Long short-term memory neural network modelling of bottleneck pedestrian evacuation based on transfer learning

Introduction

Major public infrastructures are heavily used by large crowds not only during special events but also during daily peak hours for regular commuting purposes. Bottleneck is a typical scene in public architecture facilities which usually causes a speed limit in pedestrian flow due to pedestrian gathering. In recent years, microscopic pedestrian simulation tools that are based on different behavior models have been adopted to predict bottlenecks and hazardous crowd movements. Considering that existing evacuation simulation models based on neural networks lack the ability of generalization, a new modeling approach using Long Short-Term Memory neural network with Transfer Learning is proposed to simulate the crowd evacuation at bottleneck areas. This study uses the pedestrian trajectory data collected through a controlled laboratory considering three different sizes of bottleneck structure, the proposed LSTM model is trained with the parameters representing the interactions between pedestrian, building structure and other pedestrians as independent variables, and the coordinates of the pedestrian in the next step of movement as the dependent variables.

Methodology

Data archive from experiments about thirteen groups of pedestrians passing through the bottlenecks which conducted by the institute section Civil Safety Research in the Research Centre Jülich in Germany were used to make the datasets. In the thirteen groups of experiments, the width of the bottleneck b was set from 0.9 m to 2.5 m, the length of the bottleneck l was set from 0 m to 4m. Pedestrians' trajectories were automatically extracted from the video recorded by two cameras using the software PeTrack. The original trajectories are publicly available from the website https://ped.fzjuelich.de/da/.

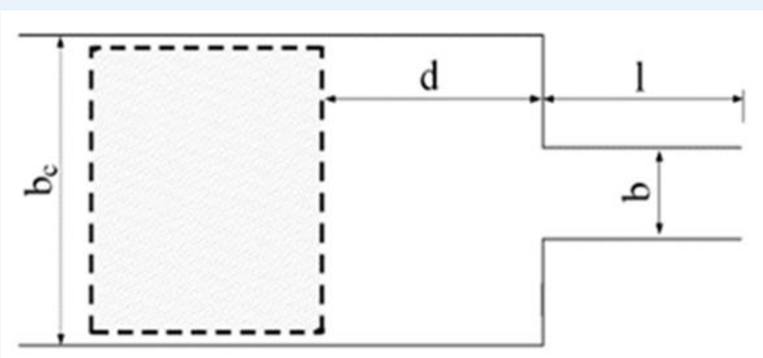


Fig. 1 Sketch of experimental setup

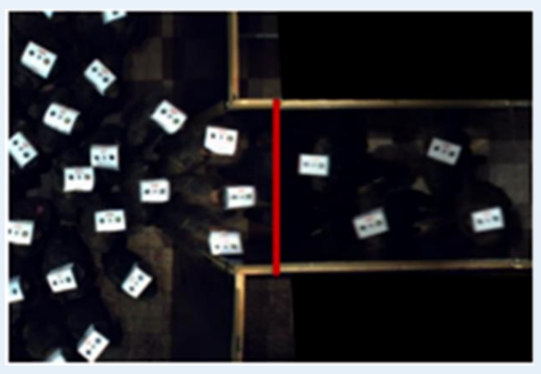


Fig. 2 Snapshot from camera

Movement behaviors of a pedestrian are usually considered to be primarily affected by the situations within his/her region of interest. In order to distinguish and quantify pedestrians movement more objectively and accurately, this study assumes that the region of interest in front of the pedestrian is a fan-shaped area with a center angle of 170° and a radius of 3 m.

(a)

(b)

