Learning behavior patterns from video for agent-based crowd modeling and simulation

Presenter: Sudeep Basnet

2018-10-18

Zhong, J., Cai, W., Luo, L. et al. Autonomous Agent Multi-Agent System (2016) 30: 990.
https://doi.org/10.1007/s10458-016-9334-8

Outline

- Introduction
- Model Design – Abstract
- Dual-Layer Agent-based Crowd Modeling Architecture
- Top layer
    1. Behavior of new pedestrians appearing in SRs
    2. Goal selection patterns of pedestrians, using probability matrix
    3. Path navigation patterns of pedestrians
- Crowd simulation procedure
- Construction of model components
- Case Study 1 (New York Grand Central Terminal)
- Case Study 2 (ETH Walking Pedestrians)

Introduction

- Data-driven modeling framework to construct agent-based crowd model based on real-world video data.
- Can be used to predict trajectories of pedestrians in the same scenario as the video.
- Dual-layer architecture:
  - **Bottom Layer** models the microscopic collision avoidance behaviors.
  - **Top layer** models the macroscopic behaviors such as goal selection patterns and the path navigation patterns.
- Automatic learning algorithm to learn behavior patterns.

Model Design – Abstract

- Objective. Simulate crowd behaviors in a well-defined area with a number of ***source regions (SRs)*** and ***destination regions (DRs)***.
- Pedestrians enter the area via SRs and leave the area via DRs.
- First Step – Determine:
    1. How frequently pedestrians enter the SRs (arrival rate)
    2. How pedestrians select their DRs.
- Second Step – After DRs are selected, determine:
    - How pedestrians move towards their DRs (i.e., path navigation).
    - How pedestrians avoid collisions with other pedestrians and obstacles

Dual-Layer Agent-based Crowd Modeling Architecture

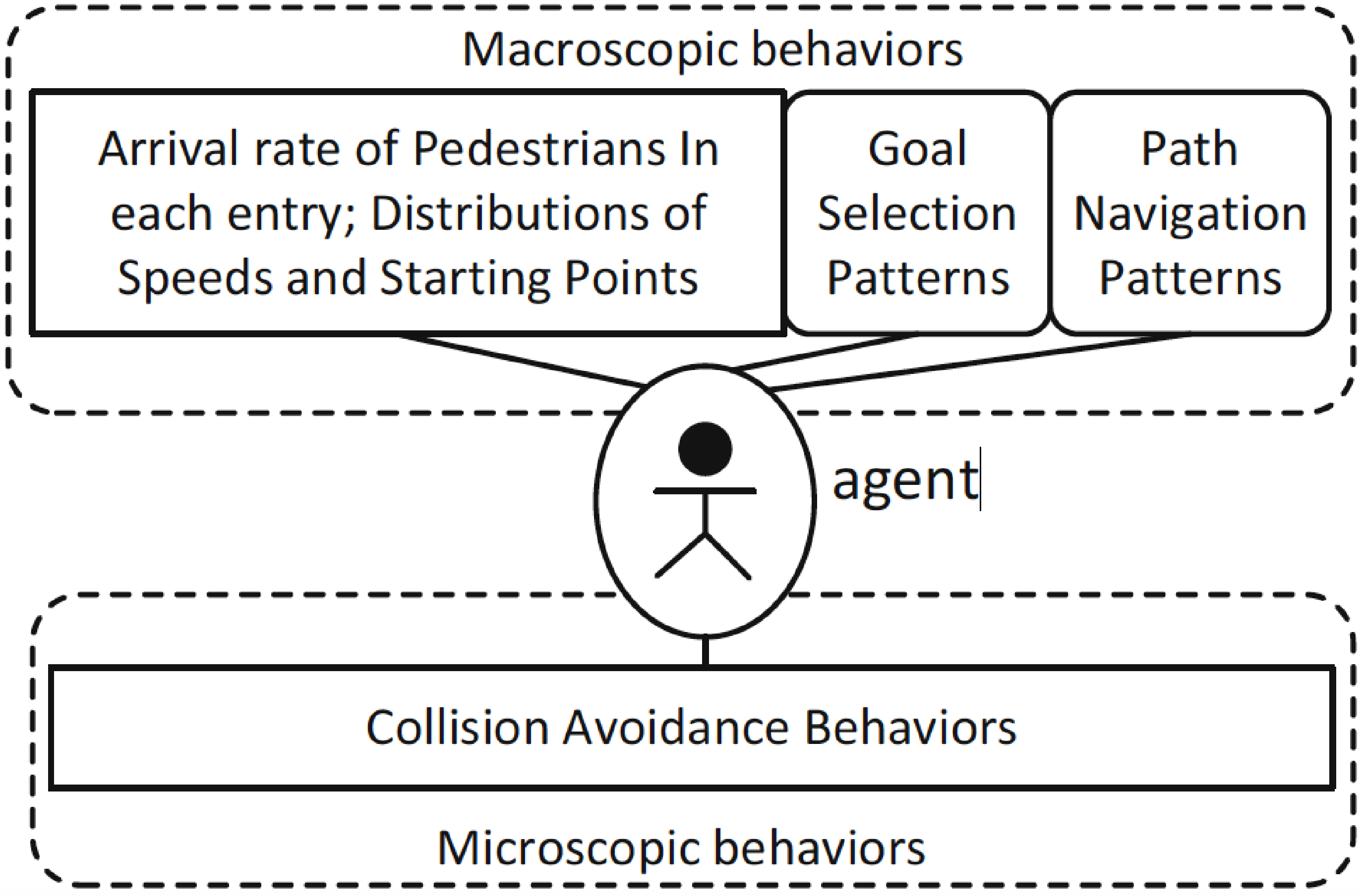


Fig. 1 The proposed dual-layer agent-based crowd modeling architecture

Dual-Layer Agent-based Crowd Modeling Architecture (cont.)

- In the bottom layer (microscopic), various collision avoidance models can be used.
  - Social-Force crowd Model (SFM) [1]
  - Reciprocal Velocity Obstacles (RVO2) [2]. This paper uses **RVO2**.
- Top layer (macroscopic) uses three components:
  1. First component describes how new pedestrians enter the simulated area.
  2. The second component models the goal selection patterns of pedestrians by using a probability matrix.
  3. The last component models the path navigation patterns of pedestrians.

Behavior of new pedestrians appearing in SRs

- Each SR (or DR) is approximately represented by a rectangle region.
- The behaviors of new pedestrians appearing in each SR is modeled as a Poisson process [3]:

$$P\{N_i(t+\tau) - N_i(t) = k\} = \frac{(\lambda_i \tau)^k \exp(-\lambda_i \tau)}{k!} \qquad (1)$$

- $N_i(t+\tau) - N_i(t) = k$ is the number of new pedestrians entering the i^{th} SR during time interval $(t, t+\tau]$.
- λ_i is the expected arrival rate of the i^{th} SR
- Starting positions of pedestrians in each SR are modelled by using a Gaussian model.

Goal selection patterns of pedestrians, using probability matrix

- The probability of pedestrians moving from the i^{th} SR to the j^{th} DR is labelled as $p_{i,j}$
- The goal selection patterns of pedestrians can be represented by the following matrix:

$$\mathbf{P} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,M} \\ \cdots & \cdots & \cdots & \cdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,M} \end{bmatrix} \quad (2)$$

- N is the number of SRs and M is the number of DRs.

Path navigation patterns of pedestrians

- A **Velocity field** [4,5] consists of a series of position-direction pairs.
- Each position-direction pair determines the future moving directions of pedestrians near the position.
- Each DR is associated with one velocity field.
- Entire region is divided into discrete grids. Suppose $H \times W$ grids.

$$\mathbf{V}_i = \begin{bmatrix} v_{i,1,1} & v_{i,1,2} & \cdots & v_{i,1,W} \\ \cdots & \cdots & \cdots & \cdots \\ v_{i,H,1} & v_{i,H,2} & \cdots & v_{i,H,W} \end{bmatrix} \quad (3)$$

- $v_{i,j,k}$ is a two-dimensional vector, represents the future moving directions of the pedestrians in the grid cell (j,k).
- The value of $v_{i,j,k}$ is scenario specific, learned from video input data.

