

# Simulating Group Formation and Behaviour in Dense Crowd

Fawwaz Mohd Nasir<sup>1,\*</sup>, Tsukasa Noma<sup>2</sup>, Masaki Oshita<sup>2</sup>, Kunio Yamamoto<sup>2</sup>, Mohd Shahrizal Sunar<sup>1</sup>,  
Shamsul Mohamad<sup>3</sup>, Yasutaka Honda<sup>2</sup>

<sup>1</sup>Universiti Teknologi Malaysia, <sup>2</sup>Kyushu Institute of Technology, <sup>3</sup>Universiti Tun Hussein Onn Malaysia

## Abstract

This paper presents a technique to simulate large groups in a dense crowd, where the groups can change their formation, and continuously avoid collision with other individual agents and groups, but still try to keep their collective behaviour until they reach their destination. To achieve this, we use the leader-follower model where the leader determines the group path while other members, driven by the modified social force model (SFM), follow the leader, maintaining the group formation. We also use density of agents in the travelling direction as the criteria to determine the appropriate formation type. Our proposed technique is easily compatible with individual agents driven by the existing SFM at moderate costs.

**Keywords:** crowd simulation, group formation

**Concepts:** • Computing methodologies ~ Animation;  
*Procedural Animation;*

## 1 Introduction

Crowd simulation has become increasingly important in recent years due to its diverse range of applications. It is widely used in movies and computer games. However, many of the current crowd simulation techniques tend to focus more on individual behaviours [Curtis et al. 2011; Thalmann and Musse 2013; Karamouzas and Overmars 2012]. The grouping aspects of the crowd is not given much attention even though it is a common phenomenon [Qiu and Hu 2010; Rojas et al. 2015]. Even when groups are simulated, they are simulated as disorganized cluster resembling animal behaviour which becomes more apparent as the number of members per group increases. This contradicts the real life situation where humans tend to organize themselves within the group to easily communicate between one another.

Hence, this paper presents a method to simulate considerably large groups in formation in a dense crowd, where groups often change their formation, continuously avoiding other individuals and groups, and still try to keep their collective behaviours to reach their destinations. Such phenomena, however, are difficult to simulate with existing techniques for small groups in sparse environments [Rojas et al. 2015].

In [Rojas et al. 2015] for example, members of a group are guided

\*e-mail: fawwaz2@live.utm.my.

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by an invisible and collision-free agent, that moves independently of surrounding agents and groups. Collision avoidance is then up to each (visible and human-like) member as local path steering. This approach works well in sparse environments. In a dense crowd, however, the local steering by individual members is insufficient for keeping group formation. Paths of the group itself should be determined depending on its surroundings.

We thus adopt a leader-follower model where a leader determines the group's path and the other members follow the leader, keeping the group formation. Our leader-follower formation model is presented in Section 4.1. The leader is driven by the social force model (SFM) [Helbing and Molnár 1995] both for approaching the target and for avoiding collisions. However, the SFM is designed for a single agent, and it is not appropriate for members in a group, particularly for followers. Therefore, we introduce a modified SFM for group members. The followers are then able to keep the formation and at the same time avoid static obstacles (for example, walls) and other agents in the same or different group. Our modified SFM is introduced in Section 4.2.

Groups in a dense crowd must also decide their proper formation depending on the environments. In [Rojas et al. 2015] for example, ray casting is used to determine the suitable formation type. Their method ensures smooth formation transitions if the group is in a relatively sparse area and its surrounding objects are static or their motions are predictable. In a dense crowd, however, many surrounding agents must be taken into account at the same time, and their motions are unpredictable due to their continuous influences on each other. We thus use the density of agents in the travelling direction as the criteria for formation selection, which is discussed in Section 4.3.

This paper is organized as follows: Section 2 overviews related crowd simulation research. Section 3 gives an overview of our method. Section 4 elaborates the method used in this research. The experiments and their analysis are discussed in Section 5, and finally Section 6 concludes this paper.

## 2 Related Work

The SFM is one of the most popular and influential model to simulate crowd. It puts forward the idea that the motion of pedestrians are affected by their internal motivation to perform certain movements [Helbing and Molnár 1995]. The motion consists of a driving force, reflecting the pedestrian's motivation to move in a particular velocity, and two repulsive forces which describes the effects of interaction with obstacles and other pedestrians. Even though the model realistically simulated the motion of pedestrians, it does not simulate group dynamics [Helbing and Molnár 1995]. In this paper, we introduce a modified model to resolve this issue.

