

# A Hyper-Heuristic Framework for Agent-Based Crowd Modeling and Simulation

## (Extended Abstract)

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### ABSTRACT

This paper proposes a hyper-heuristic crowd modeling framework to generate realistic crowd dynamics that can match video data. In the proposed framework, motions of agents are driven by a high-level heuristic (HH) which intelligently selects way-points for agents based on the current situations. Three low-level heuristics are defined and used as building blocks of the HH. Based on the newly defined building blocks and fitness evaluation function, the Self-Learning Gene Expression Programming (SL-GEP) is utilized to automatically evolve a suitable HH. To test its effectiveness, the proposed framework is applied to learn suitable HHs based on real video data. The best HH learned is then applied to generate crowd simulations and the simulation results demonstrate that the proposed method is effective to generate realistic crowd dynamics.

### Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence, Intelligent agents

### General Terms

Algorithms

### Keywords

Agent-Based Modeling; Crowd Simulation; Genetic Programming

## 1. INTRODUCTION

A fundamental and challenging issue in crowd modeling and simulations is to generate realistic crowd dynamics. To solve this problem, various methods have been proposed over the years. Existing methods generally can be classified into two groups. The first group focus on designing crowd models manually by experts [1, 3]. This group of methods require a great amount of manual efforts and domain knowledge. The second group of methods, namely, the data-driven modeling methods [2, 4], focus on automatically learning patterns from crowd data and utilizing patterns to update the movement of agents in particular situations. The data-driven modeling approaches have shown great potential to generate realistic crowd dynamics. One limitation of the existing

data-driven approaches is that the knowledge learned is not generic enough to be applied to different scenarios.

In this paper, a novel data-driven crowd modeling approach based on hyper heuristic is proposed. The key idea is to construct a generic high-level heuristic (HH) which consists of multiple low-level heuristics (LHs) to drive agents' movement. A recent published genetic programming (GP) variant named Self-Learning Gene Expression Programming (SL-GEP) [6] is utilized to evolve a suitable HH. The simulation results demonstrate that the proposed method is effective to generate realistic crowd dynamics in comparison with several simulation models.

## 2. HYPER-HEURISTIC FRAMEWORK

In this paper, we focus on simulating crowd dynamics on a common scenario where there are several destination regions. Each agent tries to reach one of the destinations by following a series of way-points. To generate the candidate way-points of agents, we divide the entire simulation region into discrete grids. The centre points of each discrete grids is considered as a candidate way-point. At each time step, an agent will choose a next way-point from multiple alternative way-point options by using a high-level heuristic (HH). Our objective is to automatically construct a suitable HH to select the next way-points of agents so that the simulation can match those observed in videos. To achieve this goal, a hyper-heuristic framework that consists of two parts is proposed.

In the first part, three low-level heuristics (LHs) are defined and used as building blocks to construct the HH. Given a destination and a candidate way-point, a low-level heuristic can return a score value of the candidate way-point. The higher the score, the better the way-point. The first LH (labelled as  $D$ ) is related to the distance between the destination and the candidate way-point. The second LH (labelled as  $R$ ) is related to the density of Pedestrians in the Opposite Direction (PODs). The third LH (labelled as  $T$ ) is related to the density of historical trajectories. After the LHs are defined, the SL-GEP is utilized to evolve HHs. During the evolution process of the SL-GP, the fitness of each newly generated HH is evaluated by using simulation results where way-points of agents are selected by the HH. In this paper, two macroscopic features are defined to evaluate the simulated results. The first feature measures the similarity in terms of the density distributions of pedestrians that have the same destinations. The second feature measures the similarity in terms of the mean speed of pedestrians moving towards their goals.

In the second part, a crowd simulation is generated by using the given HH (denoted as  $\Phi$ ) to guide the motions of agents. At

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each time step of the simulation, all agents sense the environment features and calculate the values of LHs. Then the scores of alternative way-point options of each agent are evaluated by the HH. The one with the highest score is selected as the next way-point of the agent. After the next way-points of all agents are determined, a collision avoidance model (e.g., the RVO2) is utilized to update the positions and velocities of all agents.