Crowd simulation procedure (Algorithm 1)

Algorithm 1: CROWD SIMULATION PROCEDURE.

for $step = 1$ **to** max_steps **do**
  for $i = 1$ **to** N **do**
    Sample a number of new agents according to λ_i;
    Set the starting position and velocity of each new agent;
    Set the global goal of each new agent according to $\mathbf{P}$
  for $i = 1$ **to** *total number of agents in the scene* **do**
    Suppose the global goal of the ith agent (A_i) is the jth DR;
    Update the local goal of A_i according to $\mathbf{V}_j$
  Use RVO2 to update the velocities and positions of all agents.

λ_i is the expected arrival rate of the i^{th} SR.
$\mathbf{P}$ is the probability matrix for goal selection.
$\mathbf{V}_j$ is the velocity field of the j^{th} DR.

Construction of model components

- The data extracted from videos are considered trajectories.
- Each trajectory is represented by a sequence of vectors.

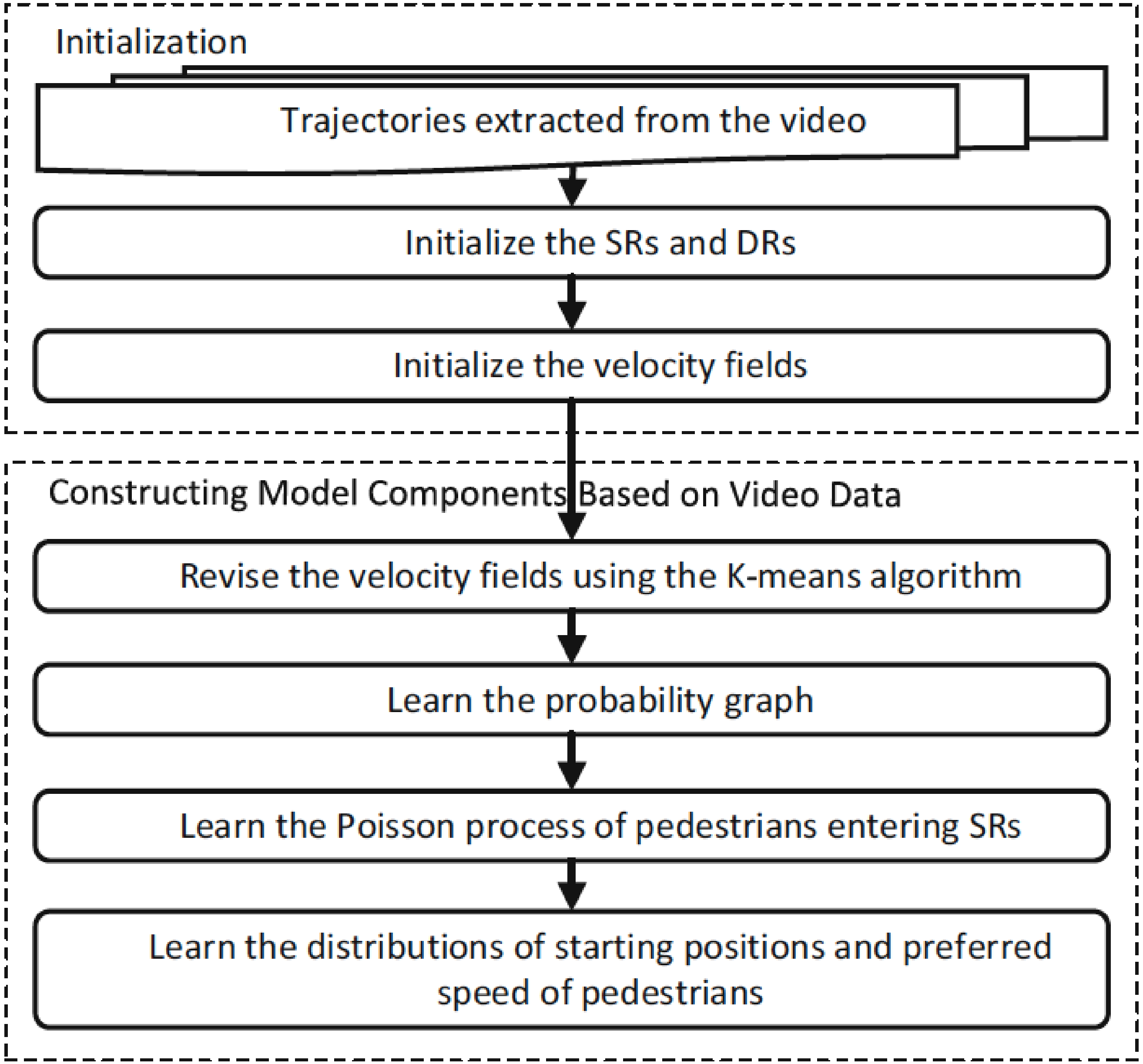


Fig. 2: The procedures of constructing an agent-based crowd model based on video data

Initialization

- Each trajectory is divided into small number of segments.
- Each grid cell contains at most one segmentation point.
- After that, the velocity field of each DR (i.e., $\mathbf{V}_i$) is then initialized by assigning each grid with a vector that directly points to the DR.

$$v_{i,j,k} = \begin{cases} \Gamma\left(\overrightarrow{AB}\right), \text{if grid cell } (j,k) \text{ contains no obstacles.} \\ (0,0), \text{if grid cell } (j,k) \text{ contains obstacles.} \end{cases} \quad (4)$$

- A is the center point of the grid cell (j,k), B is the destination.
- $\Gamma(\vec{a})$ normalizes the input vector $\vec{a}$ in such a way that the total length of $\vec{a}$ is much smaller than the size of a single grid.

Construction of model components based on off-line video

- The K-means clustering algorithm is used to cluster all trajectories into M groups, where M is the total number of DRs.
- The trajectories in the same group are expected to terminate at the same DR.
- In each iteration of the K-means clustering process, each trajectory is classified into the nearest cluster.
- After clustering all trajectories, each cluster C_i is then used as the temporary velocity field of the corresponding i^{th} DR.
- Temporary velocity field is further revised by considering neighboring influences.

Construction of model components based on off-line video (cont’d. 1)

