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# **Diversified Crowd Evacuation Method** in Large Public Places

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**ABSTRACT** Realistic crowd simulation is an important issue for crowd management, public space design, and architectural and urban planning. In this paper, we present a novel approach for planning and directing heterogeneous large-scale crowd in public places. We firstly extract group features from real-world video, and transfer them to the virtual crowd members. On this basis, we perform the crowd evacuation by combining the global path planning and collide avoidance strategy. Our method efficiently produces the most promising paths in both time and space and offers a reasonable distribution of the crowd' members over these paths such that their average evacuation time is minimized based on the probabilistic roadmaps approach. The generated paths are combined with reciprocal velocity obstacle method to handle collisions and generate the final motions of the individuals. We demonstrate its potential on large public places with 10000 individuals and evaluate the results from our simulations using some quantitative quality metrics. In practice, our method can interactively simulate large crowds with thousands of individuals on a desktop PC and naturally generates a diverse set of emergent behaviors.

**INDEX TERMS** Crowd simulation, collide avoidance, reciprocal velocity obstacle, probabilistic roadmap.

#### I. INTRODUCTION

Crowds are ubiquitous in the real world and have been studied extensively in social sciences, traffic engineering, architecture, urban planning, etc. In large public places, such as city square, sport stadiums and railway stations, evacuating large-scale crowds when an emergency occurs is an enormous challenge to public managers, and unscientific evacuation strategies have inflicted many heavy casualties over the years [1]. However, accurately conducting real-world evacuation drill is hard to organize and chaotic. Furthermore, the goal-directed drill does not always give a true picture of what will happen in the real situation. Therefore, a number of researchers proposed automatic model to realize this.

A realistic simulation of crowds involves many components including group behavior, cognitive modeling, motion synthesis, crowd movement and rendering. In this paper, we focus primarily on modeling crowd movement and dynamics based on a multi-agent simulation framework. The

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movement of agents in the environment is often governed by local rules and social forces. One of the challenges in crowd simulations is to automatically generate macroscopic level behaviors and emergent phenomena form these local rules.

A number of models have been designed to help individuals move realistically and regularly through virtual environments. The classical social force model presented by Helbing and Molnar [2] has exerted a great influence in this field. In the pioneering work, the social forces are used to simulate the behavior of pedestrians and traffic flow. Since his original work, a great many other effective models [3], [4] have been put forward to exhibit emergent crowd behaviors. However, this kind of approaches are almost closely related to flocking and reactive steering and suffer from the same local minima problems. In order to address these problems, some researchers combined the local models with global navigation strategies. Representative work for global planning is graph-based techniques, including the corridor maps [5], probabilistic road maps [6], rapidly exploring random trees [7], and waypoint graphs [8], which represent the environment by using a set of one-dimensional edges.

By contrast, a navigation mesh partitions the environment into walkable regions that are two-dimensional [9]. These walkable regions permit characters to control their movements inside each 2D region. This flexibility also makes it much easier for characters to avoid other moving characters. Although these approaches are fast and flexible, they rather limit the global behavior of the character, since a graph-based method is used for global planning.

However, there are still many challenges for reproducing and predicting real-world crowd flows because of the intrinsic diversity and complexity in crowd movements. In the simulation, we should ensure the rationality of paths' distribution firstly. In addition, these paths should have the intelligence to avoid static obstacles as well as other moving individuals. Undoubtedly, each individual wants to get the target along the shortest paths, but this will lead to path congestion when many individuals traverse the same path simultaneously. On one hand, the step length and walking frequency of each agent in a crowd are different during an actual evacuation process due to individuals' innate differences. This will result in different walking velocities of various individuals under the same environment.

