A Collision Avoidance Behavior Model for Crowd Simulation based on Psychological Findings

Jin Hyoung Park
KAIST, KIOST
jin.h.park@kaist.ac.kr

Francisco Arturo Rojas
KAIST
frojas@kaist.ac.kr

Hyun Seung Yang
KAIST
hsyang@kaist.ac.kr

Abstract

This paper proposes a collision avoidance behavior model for crowd simulation based on psychological findings of human behaviors such as gaze-movement angle (GMA), side stepping, gait motion, and personal reaction bubble (PRB) to get better results in crowd simulation. By calculating the GMA between agents, collision can be predicted and avoided without knowing the exact trajectories of the agents. The proposed model consists of four phases: (1) GMA-based collision prediction for mid/long range by using speed-variant Information Process Space (IPS), (2) collision avoidance steering, (3) gait-based locomotion generation, and (4) space-keeping based on PRB. The effectiveness of the proposed speed-variant IPS was tested on various types of agent flows with different densities. The total loss of kinetic energy accumulated during an agent's movement and the ratio of the length of the path actually traveled to the length of the original path are used as key metrics to figure out the features between the different types of flows. Finally, examples of tuning the parameters with well-known fundamental diagrams are presented.

Keywords: collision avoidance, crowd simulation, speed-variant information process space (IPS), gaze movement angle (GMA), personal reaction bubble (PRB), gait motion

1. Introduction

Crowd simulation synthetically reproduces the appearance or effect of interaction amongst a large number of people or of objects moving together. Ever since the work of [1], which proposed a rule-based behavioral modeling methodology for "bird-like objects: boids," many researchers have proposed and have developed new concepts and models for crowd simulation. The main application fields of crowd simulation are in engineering and entertainment applications. The former includes safety engineering, civil engineering, and architect. The later includes computer game and computer animation.

The research fields of crowd simulation can be divided into six different areas: (1) generation of virtual individuals, (2) crowd animation, (3) crowd behavior generation, (4) interaction with virtual crowds, (5) virtual crowd rendering, and (6) integration of crowds in virtual environments [2]. Among these areas, crowd behavior generation is a key field in determining the quality of crowd simulation that is needed for both entertainment and engineering crowd simulations.

The behavior models for crowd simulation normally fall into one of following three categories: social force models (SFM), cellular automata models (CAM), and agent-based models (ABM). Crowd behavior is the result of an individual's interaction with other individuals, groups, and/or surroundings. Different methods should be used when describing the individual level motions and the crowd level motions. Individual level motion focuses on describing the physical motion by using inverse kinematic methods or motion capture methods that help express the desired movements. On the other hand, because the latter one describes the interaction between individuals forming a virtual crowd, it focuses more on describing and modeling behaviors based on judgments and perception/cognition such as path planning, group behavior, and steering behavior.

The steering behavior of an individual or group in crowd simulation has drawn the biggest attention of researchers. Steering behavior, being a unit of the entire moving crowd, can be a critical element that can influence the accuracy and the realism of a crowd simulation. Reynolds proposed various types of steering behavior such as offset pursuit, arrival, obstacle avoidance and unaligned collision avoidance [3]. Among these, collision avoidance and obstacle avoidance can be regarded as the key feature of realistic crowd simulation because we can get more reliable data for an engineering application and have a more realistic scene for an entertainment application by making collision avoidance behavior more realistic.

In this paper, we propose a collision avoidance behavior model that is based on psychological findings to generate more human-like collision avoidance behaviors. The remainder of this paper begins with a review of related work. In the third section, algorithms for collision prediction and collision avoidance are proposed. Experiments and results are presented in the fourth section. Then we close this paper with conclusion and future work.

2. Related Work

A SFM generates collision avoidance behaviors of individuals in the crowd by summing up five virtual force terms [4]. When interactions amongst sparsely populated pedestrians occur, the SFM suffers from a short range of repulsive force, which leads to excessively frequent urgent detours of pedestrians to avoid physical contact. This behavior is not like the real world behavior. To solve this problem, Pelechano et al. and Karamouzas et al. embodied an explicit collision prediction phase in SFM [5][6]. Steffen increased the application time of the repulsive force to implement the function of foresight that gives the same effect to crowd interaction as collision prediction does [7].

A cellular automata is a discrete model that consists of a regular grid of cells, each cell having a finite number of states. No collision occurs in CAM because CAM adopts hard-core exclusion that does not permit a cell to be occupied by more than one person at the same time. There is no explicit collision prediction phase in CAM. A state transition function can be defined to imply collision prediction and collision avoidance. Loscos et al. proposed a collision prediction method for CAM [8]. They check up to five cells ahead to avoid collision. EXODUS stores potentials on the cells for a virtual crowd to use as a potential map for global or local routing [9].

