per second at low density and increases to 110 000 at high density. This inverse in processing speed per pedestrian with density is due to the fact that at low density, more counting is done in the local neighborhood of 8 cells ahead than at higher density when another pedestrian will be quickly encountered, stopping the gap counts earlier. Total run times are, thus, relatively low for higher density analysis, a positive and somewhat counterintuitive effect. Generally, CA models are valued for their efficiency in computation. Other pedestrian models that use floating-point calculations for pedestrian attraction-repulsion formulas would probably engage in more encumbered computations and especially at higher densities.

Over all the simulation tests, the region of density 0.2–0.4, where the maximum flows occur, has the largest differences in speed and volume between tests. These are presumed to be the speed–flow–density combinations that have the most volatile dynamics. This inference agrees with Paczuski and Nagel (1995) that reveals complex dynamics at work, especially in the maximum flow range of the Nagel–Schreckenberg automobile traffic model. This is evidently due in part to spatial sensitivities of lane changing that affects forward movement in this region. Since nonlinear effects occur around maximum flow, the region of maximum flow would then be the area where the greatest concentration of effort in fine-tuning the model would benefit. With further work it would be possible to reveal more about and to better understand the dynamics in the maximum flow range.

Lane changing effects yield some interesting insights into the speed–density relationship. At lower densities mode locking may occur that is efficient for forward movement, but requires and permits few lane changes. At higher volumes, lane changing may help as well as hinder overall flow and evidently has relatively small impact upon the emergent group flow behavior. Side-stepping offers some insight into the shape of the S-curve for speed–density. At the very least, lane change rules in CA models must prevent excessive mode locking from occurring while permitting reasonable amounts of self-organization of pedestrians. However, though not well studied or understood by field research to date, lane change behavior is an important feature of pedestrian movement. Its inclusion in the model is essential and adds realism. The speed distribution of walkers in some measure includes variety in lane changing distribution, since faster walkers tend to be more aggressive lane changers than the others. Pedestrians may also not change lanes whenever an advantage presents itself. The distribution of aggressiveness in lane changing is a facet to be studied in further field study of pedestrians.

The inclusion of place exchange is a contribution to pedestrian modeling that allows the model to avoid deadlocks. This innovation helps immensely to broaden the range of densities that can be modeled. Without it ($p_{exchg} = 0$) the model fails to process flows above a density of 0.15 at a 90–10 directional split. Further fieldwork needs to be done to examine high-density flows especially for the proclivity of place exchanges among actual pedestrians. It would appear that DML and separated flows would be relatively stable spatial configurations compared to interspersed flows because of the reduced need for place exchanges.

Beyond unidirectional and separated bi-directional flows, the more complex cases of interspersed and DML bi-directional flows clearly illustrate the modeling power of the CA-Ped method. The CA approach yields a viable tool for pedestrian modeling that has daunted the efforts of researchers for years. It captures micro-level pedestrian dynamics with an intuitively appealing method and offers an experimental platform for better grasping the important parameters of pedestrian flows. The authors are also investigating the modeling of four-directional flows (Blue and Adler, 1999c) and sidewalk networks. As a new method, its possibilities have only begun to be theoretically explored and considerable opportunities exist for innovative applications.

A graphical animated version of the CA-Ped simulation can be seen online at http://www.ulster.net/~vjblue.

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