DC-HEN: A Deadline-aware and Congestion-relieved Hierarchical Emergency Navigation Algorithm for Ship Indoor Environments

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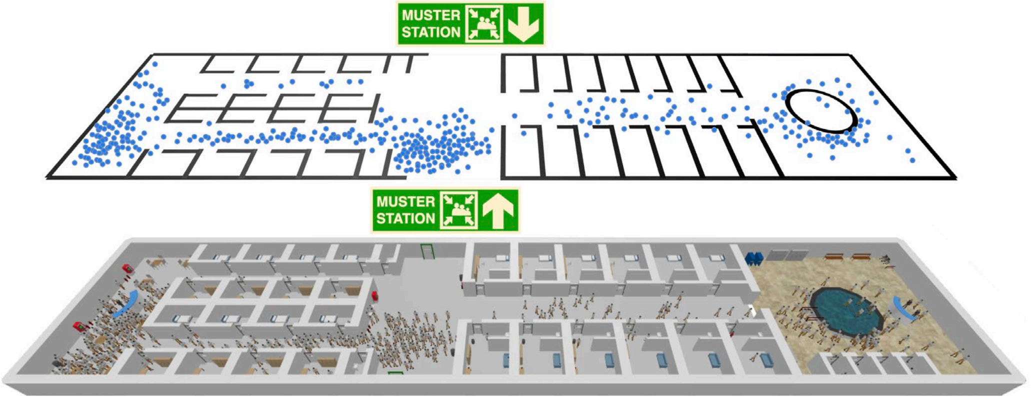
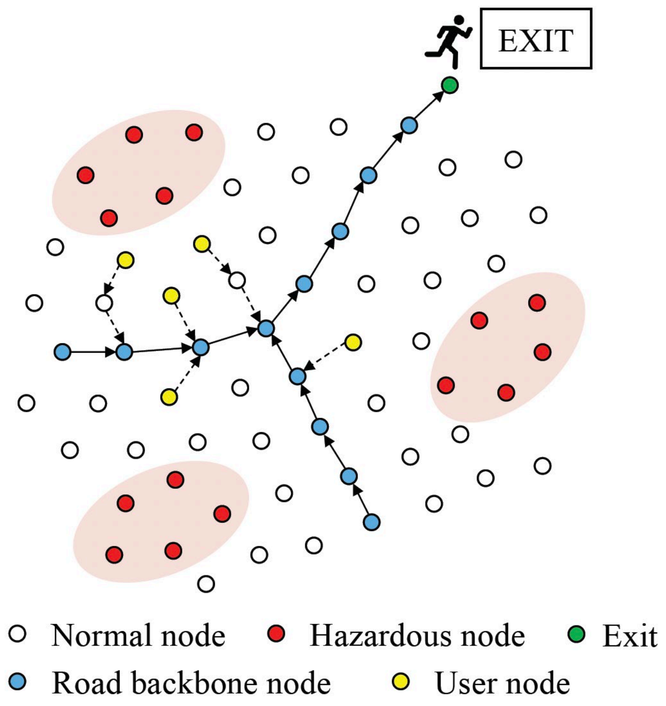
May 2023, MOST

Motivation

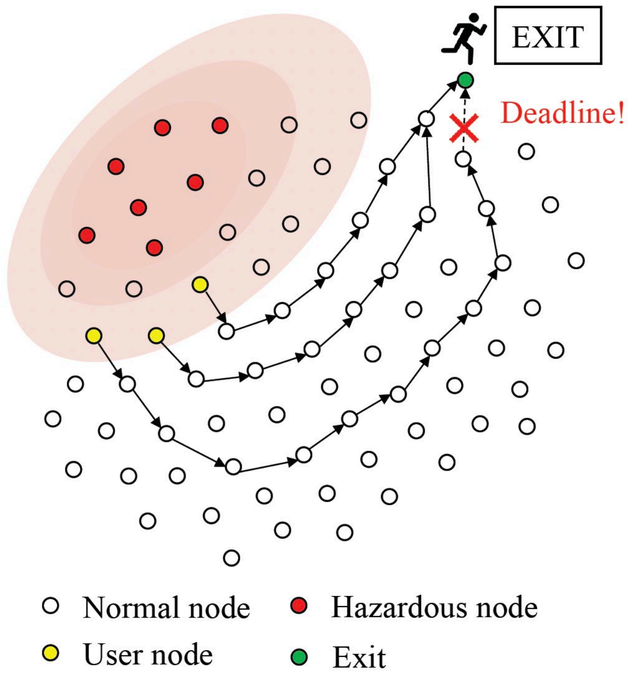
Emergency evacuation is critical following a ship accident, as passengers are required to escape the dynamic hazards and reach the muster station before the deadline.



