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SENSITIVITY ANALYSIS AND VALIDATION OF A MULTI-AGENTS PEDESTRIAN MODEL

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Abstract: We present a pedestrian movement model, which use a multi agents system for pedestrian traffic analysis. The model captures the dynamic microscopic interaction between pedestrians, which cannot be addressed using traditional macroscopic approach. The pedestrians are modeled as autonomous agents with non-linear system differential equations. The pedestrian agents may avoid other pedestrians, passing and overtaking slower pedestrians and to form a self-organization behavior of lane formations as in real pedestrian studies. A critical issue for such multi-agent pedestrian models, however, is the validation of the model against real world data. We show that the sensitivity analysis of control variables and parameters of the multi-agents model form the basis in ensuring the validation step. The model was automatically validated using real world data by minimizing the difference between the speed distributions. With the validated model, we can utilize model applications to evaluate pedestrian facilities.

Key Words: multi-agents, pedestrian, simulation, microscopic, automatic validation

1. INTRODUCTION

Recently, pedestrians as multi agents system have attracted many researchers because of its promise as a new computational paradigm to experiment and to evaluate the effects of a proposed policy on the pedestrian facilities (for example, Gloor et al (2004), Bierlaire et al (2003)). The multi-agents pedestrian model provides a novel tool to simulate the interaction of peoples' movement in a microscopic approach that can never be performed using the traditional method. In traditional pedestrian transportation research, the approach had been aggregating those interactions into macroscopic flow-speed-density equations (see more detail in Transportation Research Board (1985), Fruin (1971)). Using these set of equations, which actually derived from vehicular traffic movement, the minimum requirement of pedestrian facilities is roughly estimated. This macroscopic approach, however, is static and eliminates the basic pedestrian behavior. While this traditional model is still widely used because of its simplicity, research on a more comprehensive microscopic pedestrian model is emerging. The emergence of agent-based pedestrian modeling happens recently because of the significant improvement in computational complexity that can be carried out by our hardware and software.

Multi-agents Pedestrian Model has come in various terminologies in the pedestrian literatures. Some researchers call this model as *pedestrian dynamics (e.g* Helbing and Molnár (1995)), while the others identify it as *microscopic pedestrian* (e.g. Teknomo et al (2000a), Blue and

Adler (2000)). The approaches of the model are different by type of the model and its application, but the general concept is to simulate each individual pedestrian and its environment in the microscopic level as pedestrian agents that are capable to move and interact autonomously to achieve their goal (see Teknomo et al (2000b) for more literature review).

Pedestrian agent is a software program that represents a walker in a virtual environment, which is capable of independent (autonomous) action, interact with each other and can pursue their own goal. An example of simple interaction is a competition among pedestrian agents to occupy the neighborhood space at present state of the environment, in which they are situated. This competition interaction causes the delay on their movement. The goal of pedestrian agents is to move from one location (origin) to another location (destination) with minimum time as possible subject to constraint of their desire speed. The desire speed is the pleasant speed that the pedestrian wish to walk. The constraint of desire speed is important to distinguish walking from running. Each agent has incomplete information about the environment (i.e. barrier, wall, etc.) or the interaction problem (competition and delay) that will be faced. At each time, the agent will have a limited viewpoint only from its neighborhoods, without a global system control to guide.

Modeling pedestrians in terms of autonomous interacting agents give a more natural way to represent real-world pedestrians rather than merely gross equations on the macroscopic level. It considers a more detailed analysis for design and pedestrian interaction, which cannot be analyzed using traditional macroscopic approaches. Potentially, the pedestrian agents in the virtual world may have a wide range of useful applications from evacuation, architecture and urban design to business and military and game development. From transportation and traffic engineering point of view, however, pedestrian-agents models is valuable to simulate pedestrian related facilities such as terminal, subway stations, bus stop, parking, and pedestrian walkway and crossing, stairs, escalator and elevator. Those simulations are useful for evaluation, design and planning of such infrastructure projects. A fuller understanding of modeling pedestrian as an agent may also give implication to broaden our view and understanding on pedestrian behavior and its characteristics.

Although it is potentially possible to model pedestrian agents to perform spatial interaction to find the routes or interaction between location and land use in a wider area, these spatial interactions are beyond the scope and domain of this research. They will not be considered within this paper. Interested reader may refer Hoogendoorn and Bovy (2004) for pedestrian route-choice research.

A critical issue for such multi-agent pedestrian models is the validation of the model against real world data. The simulation of individual pedestrians involves the use of many factors. Other researchers about pedestrian multi-agent system utilized matching of speed with HCM standard (Blue and Adler (1998)) or simple observations method (Lovas (1994), Helbing and Molnar (1995)). The validation of multi-agent pedestrian model is very difficult due to a large set of parameters. Such validation requires deep understanding of behavior of the factors and parameters. In this paper, we used an automatic validation method based on the sensitivity analysis of control variables and parameters of the multi-agents model. The behavior from the sensitivity analysis forms the basis of the validation step. With the validated model, we can utilize model applications to evaluate pedestrian facilities without very costly trial and error due to the implementation cost.

This paper is organized as follow. Brief explanation on the pedestrian behavior and model building of pedestrian agents is described in the next section. The sensitivity analysis of control variables and parameters of the multi-agents model is given after the model. After that, automatic validation of the model using individual and dynamic pedestrian movement data is described. Before the conclusion, a brief description on self-organization phenomena and a model application is illustrated.

2. THE MULTI-AGENTS PEDESTRIAN MODEL

This section gives a brief explanation on the pedestrian behavior and model building of pedestrian agents. Pedestrian agents that have been built must be based on a certain pedestrian behavior and capability that exist in real pedestrians. These behaviors and basic capabilities are based on observation on the real world pedestrians.

