Self-Organized Behaviour in a Modified Multi-Agent Simulation Model Based on Physical Force Approach

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***Abstract*—The multi-agent simulation models are very useful in predicting crowd behaviours, where experiments with human are too dangerous. However, works that include intelligence in the physical force-based model are very limited. Moreover, most works based on the physical force-based model are only restricted to producing behaviours of crowds in emergency situations. Utilizing a simpler mathematical representation, this paper proposes a modification to an existing crowd simulation model based on the physical force approach. The proposed method incorporates the concept of magnetic force interaction into the existing social force model of an agent movement. It simulates the agent's interaction within their boundaries, preventing any collisions from occurring and to follow others when the agents move in a same direction. The proposed method incorporated agents' intelligence to choose the shortest path in their movements towards their destinations. When the number of agents increases in the simulation environment, the model is able to produce a self-organized behaviour, such as the lane formation behaviour pattern when the agents are in a bi-directional movement as well as in a counter flow movement at intersections.**

***Index Terms*—Crowd Modelling; Multi-Agent Model; Physical Force Approach; Self-Organized Behaviour.**

I. INTRODUCTION

Modelling crowd dynamics involves imitating the real crowd movement, including the activities and behaviours [1] of the entities in the crowd, in virtual environments. Crowd modelling has attracted tremendous research interests especially in the areas of computer graphics, animation [2] and urban or building planning [3]. The entities in the crowd, known as 'agents', can interact and react with the simulated environment in order to imitate human movements. Such models can be used in analyzing the different types of crowd behaviours that emerge under normal or emergency situations. This model plays an important role in present or future crowd management planning [4]. Thus, crowd models are capable of giving insight on human patterns and used by architectural engineers, designers or safety engineers as a tool to assist them in buildings or facilities design before the actual implementation [5].

In developing crowd models, the model type and the modeling approach must suit the modelling objectives [6]. Different environments and situations will produce different types of human behaviours, thus requiring different modelling objectives and approaches. In general, crowd modelling is developed either at the macroscopic or the microscopic levels. Each approach is characterized by its own modelling objectives. In the macroscopic approach, agents in the crowd are treated homogenously and hence, internal and external characteristics of agents, such as speed, mass, position and other behaviours, are omitted [6].Therefore, this method is characterized by its heavy computational demand, which may negatively affect the simulation runtime performance. On the other hand, the microscopic approach focuses on the heterogeneous character of agents in the crowd. In this method, modellers are able to assign different levels of agent granularity details such as specified speeds, current positions, destinations, agent gazing angles etc. The physical force approach is one of the established modelling concepts for the microscopic approach. This approach has the capability to integrate several intelligent features and behavioural factors, which qualify it to produce more natural and realistic agent movements. For these reasons, the physical force model is adopted in this work.

The physical force-based model can be classified into magnetic force (MF) model [7] and the social force (SF) model [8]. In both of these models, only physical forces between agents and their surroundings are used to represent the agent movement. In the MF model, agent motions and interactions with the surroundings use the concept of magnetic field, where the agents and obstacles have the same magnetic polarities so that they always repulse each other. On the other hand, the destination will have an opposite magnetic polarity with the agent so that the agent will be attracted to the destination [7]. However, there are some evident limitations in current agent crowd modeling based on the current physical force-based model where they are focusing more in emergency situation application instead of modeling in normal situation [8-10]. Hence, limited intelligent features embedded in the model as their objectives are mainly to study panic behaviours [11].

The proposed model has the ability to represent the details of the agent movement under normal situation including their physical characteristics. In particular, the agent pre-defined boundary is taken into account for repulsion in normal situations. Hence, the proposed model guarantees that no overlapping or body contact will be visualized during the agent movement. In more details, the socio-psychological interactions forces representing panic situation, i.e $F_{ij}(t)$ and $F_{iw}(t)$ are replaced by the MF model. Moreover, an intelligent feature of path finding during agent movement is also incorporated in the proposed model. By including this feature, each agent is guided to select optimal path [12] towards its target destination, performing more realistic, natural and intelligent movements. Furthermore, proposed model capable to simulate self-organized behaviours that normally occur in human movement.