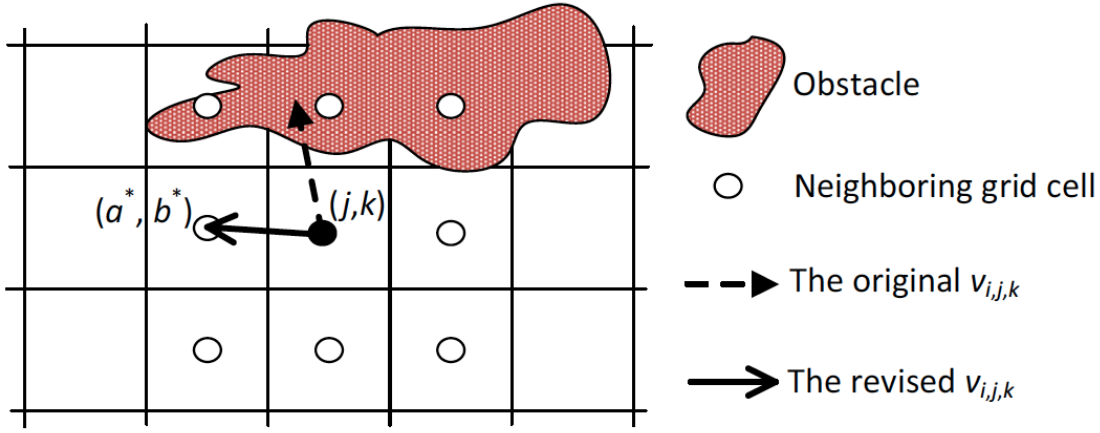


Fig. 3: Revising an infeasible velocity

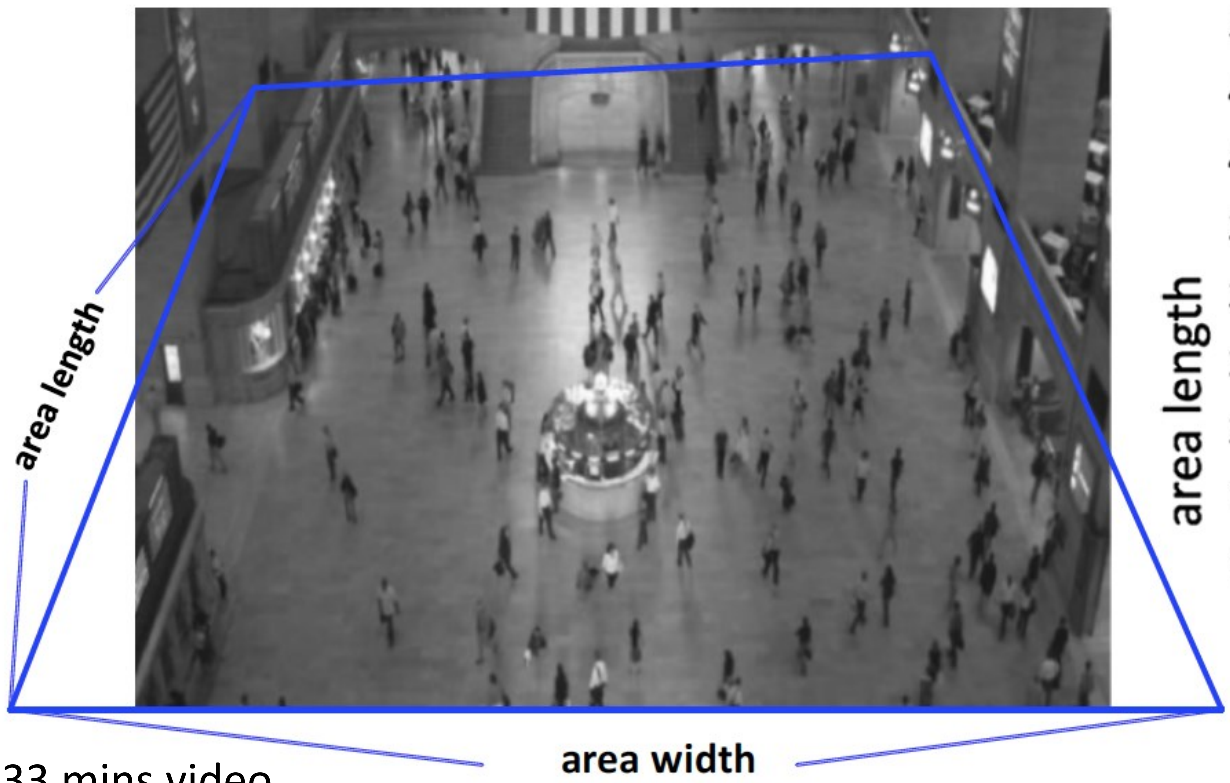
- Vector closer to the grid (j, k) will have a larger influence on $v_{i,j,k}$
- If obstacles are seen, all eight neighborhood of (j, k) are checked, the best grid that is not inside obstacle and has the least turning angle is chosen.

Construction of model components based on off-line video (cont'd. 2)

- Once the velocity fields of all DRs are obtained, they can then be utilized to learn the state transition rates between SRs and DRs (i.e., the probability matrix).
- Choose trajectories that start at i^{th} SR and end in other regions.
- $S_{i,j}$ is the total number of trajectories that have the i^{th} SR as source and the j^{th} DR as destination.
- Transition probability from the i^{th} SR to the j^{th} DR is:

$$p_{i,j} = \frac{S_{i,j}}{\sum_{k=1}^{M} S_{i,k}} \qquad (5)$$

Case Study 1 (New York Grand Central Terminal) - *Trajectories*



40,000 trajectories extracted

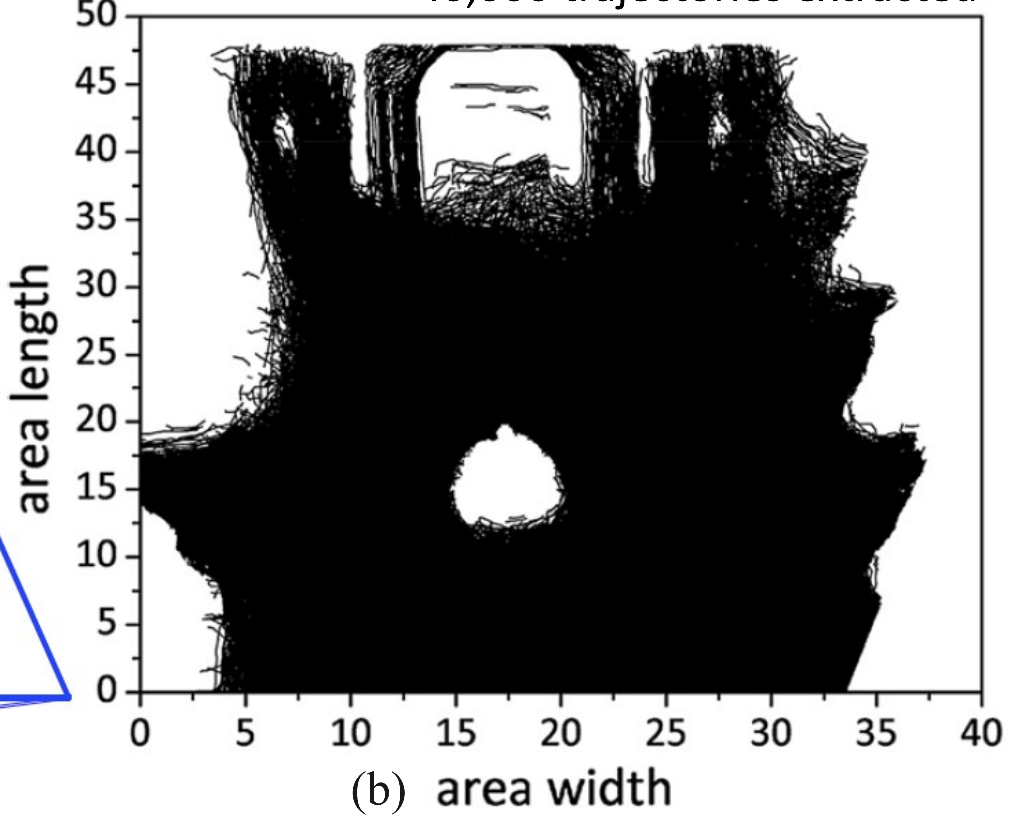


Fig 4: A frame of the video and the **transformed trajectories** used in the first case study. (a) A frame of the video; (b) the transformed trajectories