Observing pedestrians behavior, they tend to influence each other in their walking behavior either with mutual or reciprocal action. They need to avoid or overtake each other. To be able to maintain their speed, sometimes they need to change their velocity direction. Pedestrians may observe the speed and movement direction of other pedestrians. Several pedestrians may walk in-group and maintain close distance in a group. In a very dense situation, they need to maintain their distance / headway toward other pedestrians and surroundings to reduce their physical contact to each other. Each pedestrian agent shall be developed to have his or her own unique characteristics and dynamic emotional level. Each pedestrian agent shall be able to do automatic collision detection, avoid other pedestrians, passing and overtaking slower pedestrians. Collectively, the pedestrian agents should have the ability to self-organize into lane-formations exactly as can be seen in the factual pedestrian studies.

Table 1 Behavior and Capability of Pedestrian Agents

Individual	• Avoid other pedestrians • Move away • Passing • Overtaking • Maintain speed • Change speed • Change velocity direction • Maintain distance • Stop • Give way
Collective	• Walk together • lane formation self organization

Thus, a pedestrian tends to minimize his or her own competition interaction with other pedestrians to occupy the space. Because of the competition-interaction, the pedestrians feel uncomfortable, and experience delay (inefficiency). The behavior and capability that are modeled is summarized in Table 1. Building such model *without autonomous* pedestrian agents could be made by designing all the movements and actions before the simulation. Such simulation, however, is merely a computer graphic animation (i.e. movie) without any useful application for pedestrian traffic analysis. The challenge is to build such pedestrian agents that are capable of independent, autonomous action, interacting with other agents and to carry out those behavior and capability. How do we design such pedestrian agents?

Our approach to model the autonomous pedestrian agent movement behavior is based on a set of non-linear dynamical system that represents positive and negative feedback loop. The feedback loop is a closed loop structure that utilizes previous outcome of the past action of the system to direct the future action. Two classes of feedback loop are positive and negative feedbacks. Positive feedback promotes (enlargement or decline) change in the system and strengthens the change of the initial direction. Positive feedback also repulses from the goal and amplify the fluctuation caused by the negative feedback. Action within positive feedback loop increases the discrepancy between the system level and the goal. Negative feedback, on the other hand, has a goal-seeking characteristic. Negative feedback also may cause fluctuation in the system and instability. Action within negative feedback loop decreases the discrepancy between the system level and the goal. The goal is the attraction point in which the system will be driven.

The feedback loop systems are closely related to the dynamical system and system difference equations or system differential equations. The goal of the feedback loop is associated with the equilibrium value or fixed point of the dynamical system. The goal of negative feedback is equivalent to the repelling fixed point while the goal of positive feedback system is equivalent to the attracting fixed point. Using this feedback loop principle, interaction between pedestrians, as the important point in the microscopic level, can be modeled as a repulsive and attractive effect. Destination location is a goal. Thus, destination point should be set as attractive point. Other pedestrians and obstructions in the environment that should be avoided should be set as repulsive points. The feedback loop principle is the general principle that covers many pedestrian multi-agents models such as social force model as proposed by Helbing and Molnar (1995), magnetic force model proposed by Okazaki (1979), microscopic pedestrian model by Teknomo et al (2002) and Boid steering behavior by Reynolds (1999). Force models are bounded by order two of the differential equation while the feedback loop principle theoretically can be used for any order differential equations. The second order differential equation as in the force model for pedestrians are subset of this feedback loop system. Nevertheless, the force models are well developed and the dynamic principle is easily understood. Though it is theoretically possible to develop multi-agents pedestrian model based on any order of differential equation from order 1 to N, for simplicity of our explanation without loss of generality, we will derive it based on the common force model.

The force represents internal motivation of pedestrian to perform some action (i.e. to move) to achieve a goal (i.e. destination location). The force in here is not the real physical force that has the dimension of Newton (kg m/second^2) but only the analogy of the force that characterizes the internal driving force or motivation of the pedestrian. The force is assumed proportional with the discrepancy between the summation of intended velocities and the actual current velocity. Thus, the forces have dimension of meter/second^2 similar to that of acceleration.

To be precise with this principle, we will show them in a symbolical manner. Let destination point denoted by vector $\mathbf{e}(t)$ (if the destination is fixed over time, it can be simplified as $\mathbf{e}$) and $\mathbf{p}(t)$ is the current location of pedestrian. Space discrepancy between current location and destination is $\mathbf{e}-\mathbf{p}(t)$. To make the destination as an attraction point, we set a differential equation to reduce the space discrepancy over time. To model pedestrian movement, a hypothesis about the pedestrian behavior is needed. What kind of movement behavior represents pedestrian? We assume that without existence of other pedestrians or obstructions, pedestrian tends to walk as close as possible to his/her desire speed μ within a path that is almost a straight line. The velocity assumption represents a rate equation in the feedback loop. One of simplest way to model the velocity is to set the space discrepancy as a unit vector (by dividing it with its norm) and multiply this unit vector with the desire speed as shown in equation (1).

$$\mathbf{v}_f(t) = \frac{\mu}{\alpha}\left(\frac{\mathbf{e}(t)-\mathbf{p}(t)}{\left\|\mathbf{e}(t)-\mathbf{p}(t)\right\|}\right)+\xi \tag{1}$$

The random fluctuation ξ has zero mean and one standard deviation, known as Gaussian noise. Without the random fluctuation, equation (1) will give constant speed and zero acceleration. A dimensionless parameter α is given to generalize the model. When parameter α is positive, the destination $\mathbf{e}(t)$ becomes the attraction point of the feedback loop and when parameter α is negative the destination location $\mathbf{e}(t)$ become repulsive points.

Setting parameter α as a positive value makes equation (1) the basic formulation for a pedestrian agent to move forward. The intended velocity in equation (1) represents the internal motivation of the pedestrian agent. The agent will be motivated to walk ahead to reach the final destination by this internal motivation. This formulation is true only for single pedestrian agent who walks alone. Care must be taken into place in the implementation to avoid run time error due to zero distance. Thus, the agent shall be removed when certain threshold distance to the destination is reached.