Another modal based approach is the flocking technique. It is an elaboration of the particle system, where the birds are the particles. It represents a flock's complex behaviour, just by

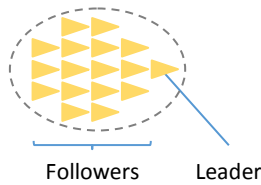
simulating individual bird behaviour following three simple rules: avoiding collisions with other birds, matching velocity with nearby birds and flying towards the flock's centre [Reynolds 1987]. The interaction between these birds leads to the emergence of the complex flock-like behaviour. While this technique presents a simple approach to realize group behaviour, it is unsuitable for the simulation of human groups as it resembles animal herds [Rojas et al. 2015]. Humans in a group, tend to organize themselves in an orderly manner, creating formation and being led by someone. This paper simulates these behaviours by using formation templates and the leader-follower model.

Besides, there are also data-driven approaches for groups. Lee et al. [2007] for instance, trained a group behaviour model from videos, making agents react to their perceived state by referring to the captured group behaviours in similar situations. Ju et al. [2010] also uses video for their morphable crowd technique. Their method blends existing crowd data to generate a continuous span of crowd styles or formation. However, simulating very dense crowd is computationally expensive for real-time applications and are commonly used for offline simulation instead [Ju et al. 2010; Karamouzias and Overmars 2012]. This paper uses the modified SFM and predefined formation templates to realize group behaviours and formation at moderate cost.

### 3 Overview

In our simulation, the crowd has several groups as well as individual agents. Each group consists of a leader and several followers (Figure 1). The leader-follower model fits for groups in the real world. For example, many families and relatives are guided by their head in tawaf, whose simulation is shown in video (See Section 5). The group motion is determined as follows:

1. **Determine Formation Orientation**  
The orientation of the group formation is determined by averaging the leader's previous orientations.
2. **Compute Density**  
The density is calculated by counting the number of agents in an enclosed ellipse in the travelling direction.
3. **Select Formation Template**  
A suitable predefined formation template is selected based on the computed density.
4. **Compute Slots Position**  
The slot position for each follower is computed based on the selected formation template.
5. **Compute Social Forces**  
The social forces for each group member are computed based on our modified SFM.



**Figure 1: Group Formation**

To control the motion, each agent has four important parameters: position  $\mathbf{p}_i$ , velocity  $\mathbf{v}_i$ , maximum velocity  $\mathbf{v}_i^{max}$ , and target position(s). Additionally, each target position is represented as a disk with centre position  $\mathbf{p}_i^{target}$  and the radius  $r$ . The number of target positions varies depending on the situation being simulated. Groups have additional parameters to control their motion.

Leaders and followers have future position  $\mathbf{p}'_{leader}$  and future slot position  $\mathbf{p}_{i,j}$  respectively. In our current simulation, a group has a leader and 16 followers assigned to it. It is assumed that they will remain in the same group throughout the simulation life time.

## 4 Method

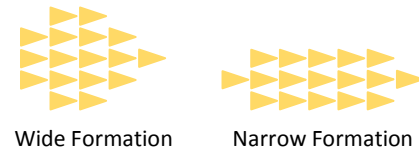
This section will thoroughly discuss the method used in this research, in order to realize group formation and behaviour.

### 4.1 Formation Templates and Slots

In this paper, we adopt dense symmetrical formations as shown in Figure 1. Each formation has several slots, each of which corresponds to an individual follower and is indexed by  $(i, j)$ . The slot position  $\mathbf{p}_{i,j}$  for the follower  $(i, j)$  is defined by the unit orientation vector  $\mathbf{v}$ , a unit upward vertical vector  $\mathbf{z}$ , and the future leader position  $\mathbf{p}'_{leader}$  as follows:

$$\mathbf{p}_{i,j} = \mathbf{p}'_{leader} - iS_r\mathbf{v} + jS_c(\mathbf{v} \times \mathbf{z}) \quad (1)$$

In Equation 1,  $S_r$  and  $S_c$  are standard intervals for rows and columns of the group, respectively. The indices  $i$  and  $j$  are:  $i = 1, 2, \dots, m$ ,  $j = -n_i, -n_i + 1, \dots, 0, \dots, n_i$ , where  $m$  is the number of the followers' rows, and  $n_i$  is the half of the width at  $j$ -th row. The number of group members is  $\sum_{i=1}^m (2n_i + 1) + 1$  in total. When the formation changes, affected followers will be assigned to the nearest slot. Some followers might give their slot to other followers so that the other followers would not have to travel far away to get to their slot.



**Figure 2: Types of Formation**

Formation templates enable the group to expand or contract depending on the environment. In this paper, we use two templates for wide and narrow formations. The two templates for 17 members are shown in Figure 2. Each of these formations has different slot arrangements. These formations are chosen as it is the common shape a group would take in sparse and dense crowd. Formation templates basically prevent followers from being left too far behind and allow a group to move easily through crowd.

