Crowd Behavior Simulation Using Artificial Potential Fields

Mohamed H. Mabrouk

***Abstract*— The fact that some facilities are usually overcrowded with human individuals drags the attention to the need for developing reliable models that can be used for the prediction of human crowd behavior especially during evacuation processes in emergency situations. In this paper, a new model that depends on using the artificial potential fields (APF) to simulate the crowd behavior is presented. The simulation of realistic behavior for human crowds is reached through the employment of the model's two main bases. Firstly, the model takes into consideration the equations of motion for each individual in a way which satisfies the fact that human crowds, like many physical systems, attempt to relax their configuration into a minimum energy state. Secondly, the behavior of each individual is linked to the components of the environment by using the artificial potential fields through a non-colliding pattern that maintains a clear nearest neighbor distance (NND) for each individual. Numerical results that match the real behavior of human individuals show the efficiency and applicability of the model as well as its fastness that allow it to handle dynamic environments with massive crowds.**

***Index Terms*— Crowd Dynamics, Agent-Based Modeling, Generalized Morse Potential, Lyapunov Stability.**

I. Introduction

MANY modeling approaches have been recently put forward into the pedestrian modeling literature to meet the need for developing reliable models that can predict the behavior of human crowds especially in crowded facilities such as airports and railway stations. These facilities are usually inhabited by a large number of moving individuals who plan their paths between different locations in the environment in a way that allow them to move toward their destinations while avoiding collisions with each other and with obstacles in the environment.

Crowd dynamics have been investigated using many approaches [1-26]. Some approaches are based on empirical data and observation to help further investigation in the field [1-9], others used the computer based modeling approaches [10-26] as the computer models generally have the ability to be re-run many times with altering parameters to evaluate crowd behavior in different situations.

The most operational ones of these models are the interaction forces-based models that define the forces then apply them to pedestrian behaviors using physical concepts rather than other models that are based on discrete choice modeling concept that consider behavioral aspects of pedestrians' reactions [1, 4]. The interaction forces-based models are widely used in many applications such as pedestrian modeling in urban planning [18, 19], assisting development of visual guidance systems and signage (VGSAS) for pedestrians inside large buildings [5], and visually convincing and physically correct simulations of large crowds that have become a necessity for interactive virtual worlds and games [27, 28]. The majority of the available studies investigated human crowds as collection of isolated individuals that happen to exist at the same place, each of which has his own speed, direction of motion, and destination point [1, 10, 24, 29].

The artificial potential field method (APF) has been an important method to simulate the interactions amongst members of biological systems [30-32]. In the artificial potential field method, both attractive and repulsive fields are formed separately and then added to form a global potential field. Different forces are associated with specific potentials such as the Columb potential, Van der Waals potential, generalized Morse potential (GMP) and the Lennard- Jones potential. Generalized Morse potential is preferable due to its exponentially decaying nature that defines a realistic way of constructing the field as well as its simple required computations especially when dealing with a large number of crowd members [10, 11, 31, 32]. Although the artificial potential field method has been used to describe the interactions amongst groups of interacting particles in physical systems by many researchers [30-32], fewer attempts were presented in the field of pedestrian dynamics [33] that either did not present realistic way to define the interactions amongst the crowd members [34-36] or were based on techniques that demand relatively high calculations especially for large crowds [37-40].

The contribution of this paper is to present the APF model, which is a new model for simulating the behavior of pedestrians through using the artificial potential fields to describe the interactions amongst the individuals in the crowd and to link the behavior of each individual to the environment, as will be explained in section II. In contrast to most of the interaction forces-based models in the literature, which use equations to represent the motion of the individuals that are not investigated from the stability point of view leaving the results exposed to noise especially when dealing with massive crowds, the stability of the equations that represent the motion of the individuals in the

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APF model is thoroughly discussed in section III to ensure that the behavior simulated by the model converges to a stable state. Numerical results show that the model leads to an efficient flow of crowd individuals, reducing at the same time the amount of energy consuming avoidance maneuvers that the individuals have to perform, as will be discussed in section IV.

II. The APF Model Definition

During the simulation of crowd behaviors, the individuals should have global goals with respect to the environment while trying to avoid collisions with each other and with the obstacles in the environment.

The model targets the realistic prediction of human crowd behavior by adopting the idea that many physical systems attempt to relax their configuration into a minimum energy state for describing the equations of motion of the crowd individuals. To define the model components that determine the behavior of each individual in each time period of the simulation and to achieve a non-colliding individual motion neither with the obstacles nor with other individuals, the potential fields that affect each individual are defined by assigning repulsive potentials (repulsive forces) to the obstacle positions and other crowd members while assigning attractive potentials (attractive forces) to the goal position.

The model is considered here for the i^{th} individual with mass m_i, position $\mathbf{r}_i$ and velocity $\mathbf{v}_i$. A dissipative friction force with positive coefficient β_i is added to control the i^{th} individual's speed. The global potential, which affects the i^{th} individual, is characterized by attractive goal and repulsive obstacle potential fields of strengths C_{ig} and C_{io} with ranges l_{ig} and l_{io} respectively in addition to the individual interaction potential function $V_{interaction}(\mathbf{r}_i)$ that represents the i^{th} individual's repulsive potential field of strength C_{ri} with range l_{ri}, which characterizes the individuals minimum value of its nearest neighbor distance (NND) that is defined as the distance between a particular individual and its closest neighbor in the crowd [41]. The equations of motion of the i^{th} individual are as follows:

$$\mathbf{v}_i = \dot{\mathbf{r}}_i \tag{1}$$

$$m_i \dot{\mathbf{v}}_i = -\beta_i \mathbf{v}_i - \nabla_i V_{global}(\mathbf{r}_i) \tag{2}$$