When other pedestrians or obstructions exist in the environment, they must be put as repulsive points. The positive feedback loop forms the basis of repulsion. The interaction between pedestrian agent and other agents or between agent and the environment happens as a superposition of the positive and negative feedback loop. The pedestrian agent is optimizing the movement by taking the best path to go to the target location while avoiding other pedestrians or obstructions. We model the repulsion effect into two types of repulsive intended velocities. The first repulsive intended velocity is driving away the pedestrian agent while still quite far from other closest pedestrian (or obstruction). The second repulsive intended velocity strongly repel against all other pedestrians (or obstructions) in the neighborhood surrounding the agent. Since obstructions are similar to static pedestrians who do not move, to simplify the explanation we consider only pedestrians case.

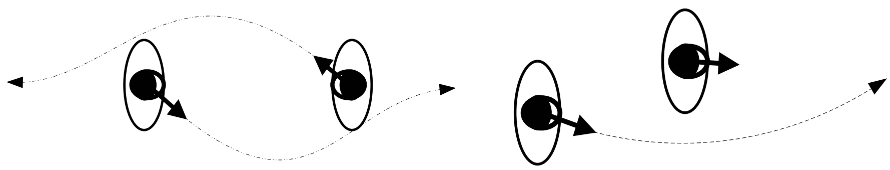


Figure 1. Effect of the First Repulsive Intended Velocity

The first repulsive intended velocity models the overtaking and meeting behavior of pedestrians. When two pedestrians meet each other, the pedestrian will move away from the other pedestrian within a certain distance that is quite far from each other. They do not wait until their distance become too close and move away unless there are many pedestrians surrounding that give them no opportunity to move away. A similar behavior happens when a pedestrian is following another slower pedestrian. The faster pedestrian will move away in quite a far distance if there is no other pedestrian. In the case where there are many pedestrians, the opportunity to move away from a certain distance is hindered by the lack of space and the pedestrian will be either be slowing down, stopping or looking for another way in the emptier space.

The first repulsive intended velocity, $\mathbf{v}_a^n(t)$ is working only if there is another pedestrian in front of the agent (within the sight distance). If there are many other pedestrians or many obstacles, it considers only the closest pedestrian or obstacle to the agent. Why do we need to consider only the closest pedestrian? It is the closest pedestrian who will affect the agent's decision to move away. If we sum up the intended velocity generated from other nearest pedestrians, the first repulsive force will be unstable. The behavior of the pedestrian becomes erratic due to many considerations that must be taken at one time. Thus, only the closest pedestrian or obstacle to the agent shall be considered. To take into account only other pedestrian or obstruction *in front* of the agent, we compute the repulsion based on the intrusion of other pedestrian (or obstruction) within sight distance of the agent.

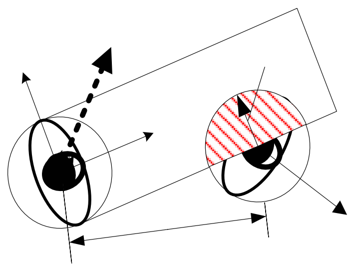


Figure 2. Intrusion to the Sight Distance Makes the Agent Move Away

If $d(t)$, $\mathbf{y}(t)$ and r are, respectively, representing the distance between the pedestrians, intrusion of the closest pedestrian in the area in front of the actor and the radius of pedestrian as shown schematically in figure , the first repulsive intended velocity of pedestrian n, $\mathbf{v}_a^n(t)$, in local coordinate is given by

$$\mathbf{v}_a^n(t) = \frac{\mu.(2r - \mathbf{y}(t))}{\chi.d(t)} = \frac{\mu.(2r - \mathbf{y}(t))}{\chi \left\| \mathbf{p}_k(t) - \mathbf{p}_n(t) \right\|} \qquad (2)$$

Since the intended velocity of equation (2) is counted in the local coordinate based on the direction of the current velocity, transformation to global coordinate is necessary using a rotation of axis. This intended velocity only works when $\mathbf{y}(t)$ is not a zero vector and it will drive the agent to turn away from the closest pedestrian (within the sight distance) with magnitude proportional to the intrusion of other pedestrian in the actor's way. The factor $\frac{\mu}{\chi.d(t)}$ is the smoothing factor to maintain the walking speed of pedestrian. Becoming nearer to the other pedestrian (or obstruction) will produce a higher intended velocity to move away. A non-dimensional constant chi χ is given to generalize the model and will be used as a constant calibration and validation of the model.

By the first repulsive force, the pedestrian agents can move away from each other within a certain distance. However, there is no guarantee that the pedestrians will not collide with each other when they are very close, especially when there are many pedestrians in the facility.

Another repulsive force is needed to ensure no collision. The second repulsive intended velocity force works to avoid the collision between pedestrians. To avoid the collision, it is assumed that each pedestrian has an influence radius that represents his or her security awareness. The intended velocity is generated with magnitude equal to the influence diameter of pedestrian minus the distance between pedestrians when the influence radius of pedestrians overlaps each other as shown in Figure 3. No repulsive intended velocity is generated if the influence radius does not overlap each other. This repulsive intended velocity considers all surrounding pedestrians and the velocity are summed up linearly.

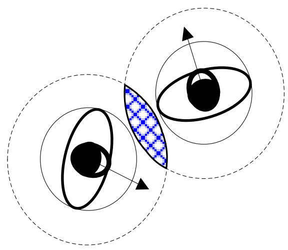


Figure 3. Intended Velocity to Avoid Collision

$$\mathbf{v}_r^n(t) = \frac{\mu}{\beta}.\sum_k \left(\frac{2r}{\left\| \mathbf{p}_n(t) - \mathbf{p}_k(t) \right\|} - 1 \right) \left(\frac{\mathbf{p}_n(t) - \mathbf{p}_k(t)}{\left\| \mathbf{p}_n(t) - \mathbf{p}_k(t) \right\|} \right) \tag{3}$$

The intended velocity must depend on the maximum walking speed of the pedestrian. The intended velocity must also increase non-linearly in proportion with the distance between the two pedestrians, thus the maximum walking speed is given in the numerator and the distance is put in the denominator. The parameter beta β, which has a spatial dimension (meter) is used to generalize the model and will be used as constant calibration and validation of the model. Since the direction of the intended velocity is already given by the vector terms, the value of the parameter β must be positive.