Case Study 1 – *Velocity Fields*

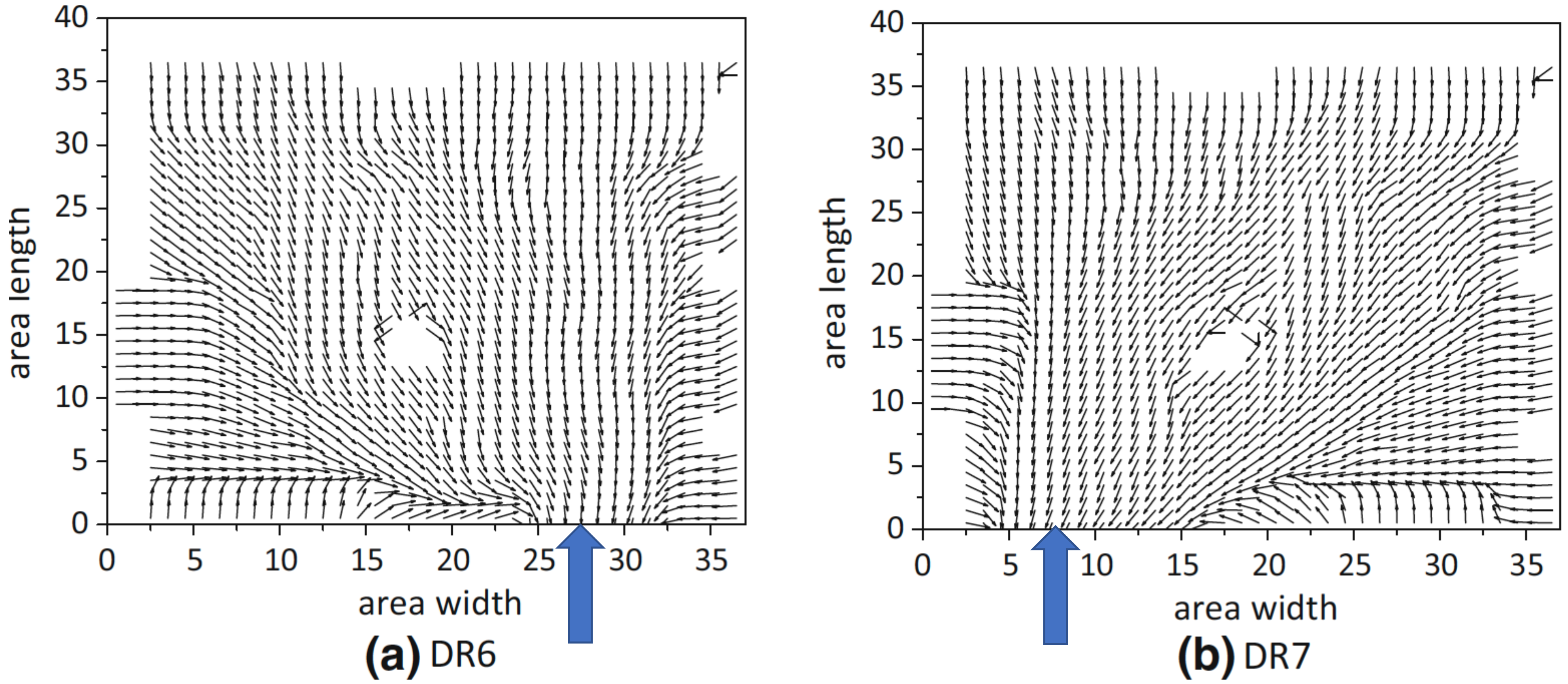


Fig 5: Two examples of the learned **velocity fields** in the first scenario

Case Study 1 – *Crowd Density*

- Objective crowd density calculated based on the video data.
- Density values of a narrow region from (20, 0) to (37, 15) are the largest.
- Density values in the center circle are very small, because there is a counter located in that region