II. METHODOLOGY

A. The Physical Force Model

The MF model uses "Coulombs Law" to represent the agent movements, as follow [9]:

$$F = k\,\frac{q_1 q_2 \boldsymbol{r}}{r^3} \tag{1}$$

where:

F	=	Magnetic force (in vector)
k	=	Constant
q_1	=	Magnetic intensity of pedestrian
q_2	=	Magnetic pole intensity
$\boldsymbol{r}$	=	Vector of magnetic pedestrian to magnetic pole
r	=	Length of r

Unlike the MF model, the SF model represents an agent motion in panic situations [13] by a mixture of physical and socio-psychological interaction forces [8]. Since this model was originally developed to represent a crowd in a panic situation, it does not consider elements such as repulsion boundaries and fields of view of the agents, which are more apparent in normal situations [13]. The major limitation of using this model for normal crowd situation is that it is difficult to integrate the SF model with other intelligent features such as path following or flee behaviour due to the panic behaviour model [11]. The SF model is represented by the following equations:

$$F(t) = F^0(t) + \sum_{i\neq j} F_{ij}(t) + \sum_{w} F_{iw}(t) \tag{2}$$

$$m\frac{dv_i(t)}{dt} = m\frac{v_o e_i - v_i(t)}{\tau} + \sum_{i\neq j} F_{ij}(t) + \sum_{w} F_{iw}(t) \tag{3}$$

$$F_{ij}(t) = \left\{A_i e^{\frac{(r_i - d_{ij})}{B_i}} + kg\big(r_i - d_{ij}\big)\right\} n_{ij} + \kappa g\big(r_{ij} - d_{ij}\big)\,\Delta v_{ij}^t t_{ij} \tag{4}$$

$$F_{iw}(t) = \left\{A_i e^{\frac{(r_i - d_{iw})}{B_i}} + kg(r_i - d_{iw})\right\} n_{iw} + \kappa g(r_{iw} - d_{iw})\,\Delta v_{iw}^t t_{iw} \tag{5}$$

$$kg(r_{ij/w} - d_{ij/w}) \tag{6}$$

$$\kappa g\big(r_{ij/w} - d_{ij/w}\big)\,\Delta v_{ij/w}^t t_{ij/w} \tag{7}$$

where $F^0(t)$ and $F_{ij}(t)$ represent physical and socio-psychological forces, respectively, and $F_{iw}(t)$ represents the agent movement, including the effect in panic situations. In $F^0(t)$, the agent movement will be influenced by the agent direction, e_i , actual speed, $v_i(t)$ and desired speed, $v_o(t)$, in respective time, τ . Other than that, to represent socio-psychological interactions in agent movement by including the interaction of repulsive force between agent, $F_{ij}(t)$ that is represent with $A_i e^{\frac{(r_i - d_{ij})}{B_i}}$ where A_i and B_i are constants. r_i and d_{ij} denotes as the agent body radius and distance between agents body centre mass respectively. Meanwhile, n_{ij} is a normalized vector pointing between agents i and j. In panic situations, the agent body compression and sliding force effect will be represented as $kg\big(r_{ij} - d_{ij}\big)$ and $\kappa g\big(r_{ij} - d_{ij}\big)\,\Delta v_{ij}^t t_{ij}$ respectively where k and κ are constants, t_{ij} is a tangential motion if the other agents come closer and Δv_{ij}^t is the tangential of velocity difference [8]. Function of g (0 or 1) will represent the occurrence of panic situations. Furthermore, the repulsive interaction with the walls treated where $d_{iw}$and n_{iw}, is denoted as the distance difference and a perpendicular vector direction with the wall respectively, including the tangential direction, t_{iw} .