Motivation



(a)



(b)

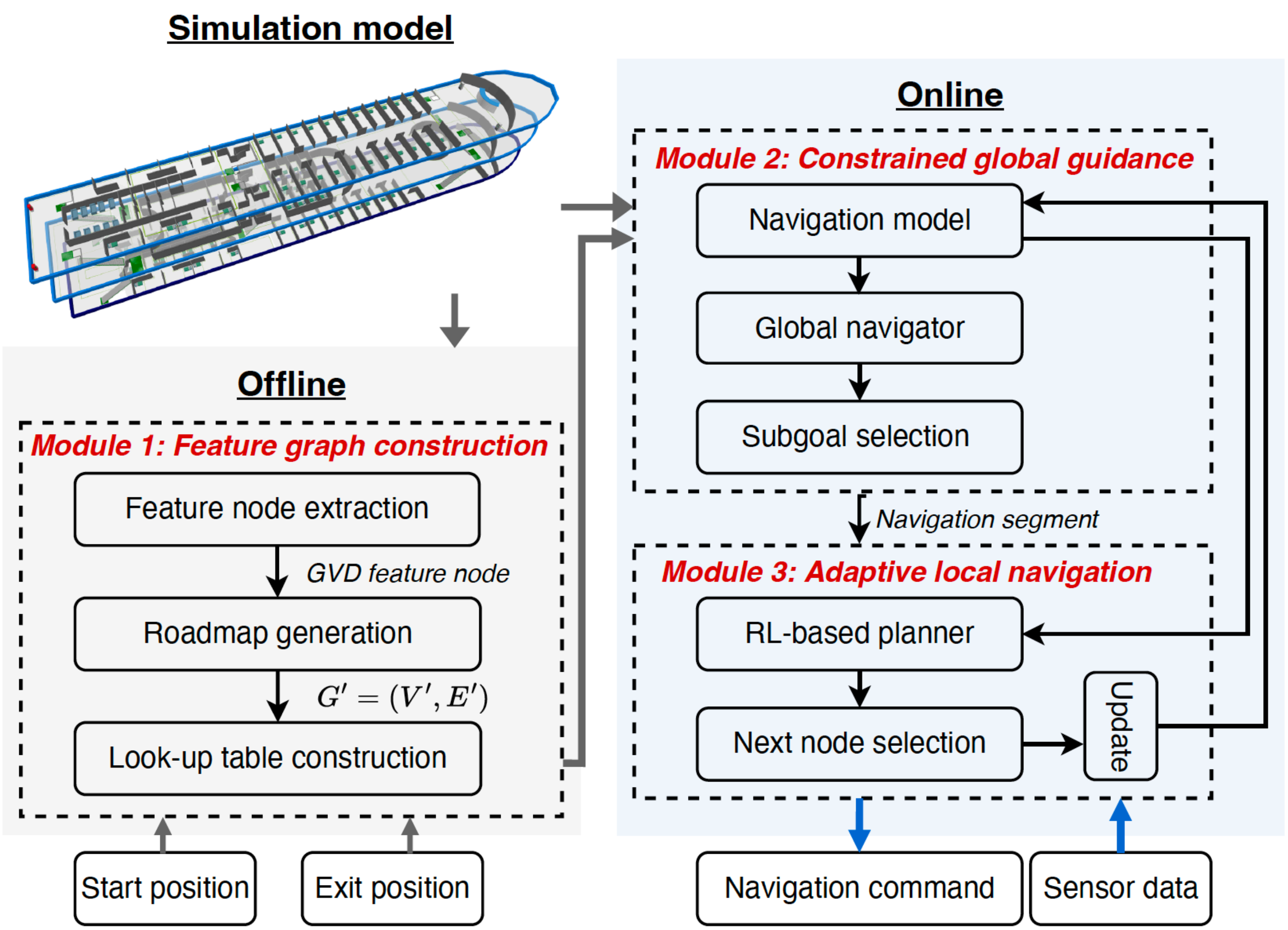
(a) A navigation scheme based on a road backbone may lead to heavy congestion.