Setting the acceleration as velocity difference between the superposition of intended velocity and the current velocity and we know from physics that $\mathbf{v}(t) = \frac{d\mathbf{p}(t)}{dt}$, $\mathbf{a}(t) = \frac{d\mathbf{v}(t)}{dt} = \frac{d^2\mathbf{p}(t)}{dt^2}$, and force $\mathbf{F}(t) = m.\mathbf{a}(t)$, the dynamic formulation can be put together in terms of the current position of pedestrian i, $\mathbf{p}_i(t)$, as a second order differential equation

$$m\frac{d^2\mathbf{p}^n(t)}{dt^2} + \frac{d\mathbf{p}^n(t)}{dt} = \frac{\mu}{\alpha}\left(\frac{\mathbf{e} - \mathbf{p}(t)}{\left\| \mathbf{e} - \mathbf{p}(t) \right\|} \right) + f_\theta \left(\frac{\mu.(2r - f_{-\theta}(\mathbf{y}(t)))}{\chi \left\| \mathbf{p}_k(t) - \mathbf{p}_n(t) \right\|} \right) + \frac{\mu}{\beta}.\sum_k \left(\frac{2r}{\left\| \mathbf{p}_n(t) - \mathbf{p}_k(t) \right\|} - 1 \right) \left(\frac{\mathbf{p}_n(t) - \mathbf{p}_k(t)}{\left\| \mathbf{p}_n(t) - \mathbf{p}_k(t) \right\|} \right) + \xi \tag{4}$$

The model contains a rotation function $f_\theta(.)$ to transform it from local to global coordinate. Equation (4) is the basic autonomous model for pedestrian agent n. Equation (4) is a set of non-linear second order differential equation of pedestrian positions that depend on each pedestrian's positions, speeds and accelerations. Though the model is quite simple, it is more practical to simulate the model rather than finding the analytical solution. The simulation also has a benefit to visualize the movement of each pedestrian in a plan like an animation. The numerical simulation was performed through numerical integration with very small dt using Euler or Runge-Kutta method to solve the differential equation.

Aside from the main parameter of α, χ and β, it could be expanded to several other additional parameters such as sight distance, maximum speed, maximum acceleration, influence radius and mass m. The simulation of individual pedestrians involves the use of many parameters. This large set of parameters make the validation of multi-agent pedestrian model is very difficult. Such validation requires deep understanding of behavior of the factors and parameters. In the next section, we attempt to understand the behavior of the factors and parameters through sensitivity analysis.

3. SENSITIVITY ANALYSIS

In this section, the microscopic simulation model will be further discussed. There are two control variables in the simulation, which are the maximum speed and the total number of pedestrian (or density because the area of the trap is fixed). The simulation model has four main parameters, which are the mass (m), alpha (α), beta (β) and chi (χ). By changing the values of the control variables and the parameters, the sensitivity of the parameters and relationships between variables can be revealed in this section. Using the speed density relationship (called *u-k graph*), the fundamental diagram of traffic flow can be determined. The density is sometimes represented as the total number of pedestrians rather than the density itself simply because it is easier to read an integer number than a decimal number.

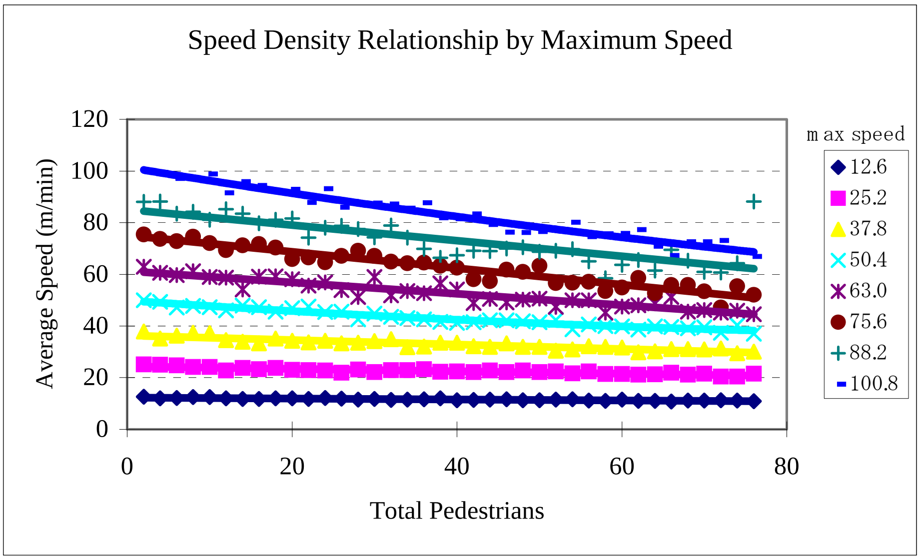


Figure 4. Effect of the Maximum Speed toward Speed-Density Graphs

The common relationship between speed and density or the u-k graph is linear. Interestingly, the pedestrian multi agents system described in equation (4) also produce linear u-k graphs if the speed represents the system average speed. The density as characterized by the total number of pedestrian is the control variable of the experiments since the area of the trap is constant. Figure 4 shows the u-k graphs as it is influenced by the maximum speed. The speed-density relationship is linear with higher maximum speed on the top of the lower one. It is interesting to note that the gradient and the intercept of the graph are changing as the maximum speed is changing. The scattered data is added to show the variation of the data toward the model. Eight categories of maximum speed were utilized as the control variable; the intercept of the u-k graphs with the vertical axis represents the free flow speed or the maximum speed. Category 1 is about 12.6 m/min and category 8 is about 100.8 m/min. The r-squared value between the maximum speeds and the intercepts is 0.999 characterizing the very strong relationship between the control variable and the data.