Lastly, ABM uses behavioral rules for modeling each person’s behavior, which varies from situation to situation [10][11][12]. In ABM, findings on human behaviors are reflected to the model by rules. Behavior rules in ABM mimic those of humans. Agents should examine their surroundings, and depending on each agent’s situation it should decide if to follow another agent, walk inline, or avoid an obstacle. Multi-resolution collision avoidance model proposed in [13]. If there is enough time to change the direction for the predicted collision, collision avoidance technique type I, which considers both the change of speed and the change of direction, is used, otherwise type II, which considers change in direction only, is used. Fuertey does analysis on obstacles’ positions and speeds in planning safe trajectories for agents in collision avoidance [14]. In the work by Metoyer and Hodgins, monitoring and yielding tasks are used to avoid collision [15]. A linear trajectory extrapolation is used for collision prediction in [16]. The collision reactions are classified into two categories: speed modification and direction modification [8]. Differently from other works, Rymill and Dodgson approached crowd simulation on the basis of psychology [17]. They applied psychological findings to their steering model for crowd simulation but their usage of psychological findings is fractional and limited to the generation of collision avoidance steering behavior.

3. Proposed Model

In this work, a collision avoidance behavior model for ABM that is based on psychological findings of human behaviors in a crowd is proposed. The psychological findings applied to the proposed model covers all phases of collision avoidance behaviors: sensing, collision prediction, collision avoidance steering, locomotion, and space-keeping.

3.1 Speed-variant Information Process Space

The area that the observing pedestrian considers is the one in which a collision with another pedestrian could occur in a short time. This area is called an Information Process Space (IPS) [18]. IPS is a conceptual area that determines the spatial boundary within which all other pedestrians are treated as potential clashers to the observing pedestrian.

By using an eye tracker and an environment mockup, Kitazawa and Fujiyma found three interesting things regarding IPS: (1) pedestrians are more interested in objects right in front to which the lateral distance is small, (2) the pedestrian seldom fixates objects with a GMA bigger than 45 degrees, and (3) the duration of the first fixation on the leading pedestrian is less than that of coming pedestrians [18]. GMA is discussed in section 3.2.

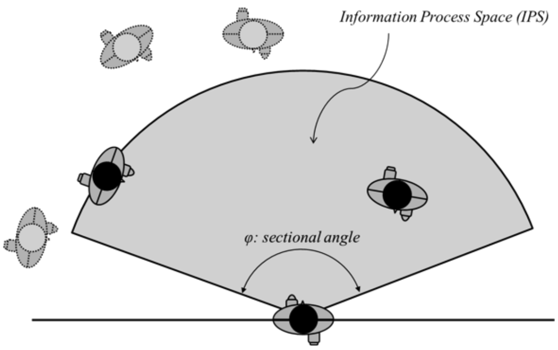

Figure 1 : The IPS of the proposed model

In considering these findings a fan-shaped and speed-variant IPS for collision prediction is applied in the proposed model (Figure 1). The proposed IPS has the longest range in the direction of zero degrees GMA. The sectional angle of the IPS is 90 degrees when a pedestrian moves at its maximum walking speed. The angle, however, increases as the pedestrian loses its speed. When it stops, the sectional angle of the IPS becomes 180 degrees. This is intuitively natural. The sectional angle of IPS is determined by expression (1).

$$\varphi = 180 - 90\left(\frac{current\_speed}{max\_speed}\right) \qquad (1)$$

3.2 GMA-based Collision Prediction

Normally, in crowd simulation, time-to-contact and distance-to-contact are calculated to predict a collision. This calculation assumes that both pedestrians maintain constant velocity. This is, however, not the process we carry out for collision prediction in our everyday life. A pedestrian does not walk in a constant velocity. Cutting et al. found a collision prediction model based on the angle between the movement direction of a person and the gaze angle to the other person, namely the gaze-movement angle (GMA) [19]. They tried to identify how people can predict collisions with stationary and moving obstacles without knowing the exact trajectory of other obstacles. Ondřej et al. introduced a GMA-based collision avoidance model for crowd simulation [20]. Their research, however, does not embrace the routines for identification of collision type. Different types of collision trigger different types of collision avoidance behavior. This paper proposes a GMA-based collision avoidance model for crowd simulation by introducing indicator functions for collision prediction and collision type identification.

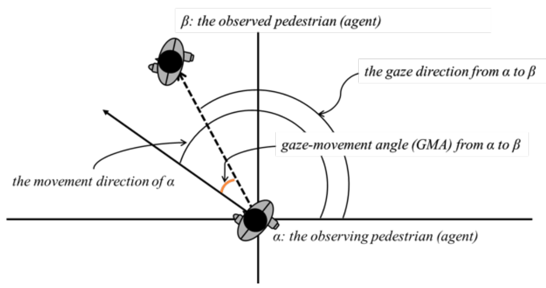

Figure 2 : GMA between pedestrians

The GMA corresponds to the difference between the angle of movement direction and the angle of the gaze direction in Figure 2. The gaze angle corresponds to the direction of the other pedestrian from the observer. In this work, the pedestrian with the smaller GMA is defined as the observing pedestrian and the other one with the bigger GMA as the observed pedestrian. In situations of approach, one of three cases will occur: (1) passing in front, (2) collision, or (3) passing behind. Positive changes in GMA occur when the observing pedestrian is going to pass in front of the observed pedestrian. Negative changes occur in the case of passing behind. No change implies collision.