(b) Unconstrained detours may increase the user’s exposure time to hazards.

Our Contribution

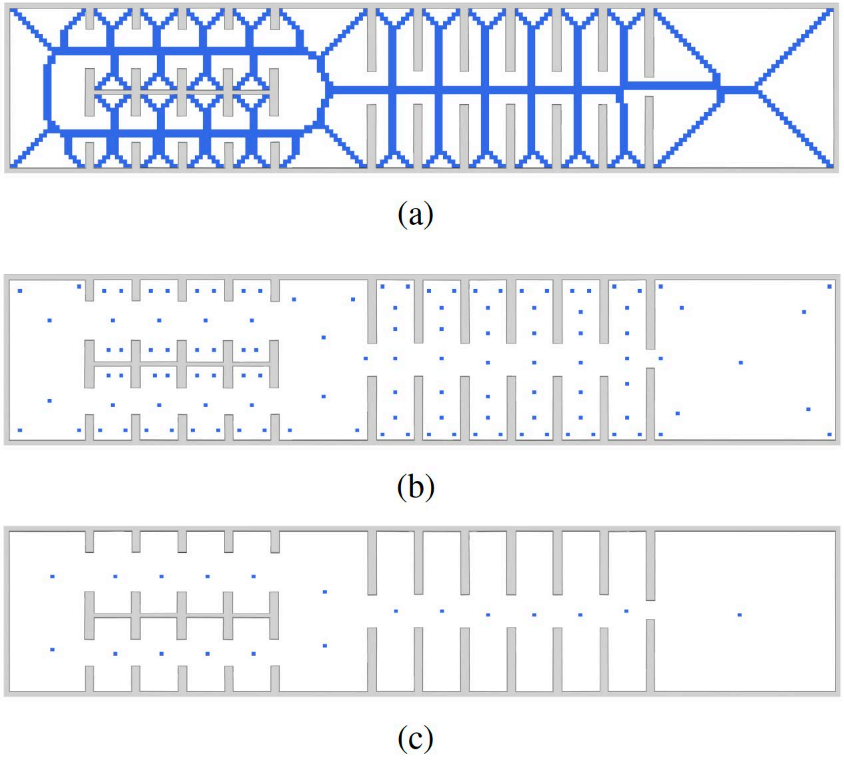
- We constructed a crowd movement data set of ship indoor evacuation via a simulation platform Anylogic for the DC-HEN training.
- We proposed a method for constructing a graph model with environmental structural features.
- We developed a hierarchical emergency navigation algorithm that combines the global reference path and local environmental information based on reinforcement learning technology.

Our Proposed Hierarchical Navigation System



Offline Feature Graph Construction

[Baruah et al. 2018]

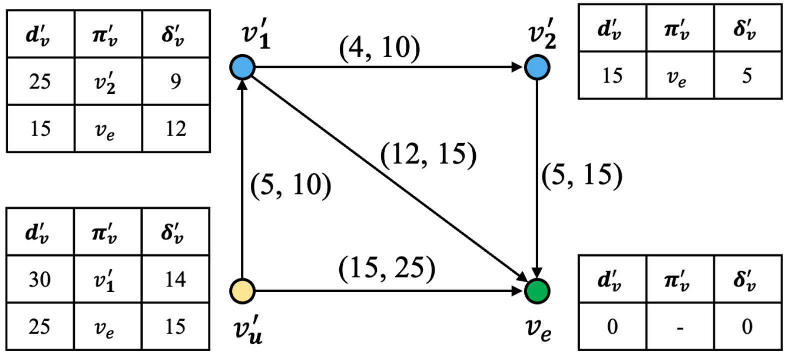


(i) Process of feature node extraction

Input:

- Typical delay: $d_T(\overrightarrow{v_i' v_j'})$
- The worst-case delay: $d_W(\overrightarrow{v_i' v_j'})$
- Deadline

Output: a 3-tuple table $\mathrm{Tab}[v'] = (d_v', \pi_v', \delta_v')$



(ii) A simple example of look-up table to the exit

Decision-making Agent Development

[Van Hasselt et al. 2016]

Local observation: the set of locations of free space, walls, other users, hazards, and global guidance segments within the observation range respectively.