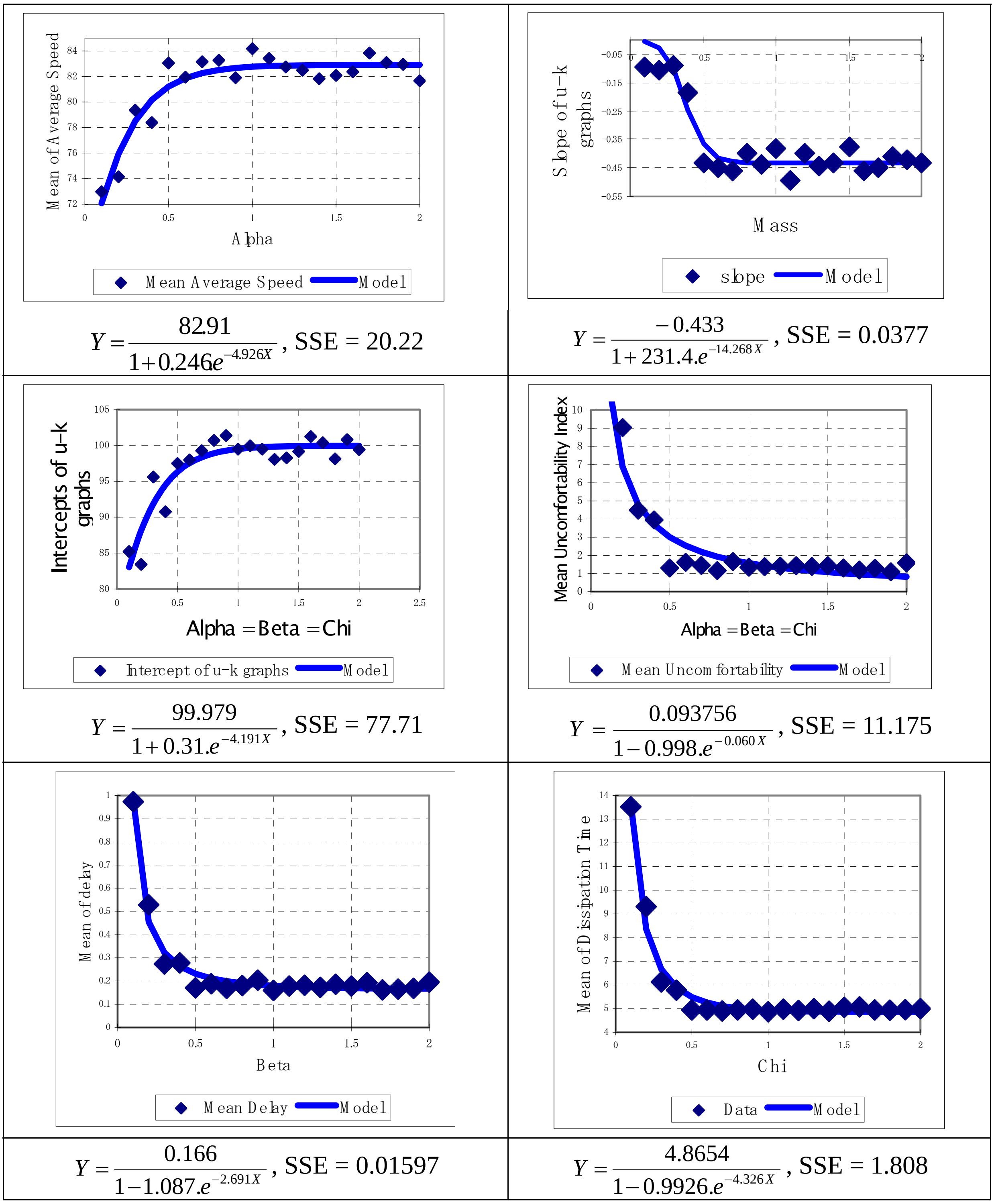
Table 2. Sensitivity of Motion Parameters

Parameters Increase	Mean of Average Speed	Slope of u-k Graphs	Free flow Speed
α	No influence	No influence	No influence
β	No influence	No influence	No influence
χ	Increase	No influence	Increase
$\alpha = \beta$	No influence	No influence	No influence
$\beta = \chi$	Increase	No influence	No influence
$\alpha = \chi$	Increase	Decrease	Increase
$\alpha = \beta = \chi$	Increase	Decrease	Increase
m	Decrease	Decrease	Increase

Intensive numerical experiments were done to get the sensitivity values of the parameters. The search was performed using exhaustive search for each parameter and the parameters' combination. For each parameter value, ten experiments were done and the average value of the output was considered for that parameter value. The value of the parameters, are then increased with a value of 0.1. The range of parameters investigated was done from zero to two. For each combination of parameter, the relationship between the parameter with the mean of average speed, slope of u-k graphs and free flow speed were investigated. The three variables mean of average speed, slope of u-k graphs and the free flow speed were set to be the standard variables of the sensitivity analysis. The choice of these three standard variables is based on consideration that they will have great influence over the validation of the simulation, especially the slope of the u-k graphs.

Figure 5 shows some sensitivity analysis of the main parameters for motion. The higher the value of parameter α, β and χ in general, will make the delay, uncomfortability and dissipation time smaller but will increase average speed. The mass parameter m tends to reduce the average speed, uncomfortability and dissipation time but increases the delay. The model and the sum of square error are shown in the bottom of each graph. When the values of the parameters are higher than one, the graphs tend to reach the asymptotic value or constant.

Some results of the exhaustive search over the axis of parameters are summarized in Table 2. If the change of the parameters has significant influence over the standard variables, the sensitivity is said to be successful. The sensitivity analysis shows that there is no significant influence of the change of individual parameters α, β, χ and m influence over the standard variables. Combination of two or three parameters has better influence over the standard variables. It was found that those parameters have greater influence when these values are smaller than one. These phenomena happen because in the formulation of the intended velocity, the parameter is set in the denominator. As the parameter values are between zero and one, the intended velocities are getting stronger due to the parameters value. If the value of any parameter is higher than one, the influence of that parameter is smaller.



