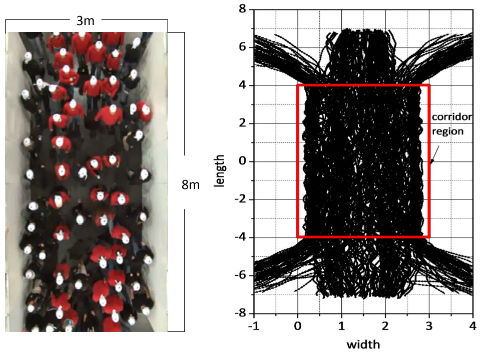
each time step of the simulation, all agents sense the environment features and calculate the values of LHs. Then the scores of alternative way-point options of each agent are evaluated by the HH. The one with the highest score is selected as the next way-point of the agent. After the next way-points 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



(a) A frame of the video. (b) All extracted trajectories.

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[1]. 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

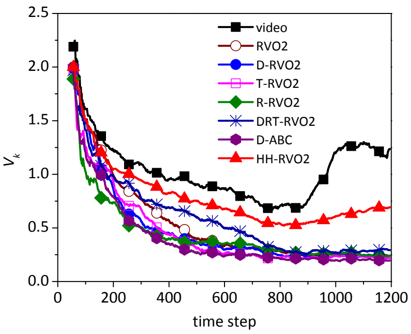


Figure 2: Speed over time.

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