where the global potential corresponding to the i^{th} individual, $V_{global}(\mathbf{r}_i)$, is defined as follows:

$$V_{global} = V_{interaction} + V_{obstacles} + V_{goals} \tag{3}$$

The obstacles, goals and interaction potentials are defined as:

$$V_{ineraction}(\mathbf{r}_i) = \sum_{j\neq i}^{N_p} C_{r_j} e^{-|\mathbf{r}_i - \mathbf{r}_j|/l_{r_j}} \tag{4}$$

$$V_{obstacles}(\mathbf{r}_{io}) = \sum_{z=1}^{N_o} C_{io_z} e^{-|\mathbf{r}_i - \mathbf{r}_{o_z}|/l_{io_z}} \tag{5}$$

$$V_{goals} = -\sum_{k=1}^{N_g} C_{ig_k} e^{-|\mathbf{r}_i - \mathbf{r}_{gk}|/l_{igk}} \tag{6}$$

$$V_{global}(\mathbf{r}_i) = \sum_{j\neq i}^{N_p} C_{r_j} e^{-|\mathbf{r}_i - \mathbf{r}_j|/l_{r_j}} + \sum_{z=1}^{N_o} C_{io_z} e^{-|\mathbf{r}_i - \mathbf{r}_{o_z}|/l_{io_z}} - \sum_{k=1}^{N_g} C_{ig_k} e^{-|\mathbf{r}_i - \mathbf{r}_{gk}|/l_{igk}} \tag{7}$$

where N_o is the total number of point obstacles that constitute the boundaries (walls), N_p is the number of crowd members, N_g is the total number of goals (destination points), $\mathbf{r}_{gk}$ is the k^{th} goal position and $\mathbf{r}_{oz}$ is the z^{th} obstacle point position. Equations (1-7) have the advantages of taking the physical terms of velocity and acceleration into account as well as the simple required calculations. However using the APF to simulate the behavior of the individuals runs the risk of getting stuck in local minima and not being able to reach their goals, this will not be the case here as the interaction parameters are set to values that ensure waiving of local minima in the environment [11].

The main elements of the model that define the components of the environment in which the individual navigates should include the individuals' perception about the environment. Utilizing the perception techniques in biological systems can be useful to increase the perception of each individual about the environment [42] that is simplified here by representing the repulsion potential range (l_{io}) affecting the i^{th} individual as a function of an obstacle constant (l_o), which characterizes the physical nature of the obstacle, and the individual repulsion potential range (l_{ri}). This way of defining (l_{io}) increases each individual's perception about the obstacles (boundaries and other individuals) in the environment, while the repulsion potential strength affecting the i^{th} individual (C_{io}) can be represented as the obstacle constant (C_o) for simplification. Also, the attraction potential range of the goal affecting the i^{th} individual (l_{ig}) can be represented as a function of the goal constant (l_g), which characterizes the physical nature of the goal, while the attraction potential strength of the goal affecting the i^{th} individual (C_{ig}) can be represented as the goal constant (C_g) such that

$$C_{io} = C_o \tag{8}$$

$$l_{io} = l_o + l_{ri} \tag{9}$$

$$C_{ig} = C_g \tag{10}$$

$$l_{ig} = l_g \tag{11}$$

This way of defining the model elements gives the model the advantages of adaptation to real situations in addition to the employment of Morse potential to define the social forces amongst the individuals that gives more realistic flavor to the model along with simple required calculations especially when dealing with large size crowds.

III. Stability Analysis

The approach from [42] is adopted to prove the stability of a system of interacting particles where the system members tend to relax into a minimum energy state [43].

A. Model Analysis for Obstacle Free Scenario

Considering the potential field defined in (3-7), the potential field is a function of each individual's interaction parameters. According to the equations of motion and assuming unit mass, the equation of motion of a single individual i at position $\mathbf{r}_i$ is:

$$\ddot{\mathbf{r}}_i = -\beta_i \mathbf{v}_i - \nabla_i V_{global}(\mathbf{r}_i) \tag{12}$$

where $V_{global}(\mathbf{r}_i)$ is the global potential that affects the i^{th} individual. Considering (3-7) and for an obstacle free system, the global potential function for a single individual at position $\mathbf{r}_i$ attracted by a goal located at $\mathbf{r}_g$ is defined as

$$V_{global} = -C_{ig} e^{-|\mathbf{r}_{ig}|/l_{ig}} \tag{13}$$

The system effective energy ϕ, for N_p members of the system that behave individually, will be defined as follows

$$\phi = \frac{1}{2}\mathbf{v}_i^2 + V_{global} \tag{14}$$

so that its time derivative is

$$\dot{\phi} = \mathbf{v}_i.\dot{\mathbf{v}}_i + \nabla_i V_{global}.\mathbf{v}_i \tag{15}$$

Substituting from (2) in (15), it can be seen that

$$\dot{\phi} = -\beta \mathbf{v}_i^2 \tag{16}$$

Since $\beta > 0$, it is clear that $\dot{\phi} < 0$ and therefore the system is *Lyapunov* stable [42- 43].