$$Y = \frac{82.91}{1+0.246e^{-4.926X}}, \text{ SSE} = 20.22$$

$$Y = \frac{-0.433}{1+231.4.e^{-14.268X}}, \text{ SSE} = 0.0377$$

$$Y = \frac{99.979}{1+0.31.e^{-4.191X}}, \text{ SSE} = 77.71$$

$$Y = \frac{0.093756}{1-0.998.e^{-0.060X}}, \text{ SSE} = 11.175$$

$$Y = \frac{0.166}{1-1.087.e^{-2.691X}}, \text{ SSE} = 0.01597$$

$$Y = \frac{4.8654}{1-0.9926.e^{-4.326X}}, \text{ SSE} = 1.808$$

Figure 5. Sensitivity of Motion Parameters

4. MODEL VALIDATION

This section describes the validation of the simulation using the real world data. The calibration is concerned with the determination of the numerical value of the parameters and the results of the simulation. This can be easily done by setting the space and time based on the pedestrian body (radius about 60 cm) and mean speed (1.34 m/s). The validation, however, is done to see whether there is an adequate agreement between the model and the system being modeled. The validation step ensures that the simulation model behaves as expected. One way to inspect this behavior is the decline of the average speed as the density increases. The previous sections on the sensitivity analysis have proven that this behavior is guaranteed. The regression results have strongly revealed not only the behavior of the declining average speed as the density increases, but it even showed that this relationship is linear with a very high correlation. It is the sensitivity analysis that ensures the validation step that the agents' model behaves as expected.

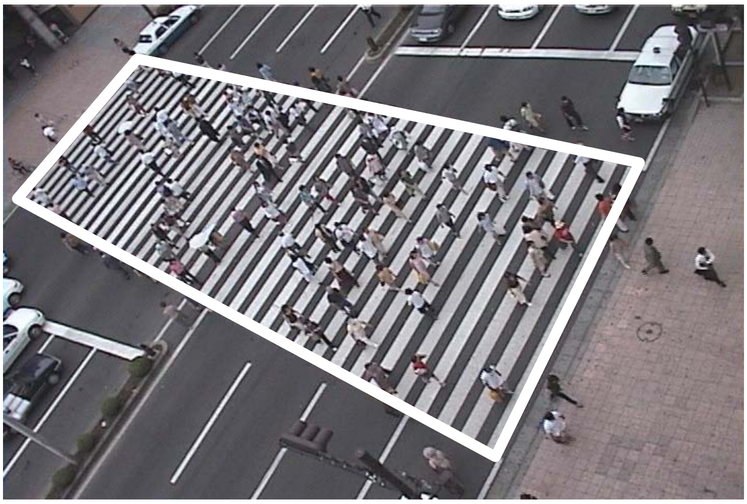


Figure 6. Real World Pedestrian Trap

The data was gathered through video from a pedestrian crossing locations in the city center of Sendai, Japan, from the 5th floor of parking building (about 16 meter height from the surface), as seen in Figure 6. Each set of data is about 60 seconds (one green time) with about 150 pedestrians involved. The pedestrian trap is set as the whole crossing area (11.23 meter by 31.10 meter). The microscopic pedestrian data was gathered and tracked using image processing method developed by Teknomo et al (2001a) since the manual data collection is implausible.

After the conversion from video into file and the collection of path coordinates, the data was trimmed into pedestrian trap only. The data was taken every 0.5 second (2Hz). More slices in every second (higher frequency) do not produce much movement of pedestrian due to the size of the picture. Smaller frequency will produce a rough behavior of pedestrians' movement. The conversion image coordinate to the real world coordinates was found using 136 manual data points using affine regression as suggested by Teknomo (2002). In principle, the conversion procedure is a simple skew coordinate transformation combined with ordinary least square method.

A total of 27187 speed data and 26668 acceleration data from 519 pedestrians were analyzed. Figure 7 shows the speed profile and speed distribution of these data. In the beginning, the speed is slow and going up to the average speed. About the last 10 seconds before the end of the green time, the speed profile of the real world pedestrian crossing is erratic due to the intention to be fast (blinking signal) and some of the pedestrian begin to run. The speed distribution nearly resembles a normal distribution with an average of 1.359 meter/second and variance of 0.482 $(m/s)^2$.