On the basis of such findings, a collision prediction method based on the GMA for crowd simulation is proposed. The method predicts that there is to be a collision if two conditions between the observing pedestrian and the observed pedestrian are met simultaneously: (1) both pedestrians maintain constant GMAs between them and (2) the distance to the observed pedestrian from the observing pedestrian consecutively decreases. In real life, according to the findings by Cutting et al., pedestrians check the variations on the appearance size of an object while predicting collisions. If the object comes to the observer, the appearance size of the object increases. In the proposed model, the distance to the object is calculated instead of measuring the appearance size of the object.

$$I_{cp}\left(\{g_i\}_{i=t}^{t+n-1}, \{d_i\}_{i=t}^{t+n-1}\right) = \begin{cases} \text{true, if } |g_i - g_t| < \varepsilon_i \text{ and } \left|\frac{d_{i+1}}{d_i}\right| < 1 \\ \text{false, otherwise} \end{cases} \quad (2)$$

The GMA-based collision prediction I_{cp} of an observing pedestrian α basing its observations on an observed pedestrian β for n simulation clocks is defined as expression (2) where $i, j \in \{t, t+1, \ldots, t+n-1\}$, g_i is the GMA of β observed by α at simulation time i, d_i is the distance between α and β at simulation time i, r is the radius of the torso of pedestrian s, and $\varepsilon_i = \sin^{-1}(2r / d_i)$.

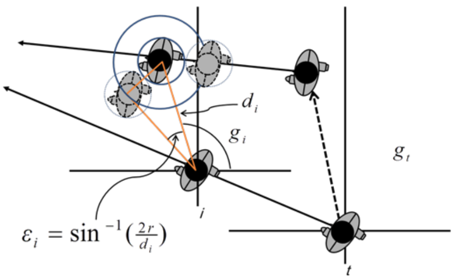

Figure 3 : ε_i for side collision

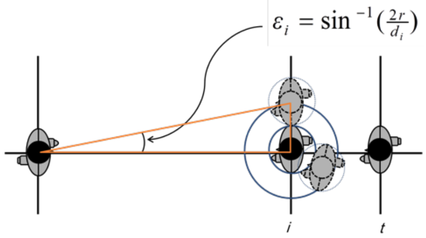

Figure 4 : ε_i for head-on collision

In the indicator function, I_{cp}, the threshold for being a constant GMA is represented by ε_i. If the deviation of GMA values in a collision prediction cycle is smaller than ε_i, those GMA values are considered constant (Figure 3 and 4).

There are three types of collision a pedestrian can encounter while he or she moves: (1) head-on collision, (2) rear-end collision, and (3) side collision.

If I_{cp} is true, a collision between the observing pedestrian and the observed pedestrian would occur soon. In this work, side collision is treated as a general and inclusive collision model. A head-on collision and a rear-end collision can be considered as special cases of side collision. If only I_{cp} is true, side collision is predicted. Head-on collision and rear-end collision require additional conditions. A head-on collision or a rear-end collision can occur when the GMA of β from α is zero. Because I_{cp} already has the error term ε_i, in considering the radius of the human torso, g_t for I_{cp} is zero when determining a head-on collision or a rear-end collision. The condition for head-on collision and rear-end collision is described in expression (3). This means that a head-on collision or rear-end collision can occur when β moves directly in front of α consecutively and the distance between α and β monotonously decreases.

$$I_{cp} = true \text{ with } g_t = 0 \quad (3)$$

In addition to the satisfaction of (3), if the movement direction of α and that of β is the same, the collision would be rear-end (4) where M_α and M_β are the average movement direction of α and β respectively, and Θ is the threshold for being collinear.

$$\begin{aligned} &|M_\alpha - M_\beta| < \Theta \quad \text{or} \\ &|M_\alpha - M_\beta| > 360 - \Theta \end{aligned} \quad (4)$$

On the other hand, if the movement directions of two pedestrians are opposite, the collision would be head-on. The expression (5) describes the conditions of head-on collision where M_α and M_β are the average movement direction of α and β respectively, and Θ is the threshold for being collinear.

$$180 - \Theta < \left|M_\alpha - M_\beta\right| < 180 + \Theta \qquad (5)$$

GMA-based collision prediction has several advantages over the time-to-contact approach. It is more robust to variations in the speed and the path of the other pedestrian. It does not assume either constant speed or a linear path; the accuracy of the prediction is not affected by these variations. During a step period, the pedestrian's GMA and distance is calculated just a several times because the accuracy of the prediction would be good enough just with seldom calculations, which is normally not the case in other models.