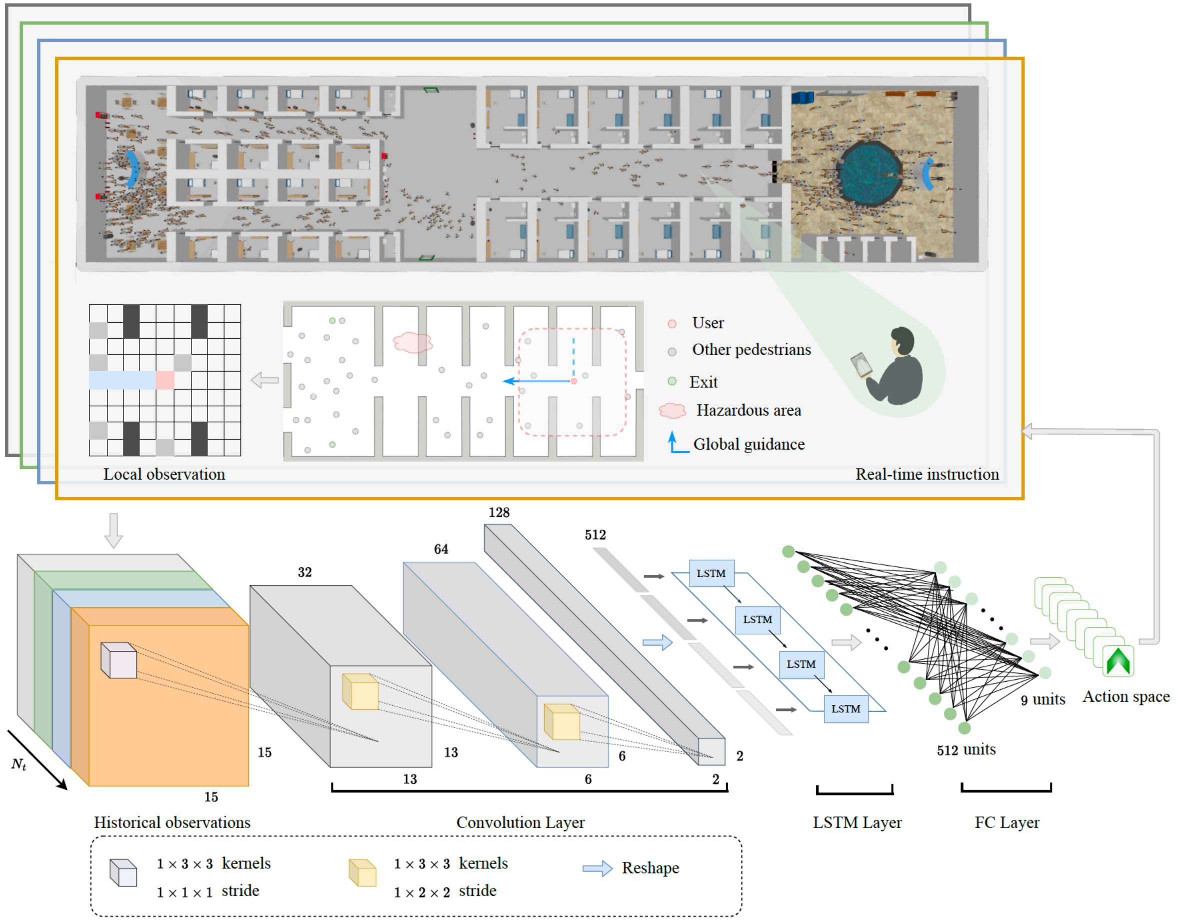
Action space: a discrete set of navigation decisions.