B. The Modified Agent Movement Model

Inspired by Helbing's model, in this work, the agent physical and socio-psychological interaction to move is represented by the "Newton Second Law', which has the following equation:

$$F(t) = m\,\frac{dv}{dt} \tag{8}$$

Based on (8) above, the movement of an agent is influenced by four main forces, as follows:

$$F(t) = F^0(t) + \sum_{i\neq j} F_{ij}(t) + \sum_{w} F_{iw}(t) + F^e(t) \tag{9}$$

where, $F^e(t)$ is the proposed repulsion force to evade agents from ahead. This force can provide additional ability for the agents to handle movement in different directions. In (9), the motivational force, $F^0(t)$ is represented by the following equation:

$$F^0(t) = m\,\frac{v^0(t)\,e^0(t) - v(t)}{t} \tag{10}$$

where, m is the mass of the agent, $v^0(t)$ is the desired speed of the agent, $e^0(t)$ is the desired direction, which is obtained by normalizing the agent vector position with the destination point, and $v(t)$ is the current speed of the agent at time t. As a modification to Helbing's model, the proposed model utilizes the concepts from the MF model, by including the agent's Field of View (FoV) and the pre-defined boundary to repulse. Particularly, the modification was made by replacing $F_{ij}(t)$and $F_{iw}(t)$ in the original Helbing's model by the proposed MF model. Therefore, the new equation for agent basic movement to repulse other agents, $F_{ij}(t)$, is given by the following formula:

$$F_{ij}(t) = K_r \frac{M_i M_j}{x^2} \cdot n_{ij} \quad (11)$$

where K_r is the repulsion constant, M_i and M_j are the social mass constants for the ith and the jth agents, respectively, n_{ij} is a normalized vector perpendicular with the agent. The repulsion constant, K_r, is represented by a positive number which can take any value between 0 and 10, i.e $0 < K_r \leq 10$. For the current application, after several simulations, the best value for K_r was found to be 5. This value guarantees sufficient performance for the proposed model. To calculate the distance, x, between two agents in (11), the following equations are used:

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (12)$$

$$x = D_{ij} - R_i - R_j \quad (13)$$

where $\{x_i, y_i\}$ and $\{x_j, y_j\}$ are the position coordinates of the ith and the jth agents, respectively, R_i and R_j are the radii of the ith and the jth agents, respectively, and D_{ij} is the distance between the centers of the two agents. From the modified model in (11), the condition for an agent to repulse is based on its navigation Field of View (FoV) as well as the pre-defined comfort area. Table 1 summarizes the physical characteristics of the agents used in this work.

Table 1
Agent Physical Characteristics

Characteristics	Parameters
Position, (x, y)	Random distributed
Mass, m	50 kg
Walk speed	1.5 m/s
Body radius, R_n	0.25 – 0.3 m
Field of View, θ	180^0
Comfort area, x	0 – 7 m
Social mass, (M)	1

Using the same strategy in calculating the repulsion forces among agents described above, the repulsion force between an agent and an obstacle is found by the following equations:

$$F_{iw} = \frac{K_w}{x_w^2} \cdot n_{iw} \quad (14)$$

$$x_w^2 = x_i - x_w \quad (15)$$

where K_w is a constant, x_w is the agent distance check based on the agent comfort area, x as tabulated and described in Table 1 and (15), respectively, n_{iw} is the normalized vector perpendicular to the agent if the repulsion force is exerted, x_i and x_w are the positions of the agent and the obstacle, respectively. Similar to the range used for the repulsion constant, K_r, in (11), the range of K_w used in this work is given by $0 < K_w \leq 10$. From several simulations, the value of K_w was selected to be 10 and this value provides accurate modelling performance.

Another modification made to the original model is the force to evade, $F^e(t)$. This force determines how a given agent can evade other agents coming from different directions in the simulation model. Existing MF model does not include evading force feature in their proposed model [7].To ensure realistic agent movements, agents in this work can handle movements in bi-directional flow using agent heading angle to evade to the left or to the right. The proposed additional force to evade is demonstrated in [14].