3.3 Collision Avoidance Steering Model

In the previous section, a method for collision prediction between two pedestrians has been proposed that checks if the following two conditions are satisfied: (1) that there are constant GMAs of the observed agent from the observing one and (2) that there is a consecutive decrease of distances from the observing pedestrian to the observed one.

We propose a steering algorithm that makes the agents in crowd simulation (1) change their movement direction and speed for collision avoidance according to collision type, (2) keep space properly with other agents, and (3) execute locomotion based on human gait-motions.

For a given agent β that is identified to collide with an observing agent α, the proposed algorithm checks collision type first. If a head-on collision with β is predicted to happen, α should select a direction to avoid the collision: right or left of β. If the observing agent α is to collide with the observed agent to its right side, α will move to the left and vice versa. If a rear-end collision is predicted, α would decide if to overtake β or not in the real world. It is, however, assumed that α would overtake β if possible because a rear-end collision would occur only when the observing agent is faster than the observed agent. If a side collision is predicted, the observing agent reduces its speed to avoid collisions. The output of the proposed algorithm is the direction and the length of a new step. These steering parameters would be realized by real gait motion.

3.4 Gait-based Locomotion

To avoid collisions with other agents, the steering action that was decided in the previous phases is yet to be realized in the locomotion of an observing agent. The steering action just determines the speed and movement direction of the agent. Because gait motion carries out the actual locomotion of an agent, realization of the locomotion should reflect features of the gait motion.

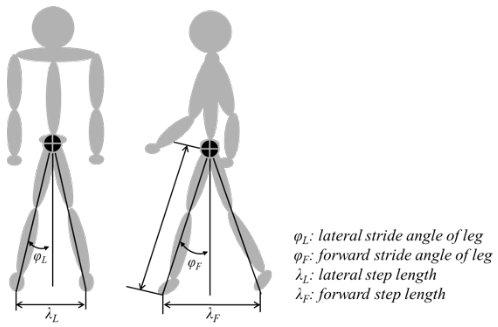

Figure 5 : Four parameters of gait motion used in the proposed model

In this work, to make the locomotion of agents, two parameters of the gait motions, stride pitch and direction, are controlled by simply changing the leg angles. Stride length is controlled by the angle between the forward leg and the backward leg, which is twice the forward step length, or $2 \cdot \lambda_F$. The stride direction is controlled by φ_F and the lateral stride angle of a leg φ_L (Figure 5). By controlling φ_L, an agent can change its movement direction without changing the direction of its whole body.

Accelerations and decelerations are carried out by increasing and decreasing φ_F in a single gait cycle and in two gait cycles respectively as it was found by [21]. A constant stride period is used although it seems to have a relationship with λ_F. On the contrary, λ_F and λ_L are influenced by each other because it is unrealistic for both of them to have their maximum value at the same time. To control the gait motions in changing the direction of the locomotion, three types of directions are used: (1) heading direction, (2) stride (or moving) direction, and (3) target direction (Figure 6). The heading direction is the direction to which the upper part of an agent's body faces. The moving direction is the actual movement direction by controlling φ_F and φ_L. For a side step while going forward to avoid a head-on collision with an oncoming agent, the moving direction of an agent is changed while the heading remains unchanged. The target direction is the direction from the agent's current position to the position to which an agent wants to go. In changing the movement direction, the difference between the heading and the target direction is first calculated. If the difference is bigger than the threshold, the heading is changed to have the same value with the target direction, which leads to a directional change of the whole body of an agent. In the other case, a side step is added while going forward until the heading and the target direction become the same.

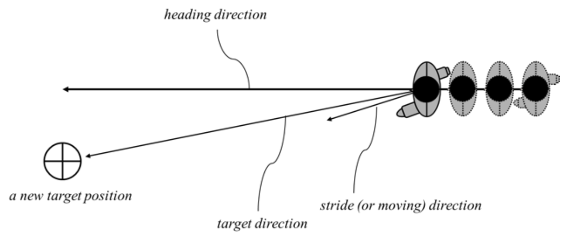

Figure 6 : Three types of directions used in controlling gait motions

By aligning the heading direction with the moving direction, the proposed method naturally implements one of the very interesting behaviors of a pedestrian: returning to his or her original course after overtaking or performing collision avoidance. After changing his or her direction to avoid a collision, rather than going straight towards his or her goal, the pedestrian returns to the original path (or line of walk) that he or she was on before the detour [22].

3.5 Personal Reaction Bubble Space-keeping

According to the findings by Hall [23], there are four layers of spaces around a person, from the inner to the outer: (1) intimate space, (2) personal space, (3) social space, and (4) public space. These spaces together are named as the personal reaction bubble (PRB). Although the radiuses of bubbles may vary from culture to culture and from situation to situation, people keep the concept of PRB when they interact with people. For collision avoidance steering behavior, ellipse-shaped personal space is usually applied. The investigation by [24] on the size and shape of personal spaces for different speed and gaze angles on an obstacle supports the usage of an ellipse-shaped personal space (Figure 7).