B. Model Analysis for (Goal / Obstacles) Environment

According to (1-7) and for a single individual at position $\mathbf{r}_i$, it can be seen that

$$\ddot{\mathbf{r}}_i = -\beta \mathbf{v}_i - \nabla_i V_{goal}(\mathbf{r}_{ig}) - \nabla_i V_{obstacles}(\mathbf{r}_{io}) \tag{17}$$

where $V_{goal}(\mathbf{r}_{ig})$ and $V_{obstacles}(\mathbf{r}_{io})$ are the potential field of a single goal and the obstacles potential field that affect the i^{th} individual, respectively. However, from (4-7) it can be seen that

$$V_{obstacles}(\mathbf{r}_{io}) = \sum_{z=1}^{N_o} C_{io_z} e^{-|\mathbf{r}_i - \mathbf{r}_{o_z}|/l_{io_z}} \tag{18}$$

where N_o is the number of obstacles. Then, from (18) it can be seen that

$$\nabla_i V_{obstacles}(\mathbf{r}_{io}) = -\sum_{z=1}^{N_o} \frac{C_{io_z}}{l_{io_z}} e^{-|\mathbf{r}_i - \mathbf{r}_{o_z}|/l_{io_z}} \hat{\mathbf{r}}_{io_z} \tag{19}$$

Noting that C_{io} is given very small values compared to C_g to avoid formation of local minima inside the trap [11], then the term $\nabla_i V_{obstacles}(\mathbf{r}_{io}) \approx 0$, then (17) will approximate to:

$$\ddot{\mathbf{r}}_i + \beta \dot{\mathbf{r}}_i = -\nabla_i V_{goal}(\mathbf{r}_{ig}) \tag{20}$$

which is the equation for a damped oscillator with an external forcing term generated by the goal. This indicates the tendency of each individual to move to the goal position and then come to rest, which proves the tendency of the individuals to relax into a minimum energy state [44].

IV. Numerical Results and Discussion

Models to simulate crowd dynamics during emergency situations are considered the most recent amongst the crowd dynamics simulation attempts [11, 12, 45, 46]. From the observations recorded and presented in [1], the behavior of people in panic situations is irrational due to the fact that in emergency conditions they get nervous and try to escape in a speedy random fashion, which is too unmanageable to be predicted and is considered out of the scope of this paper. However, if people do not panic in emergency situations, they seem to follow the crowd members, who succeed to pass the exit, with higher speed than that in the normal conditions. Also the number of pushing pedestrians becomes less with time as the crowd members pass the exit in a way that increases the chance to evacuate the room in lower time than that in the normal conditions.

All the aforementioned features are taken into consideration during the design of the APF model presented in this paper by linking the behavior of each individual to the environment components (destination point, boundaries, and other individuals in the crowd) using (1-11). Also using the potential fields to define a destination point for each individual can make all individuals have the same desire to reach their destinations at the same time giving the model flexibility as well as adaptation to realistic human behavior.

This section contains two main parts; the first part considers comprehending the main features of the model through testing the behavior in two simple situations; the evacuation of a single exit room in both normal and emergency conditions. Then the behavior of the individuals, which is simulated by the model in more challenging situations, is considered to show further advantages of the model in contrast to other models in the literature. The second part of this section is dedicated to signify the APF model results by comparing its results to the results obtained by another model in the same testing conditions.

A. The APF Model Features and Specifications

In order to illustrate the use of the model in a simple way, we will investigate a problem of low population crowd whose members attempt to evacuate a single-exit room, from random initial positions and velocities, in both normal and emergency conditions. In normal condition the motive of the individuals to leave the room is not strong, therefore their average speeds are low and there is no pushing among them which means that each individual keeps a certain distance from its nearest neighbor in the crowd. Potential fields parameters should be chosen in a way that matches the situation features. Therefore, a moderate attraction potential goal point outside the room that affects all the individuals, moderate dissipation factor, and low repulsion potential parameters amongst the individuals are chosen. On contrary, when crowd individuals attempt to leave the room under emergency conditions, a stronger attraction potential goal point that affects all the members of the crowd, lower dissipation factor, and high repulsion potential parameters amongst the individuals are chosen.