As Ulicny and Thalmann pointed out that [10], a group consisting of the identical individuals with uniform behavior would not be cogent, though each agent independently looks very realistic. They also stressed that the crowd simulation systems need different conceptual and technical requirements and constraints for the design of the system comparing to the simulation of single virtual human. The main technical challenge mainly includes the increased demand on computational resources due to the growing number of agents. In addition, there exist some conceptual difference for the visualization, motion control and animation. Hence, to realistically simulate the crowd motion, each individual should be move and react differently to each other, such as the individuals' velocity, location distribution and crowd density. The crowd density in actual-world concept is usually expressed as the number of individuals per square meter. Some studies have indicated that when crowd density is high, the individuals will move slowly. When crowd density decreases, the individuals will move fast in the virtual environment. We call the phenomenon negative correlation between crowd movement velocity and density.

However, most available crowd evacuation models neglect inter-individual disparity and surrounding factors, thereby affecting model authenticity. In this paper, we proposed a video-driven crowd evacuation simulation method. First of all, we extract crowd movement features such as density, velocity and initial position from real-world videos. Furthermore, the relational model between movement velocity and crowd density is constructed. At last, the crowd simulation is performed by combining the global path planning based on probabilistic roadmap (PRM) and collide avoidance strategy based on reciprocal velocity obstacle (RVO) [11]. This paper fully considered the diversity in individuals' initial velocity and position distribution, and the negative correlation between movement velocity and crowd density. Experiment results show that the proposed model can realistically and efficiently simulate the evacuation process and provide supports to crowd management in emergency.

## II. RELATED WORKS

Crowd simulation is a very active topic and many different kinds of models have been proposed to perform simulation. In this section, we briefly review related work about crowd model and path planning.

## A. CROWD MODEL

There is a great deal of research in the topic of modeling behavior of a crowd. These solutions can be divided into two diverse categories: global and local approaches [12].

In the global models, a crowd is regarded as a continuous group and can be formulated as fluid flows. Hughes [13] proposes a continuum theory for the flow, Treuille et al. [14] extend the work using a dynamic potential field to integrate global navigation with moving obstacles and people, [15] focus specifically on the problem of simulating the inter-agent dynamics of large, dense crowds in real time. In addition, Chenney [16] employs the flow tiles to design velocity fields ensures the smooth flow of agents, Jin et al. [17] proposes a simple method to generate fields for the interactive control of crowd navigation, Patil et al. [18] offer a goal-directed navigation field for multiple groups. These approaches are particularly suitable for high-density simulations. However, such approaches model a global optimum, whereas humans generally behave less optimally and can even get stuck in very dense situations.

Local models for agent behavior can be traced back to the seminal work of Reynolds [19] by means of a set of rules and the particle system [2], [20] which resort to forces. Many future crowd simulation methods derive from the two kinds of work. They have accounted for sociological factors [21], directional preferences [22], and other models of pedestrian behavior, including [23]–[27]. Local approaches are hard to properly model the behavior of agents that aim to move towards specified goals due to easily getting stuck behind an obstacle. Thus, local models are often combined with global planning techniques for practical crowd simulation which will be elaborated on the next section.

Additionally, the example-based methods to crowd simulation has recently emerged as a new way of reproducing complex crowd behaviors mimicking real crowd. The key idea is to reedit the pre-recorded trajectories [28], [29] or learn the motion model [30], [31]. These methods can maintain the realism of local trajectories, but do not generalize as well as the microscopic approaches which try to mathematically formulate the main principles by which humans move in crowds.

# **B. PATH PLANNING**

Extensive literature exists on path planning in terms of graph, roadmap, or static potential field. Pettr'e uses navigation

graphs of static scenes to find pedestrian paths in real-time but does not account for collisions or congestion. The roadmap approach consists in computing a network of standardized paths (lines, curves) passing through free spaces. Early methods directly sampled roadmap nodes from space-time volume [32]. More recent methods construct the roadmap by a static spatial probabilistic roadmap [33]. Later, some algorithms [34] are extended to dynamic environments, multiple agents and deformable models [35], [36]. However, they may not adapt to environments with a wealth of independent agents.