Reward function:

- a small negative reward at each time step to encourage the agent to reach the exit with less time compensation;
- a penalty of when the agent collides with walls or other users;
- a great penalty for exposure to hazards;
- a positive reward denoted as $N_t \times 10$ for following the global guidance;
- a great positive reward when the agent reaches the exit.

Hierarchical Emergency Navigation System

[Van Hasselt et al. 2016]



The target Q-value:

$$Y_t^{DoubleDQN} = r_t + \gamma Q\left(s_{t+1}, \underset{a_t}{\operatorname{argmax}}\, Q(s_{t+1}, a_t; \theta)\,; \theta'\right)$$

The loss function:

$$L(\theta) = \frac{1}{N_b}\sum_{i=1}^{N_b}[Y_t^i - Q(s_t^i, a_t^i; \theta)]^2$$

Simulation Setup

Data set generation: we simulate the evacuation process on a single deck using the visualization simulation platform Anylogic to generate the crowd movement data set.

Ablation study:

ABLATION STUDY ON DIFFERENT OBSERVATION SIZES

$H_o \times W_o$	9×9	11×11	13×13	15×15	17×17
Crowd-50	1.12	1.10	1.08	1.08	1.07
Crowd-100	1.25	1.24	1.18	1.12	1.10
Crowd-150	1.44	1.37	1.25	1.15	1.15

ABLATION STUDY ON DIFFERENT INPUT SEQUENCE LENGTHS

N_t	1	2	3	4	5
Crowd-50	1.28	1.19	1.12	1.08	1.06
Crowd-100	1.43	1.33	1.27	1.12	1.10
Crowd-150	1.47	1.36	1.28	1.15	1.15