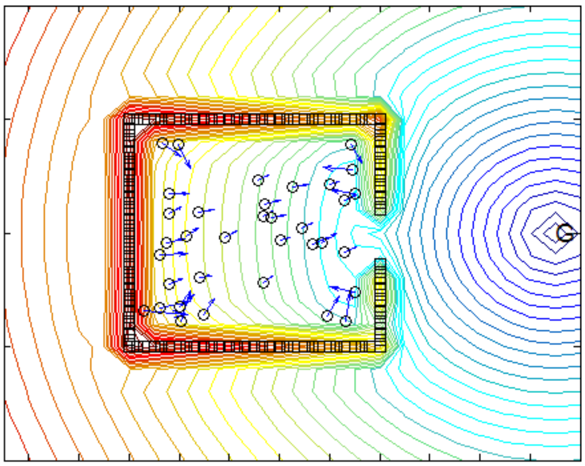

Fig. 1.a. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, t = 5

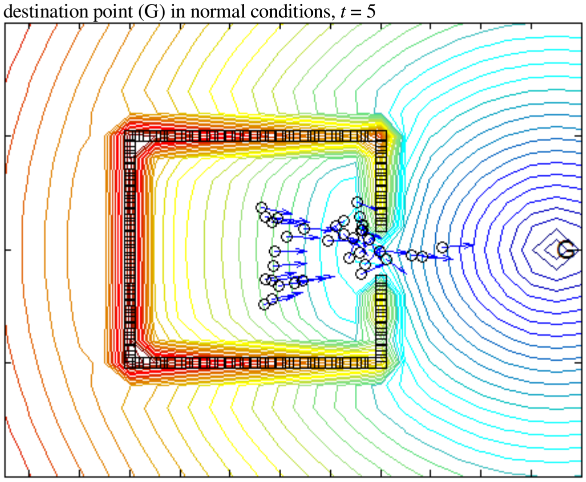

Fig. 1.b. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, t = 32

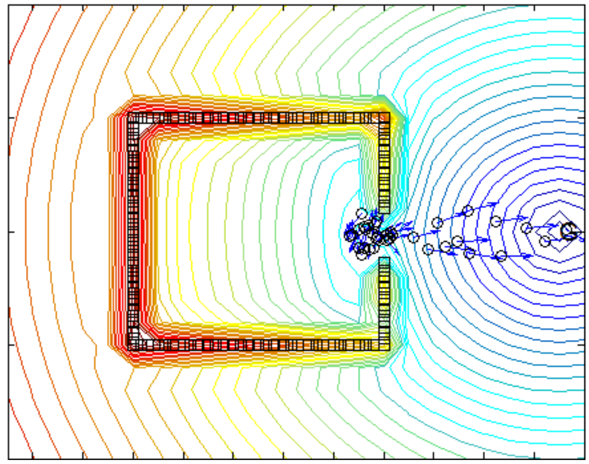

Fig. 1.c. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, t = 65

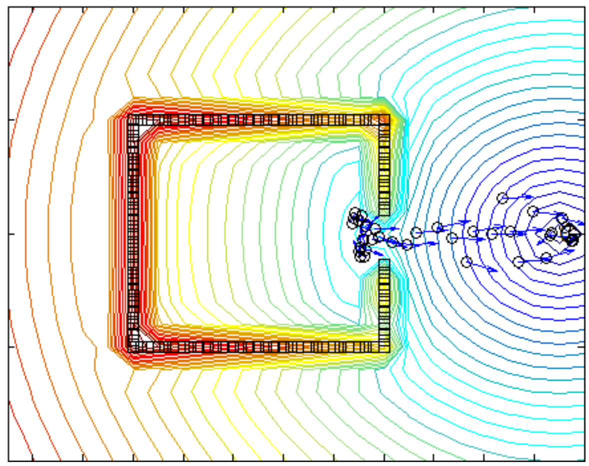

Fig. 1.d. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, t = 93

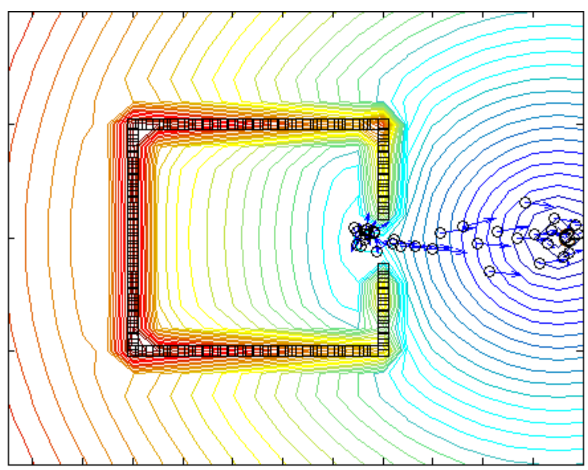

Fig. 1.e. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, t = 101

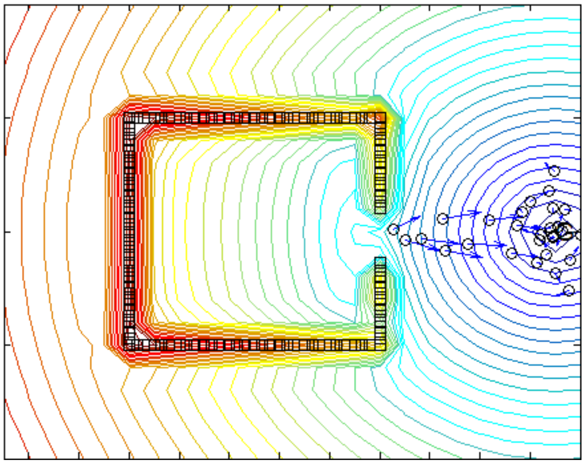

Fig. 1.f. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions, *t* = 165

Fig. 1. Simulation of crowd members that attempt to leave a trap to a destination point (G) in normal conditions.