Many other methods such as the potential field have been introduced for path-planning. These methods have the ability to execute smooth paths, but requires appreciable computational resources, thus is hard to be performed in real time. Later, Treuille *et al.* [14] present a dynamic potential field simultaneously integrates global navigation with moving obstacles such as other people.

The methods mentioned above are devised to generate collision-free paths, but they do not take into account the physical characteristics of the agents. For this reason, the preliminary approach is proposed by Choi et al. [37]. In this approach, a deformable motion model is presented to allow animated characters to navigate through cluttered environments by real-time interactive navigation and path planning. But the method didn't ensure the energy efficiency of agents. But some methods highlight the computation of expended energy. Levine et al. [38] combine path planning in space and time with parameterized controllers by integrating various cost functions. However, the energy minimization has not yet been examined and implemented. Guy et al. [39] use an optimization method to compute a biomechanically energy-efficient, collision-free [40] trajectory that minimizes the amount of effort for each heterogeneous agent in a large crowd. In [41], the authors use a mathematical equation that returns an approximation of the VO2 (vanadium dioxide) expenditure for different actions as a parameter to describe the expended energy of a character performing a given task.

## **III. CROWD PATH GENERATION**

In this section, we present a new path planning strategy for crowd based on combination with the PRM and the RVO algorithm. In our method, we first apply the PRM algorithm to conduct global path planning for the whole crowd, and the output is a set of paths for the crowd. Then the RVO algorithm is adopted to drive the crowd and avoid local obstacles.

## A. GLOBAL PATH PLANNING BASED ON PRM

The PRM path planner is proposed by Lydia E. et al and constructs a roadmap in the free space of a given map using randomly sampled nodes in the free space and connecting them with each other. Once the roadmap has been constructed, we can query for a path by the graph-based search method from a given start location to a given end location on the map.

It is a sampling-based planning algorithm that converts continuous space into discrete space. To get higher searching

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efficiency, the method uses the graph-based search method such as  $A^*$  to find the path on the road map. The advantage is that it overcomes the shortcomings that the path planning method is easy to fall into local optimum, and can be applied to path planning in large-scale group evacuation. And its calculation is less than other path planning algorithms. The PRM algorithm is represented by a random network. Its purpose is to find the path between two points in a given scene. It focuses on learning and searching step. In the learning phase, randomly generate landmark points in the free space of a given scene, and construct a path network diagram. In the query phase, query the path from a start point to an end point.

The main task of the PRM in the learning phase is to construct an undirected path network graph G = (N, E), where N represents a set of random roadmap points and E represents a set of paths between all possible two points. The pseudo code of the algorithm is shown in **Algorithm 1**.

Algorithm 1 The Pseudo Code of the PRM Algorithm					
$N \leftarrow \varnothing$					
$E \leftarrow \varnothing$					
Loop					
$c \leftarrow$ a random chosen free configuration x					
$N_c \leftarrow$ a set of candidate neighbors of c chosen from N					
$N \leftarrow N \cup \{c\}$					
for all $n \in N_c$ , in order of increasing $D(c, n)$ do <b>do</b>					
if $\neg$ same connected component $(c, n) \land \triangle(c, n)$ then					
$E \leftarrow E \cup \{(c, n)\}$					
Update $G's$ connected components					
end if					
end for					

Taking a school teaching building as the test scene, a number of roadmap points are generated and randomly distributed in the scenario with our method. The scene as shown in Figure 1 is one floor of the school teaching building, consisting of multiple classrooms and corridors. In general, there are hundreds of students having class in the classrooms. These students walk from classrooms to the building exit in small groups when class is over. To simulate the scenario, the individuals' paths should traverse every classroom door, therefore we set a fixed roadmap point for each door. However, the other roadmap points are randomly generated and distributed on the floor, thus we need to choose part of them to construct the path. We employ the  $A^*$  algorithm to search the shortest paths ensuring all the generated paths are optimal. It adopts the greedy best-first-search strategy in that it can use a heuristic to guide itself. The green lines in Figure 3 represent the shortest paths of crowd generated by the PRM and the  $A^*$ algorithm.