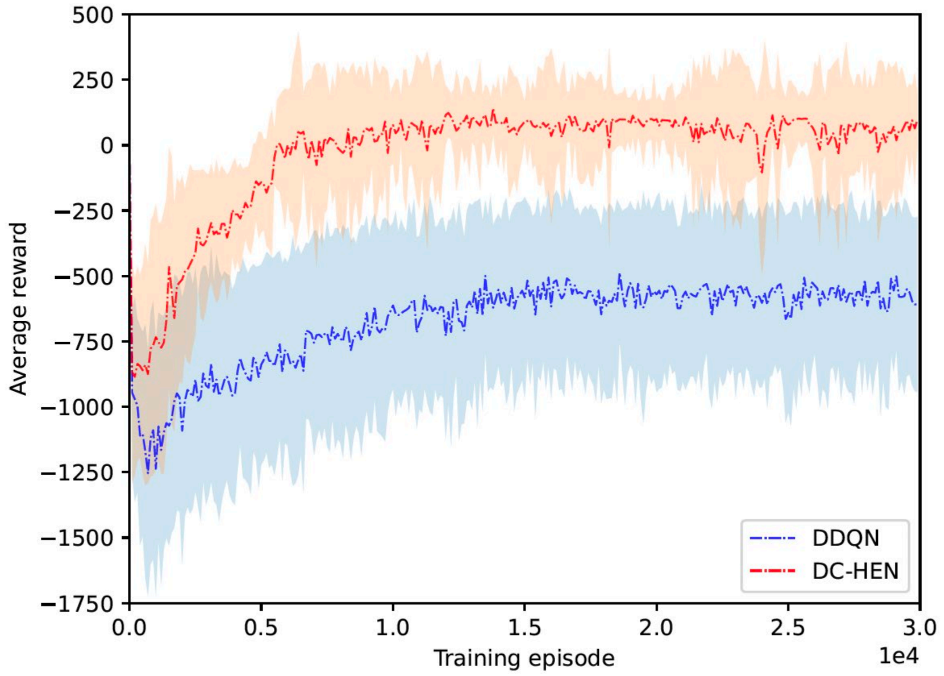
Compared Approaches

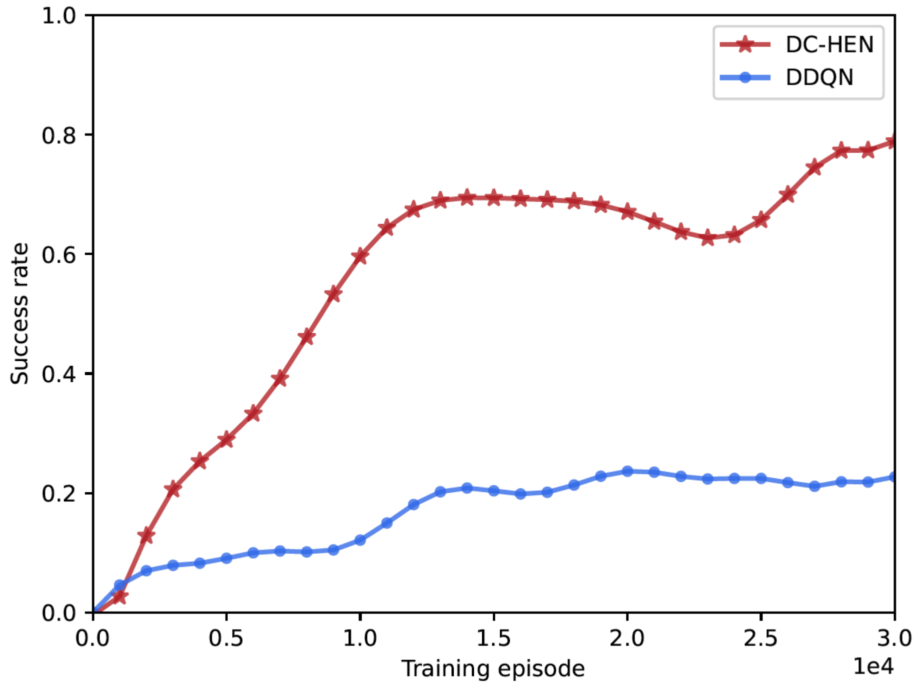
[Van Hasselt et al. 2016; Wang et al. 2016; Jindal et al. 2022]

Approach	Description
DC-HEN	Hierarchical emergency navigation, our proposed approach
DDQN	Deep RL-based emergency navigation without global guidance
CANS	A congestion-adaptive method with potential map and hazard level map
ECSSN	Clogging-free and shortest-safe path navigation method