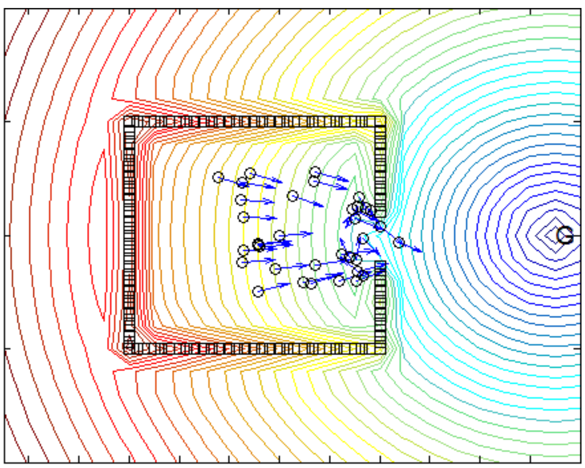

Fig. 2.a. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions, *t* = 15

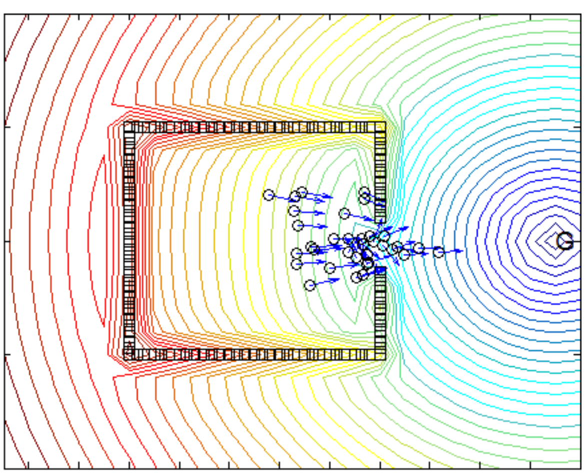

Fig. 2.b. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions, *t* = 25

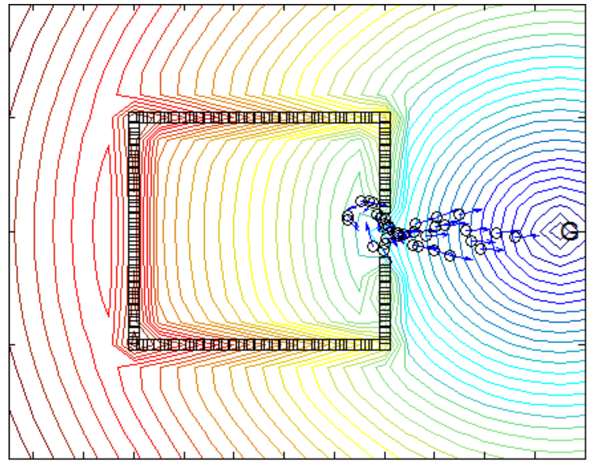

Fig. 2.c. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions, *t* = 40

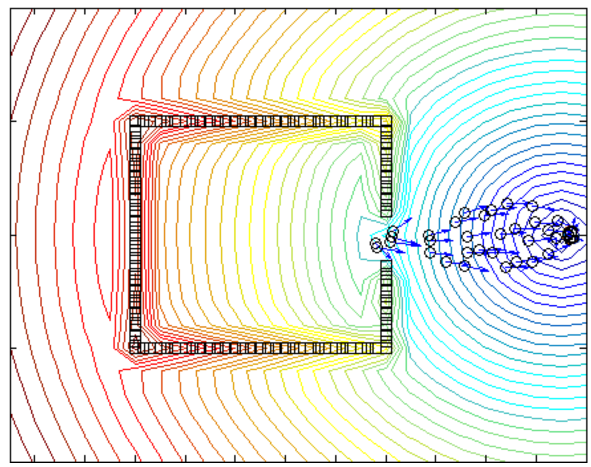

Fig. 2.d. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions, *t* = 61

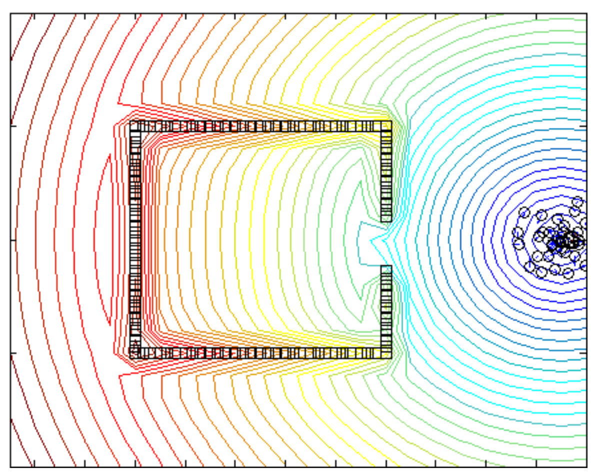

Fig. 2.e. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions, *t* = 90

Fig. 2. Simulation of crowd members that attempt to leave a trap to a destination point (G) in emergency conditions.

The simulation results, shown in Fig. 1, demonstrate the behavior of crowd members that attempt to leave the room in normal conditions through a neck exit using random initial positions and velocities, as shown in Fig. 1(a). It can be seen that some individuals pass the neck according to their close initial positions to it, as shown in Fig. 1(b), hence the rest of the individuals seem to follow them and aggregate around the neck, as shown in Fig. 1(c).

The aggregated members leave the room in a line which can be clearly seen in Fig. 1(d-e). The process continues until each individual reaches the destination point while keeping a distance from its nearest neighbor in the crowd, as shown in Fig. 1(f).

The simulation results shown in Fig. 2 demonstrate the behavior of crowd members that attempt to leave the room in emergency conditions through a neck exit using random initial positions and velocities.

It can be seen that some individuals pass the neck according to their close initial positions to it, as shown in Fig. 2(a), hence the rest of the individuals haste towards the exit and aggregate around the neck pushing those individuals who are nearest to the exit which makes them squeezed out of the room rather than leaving the room in line, as shown in Fig. 2(b-c).

The number of individuals in the room decreased with time which decreases the pushings amongst the individuals and the evacuation process becomes faster, as can be noted in Fig. 2(c-d). The evacuation process continues until each individual reaches the destination point then comes to rest, as shown in Fig. 2(e).

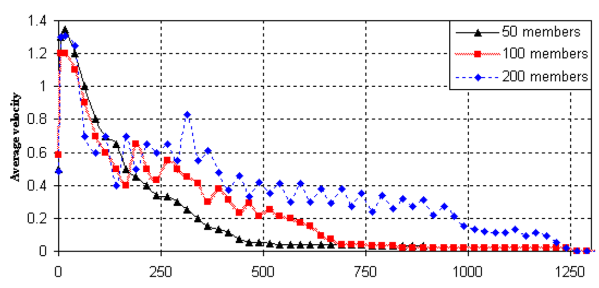

Fig. 3. Individuals' average velocity with time during normal conditions for crowds of (200 – 100 – 50) members.

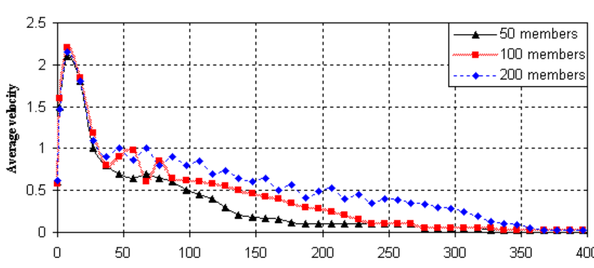

Fig. 4. Individuals' average velocity with time during emergency conditions for crowds of (200 – 100 – 50) members.