# B. LOCAL COLLISION-AVOIDANCE STRATEGIES OF THE RVO

The crowd evacuation method based on RVO has introduced the global path planning method alongside its existing advantages of the RVO model in terms of high performance and



FIGURE 1. The 2D environmental model.



FIGURE 2. The generated roadmap points.

avoidance of individual collision. It can not only simulate efficiently a crowd collision-avoidance effect but also can improve evacuation efficiency. In this part, we briefly review the concept of RVO.

For individuals *A* and *B*, the velocities of them are represented as  $v_A$  and  $v_B$  respectively, then the velocity obstacle can be expressed as:

$$v_A - v_B \in VO_{A|B}^{\tau} \tag{1}$$

In Equation (1), the  $VO_{A|B}^{\tau}$  is the relative space of  $v_A$  and  $v_B$  and denoted as:

$$VO_{A|B}^{\tau} = \{ v \mid \exists t \in [0, \tau] :: t \cdot v \in D(p_B - p_A, r_A + r_B) \}$$
(2)

$$D(p, r) = \{q \mid || p-q || < r\}$$
(3)

where the D(p, r) is an open interval with p as the center of the circle and r as the radius, as depicted in Figure 4(a).

The geometric significance of velocity obstacle is displayed in Figure 4(b). The individuals *A* and *B* will collide within time  $\tau$  when they move at their current velocities. If  $v_A - v_B \notin VO_{A|B}^{\tau}$ , then the individuals will not collide within time  $\tau$ .

Suppose  $A \oplus B$  is expressed as follows:

$$A \oplus B = \{a + b \mid a \in A, b \in B\}$$

$$\tag{4}$$

and the velocity set of *B* is  $V_B$ . If  $v_B \in V_B \wedge v_A \notin VO_{A|B}^{\tau} \oplus V_B$ , then individuals *A* and *B* will not collide within time  $\tau$ , and we can get the collision-avoidance velocity set  $CA_{A|B}^{\tau}$ ,

$$CA_{A|B}^{\tau} = \{ v | v \notin VO_{A|B}^{\tau} \oplus V_B \}$$

$$(5)$$

The resulting velocities  $V_A$  and  $V_B$  obtained by applying the RVO algorithm are the only velocities during the



FIGURE 3. The shortest paths generated by A\* algorithm.



**FIGURE 4.** Principles of the RVO algorithm. (a) Position set of individuals *A* and *B* at the next time. (b) Velocity obstacle set of a relative to *B*.

movement of individuals, whose collision is avoided. If the planning path of the individual movement is not provided, then the individuals may not easily reach the preset exits within the optimal period.

# IV. MODELLING THE VELOCITY-DENSITY RELATIONSHIPS

We extract the crowd density and velocity parameters from actual-world videos to analyze their correlation and establish a relational model. Furthermore, our model is applied to simulate a virtual scene through coordinate transformation. Thus, the movement velocity of individuals is slow on dense crowd scene and high on sparse crowd scene, thereby resulting in a favorable simulation of crowd evacuation movement on actual scenes.

For a clear and intuitive description of emergency crowd evacuation problem on complicated scenes, a Floor scene

is constructed with a few classrooms and exit passageways. There are four exits, more than twenty classrooms and three halls arranged on a single floor plan in a building. The scene is abstracted into a 2D spatial plane with several individuals. Each individual is represented by a circle whose radius is r. The final goal is that each individual should reach the preset exits quickly on the condition that collision among individuals and between individuals and obstacles is avoided on the preset scene. Each individual has a corresponding movement parameter, such as current position p, velocity v, direction of movement, and crowdedness degree (density  $\rho$ ) under a movement status at any time.