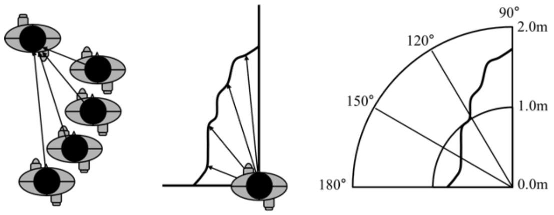

Figure 7 : Personal space for different gaze angles by Gérin-Lajoie et al.

In this work, a space-keeping algorithm for the personal space of a pedestrian in a crowd simulation applying the findings of [24] is proposed. In the algorithm, the personal space for a different gaze angle is modeled by checking that the distance from the observing agent α to the observed pedestrian β in the next step of α is sufficient for the personal space of both α and β (Figure 8). To make two agents confronting with each other avoid a collision collaboratively, the observed agent also tries to find a collision-free direction when the observing agent is finding a direction for next step.

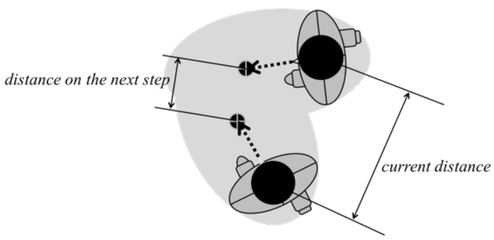

Figure 8 : Checking the distance between agents on the next step

4. Experiments and Results

4.1 Geometries and Scenarios

The proposed model was tested for various numbers of agents on a crossroad to simulate three kinds of collisions: side collisions, head-on collisions, and rear-end collisions. The dimensions for the tested crossroad is shown in Figure 9. In addition to the variations in the flow of pedestrians, various densities of pedestrians were tested due to the fact that the specific flow rate of pedestrians is heavily affected by the density of pedestrians.

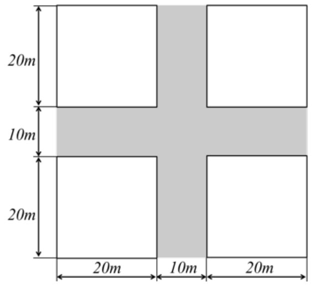

Figure 9 : Dimensions of crossroad experiment

4.2 Changes Influence in IPS Sectional Angle

Various sectional angles of the IPS were tested to show how it influences side collision detection. Agents with a fixed sectional angle of 20, 45, 90, and 180 degrees were test for densities (*persons*/m^2) between 0.1 and 1.0. Agents with a speed-variant sectional angle that varies from 20, 45, and 90 degrees to 180 degrees according to their movement speed were also tested with the same range of density.

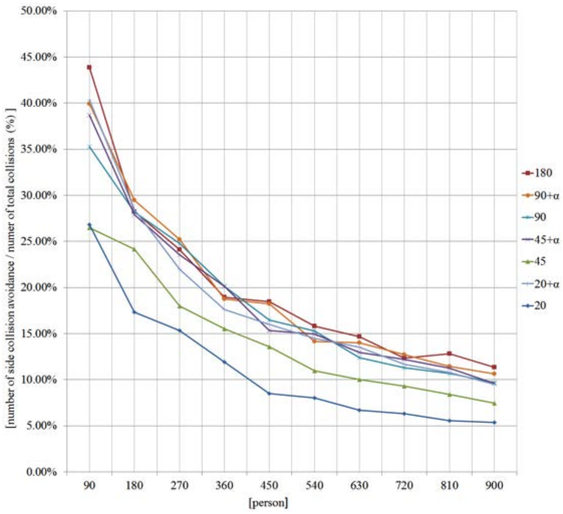

Figure 10 : The ratio of side collision avoidances to total collision avoidances versus number of people

The results show that the ratio of side collision avoidances to total collision avoidances increases as the sectional angle increases (Figure 10). A smaller sectional angle restricts the agent to have more chances to detect side collisions. Because agents would just reduce (or change) their speeds to avoid side collisions, while head-on collision or rear-end collision changes their moving directions leading to consumption of more energy, the side collision avoidance is a more efficient way of collision avoidance. Another interesting finding from this test is that a 90 degree sectional angle gives the agent a similar number of chances for detecting side collisions to that of a wider sectional angle. Speed variant sectional angles also generate similar results. It is believed that these results explain the finding of Kitizawa and Fujiyama very well. If the sectional angle of an observing agent is smaller than 90 degrees, it would fail to detect side collision with other agents that also have sectional angles smaller than 90 degrees. People seem to know this rationale without recognizing the principle of their collision avoidance behaviors.