### 3. EXPERIMENT STUDIES

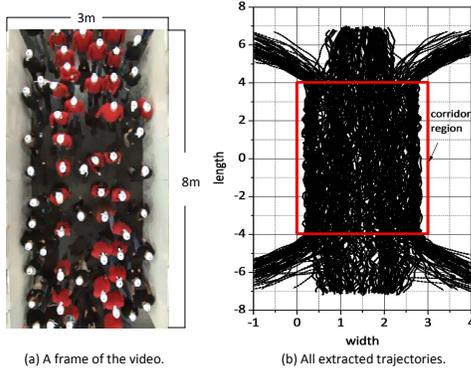


Figure 1: Corridor dataset. (a) A frame of the video; (b) All extracted trajectories in this scenario.

First, the proposed framework is applied to learn a suitable HH based on a real trajectory dataset. The dataset contains trajectories of 219 pedestrians which are walking through a corridor<sup>1</sup>. The trajectory points are annotated at 16 fps (i.e., with a time step of 0.0625 seconds). Fig. 1(a) shows a sample frame of the video and Fig. 1(b) plots all extracted trajectories in the dataset. The parameter settings of SL-GEP are set as follows:  $NP = 20$ ,  $h = 20$ ,  $h' = 5$ ,  $K = 3$ , maximum generation = 200,  $L1 = 3$ ,  $L2 = 6$ . The SL-GEP is performed for 20 independent runs with different random seeds. The best HH found by the SL-GEP is as follow:

$$\Phi = (pow(fabs((G_1((D - T), D) * G_0(D, D))), ((R/pow(fabs(R), R) + T)) * G_1(G_1(R, G_1(G_1(D, T), R)), D));$$

$$G_0(t_1, t_2) = (t_1 * ((t_1/t_2) + t_1))$$

$$G_1(t_1, t_2) = (t_1 * t_2)$$

$$G_2(t_1, t_2) = (pow(fabs(t_1), (t_1/t_1))/(t_1/t_2))$$

The best HH is then applied to simulate the crowd behaviors in the corridor scenario as shown in Fig. 1. To facilitate description, the simulation model with the best HH is denoted as HH-RVO2. Six other simulation models are used for comparison. The first model is the commonly used RVO2 model. The second model is the same as HH-RVO2 except that it uses  $D$  as the heuristic. We denote the second model as D-RVO2. Similarly, we define the third and the four models (denoted as T-RVO2 and R-RVO2) by using  $T$  and  $R$  as the heuristic respectively. The fifth model is denoted as DRT-RVO2 which uses  $D \cdot R \cdot T$  as the heuristic. The last model is a recently published data-driven approach named D-ABC [5], which learns velocity fields from video to determine the next way-points of agents.

We adopt the average speed over time as the performance metric. For each simulation model, 20 independent runs with different random seeds are performed and the average speed over time is used for comparison. Fig. 2 shows the simulation results. It can be observed that the curve of HH-RVO2 is the most similar to

<sup>1</sup>The video and extracted trajectories are downloaded from <http://www.asim.uni-wuppertal.de/datenbank/own-experiments/corridor/2d-bidirectional.html>

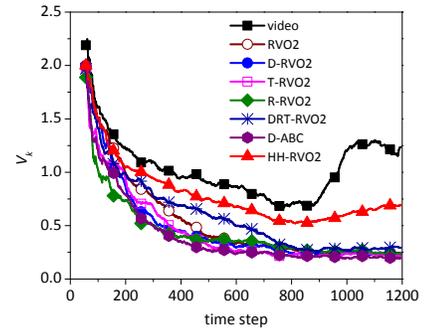


Figure 2: Speed over time.

that of the video, which indicates that the proposed method is more effective to generate realistic crowd dynamics in this corridor scenario.

### 4. CONCLUSIONS

This paper has proposed a hyper-heuristic framework for agent-based crowd modeling. The key idea is to use high-level heuristic (HH) to guide agents' motions and use genetic programming to automatically evolve the HH so that the simulated crowd dynamics can match those observed in the video. The simulation results have demonstrated that the simulation model using the learned HH (HH-RVO2) can offer better performance than other six models when it is applied to the same corridor scenario.

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