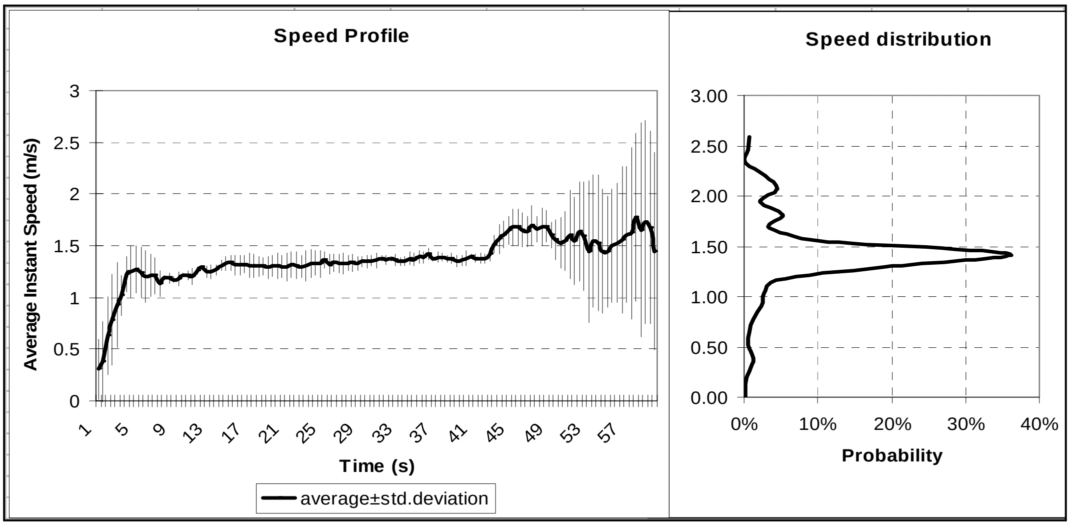


Figure 7. Speed Profile and Speed Distribution of Real World Data

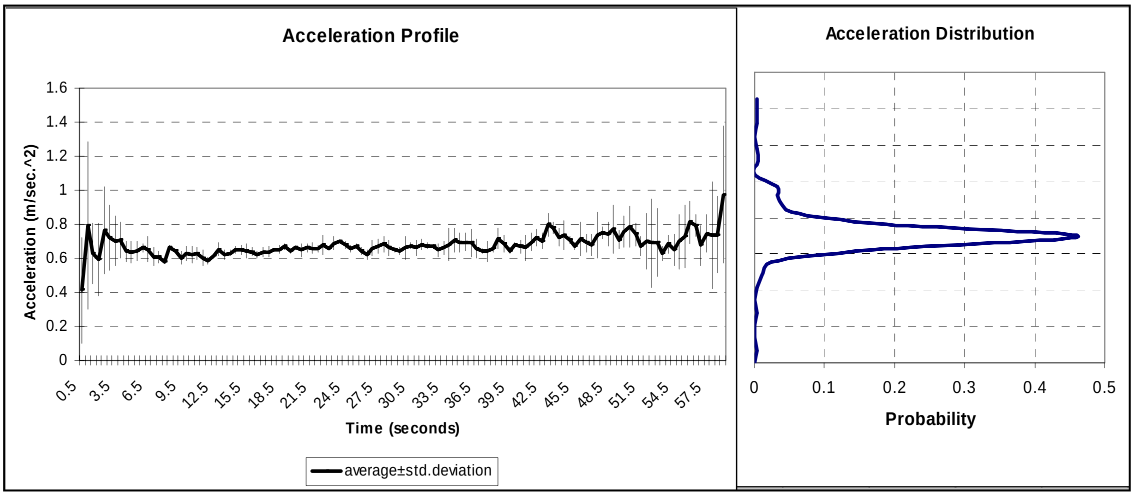


Figure 8. Acceleration Profile and Distribution of Real World Data

The acceleration profile, as shown in Figure 8 exemplifies that the acceleration is almost constant. In the beginning of the crossing time, the acceleration tends to be high because the pedestrians start from zero speed and tend to increase their speed into the average speed. In the end of the crossing time, the acceleration again becomes high because some pedestrians are running. The acceleration distribution bears a resemblance to the normal distribution with an average of 0.68 meter per square second and variance of 0.156 $(m/s^2)^2$. The statistics performances from these real world data was used for the validation of the simulation. The shoulder-to-shoulder length that has been measured by the authors reveals that the average length (i.e. diameter) of a human body is about 60 cm. Based on this value the default of pedestrian diameter is established.

Once the speed and acceleration distribution was obtained, the validation of the model was performed automatically through Monte Carlo search. The Monte Carlo search method has been proven that able to find the global optimum similar to Genetic Algorithm. The Monte Carlo search is utilized due to its reliability. The goal of the search is to minimize the root mean square difference between speed distributions and acceleration distribution. The specific value of these input variables including the parameter setting is done to minimize the error between mean and standard deviation of the two distributions. Since the distribution of the speed can be assumed normal, the mean and standard deviation are the basis for the comparison. Let μ_s, σ_s, μ_a and σ_a represent respectively mean of instants speed, standard deviation of instant speed, mean of instant acceleration and its standard deviation. Let superscript w and m symbolize real word data and the simulation model respectively, then the automatic validation is done to find tuple parameters $\langle m, \alpha, \beta, \chi \rangle$ which minimize the root mean square

$$rms = \sqrt{\left(\mu_s^w - \mu_s^m\right)^2 + \left(\sigma_s^w - \sigma_s^m\right)^2 + \left(\mu_a^w - \mu_a^m\right)^2 + \left(\sigma_a^w - \sigma_a^m\right)^2} \tag{6}$$

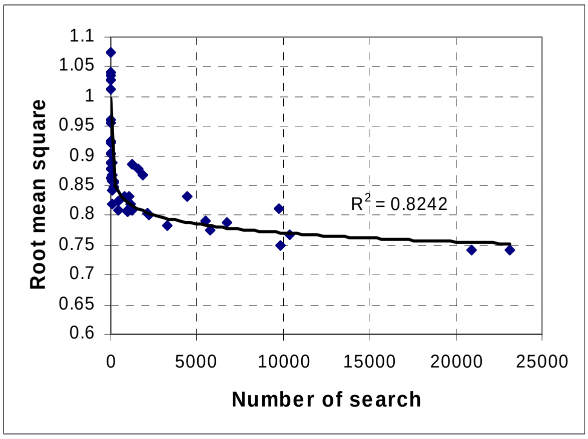


Figure 9. Convergence of the Root Means Square of the Automatic Validation

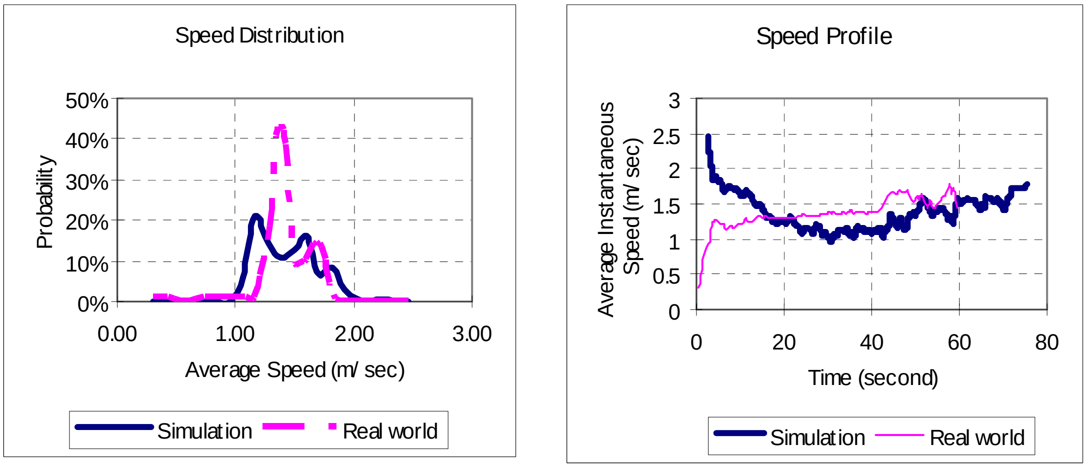


Figure 10. Comparison of Speed Profile and Distribution of Simulation and Real World Data

The real world value of the input variables has provided important hints for the value or the range of the input variables of maximum speed, maximum acceleration, pedestrian diameter, influence diameter, and sight distance, total number of pedestrians, number of ways and pedestrian trap size. Thus, these input variables are set before hand. The search was bounded for parameters' value greater than zero and lower than two. Each series of search performed about 10,000 number of search, and it was done for several series of experiments. Global minimum was found with approximate value of the parameters as follow: Mass $m = 1.870$, Alpha $\alpha = 0.453$, Beta $\beta = 0.883$ and Chi $\chi = 1.567$ for $rms = 0.741$. The convergence of the root mean square value of the search is shown in Figure 9. The points represents the best search so far for different series search.