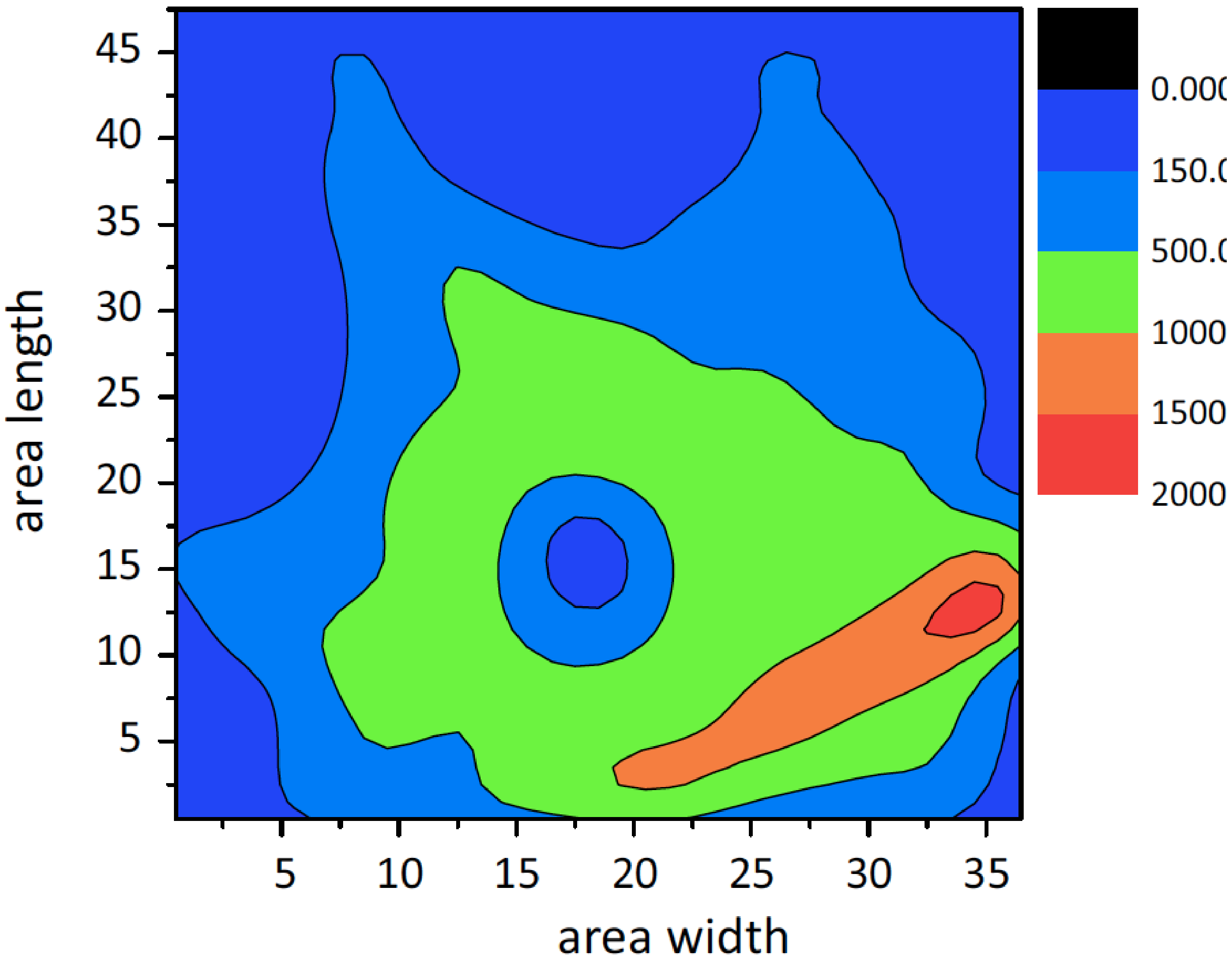


Fig 6: The objective crowd density distributions in the first scenario

Case Study 1 – *Crowd Density – Comparisons*

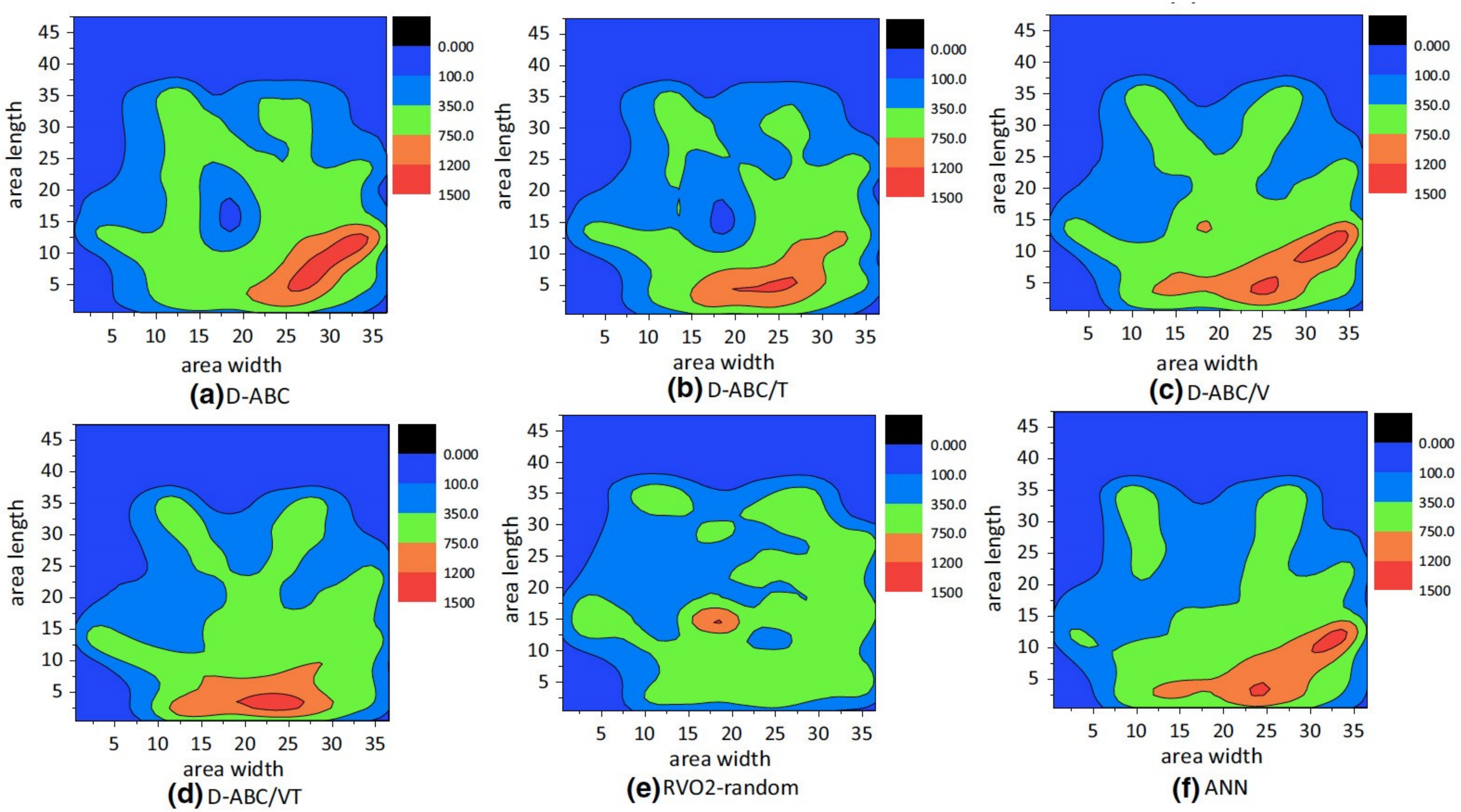


Fig 7: The crowd density distributions of the six methods in the first scenario

Case Study 1 – *Predicted Trajectories – Comparisons*

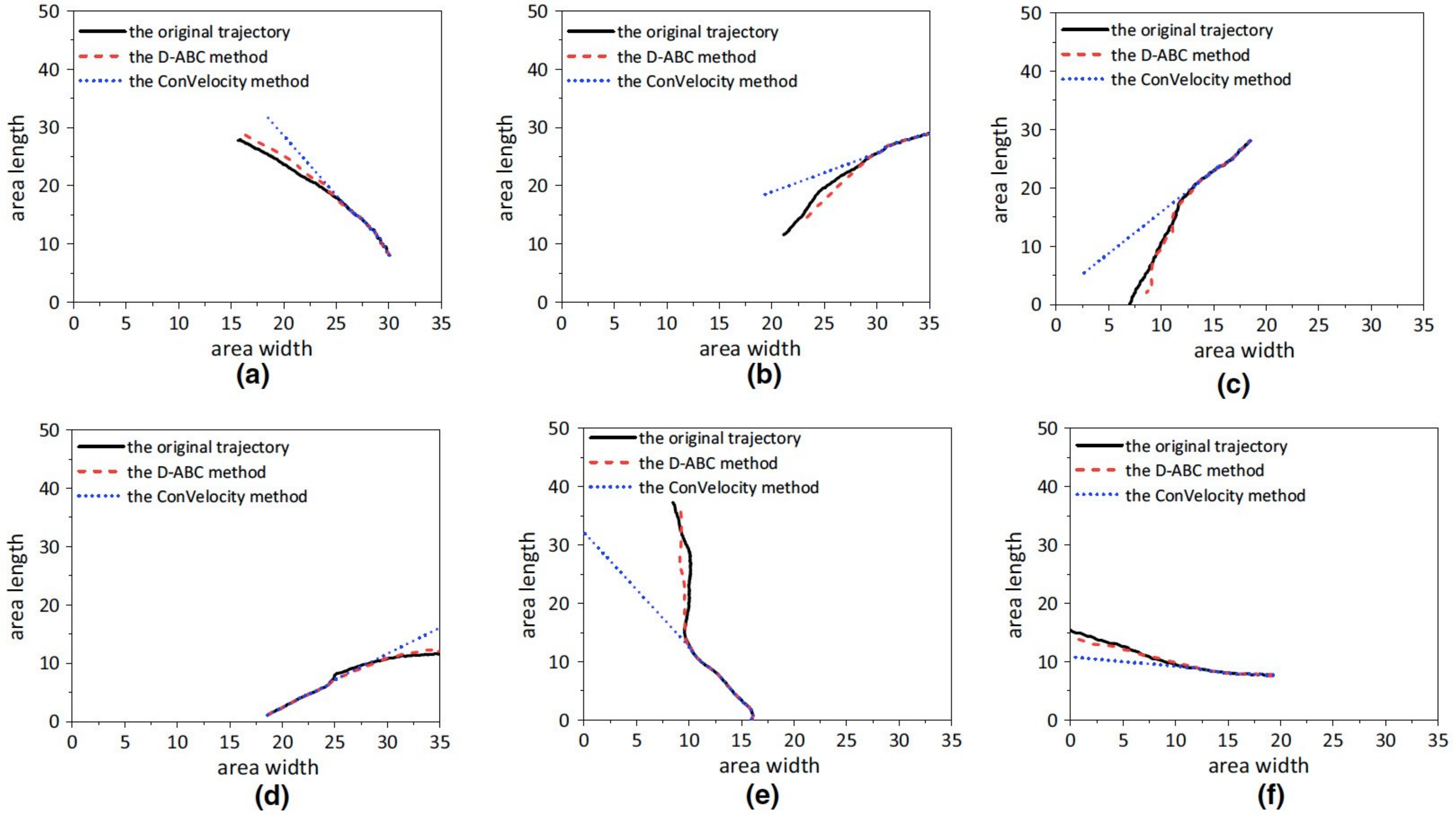


Fig 8: Examples of the predicted trajectories found by the D-ABC and the ConVelocity in the first scenario

Case Study 1 – Error Analysis

Method	$perror$
D-ABC	274.8
D-ABC/T	295.3
D-ABC/V	292.0
D-ABC/VT	318.1
RVO2-random	336.0
ANN	290.4

Table 1: The perror results of the six methods in the first scenario

Method	$Error$
ConVelocity	2.58^{a}
D-ABC	1.79

Table 2: Average of the final prediction errors in the first scenario

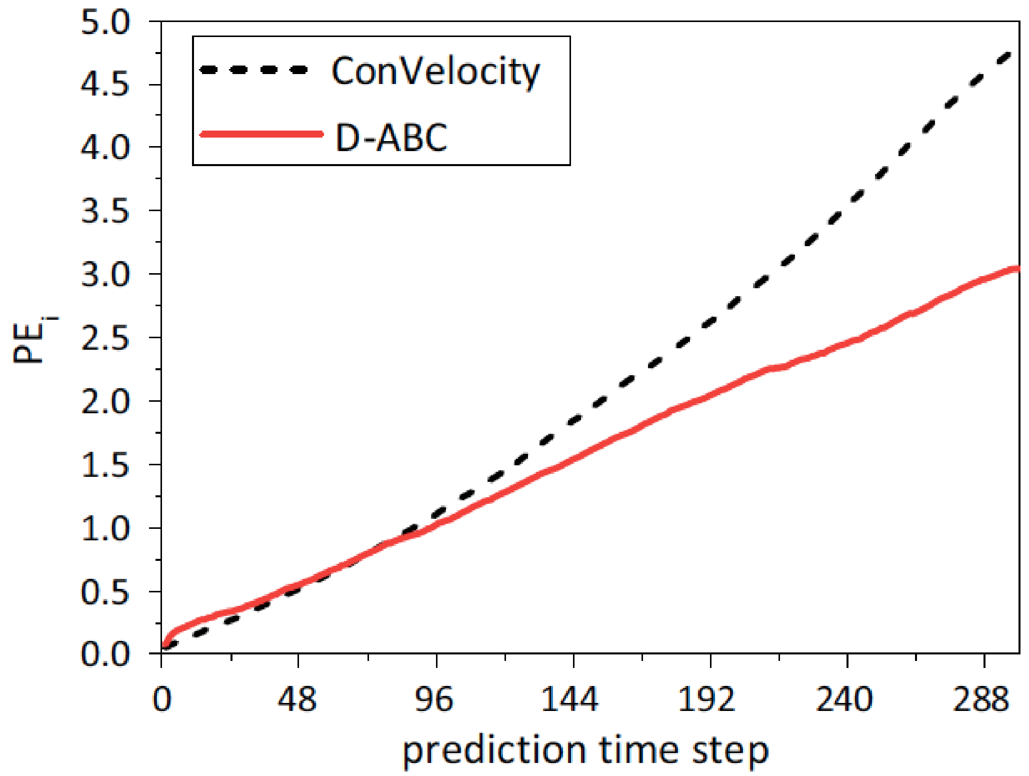


Fig 9: Average prediction errors of the D-ABC and the ConVelocity in the first scenario

Case Study 2 (ETH Walking Pedestrians)