4.3 The Influence of the Type of Agent Flow

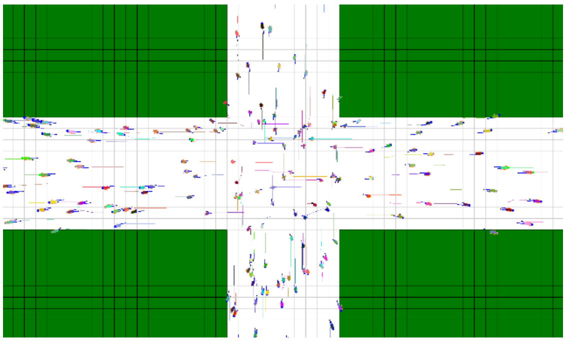
Figure 11 : Trajectories of agents in all-directional flow

The length of the path traveled P_t with that of the original path P_o was selected as the metric to identify the influence of agent flow. The original path is straight whereas the traveled path is winding. The ratio values of P_t/P_o are equal or bigger than 100%. Figure 11 shows much more realistic trajectories of pedestrians in the proposed model than those in SFM for the all-directional flow at crossroad. In Figure 12, the path ratios percentage is mapped to area densities (*persons*/m^2) that are shown for all crowd simulation flow types experimented and reran for each density. When considering the density, counter flow is most expected to force people to deviate from their original walking paths, followed by all-directional flow, then cross flow. Unidirectional flow of course doesn't cause deviating paths unless a fast walking pedestrian encounters a slow walking pedestrian from directly behind, so the ratio climbs at a much slower rate when density increases compared to the other experimental flows. It is confirmed that the more the traveled path deviates from the original path, the higher the ratio because more people are found in the particular density that force others to move out of their way. Lower density means less people per square meter, which means less chance for deviation from original paths. Thus with increasing density there is more people to cause path deviations, which explains the increasing ratios.

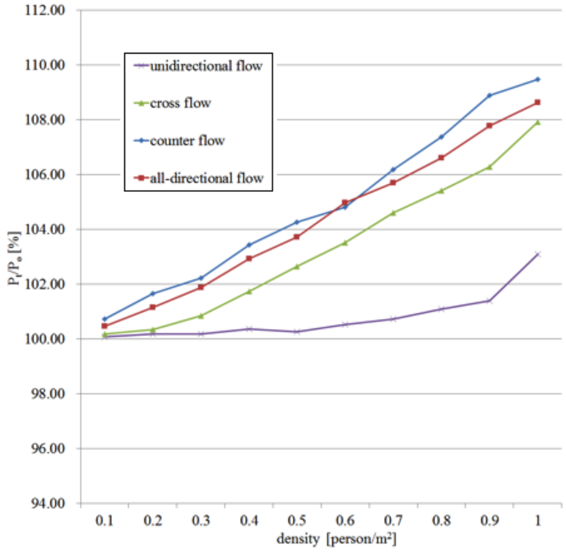

Figure 12 : P_t/P_o versus densities in different types of pedestrian flow

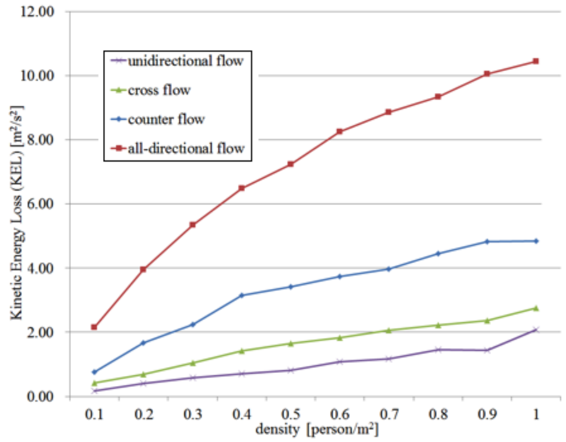

Figure 13 : Kinetic energy loss versus densities in different types of pedestrian flow

In addition to the length of the path traveled, accumulative kinetic energy loss can be a good metric to represent the characteristic of collision avoidance behavior of agents. In the real world, when pedestrians are required to avoid collisions, they would change their moving direction or speed. Kinetic energy loss may occur during the reduction of speed in avoiding collision.

In Figure 13, the average accumulative kinetic energy loss among pedestrians is mapped to densities (*persons*/m^2) for the four experimental flow types. Each simulation flow was rerun for each density. Accumulative kinetic energy loss in our case is the accumulation of the wasted kinetic energy that occurs when a pedestrian cannot maintain speed by slowing down to avoid a collision with another pedestrian. If speed is maintained, no kinetic energy is lost, and any gained kinetic energy by recovering speed is ignored because measuring the average accumulative kinetic energy loss shows how well the simulation can handle collision avoidance.

As the density increases, more people contribute to people walking deviating paths. Walking the deviating path increases the chance for additional kinetic energy loss compared to walking the straight original path to the same destination. So it comes to no surprise that unidirectional flow causes the least kinetic energy loss because all people are just walking straight to their destination from the same direction with little maneuvering due to walking speed differences. Cross flow is a bit similar except pedestrians also avoid bumping into crossing people by slowing down a bit and regaining original speed (and thus maintaining original straight paths for the most part). Where the noticeable difference regarding average accumulative kinetic energy loss is, is in all-directional flow, where much path deviation can be expected because of expected head-to-head confrontations in addition to side collisions.