C. Path Finding Feature Using the Dijkstra Algorithm

As mentioned before, a path finding feature is proposed in this work as a modification to the original model. The aim of this feature is to guide an agent in selecting the shortest route towards its target destination. For this purpose, the 'Dijkstra Algorithm' was adopted to achieve the path finding feature. This algorithm uses simplified nodes calculation in all directions of the agent movement [15]. The Dijkstra Algorithm has been successfully applied in various applications [16, 17]. In the Dijkstra algorithm, the shortest path is calculated from node to node. To search these nodes, the simulation environment is first segmented into a grid of size $n \times n$, which is pre-defined by the user. In this work, a grid of size $1m \times 1m$ is adopted. In order to include obstacles in the simulated environment, each obstacle is marked with a specific value in order to avoid it in calculating the shortest distance. Figure 1 demonstrates the simulation environment represented by the segmented grid. In particular, the blue cells in Figure 1 represent the segmented environment. In this environment, red cells represent an obstacle. While the black and the yellow nodes represent the starting and the ending nodes, respectively.

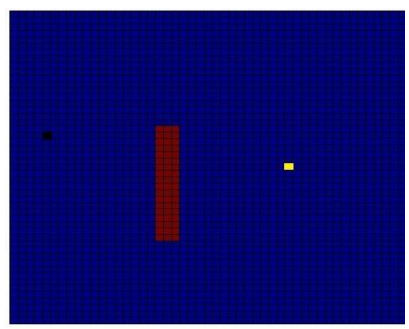

Figure 1: Segmented grid based from Dijkstra algorithm

According to Dijkstra method, all nodes from segmented cells will propagate until it reaches desired point by calculating interconnecting nodes distances. As depicted in Figure 2 the distance between the nodes is set to 1 m adjacently in cells numbered 1, 2, 3, 4 and $\sqrt{2}$ m diagonally in cells numbered 5, 6, 7, 8. Generated waypoint of nodes propagate from Figure 1 have been selected with the lowest distance cost for an agent optimal path to move towards their target destination. This intelligence will be useful for simulation studies including complex environment of agent model on how the agent will be searching optimal route in their movement.

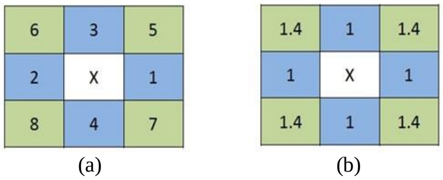

Figure 2: Number of cells and distance between cells (a) cells neighborhood (b) distance between cells

III. RESULTS AND DISCUSSIONS

This section demonstrates the effectiveness of the proposed modified simulation model based on several simulation studies.

A. Agent Movement in a Uni-Directional Based on Repulsion Forces

In this simulation, the proposed model, previously defined in (9), is used. However, the force to evade, $F^e(t)$ is not included here. In this experiment, the initial locations of five agents are randomly selected in the environment that includes an obstacle at the middle of the pathway. This experiment aims at analyzing the agents' psychological interactions with each other and the nature of their movement towards their desired destinations in a uni-directional flow. Figures 3 and 4 illustrate the snapshot and the trajectories of the agents, respectively. The results in Figure 3 show that the agents have successfully moved towards their target points by maintaining the repulsion forces exerted among them. On the other hand, Figure 4 clearly shows that the agents can keep safety boundary during their movements and, at the same time, avoid any collisions among them.