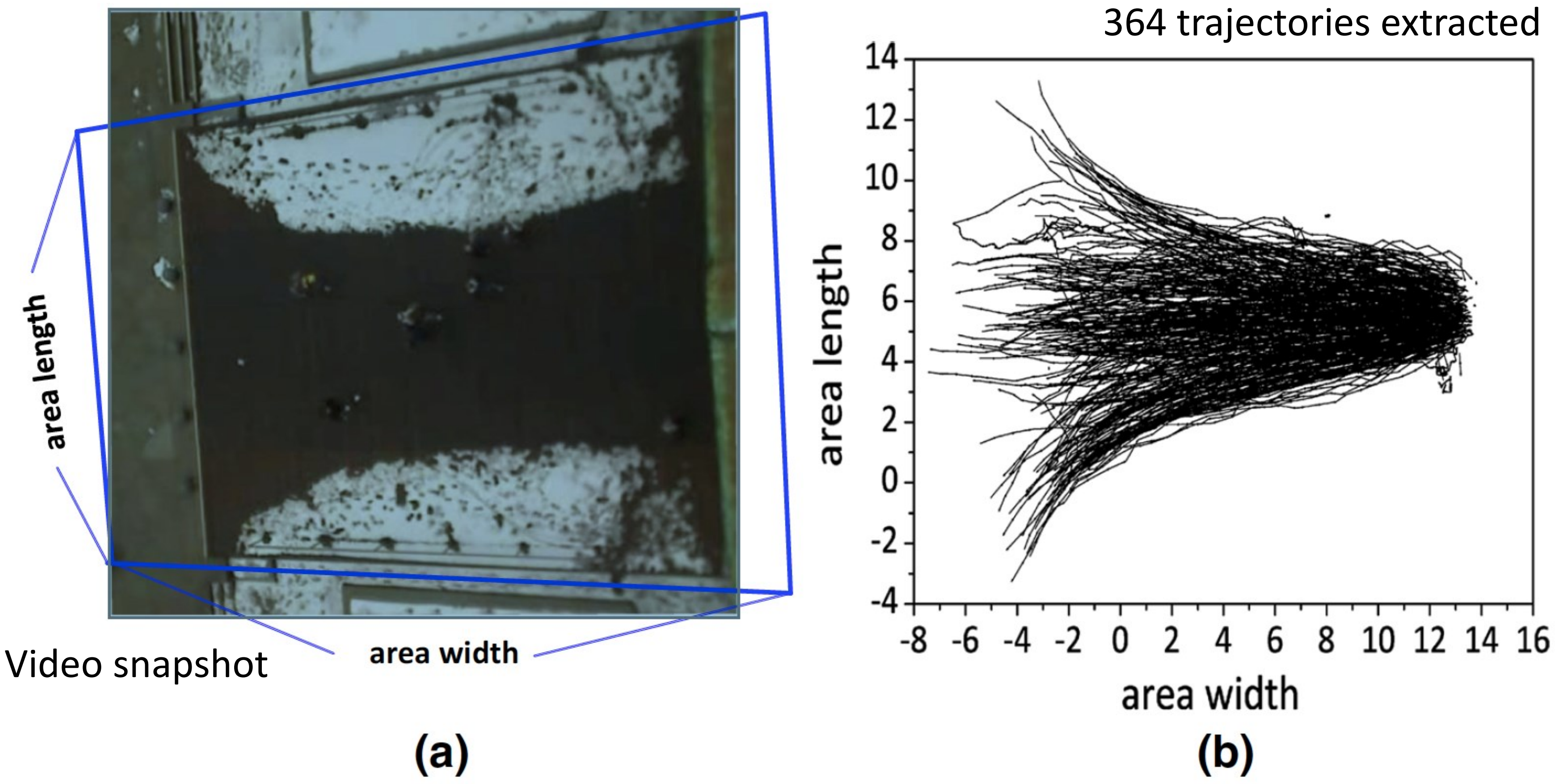


Fig 10: The video and the trajectories used in the second case study. (a) A frame of the video; (b) the trajectories used

Case Study 2 – Velocity Fields

- velocities do not always directly point to the destinations.
- In regions near obstacles, they point to other directions so as to guide agents to avoid obstacles.

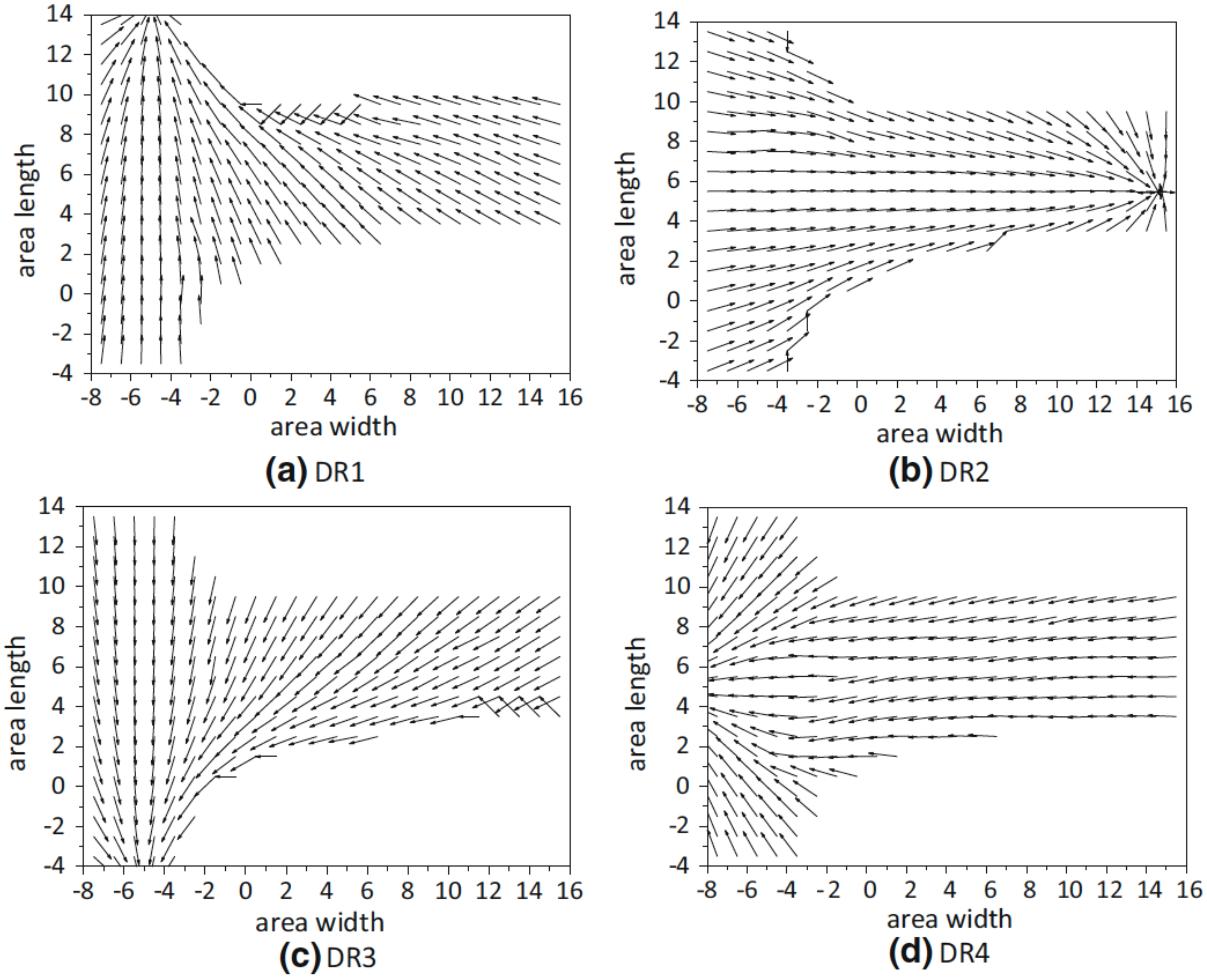


Fig 11: Examples of the learned velocity fields of the second scenario

Case Study 2 - *Crowd Density*

- crowd density of the video data.