It is crucial for a large group to determine its orientation in a dense crowd. In the case of an individual agent or a small group, its orientation is often identified with the direction of its motion. This works well particularly in sparse environments. For a large group in formation, however, the slot positions of its followers are relatively determined by the leader's orientation as well as his or her position, and in a dense crowd, the leader's direction of motion changes frequently and noticeably, resulting in drastically swaying the rear of the group. To avoid such undesirable phenomena, we applied smoothing to group orientations.

The orientation  $\mathbf{e}$  is determined by calculating the leader's average orientation based on five previous orientations (Figure 3) as shown in Equation 2. The orientation is counted in only when the group is moving. If the group does not move or if the resulting orientation becomes zero, the most recent orientation will be used.

$$e = \frac{\sum_{i=0}^4 e_{k+i}}{5} \quad (2)$$

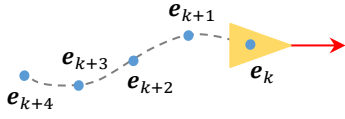


Figure 3: Previous Orientations

## 4.2 Modified Social Force Model

The existing SFM by Helbing and Molnár [1995] consists of a driving force component and two repulsive force components, summarized in Equation 3.

$$f_i = f_i^0 + f_i^{wall} + f_i^{agents} \quad (3)$$

The first component,  $f_i^0$  reflects the motivation of agent  $i$  to move towards its target position. This is computed based on Equation 4 where  $v_i^0$  represents the desired speed,  $p_i^{target}$  represents the target position,  $p_i$  represents the current position,  $v_i$  represents its current velocity and  $\tau$  represents the relaxation time (time to approach the desired velocity) with value 0.54. (In the rest of this paper, time and distance are in seconds and metres, respectively.)

$$f_i^0 = \frac{v_i^0 \left( \frac{p_i^{target} - p_i}{\|p_i^{target} - p_i\|} \right) - v_i}{\tau} \quad (4)$$

The second component,  $f_i^{wall}$  describes the effects of interaction between agent  $i$  and the obstacle walls, as shown in Equation 5.  $e_i^{wall}$  represents a unit direction vector from agents  $i$  to the nearest point on the wall,  $d_w$  is the distance between agent  $i$  and the wall, while  $a$  and  $b$  are constants with value 3 and 0.1.

$$f_i^{wall} = -a \frac{d_w}{b} e_i^{wall} \quad (5)$$

The final component,  $f_i^{agents}$  describes the effects of interaction between agent  $i$  and other agents, as shown in Equation 6. Parameters  $d$  and  $m$  are both constants with value 0.2 and 2 respectively.  $r_{ij}$  represents the distance between agents  $i$  and  $j$ , and  $e_{ij}$  represents the unit direction vector from agents  $i$  to  $j$ .

$$f_i^{agents} = \sum_{j \neq i} \left( -\frac{d}{r_{ij}^m} e_{ij} \right) \quad (6)$$

Note that all constant values used in Equations 4 to 6 are based on values validated through actual experiments by Moussaïd et al. [2009]. It is also crucial for a simulation to mimic the movement of agents in a smooth manner regardless of the machine's computing power. Thus, the position of each agent is updated at each simulation step by computing  $f_i$ , computing the new velocity  $v_i^{new}$  by adding the product of  $f_i$  and the step time  $t^{step}$  with the agent's current velocity, verifying  $v_i^{new}$  does not exceed  $v_i^{max}$ , and finally computing the new position by adding the product of  $v_i^{new}$  and  $t^{step}$  with the agent's current position.

However, the existing SFM simulates the interaction between individual agents only, while interactions between group

members, and between a group and other individual agents are not considered. Therefore, we need to modify the model to incorporate these interactions into the SFM. The modified model must enable the groups to change formation and try to keep their collective behaviours to reach their targets, while at the same time avoiding collision with other agents and obstacles. Each group will be driven by their respective leader towards  $p_i^{target}$  while followers will try to maintain their position within the group by making  $p_{i,j}$  as their own target position.

Hence, to achieve this, we modify the third component of the existing SFM and add a fourth component to it as shown in Equation 7. This equation is used to calculate the forces for all agents.  $f_i^{member}$  represents the repulsive force between members of the same group while  $f_i^{group}$  is the repulsive force between the group, and other individuals and groups. They have similar expressions to  $f_i^{agents}$ , but have different scaling parameters,  $s^{member}$  and  $s^{group}$ . If the agent is part of a group,  $s^{member}$  will be set to 0.3 while if it is not, it will be set to 0.  $s^{group}$  is set to 1 by default. If the group selected the narrow formation, the group will have smaller  $s^{group}$  value of 0.4 and its neighbouring agents (agents in the enclosed ellipse) will have higher  $s^{group}$  value of 5. At the same time,  $f_i^0$  will ensure the follower maintains its position within the group.

$$f_i = f_i^0 + f_i^{wall} + s^{member} f_i^{member} + s^{group} f_i^{group} \quad (7)$$