4.4 Parameters for Fundamental Diagrams

There has been much research to find out the relation between density ρ and pedestrian flow J (or specific flow per unit width $J_s = J/w$). The fundamental diagram shows the characteristics of a group of pedestrians. For a given density of crowd, the average flow rate (or average walking speed) of the crowd is determined. The fundamental diagram of certain crowd differs from country to country and from culture to culture. In case of the proposed model, it was found that the fundamental diagram of a pedestrian group with an average height of 1.75

m (or 0.72 m of leg) is very similar to that of Predtechenskii and Milinskii [25] [26]. If the average height of a pedestrian group becomes 1.85 m with 22 degrees of the forward rotation angle of the leg, the group produces a fundamental diagram similar to that of Older [27] (Figure 14). Figure 15 is a snapshot of the experiments.

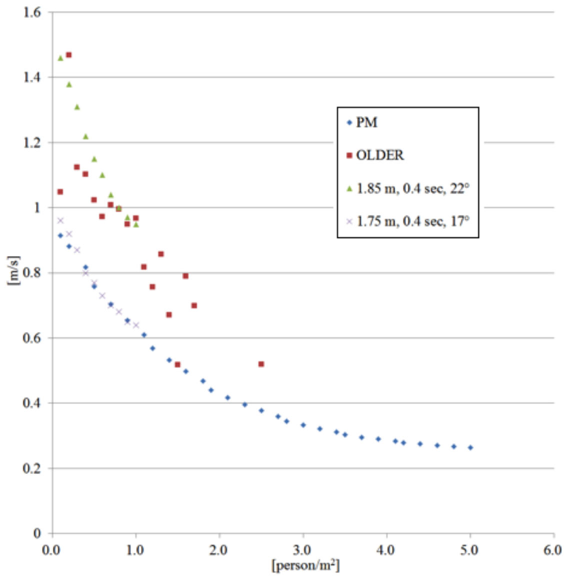

Figure 14 : Fundamental diagram of the proposed model

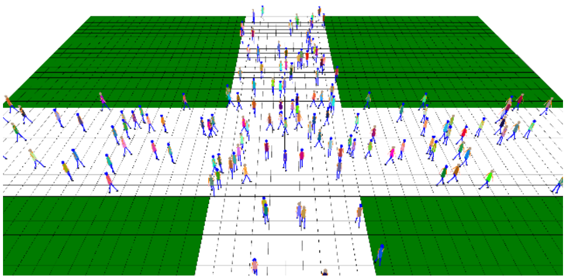

Figure 15 : A snapshot of experimentation

5. Conclusions

We proposed a collision avoidance behavior model that is based on the psychological findings of human behaviors to make the simulation act like the pedestrians in the real world. The contributions of the proposed model are: (1) GMA-based collision prediction for mid/long range by using speed-variant Information Process Space (IPS), (2) collision avoidance steering, (3) gait-based locomotion generation, and (4) space-keeping based on PRB. A fan-shaped (longest at zero degrees GMA) and speed-variant IPS has been implemented to make the collision prediction more human-like. When people are moving very fast, the field of vision is limited to 90 degrees, but when losing speed, this angle widens until about 180 degrees, which means the person stopped. This is a big contrast to the semicircle shape for IPS in other simulations.

The advantage of GMA-based collision prediction is the robustness to variations in the speed and the path of the pedestrians. Real people change GMA to avoid walking or running into other people whether they realize it or not. The combination of speed reduction and the change of the heading direction is only used as a last resort when the pedestrians are too close to each other, or when the pedestrian has winded far off the original path and the angle to the destination is large enough such that side-stepping is unnatural. Furthermore, our model has more human-like behavior due to prioritizing side-stepping in steering from a distance over simply changing the heading direction.

Like in real life, personal space is simulated in our PRB algorithm which makes sure that realistic space-keeping is kept between pedestrians. The effectiveness of the proposed speed-variant IPS was tested on various types of agent flows with different densities. Total loss of kinetic energy accumulated during an agent's movement and the ratio of the length of the path actually traveled to the length of the original path are used as key metrics to figure out the features between different types of flow. Finally, the proposed model has shown its applicability to crowd simulation for engineering by being tuned to well-known fundamental diagrams.

Acknowledgements

This research was supported by the IT R&D program of MKE/KEIT, (10039165, Development of learner-participatory and interactive 3D virtual learning contents technology) and the research project of KIOST (The Development of Human Factors Experimental Evaluation Techniques for Maritime Traffic Safety Assessment-PES160C).

References

[1] Reynolds CW. Flocks, Herds, and Schools: A Distributed Behavioral Model. *Computer Graphics* 1987; 21(4): 25-34.