# A. INITIALIZE THE COORDINATES AND VELOCITY OF INDIVIDUALS

Because the starting positions of all the individuals are randomly generated, hence this may lead to uneven crowd



FIGURE 5. A simple test design. (a) Small framework. (b) 2 persons/m<sup>2</sup>. (c) 4 persons/m<sup>2</sup>. (d) 6 persons/m<sup>2</sup>.



FIGURE 6. The test scenario.

distribution and does not conform to the actual situation. In order to resolve the problem, we extract the individuals' position from real-world videos and learn their distribution law. Taking the Floor scene as the test scenario, we acquire the surveillance videos during class hours and extract the students' positions as the initial individual coordinates.

The initial velocities of all individuals in the original RVO algorithm are identical without considering individual diversity. But individual velocities are not same in real life due to the differences among the crowd in terms of age, gender, and height. We fully takes into account these factors and pick the Gaussian normal distribution function to depict the individuals' velocities.

Usually, the crowd walk along a channel at the speed of 1.25 m/s averagely when crowd density is smaller than 2 *persons/m*<sup>2</sup>, while the speed could reach 2 m/s in case of an emergency. Based on this, we set the average movement velocity of individuals under an emergency  $v_d$  is 2 m/s. In order to reflect the individual differences, the velocity of each individual  $v_i$  can be expressed by the Gaussian normal distribution function.

$$v_{i} = \begin{cases} v_{d} * (u * sqrt(-2 * log(s)/s)), & r \ge 1 \parallel r == 0\\ v_{d} * (v * sqrt(-2 * log(s)/s)), & other \end{cases}$$
(6)

In which, *u*, *v* and *s* are random variables, they are calculated as follows:

$$\begin{cases}
u = rand_1 * 2 - 1 \\
v = rand_2 * 2 - 1 \\
s = u^2 + v^2
\end{cases}$$
(7)

where the  $rand_1$  and  $rand_2$  are two random numbers between 0 and 1.

## B. RELATIONSHIP BETWEEN CROWD DENSITY AND VELOCITY

In the original RVO algorithm, all individuals are assumed to have uniformly motion features during the entire evacuation process. However, the assumption is not in line with the actual crowd evacuation. The individual movement is accelerated when a few people are surrounded by individuals (density is low), and movement is decelerated when the number of people that surrounds the individuals (density is large) is large. This phenomenon is called negative correlation. It is fully considered in this study.

we obtain the negative correlation between crowd density and average velocity during the evacuation process through a study of the influence of crowd density on walking velocity and step length. The influence of density [42] on movement velocity during crowd evacuation under actual situation was calculated through a test.

The test scene is the hall of the teaching building, which is a straight way with a length of 30m and width of 3m. The walkway is inside the hall with no obstacle. The test objects are college teachers and students, who bore no weight during the process, except a pedometer. They are fenced through a  $1m \times 1m$  small framework. Recorders are assigned outside the test field to record the steps and evacuation time of each object because errors might exist in pedometers. Five groups are formed according to different crowd densities, as follows: 2, 3, 4, 5, and 6 *persons/m*<sup>2</sup>. The test is repeated five times in each group, and the average values of the five tests are obtained as movement velocity values under present crowd density. The test design is illustrated in Figure 6.

Table 1 lists the comparison of evacuation time and movement velocity under different crowd densities. We can see that

No.	Path Lengh(m)	Crowddensity	$ET_1(s)$	$ET_2(s)$	$ET_3(s)$	$ET_{ave}(s)$	$V_{ave}(m/s)$
1	30	2	15.2	13.2	15.3	14.5	2.07
2	30	3	18.1	20.5	19.9	19.5	1.54
3	30	4	30.5	31.5	28.8	30.1	1.02
4	30	5	37.3	41.3	41.7	40.6	0.75
5	30	6	89.2	80.3	76.7	82.4	0.37
	84 70 () aug coler 56 56 56 52 70 56 56 56 50 50 50 50 50 50 50 50 50 50 50 50 50	3 4 5 spulation density	c 2. (s,u),(ijoojaA eBeuave 6		3 Population de	, , , , , , , , , , , , , , , , , , ,	6

 TABLE 1. Evacuation time (ET) and movement velocity under different crowd density.