The results of the simulation based on the validated parameters, are then examined further using best-fit distribution between simulation results and the real world data. The t-test reveals that the two distributions have no rejection to come from the same population. Figure 10 shows the speed distribution and speed profile of both simulation and real world data.

5. SELF-ORGANIZATION

Both simulation and real world pedestrians who are crossing show that they automatically create a lane formation while they are walking. Figure 11 shows the velocity diagram of pedestrian from the real world data with a raster of the lane formation. Though the velocity of each pedestrian is not the same, pedestrians prefer to follow other pedestrians rather than make their own path. This microscopic behavior happens because the pedestrian tends to reduce their competition-interaction effect, especially with a pedestrian from a different way.

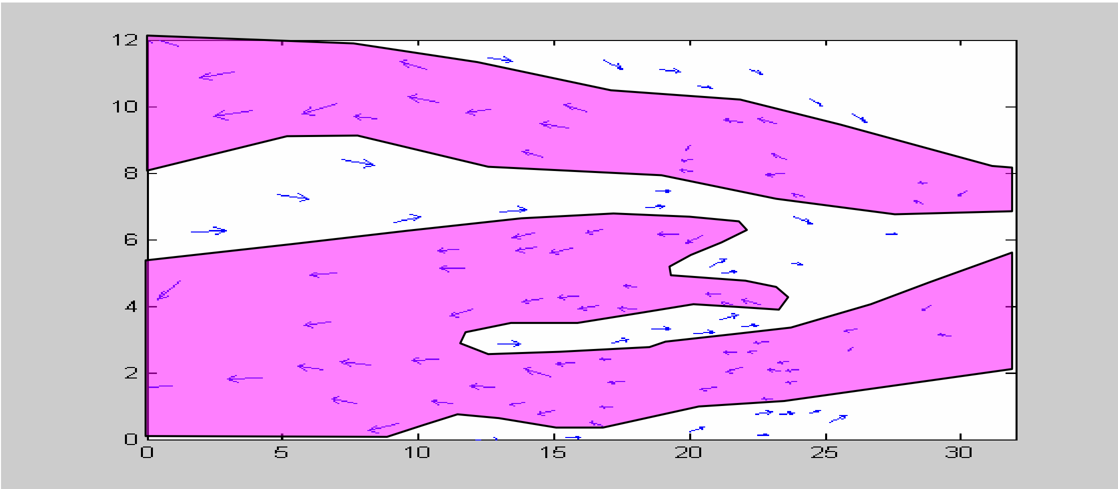


Figure 11. Self-Organization of Lane Formation

Interestingly, the simulations also produce lane formation of self-organization similar to the real world phenomena.

6. APPLICATION

To demonstrate a practical usage of the simulation, we applied it for a case study of policy analysis on a pedestrian crossing. A typical pedestrian crossing is a “mixed-lane” where pedestrians from both directions meet in the middle of the crossing and try to avoid each other. As the result of those interactions, the walking speeds of the pedestrians may slow down and there may be an increase in the delay and dissipation time to cross the road for the same number of pedestrians.

A simple policy such as to keep left (or right), or called “lane-like segregation” might be proposed to reduce the interaction. The implementation of this policy is straightforward. It can be done by marking an arrow on the left side of the starting point of the zebra cross. Using those markings, the pedestrians may be guided to keep left during the crossing. The reduction of the interaction due to lane-like segregation policy may increase the average walking-speed; reduce the delay and the dissipation time.

An experiment on pedestrian crossing was done in two scenarios. The existing condition is called “mixed-lane” where the pedestrians’ initial and target locations are randomly generated at both ends of the crossing. The keep right policy or the “lane-like segregation” was implemented by generating the pedestrians in the lower half (for west to east) and the above half (for east to west). The numerical experiments using the multi agents simulations shows that the keep-right policy or the lane-like segregation policy is inclined to be superior to do minimum or mix-lane policy in terms of average speed, uncomfortability, average delay and dissipation time. More detail about this application can be found at Teknomo et al (2001b).

7. CONCLUSIONS

We have presented a multi agents system for pedestrian traffic analysis and its parameter validation. We have shown that the sensitivity analysis of control variables and parameters of the multi-agents model to investigate the behavior of the model could form the basis to ensure the validation step. The model was automatically validated using the real world data by minimizing the difference between the speed distributions using Monte Carlo search. Without such validation, the model remains as theoretical study without foundation for real application. This study has opened up a connection between theoretical works of multi agents system and real world application because the model was validated to have similar output as pedestrian studies. A successful attempt to link microscopic model with the macroscopic pedestrian studies was also described. The aggregation of microscopic model of multi agent system produces the decline behavior of the average speed as the pedestrian agents’ density increases as suggested by many literatures of classical macroscopic pedestrian studies. The regression analysis has further discovered that this relationship is linear with a very high correlation. Collectively, the pedestrian agents have been appeared to have ability to form even self-organization behavior of lane formations exactly as can be seen in the factual pedestrian studies. The lane formation self-organization of pedestrian shall become one of the inspections to ensure that the multi-agents model behaved correctly as pedestrians. The model was applied for crossing policy analysis with good results that the lane-like segregation policy is inclined to be superior to do minimum or mix-lane policy in terms of average speed, uncomfortability, average delay and dissipation time.

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