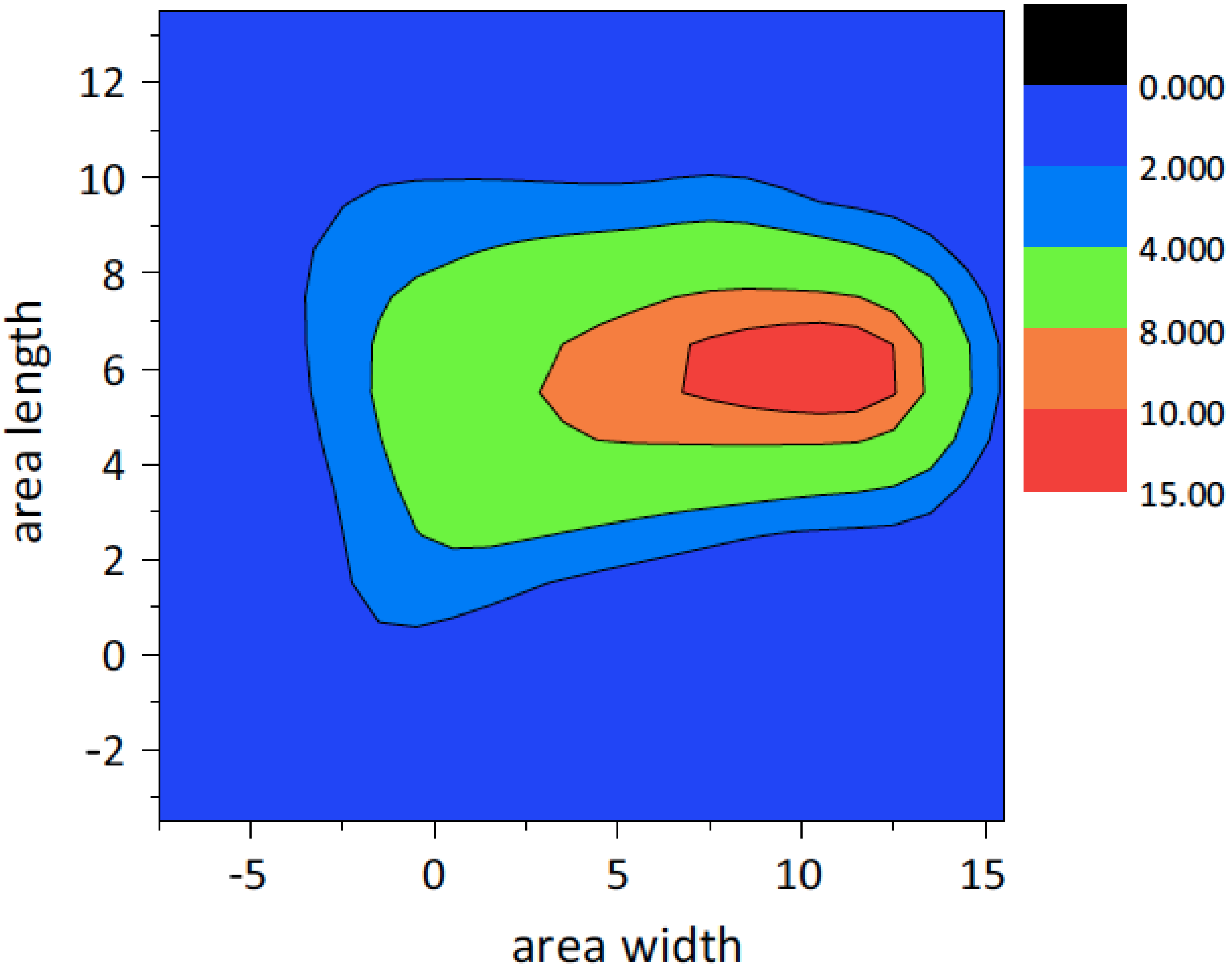


Fig 12: The objective crowd density distributions in the second case study

Case Study 2 – *Crowd Density – Comparisons*

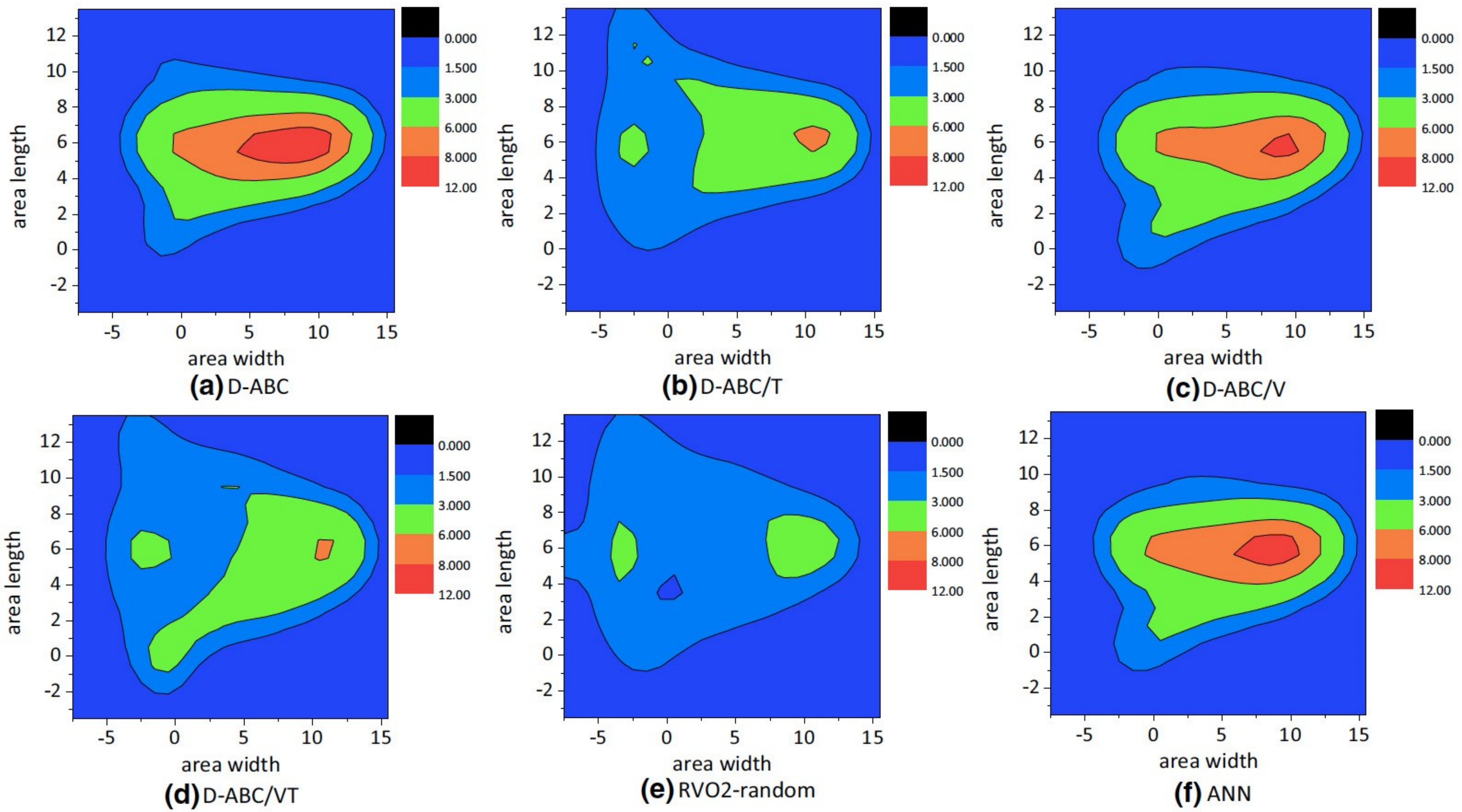


Fig 13: The crowd density distributions of the six methods in the second case study