[2] Thalmann D, Musse S. *Crowd Simulation* 2007 Springer.

[3] Reynolds CW. Steering Behaviors for Autonomous Characters. In *Proceedings of Game Developers Conference*, Miller Freeman Game Group, San Francisco, California, USA, 1999; 763-782.

[4] Helbing D. Social force model of pedestrian dynamics. *Physical Review* 1995; E51: 4282-4286.

[5] Pelechano N, Allbeck J, Badler N. Controlling Individual Agents in High-Density Crowd Simulation, In *Proceedings of Eurographics/ACM SIGGRAPH Symposium on Computer Animation*, 2007; 99-108.

[6] Karamouzas I, Heil P, Beek PV, Overmars MH. A Predictive Collision Avoidance Model for Crowd Simulation, *LNCS* 2009; 5884: 41–52.

[7] Steffen B. A Modification of the Social Force Model by Foresight, In *Proceedings of Pedestrian and Evacuation Dynamics*, Springer 2008; 677-682.

[8] Loscos C, Marchal D, Meyer A. Intuitive Crowd Behaviour In Dense Urban Environments using Local Laws, In *Proceedings of Theory and Practice of Computer Graphics*, IEEE Computer Society 2003; 122-129.

[9] Galea ER, Owen M, Lawrence PJ, Emergency Egress from Large Buildings under Fire Conditions Simulated Using the EXODUS Evacuation Model, In *Proceedings of the 7th International Fire Science and Engineering Conference Interflam'96*, Cambridge, Mar. 1996; 711-720.

[10] Musse SR, Garat F, Thalmann D. Guiding and Interacting with Virtual Crowds in Real-Time, In *Proceedings of Eurographics Workshop on Animation and Simulation*, SpringerVerlag 1999; 23-34.

[11] Strassner J, Langer M. Virtual humans with personalized perception and dynamic levels of knowledge, *Computer Animation and Virtual Worlds*, 2005; 16: 331–342.

[12] Badler NI, Diane M. Chi DM, Chopra-Khullar S, Virtual Human Animation Based on Movement Observation and Cognitive Behavior Models, In *Proceedings of Computer Animation*, 1999; 128-137.

[13] Musse SR, Thalmann D. A Model of Human Crowd Behavior: Group Inter-Relationship and Collision Detection Analysis, In *Proceedings of Eurographics workshop*, Budapest, SpringerVerlag, Wien, 1997; 39-51.

[14] Feurtey F. Simulating The Collision Avoidance of Pedestrian, Master thesis, University of Tokyo, 2000.

[15] Metoyer RA, Hodgins JK. Reactive Pedestrian Path Following from Examples, In *Proceedings of the 16th International Conference on Computer Animation and Social Agents*, Newark, NJ, 2003: 149-156.

[16] Lamarche F, Donikian S. Crowd of Virtual Humans: a New Approach for Real Time Navigation in Complex and Structured Environments, *Computer Graphics Forum*, 2004; 23(3): 509-518.

[17] Rymill SJ, Dodgson NA. A Psychologically-based Simulation of Human Behaviour, *Theory and Practice of Computer Graphics*, 2005; 35-42.

[18] Kitazawa K, Fujiyama T. Pedestrian Vision and Collision Avoidance Behavior (Investigation of the Information Process Space of Pedestrians Using an Eye Tracker), In *Proceedings of Pedestrian and Evacuation Dynamics*, 2008; 95-108.

[19] Cutting J, Vishton P, Braren P. How We Avoid Collisions With Stationary and Moving Obstacles, *Psychological Review*, 1995; 102(4): 627-651.

[20] Ondřej J, Pettré J, Olivier AH, Donikian S. A Synthetic-Vision Based Steering Approach for Crowd Simulation, *ACM Transaction on Graphics 2010*; 29(4): 123:1-123:9.

[21] Orendurff MS, Bernatz GC, Schoen JA, Klute GK. Kinetic Mechanisms to Alter Walking Speed, *Gait Posture*, 2008; 27(4): 603-610.

[22] Goffman E. *Relations in Public*. Harper & Row, 1972.

[23] Hall ET. *The Hidden Dimension*. Anchor Books, 1966.

[24] Gérin-Lajoie M, Richards CL., Fung J, McFadyen BJ. Characteristics of personal space during obstacle circumvention in physical and virtual environments, *Gait Posture*, 2008; 27(2): 237-247.

[25] Kholshevnikov VV, Samoshin DA. Parameters of Pedestrian Flow for Modeling Purposes, In *Proceedings of Pedestrian and Evacuation Dynamics*, Springer, 2008; 157-170.
[26] Predtechenskii VM, Milinskii AI. Planing for Foot Traffic Flow in Buildings, *Amerind Publishing*, New Dehli, 1978.
[27] Older SJ. Movement of Pedestrians on Footways in Shopping Streets, *Traffic Engineering & Control*, 1968; 10: 160-163.