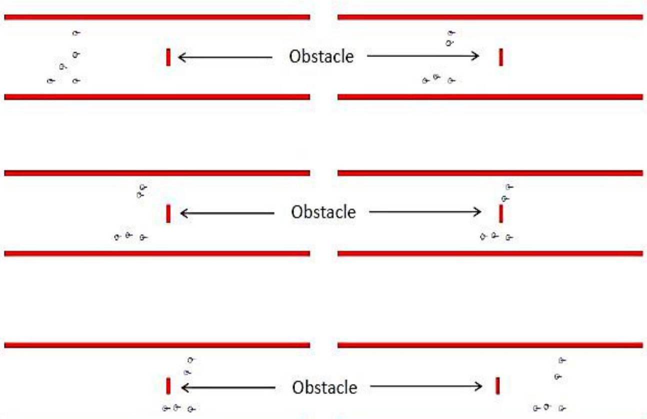

Figure 3: Snapshots of the simulation model with 5 agents

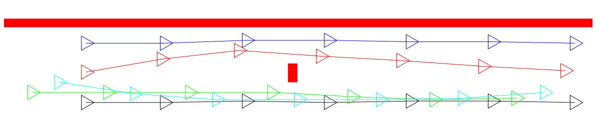

Figure 4: Agent trajectories with interaction forces

As mentioned before, the previous test dealt with agent movement in a uni-directional flow. In order to consider the agent movement in a bi-directional flow, the agent in the following test move in two opposite directions. It is worth mentioning that a drawback of the original model (without the proposed force to evade) is that when two agents are approaching each other in an opposite direction they will get stuck at some point since the total forces (movement and repulsion forces) applied on them will be zero. In order to handle this limitation, the present work proposes an additional force to evade which can solve the above problem. Figure 5 illustrates the situation in which two agents approach each other without the proposed force to evade, $F^e(t)$.

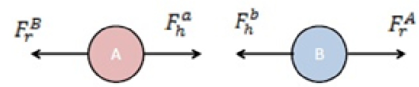

Figure 5: Movement agent with zero forces (total force to move and repulse)

B. Agent Movement in a Bi-Directional Flow using the Proposed Force to Evade

This simulation evaluates the agent behaviour when a bi-directional flow is encountered using the same agent movement model used in the previous section with the additional proposed force to evade. Figure 6 shows the snapshot of this experiment where three agents move from left to right and two other agents move in the opposite direction from right to left, while Figure 7 shows the agent trajectories generated from this experiment. From both Figures 6 and 7, it can be seen that the agents behave in such a way that would ensure evading each other in the opposite direction by slowing down their speeds and maintaining their boundary from colliding with other dynamic and static obstacles in their surroundings.

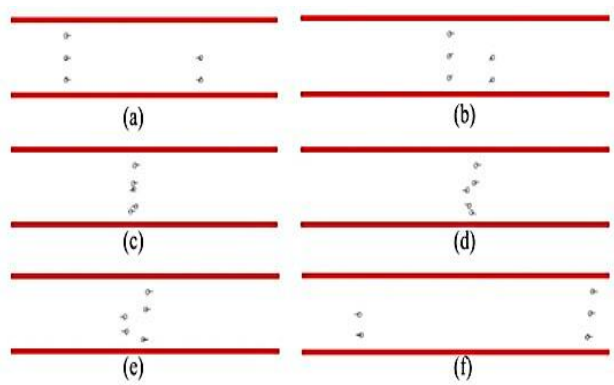

Figure 6: Snapshot of simulation agent movement in bi-directional flow

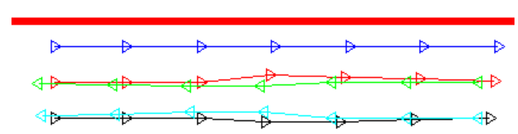

Figure 7: Agent trajectories in bi-directional flow

C. Simulation of Agent Basic Movement Model Combined with an Intelligent Path Finding Feature

In complex environments, humans have the capability to find the shortest ways to reach their destinations. In the proposed crowd simulation model, the Dijkstra algorithm has been used to imitate this feature. Besides the ability to find the shortest path, the Dijkstra algorithm has also resulted in a self-organized behaviour for the agents during their movement as would be expected from a real crowd and will be shown in the next sections.

a. Shortest Path-Finding

Table 2 summarizes the processing time for five agents for an environment with obstacles with and without utilizing the Dijkstra algorithm. The results in Table 2 evidently show that the Dijkstra algorithm has provided an intelligent feature by finding the shortest path for each agent, and hence each agent took less time to reach its destination compared to the situation when the Dijkstra algorithm was not used. This result indicates that the Dijkstra algorithm is a suitable option in guiding the agent towards their targets with the shortest time. Beside finding the shortest distance, the following sections show the ability of the Dijkstra algorithm in producing self-organized agent behaviours.