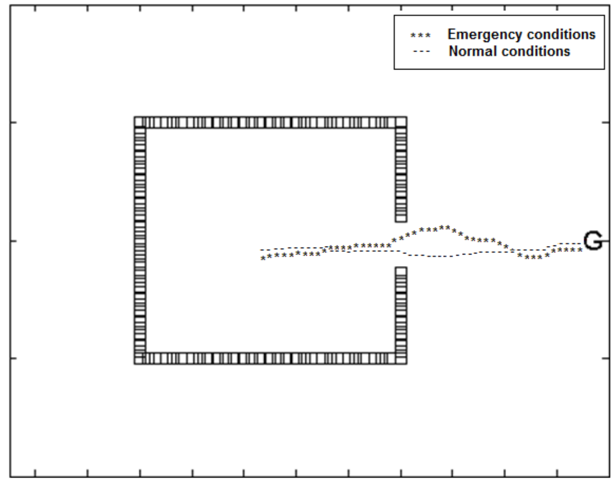

Fig. 5. Center path of a crowd that contains 300 members until reaching a destination point (asterisk line during emergency conditions – dash line during normal conditions).

The average velocity $\mathbf{v}_c$ for different population crowds, calculated as ($\mathbf{v}_c = \frac{1}{N_p}\sum_{i=1}^{N_p}\mathbf{v}_i$) [47], is shown in Fig. 3 and Fig. 4 during normal and emergency conditions respectively. It can be seen that the average velocity in case of emergency conditions is generally higher than that in the normal conditions. Also for both cases, the average velocity is almost the same for crowds with higher population at the start of the evacuation process then as the process continues with time, individuals' average velocity is higher for higher crowd populations. This is due to the fact that during the aggregation of the individuals around the exit in the early regime of the process, there is no enough space for the individuals to have higher speeds, then crowds of different populations almost has same average velocities. Then with time, the number of individuals in the room decreased which increases the space around the individuals. This makes the pushings amongst the individuals (consequently the average velocity) higher for the crowds of higher populations. Then crowds members in both cases tend to come to rest when reaching the destination point. This match the stability analysis of the model which proves that the crowd members tend to relax into a minimum energy state achieving real features of crowd members, who desire not to move too far in a short amount of time and to reach their destinations while avoiding other members in the crowd. These results match the observed data that attempted to be simulated by other models [7, 20, 46] yet with lower calculations required for the same population sizes.

The path of crowd centre $\mathbf{r}_c$, calculated as ($\mathbf{r}_c = \frac{1}{N_p}\sum_{i=1}^{N_p}\mathbf{r}_i$) [47], for a crowd that contains 300 members until reaching a destination point is shown in Fig. 5 (dash line during normal conditions while asterisk line during emergency conditions). The notches in the crowd path centre shown in asterisk line for emergency conditions, emphasis that there are more fluctuations (pushings) amongst the crowd members during the evacuation process in emergency conditions than that in the normal conditions represented by dash line, which is almost a straight line. This means that the model achieves local as well as global shortest paths through automatically self optimized technique, which depends on the representation of the individuals' goal physical nature using the artificial potential fields, to assure each individual's straight path directly toward the goal position. It is important to note that the crowd behavior shown in Fig. 1, Fig. 2 does not fulfil the conditions defined in [48] for swarming behavior. In both results, each individual is repelled from other individuals, which represents the concept of dealing with the problem on an individual basis rather than collective one.

Considering a more challenging situation, the APF model is now used to predict the behavior of crowd members that attempt to leave a room through a narrow corridor from random initial positions and velocities. The simulation results, shown in Fig. 6(a), demonstrate the predicted behavior of the crowd members that attempt to leave the room through a narrow corridor using the APF model. The crowd behavior predicted by the model is similar to the formerly published recorded observations for real behavior of human crowd in the same situation [49], as shown in Fig. 6(b).

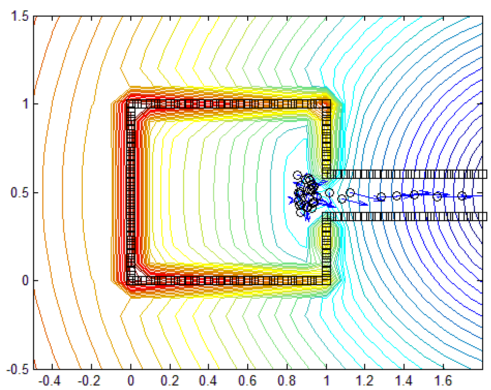

Fig. 6.a. Simulation of crowd behavior at bottleneck using the APF model

Fig. 6.b. Video recordings [49] for real crowd behavior in normal conditions.

Fig. 6. Simulation of crowd behavior at bottleneck using the model at t=90 (top) versus video recordings [49] for real crowd behavior (bottom) in normal conditions.