## 4.3 Formation Selection

In our method, a group determines its formation depending on the density in the traveling direction. We calculate the density by counting the number of agents in an enclosed ellipse. The ellipse centre  $(x_c, y_c)$  is positioned 0.2 units ahead of the leader's position in the travelling direction, and let the  $x$ -axis of the local coordinate system be parallel to the leader's orientation. An agent at  $(x, y)$  is within the enclosed ellipse if the Equation 8 is satisfied. Its major radius  $a$  and minor radius  $b$  are constants with value 2.25 and 2 respectively.

$$\frac{(x - x_c)^2}{a^2} + \frac{(y - y_c)^2}{b^2} \leq 1 \quad (8)$$

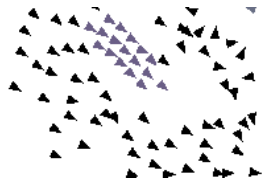
After identifying the agents in the ellipse, we divide their number with the area of the ellipse ( $4.5\pi$ ) to get the density. A formation is then selected by comparing the density to a threshold value. If the enclosed ellipse holds more than 14 agents, the narrow formation is selected; otherwise the wide formation is selected. The change from a wide to a narrow formation is important in order to enable the group to easily move through the crowded areas. The formation will then revert back to the wide formation once the group moves to a less crowded area.

## 5 Results and Analysis

During simulation initialization, all individual agents and group leaders are given a random initial position and target position(s) within a specified range. As recommended by Moussaïd et al. [2009], the maximum velocity for each individual agents is normally distributed with mean  $1.29 \text{ m s}^{-1}$  and standard deviation  $0.19 \text{ m s}^{-1}$ . The maximum velocity for group leaders and followers are also normally distributed, but with a mean and standard deviation of  $1.2 \text{ m s}^{-1}$  and  $0.29 \text{ m s}^{-1}$  respectively, to give it a wider variation.

Results for this paper are generated using an 8 GB RAM machine, equipped with the Intel Core i7 at 3.4 GHz and AMD Radeon HD 8570 processing units. We have simulated several situations which are the corridor, crossroad, tawaf and bidirectional circular movement. For the purpose of conducting the experiment, we limit the number of members to 17 members per group.

Several key behaviours of groups can be observed from these simulations. First, we can see throughout these situations that the group changes its formation depending on the surrounding density. This simulates real world situation where people in groups tend to organize themselves into narrower formation when they encounter high density areas. Secondly, we can also see that individual agents will give way for groups to move through dense areas of crowd (Figure 4). This is also a common phenomenon as individuals tend to be more evasive especially in the presence of a large group. We refer the readers to the supplemental video for the demonstration on the changes in formation.



**Figure 4:** Group in Narrow Formation Moving Through Crowd

We have also made comparisons on the frame rate in seconds between the existing and modified SFM for various all situations. Equal number of individual agents and groups were added in each test. Test are carried out by averaging the frames per second (FPS) readings (Table 1). It is clear that the modified model recorded a lower frame rate compared to the existing model. This is expected as the modified model is more complex than the existing one, thus, requiring more computation time.

**Table 1:** Frame Rates for Various Situations

Model	Corridor	Crossroad	Tawaf	Bidirectional Circular
Existing	203.2	217.3	87.29	79.18
Modified	137.6	163.4	66.03	69.02

The tawaf and bidirectional circular situations are also more complex than the other two. For instance, these situations have several targets (which makes up a path) while the first two have a single target. Compared with the existing SFM, however, group behaviour can be realized with our method at moderate cost.

Comparison has also been made on how formation changes affects the time taken by the group to reach its target. The group with formation changes recorded a relatively shorter time to reach its target compared to the group without formation changes. We refer the readers to the side by side comparison included in the supplemental video.

## 6 Conclusion

As a conclusion, this paper presents a method to simulate group formation using formation templates and at the same time realizing the group behaviour by modifying the SFM. Simulations are made in dense crowd. We can also see that the method is easily compatible with individual agents, driven by the existing SFM at moderate cost. This research have also created simulations in several situations, where formation changes depending on density are successfully simulated.

While our method is able to simulate large group dynamics, there are room for improvements: For example, the group sometimes chooses to go through a dense area instead of passing through less dense areas. This can be solved by using a path planning or a machine learning technique for the group leader, thus, enabling the group to find a better route to the target position.

Our current work simulates only 17 members per group. Hence, in our future work, we plan to allow variable number of followers in order to better see the effects of group formation and behaviour on the group and its neighbouring agents. The current simulation also consists of only two formations. We intend to add more formations to make the formation changes look smoother. Apart from that, the current group formation looks stiff especially in circular moving crowd situations. This can be solved by deforming the formation, thus, enabling it to bend.

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