Experimental results

➢ Evaluation of the training process

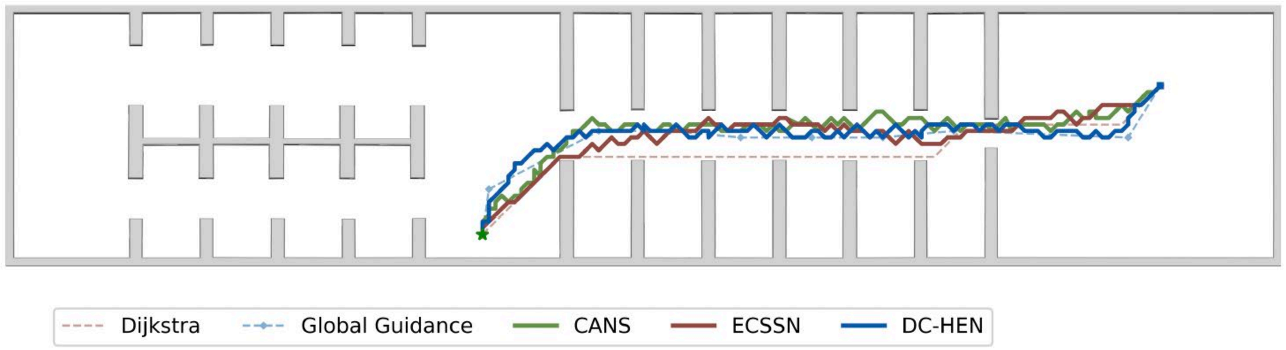


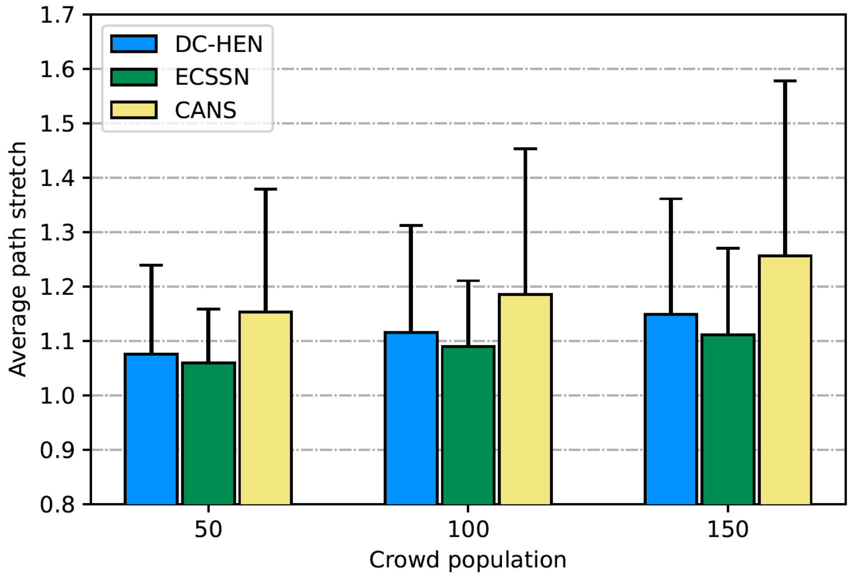


- DC-HEN's training curve rises faster than the DDQN method.
- DC-HEN's navigation success rate rises rapidly with the increase of training times and finally reaches 78.3%.

Experimental results

➢ Average path stretch

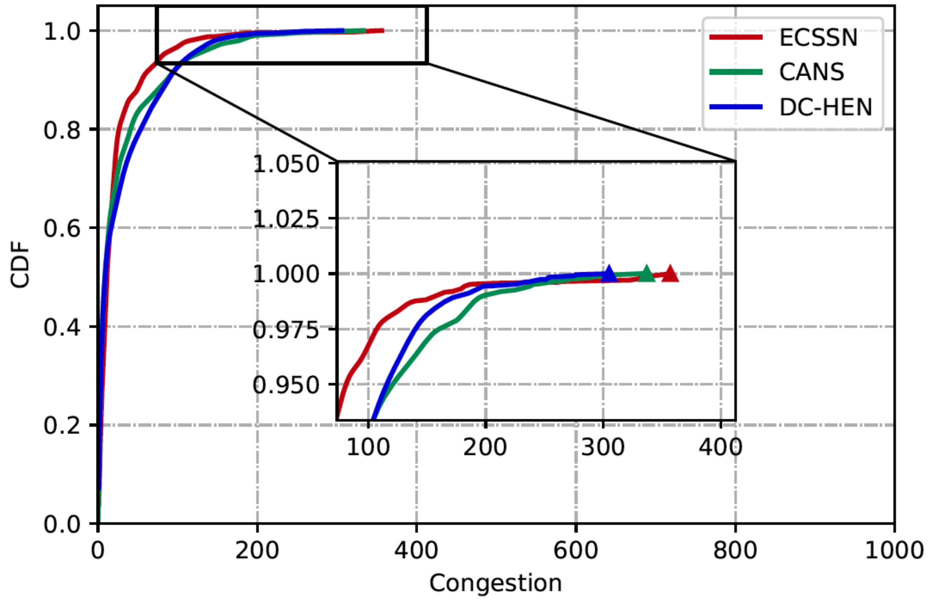




- The path planned by DC-HEN has a certain distance from the static obstacles, while the trajectory of ECSSN is close to the wall.
- The path stretch results for DC-HEN are similar to those of ECSSN in all cases.

Experimental results

➢ Congestion distribution



- Nodes involved in DC-HEN are at most participate in about 300 navigation paths, and the blue curve rapidly reaches 1.

Conclusions

- DC-HEN utilizes reinforcement learning and designs a novel reward function to provide congestion-relieved evacuation guidance for each user in real-time.
- DC-HEN has a higher success rate with 78.3%, relatively short average path stretch, and better congestion avoidance performance.

Future work

- Designing a multi-agent decision system that takes into account the allocation of limited life-saving resources.
- Incorporating users' personalized preferences.

Thank you!

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