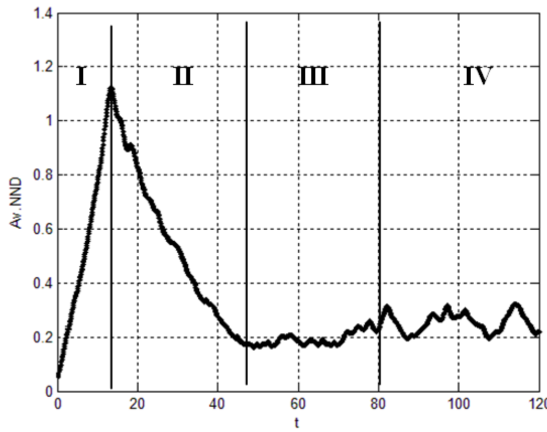

Fig. 7. Average nearest neighbor distance for the crowd in Fig. 6(a) with time

For good understanding of the results, the nearest neighbor distance (NND) for each crowd member is calculated. Considering that the nearest neighbor distance varies for each individual in the crowd, therefore calculating it for a particular member does not give a true impression about the crowd behavior as a whole. The average nearest neighbor distance (Av. NND) for a crowd that contains N_p members (Av. NND = $\frac{1}{N_p}\sum_{i=1}^{N_p}\min_{j\neq i}|\mathbf{r}_i-\mathbf{r}_j|$) [47] gives an indication about the spacing amongst the members of the crowd which helps in further understanding of the entire crowd behavior. Fig. 7 demonstrates the average nearest neighbor distance (Av. NND) for the crowd shown in Fig. 6(a). In region (I) of Fig. 7, it is clear that the value of (Av. NND) overshoots to a relatively high value, which is due the dispersion of the crowd individual at the begging of the simulation as the initial value of the (Av. NND) is so small according to use random initial positions for the crowd members. Region (II) of Fig. 7 shows that the (Av. NND) decreases with time representing the fact that the majority of the crowd individuals cluster near the bottleneck. Regions (III) and (IV) of Fig. 7 represent the individuals' orderly evacuation pattern, a capture of this pattern is shown in Fig. 6(a). The (Av. NND) remains almost constant during regions (III) and (IV) of Fig. 7 until the end of the evacuation process confirming the adaptation of the model to real behavior of human crowds whose members usually keep a distance among each other especially in non emergency conditions.

In contrast to many models that are limited to simulate groups of individuals that move toward a common goal, the APF model focuses on simulating individuals that have distinct goals, which gives the model the ability to handle challenging situations. To show this, another challenging evacuation planning scenario is now considered. The evacuation plan assumes a crowd of individuals that attempt to evacuate a room through three different exits. The individuals are divided into three different groups each of which has been assigned a specific exit. It is assumed that the individuals have random initial positions and velocities at the beginning of the process.

The behavior of the individuals in such situation can be simulated by the model through defining three different virtual goals (G1, G2, and G3) that are activated in the proximity of the exits (exit1, exit2, and exit3) respectively, each of which is assigned to attract a specific group of individuals (the square group, the triangle group and the diamond group) respectively, such that each goal attracts its corresponding group while the other two groups are not attracted to it. The results of the individuals' behavior in such evacuation process are shown in Fig. 8.

As soon as the emergency alarm is launched, all the individuals are given slightly increased repulsion potential parameters, which helps to provide space necessary for the evacuation process to occur, and are given lower β to permit the individuals to gain higher speeds. This makes the individuals seem to sort into groups before reaching the three exits, as shown in Fig. 8(a-c), in a way that matches the human behavior in similar situations. As the evacuation process continues, each group succeed to evacuate the room through the exit that has been assigned to it, as shown in Fig. 8(d).

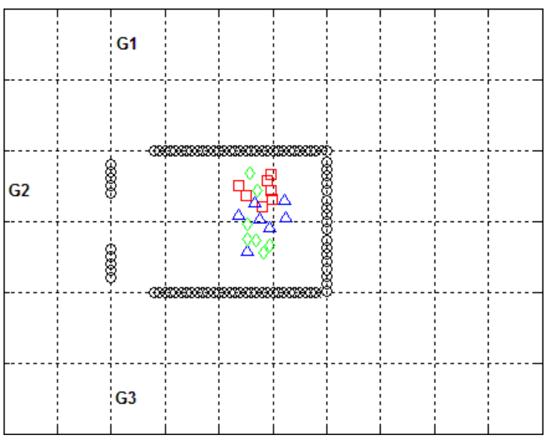

Fig. 8.a. Simulation of crowd members that attempt to leave a room through pre-assigned exits, $t = 5$

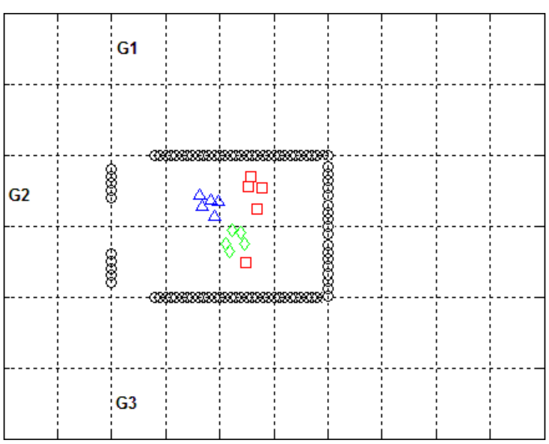

Fig. 8.b. Simulation of crowd members that attempt to leave a room through pre-assigned exits, $t = 31$

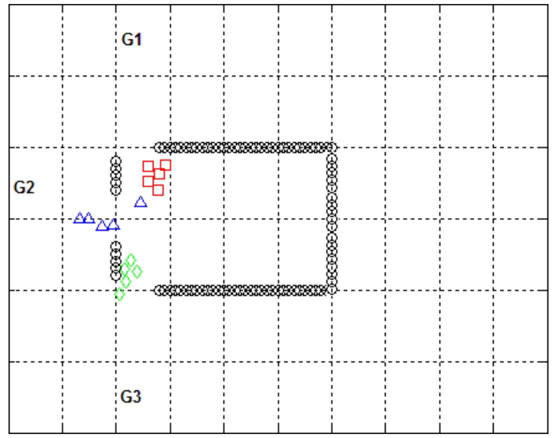

Fig. 8.c. Simulation of crowd members that attempt to leave a room through pre-assigned exits, $t = 85$

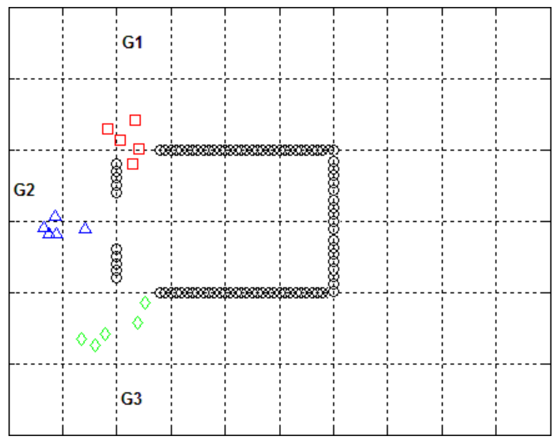

Fig. 8.d. Simulation of crowd members that attempt to leave a room through pre-assigned exits, $t = 106$

Fig. 8. Simulation of crowd members that attempt to leave a room through pre-assigned exits.