Table 2
Comparisons in Shortest Path (Time Taken)

Test No. of Agents	Without Dijkstra	With Dijkstra
1	Task was not completed	13s
2	42s	12s
3	10s	10s
4	44s	13s
5	10s	10s

b. Validation Metric 1: Lane Formation in a Bi-Directional Movement

The lane formation is one of the self-organized behaviours produced by the developed agent simulation model. Lane formation normally occurs when there are two directions of movement. The tendency of agents (or humans) to follow people walking in the same direction in front of them is high, since they are all in the same path of walking direction. In order to simulate such behaviour, 30 agents are located in the pathway environment shown in Figure 8 without any re-programming [13] for this specific situation. The agents in Figure 8 are moving in a bi-directional kind of movement. As shown in Figure 8, the agents have formed lanes in their movements in order to avoid colliding with other agents moving in the opposite direction. Figure 8 shows that six lanes were produced during the agent movement in the 10-m wide pathway used in this simulation.

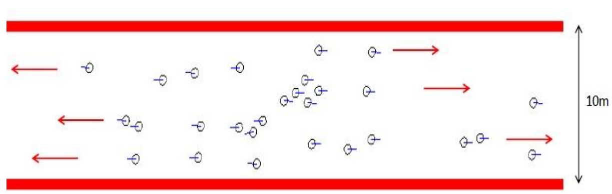

Figure 8: Lane formation in agent movement

It is also observed that when the pathway width decreases, the number of lanes formed also decreases. The agents slow down their speeds and form smaller number of lanes as shown in Figures 9 and 10, where the pathway widths have been reduced to 5 m and 2 m, respectively.

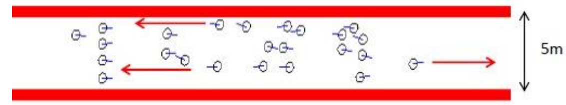

Figure 9: Number of lanes for a 5-m width corridor

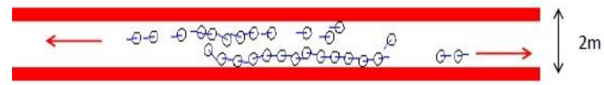

Figure 10: Number of lanes formed for a 2-m width corridor

c. Validation Metric 2: Lane Formation in a Counter Flow Movement at an Intersection

As another self-organized behaviour, Figure 11, shows 40 agents which have been randomly positioned at 40 initial locations near an intersection area. These agents move in four different directions. This figure, illustrates the movements at the intersection area, where all agents move smoothly along each other, forming lanes as they move.

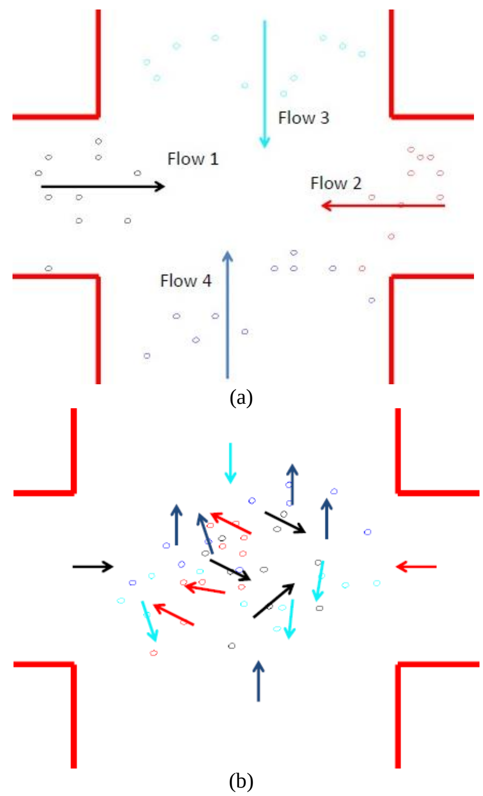

Figure 11: Counter flow at intersection (a) counter flow movement (b) movement pattern

IV. Conclusion

This paper presents a modified crowd simulation model based on the physical force approach. The proposed model incorporates the magnetic force interaction into the existing social force model of crowd movements. From the simulation studies presented, the proposed model has shown its effectiveness in terms of producing realistic agent movement. The agents in the proposed model have successfully shown their ability to interact in the simulated environment based on their physical and psychological forces including motivational, repulsion and evading forces. Moreover, by providing an intelligent feature of path finding for each agent, the agents have successfully shown self-organized behaviours in both bi-directional and counter flow movements.

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