(a)

FIGURE 7. Density correlation curves. (a) Crowd density and evacuation time. (b) Crowd density and movement velocity.



**FIGURE 8.** Density correlation curves and fitting functions. (a) The density-time fitting function. (b) The density-velocity fitting function.

the crowd presents the diversified characteristics in different stages during evacuation and conforms to the actual situation. Specifically, the movement speed of the crowd is basically kept above 1 m/s when the crowd density is less than or equal to 4 *persons/m*<sup>2</sup>, and the crowd move slower when the crowd density is greater than 7 *persons/m*<sup>2</sup>. We also test the crowd movement when the density is reach 7 *persons/m*<sup>2</sup>. In this case, the crowd hardly move because there is no space available among individuals. Therefore, crowd density should be maintained below 7 *persons/m*<sup>2</sup> to avoid congestion and stampede.

We also have made a quantitative analysis on the experimental data in Table 1. The relationship between crowd density and average evacuation time is shown in Figure 7(a), as the density value of a walkable region increases from 0 to 6, the average evacuation time increases linearly to 0 m/s. The relationship between density and velocity is shown in Figure 7(b), as the density value of a walkable region decreases from 2.5 to 0.3, the walking speed of a character decreases linearly to 0 m/s. The simulation step time is set to 10 frames per second.

(b)

The results verified that the fitting degree between the function obtained through the linear fitting and the original function is the highest. The fitting functions between the original density-time and density-velocity relational functions and the fitting function are illustrated in Figure 8(a) and Figure 8(b). The formulas for the fitting functions are as follows.

$$\begin{cases} t = 3.71\rho^2 - 13.17\rho + 22.56R^2 \\ v = 0.02\rho^2 - 0.63\rho + 3.11R^2 \end{cases}$$
(8)

In which the  $R^2$  is the coefficient of determination whose value is approximately 1. This indicates that the empirical formulas obtained through the fitting functions between the



FIGURE 9. Crowd density-velocity data in actual videos. (a) First second since movement; (b) Third second during the movement process; (c) Sixth second during the movement process; (d) Ninth second during the movement process. Routes with little utilization are highlighted in red.



FIGURE 10. Crowd evacuation simulation on the simple scene.

crowd density and evacuation time and that between crowd density and movement velocity are basically identical to the experimental data and agreed with the actual situation.

At the same time, in order to verify the authenticity and usability of the density-velocity formula obtained from the experiment, we analyze the crowd movement in real-world video and calculate the crowd movement speed under a certain density using OpenCV. Specifically, the process of extracting the crowd density and velocity parameters from actual-world videos is as follows. Firstly, the visual field angle is calculated according to the height of the camera off the ground. Secondly, the walking distance in the actual scene is computed based on the walking distance by referring to the scale of the picture and the transformation formula of the coordinate system, and the motion time is recorded at the same time. Finally, the walking speed is obtained based on the walking distance and the motion time. As shown in Figure 9, the red box represents a rectangular area of  $3m \times 3m$ , in which there are 8 people, i.e. the population density is 0.89  $people/m^2$ . The distance between the starting position (see Figure 9(a)) and the ending position (shown in Figure 9(d)) is 8.5m, from which the average speed of crowd movement can be calculated to be 0.94 m/s.

Considering that the video is recorded in the scenic spot and the crowd is mainly tourists, most people move slowly. Therefore, the individual's moving speed is set as 1.5-2.5 times of the normal walking speed in the evacuation process. This proves that the result of Formula 7 is consistent with the reality. In addition, the movement velocity of individuals can be adjusted by the modified RVO algorithm according to the current density of the crowd.

## **V. EXPERIMENTS**

We have implemented a diverse of crowd simulations with our system and found that our method can produce efficient evacuation behavior for 1000 agents in emergency. All the simulation performed on a personal computer with a 3.4 GHz Core CPU with NVIDIA GeForce GTX 1050 Ti graphics card.