B. *The APF Model Results Signification*

To signify the results of the APF model, predictive model that was presented in [28] to predict the behviour of individuals in crowds is used. The predictive model is mainly based on the assumption that each individual scans the environment to detect future collisions with other crowd members, then it predicts how these collisions will take place and tries to resolve them in the current simulation step by making the most efficient move. However it sounds like it needs heavy calculations, the method yields to real-time performance [28].The phenomenon of lane formation that is widely noted in the pedestrian literature [1, 28] is now considered to determine how significant the results obtained by the APF model are by comparing the results obtained by the predictive model in the hallway scenario, shown in Fig. 9, that was performed in [28] to the results obtained by the APF model in the same conditions.

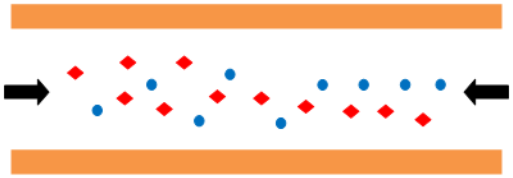

Fig. 9.a. Hallway scenario used in predictive model [28]

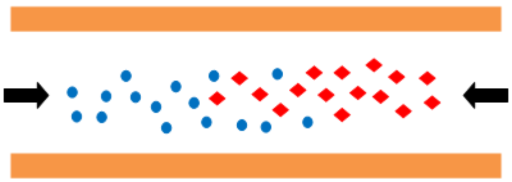

Fig. 9.b. Hallway scenario used in the APF model

Fig. 9. Hallway scenario using predictive model in [28] (top) and using the APF model with low repulsion ranges (bottom).

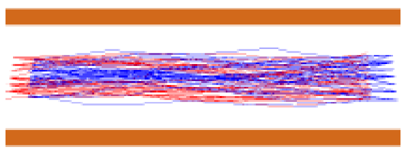

Fig. 10.a. Example paths of the individuals in the hallway scenario for the predictive model [28]

Fig. 10.b. Example paths of the individuals in the hallway scenario for the circle group moving from left to right using the APF model.

Fig. 10.c. Example paths of the individuals in the hallway scenario for the diamond group moving from right to left using the APF model.

Fig. 10. Example paths of the individuals in the hallway scenario (a) for the predictive model [28] (b) for the blue group moving from left to right using the APF model (c) for the red group moving from right to left using the APF model.

TABLE I
STATISTICS OF THE HALLWAY SCENARIO FOR 100 INDIVIDUALS

	Time		Path Length		Avg. Speed	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Pred. Model	25.05	2.1	35.14	1.79	1.4	0.05
APF Model	24.87	1.9	35.05	1.73	1.40	0.005

Table I demonstrates the statistics of the hallway scenario for 100 individuals using both predictive model and the APF model. It can be seen that while allowing the individuals to move with average speed equal to that of the individuals in predictive model, the APF model designs shorter individuals' paths compared to the paths generated by the predictive model as expected since the APF model uses the artificial potential fields to define the destination point for each individual

The individuals' paths in the hallway scenario are shown in Fig. 10(a) using the predictive model [28], Fig. 10(b) for the blue circle group moving from left to right using the APF model, and Fig. 10(c) for the red diamond group moving from right to left using the APF model. It can be seen from Fig. 10 that using the APF model, the flow of the individuals looks smooth and the paths of the individuals are almost as curved as the paths obtained using the predictive model. Therefore it can be inferred that using the APF model, the number of local interactions between the individuals is similar to that obtained using the predictive model, which means that the individuals reaches their destinations through shortest paths and with small amount of local interactions between individuals yet with considerably lower calculations than the calculations needed by the predictive model especially for massive crowds scenarios.

In conclusion, the experiments show that, using the APF model, the individuals reaches their destinations through shortest paths and with small amount of local interactions amongst individuals, which leads to time and energy efficient movements. The experiments also show the flexibility of the model through its adaptation to simulate real behavior of human crowds in different situations as well as its fastness that allows it to deal with scenarios with massive crowds.

V. CONCLUSIONS

This paper presents the APF model, which is a new computer based model to predict human crowd dynamics. To describe the motion, the model takes the physical terms of velocity and acceleration into account, employs artificial potential fields to define the interaction forces amongst the individuals, and links the behavior of each individual to the environment components such as other individuals, boundaries, and destination points. This efficient way of defining the motion gives the model the advantages of adaptation to real human behavior as well as the relatively simple required calculations. The stability analysis proves that, using the APF model, each crowd member tends to relax into a minimum energy state which achieves the desire of humans not to move too far in a short amount of time and to reach their destinations while avoiding other individuals. This not only leads to a smooth and effective individuals' flow, but also minimizes the amount of time and energy consuming interactions between individuals enabling the model to simulate the behavior for thousands of individuals in real-time. The numerical results that match the real observed data in similar situations show the ability of the model to predict the human crowd behavior in both normal and emergency conditions such that the model can be used as a powerful tool for planning evacuation processes with the possibility of changing many parameters to adapt many different scenarios.

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