Case Study 2 – *Predicted Trajectories – Comparisons*

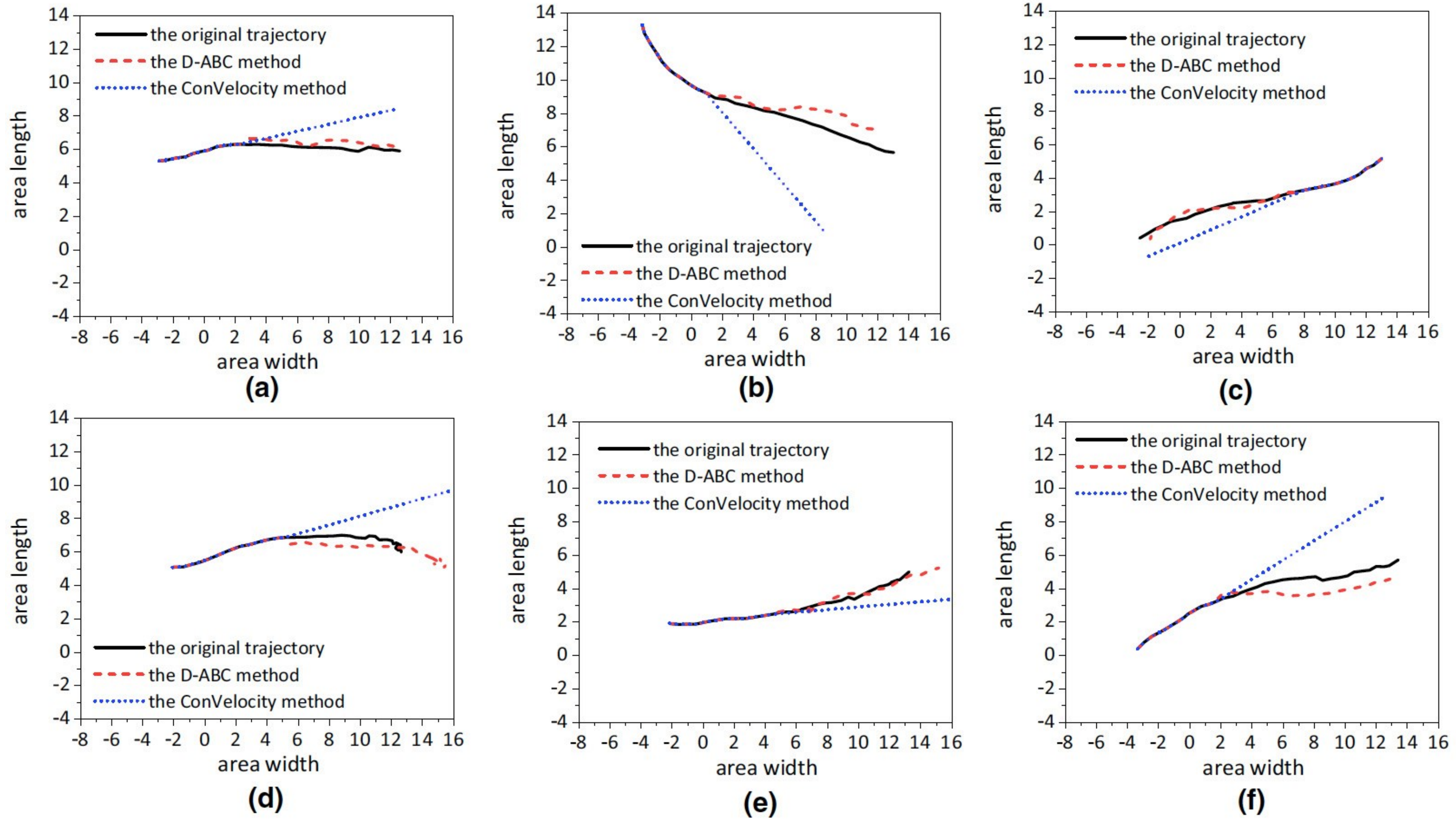


Fig 14: Examples of the predicted trajectories found by the D-ABC and the ConVelocity in the second scenario

Case Study 2 – Error Analysis

Method	$\rho error$
D-ABC	1.97
D-ABC/T	2.40
D-ABC/V	2.12
D-ABC/VT	2.57
RVO2-random	2.86
ANN	2.04

Table 3: The ρerror results of the six methods in the second scenario

Method	$Error$
ConVelocity	1.48^{a}
D-ABC	1.23

Table 5: Average of the final prediction errors second scenario

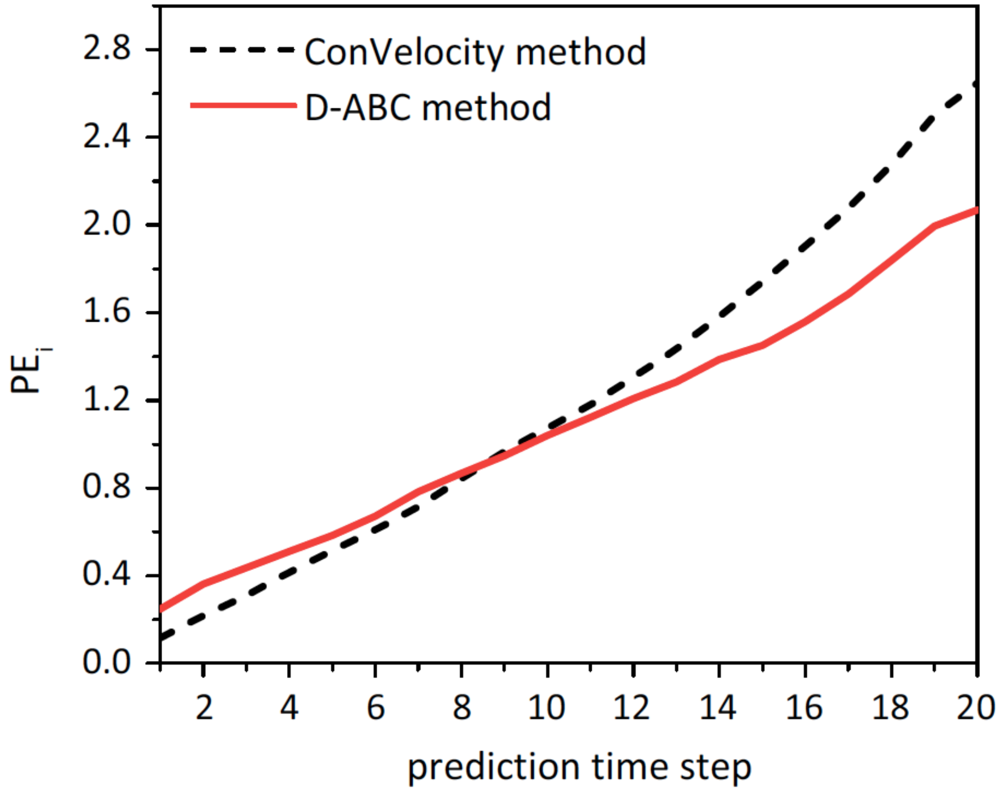


Fig 15: Prediction errors of the D-ABC and the ConVelocity in the second scenario

Conclusion – Authors

- Proposed a generic data-driven crowd modeling framework to generate realistic crowd behaviors that can match the video data.
- Both the microscopic collision avoidance behaviors and multiple macroscopic behaviors.
- Results have shown that our proposed framework is effective to generate crowd behaviors, in terms of crowd density.
- Future work could include modelling for different types of agents.
- Using machine learning techniques to distill generic behavior instead of modelling specific scenarios, is promising future work.

My Conclusions

- It would be interesting to apply this concept in a chaotic scenario. To track and study trajectories of people in the presence of danger or during an unrest.
- Agent are of uniform characteristics, variables such as age or gender could not be considered with this method.
- The method of considering shortest paths from point A to point B, may only be true during rush hours and in places such as transport stations.
- While some limitations have been discussed in the paper, there have been no experiments to test exactly where the limitation lie in finding complicated trajectories such as a "W" shaped trajectory.
- It is not clear how obstacles are generated in the simulation models. The paper only shows how the model avoids obstacles.
- A general relationship of the error and grid size is needed, the choice of grid sizes used for experiments are not explained. It seems to be too scenario-specific.
- In case study 1 (New York), 40000 trajectories are extracted from the video. The amount of computation seems to be very large, yet the paper doesn't discuss such challenges.

References

[1] Helbing, D., &Molnar, P. (1995). Social force model for pedestrian dynamics. Physical Review E, 51(5), 4282.

[2] Van den Berg, J., Lin, M., & Manocha, D. (2008). Reciprocal velocity obstacles for real-time multiagent navigation. In IEEE International Conference on Robotics and Automation, 2008 (ICRA’08) (pp.1928–1935). Piscataway: IEEE.

[3] https://www.randomservices.org/random/poisson/index.html

[4] Helbing, D., Johansson, A., & Al-Abideen, H. Z. (2007). Dynamics of crowd disasters: An empirical study. Physical Review E, 75(4), 046109.

[5] Jin, X., Xu, J.,Wang, C. C., Huang, S., & Zhang, J. (2008). Interactive control of large-crowd navigation in virtual environments using vector fields. IEEE Computer Graphics and Applications, 6, 37–46.