The software environment for simulation is developed based on the Microsoft Visual Studio 2013, MFC and XNA Game Studio 2013. The proposed model is implemented in C++ and Matlab programming language.

To reduce random effects, all the simulations based on our proposed model is run 10 times for each scene in this paper.



FIGURE 11. Crowd evacuation simulation under the complicated scene.

## A. ENVIRONMENTS AND SETTINGS

Our experiments are performed in three 2D environments. We refer to the 2D environment in Figure 10 and Figure 5 as the Layers environment. Figure 6 illustrates our three 2D environments. The Room environment is a small example that has only one exit and its width is 1.5m. It is 200 square meters in area and the length and width is 20m and 10m, respectively. In addition, there is no evident obstacle in this room for simplicity. The Floor environment is a medium-sized example of a building that arises from a real-world campus teaching building. The floor consists of four exits, more than twenty classrooms, and three halls. The Square environment is a large-scale squares that contains many polygonal obstacles and routes.

## **B. EXPERIMENTAL COMPARISON**

In the first experiment, we simulate a group with fifty persons evaluating from a small room. Figure 10 displays the states since the evacuation started, 50th, 100th, 150th, and 200th s, respectively. As can be inferred from the comparison, our approach is in accordance with empirical data of pedestrian groups collected by means of video recordings.

In order to verify our method is applicable to a larger scale crowd. Our third experiment used the Square environment to test the effect of planning paths algorithm. We simultaneously added 5000 characters to the Square environment with random start and goal positions.

Besides the visual inspection of the generated simulations, we are also interested in a quantitative evaluation of our model. We made a comparison between our methods with the original RVO model. Table 2 highlights the performance of our approach. As can be inferred from the table, the running time of our algorithm much better than the original RVO model. Even for 1000 people we were able to generate more than 20 *fps* in our scene.

Compared with the original RVO model, the experimental results confirmed the advantages of the improved RVO model over the original RVO model through different evacuation times on simple (Number of people is 10, 20, and 50 respectively) and complicated scenes (Number of people is 100, 200, 500, and 1000 respectively). The evacuation times are presented in Table 2 and Figure 12.

In addition, almost all the agents can avoid collisions with other agent by virtue of the RVO algorithm embedded with the relationship between the crowd velocity and density.



FIGURE 12. Screenshots of a crowd simulation with a variety of settings.

 TABLE 2. Evacuation time (ET) and movement velocity under different crowd density.

Scene	Number of people	<b>Running time of original RVO model</b> (s)	<b>Running time of our model</b> (s)
	10	340	53
Simple scene	20	445	83
	50	625	215
	100	945	322
Complicated	200	1323	433
scene	500	1986	696
	1000	2875	997

## **VI. CONCLUSION**

We presented a novel approach for planning and directing groups of virtual characters by combining the RVO technique with real-world crowd video. We have demonstrated the applicability of our method through a wide range of challenging scenarios. Despite the computational complexity raised by the ILP formulation, our system runs at interactive rates by using the column generation algorithm and choosing an appropriate discretization of time. i The correlation between crowd movement velocity and density (agent movement velocity and density) was added based on the original RVO model. The crowd movement presented diversity based on the guarantee of the high efficiency of crowd evacuation and local collision avoidance through the combined global path planning algorithm; the result agreed with the actual situation. The proposed improved model was placed under experiment through simple single-room and complicated multi-room and multi-channel scenes. The experimental results showed that the improved evacuation model can simulate crowd evacuation on the complicated scene.

However, our approach demonstrated certain deficiencies. For example, this model disregarded the interference of small obstacles to crowd movement on the scene, the exit position during evacuation became seriously congested; thus, the proposed model cannot effectively simulate multi-floor crowd evacuation.

Therefore, our future extensions will focus on detailing obstacles on the scene, perfecting multi-floor model, and further enhancing complexity and accuracy of the simulation process.

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