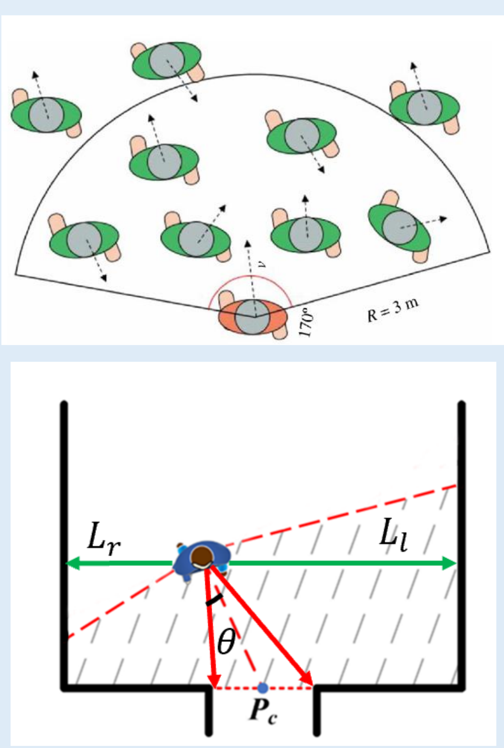


Fig.3 The region of a subject pedestrian

k	The nearest neighbors
γ	The number of the sectors divided
D_{ik}	The minimal distance from the k in the region of interest.
M_{ik}	The minimal relative angle of movement directions to the k in the region of interest.
M_k	The angle of movement directions of the k in the region of interest.
D_l	Distance from the left wall
D_r	Distance from the right wall
V_{ik}	The relative speed of movement to the k in the region of interest.
V_i	The instantaneous speed of the pedestrian i
θ	The angle deviated from the center of exit p_c

Fig.4 Definition of the pedestrian behavioral characteristic parameters

Discussion

To set an accurate microscopic simulation model of pedestrian flow, the hidden layers of LSTM model and the frame number of input data used in the model are discussed. Firstly, the LSTM model with one hidden layer is trained using the current frame (t) data (i.e. 1 backward time step), t-4 to t frame data (i.e. 5 backward time steps), and t-9 to t frame data (i.e. 10 backward time steps) as inputs to determine the optimal data input form for the model. The three evaluation indicators (RMSE, ADE,FDE) as shown in Fig.5. Through comparison, it was found that the model containing two LSTM hidden layers had the best performance. The model frame is shown in Fig. 6.

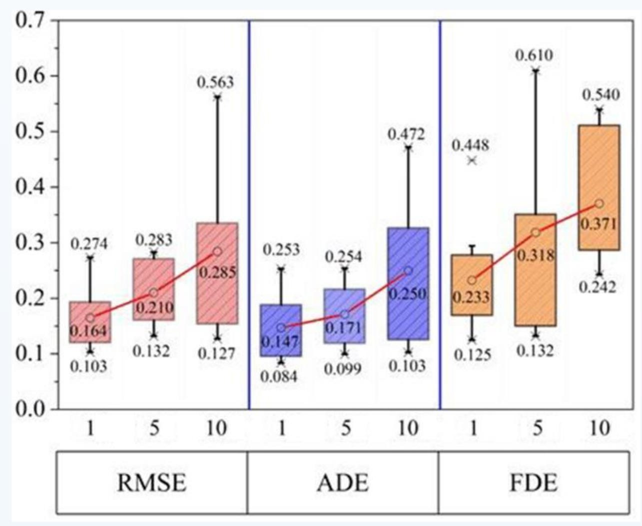


Fig.5 Comparison of The three evaluation indicators

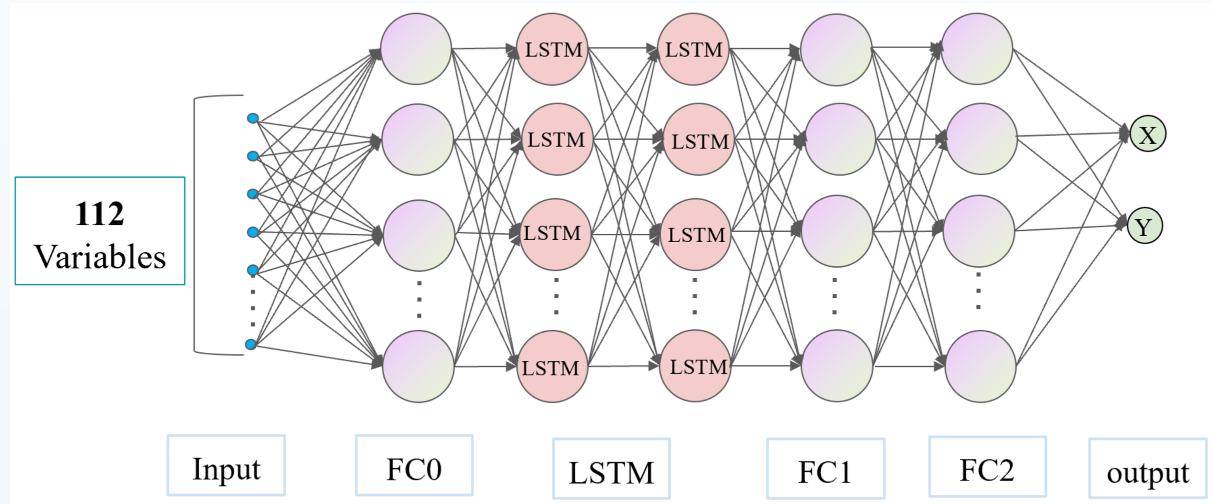


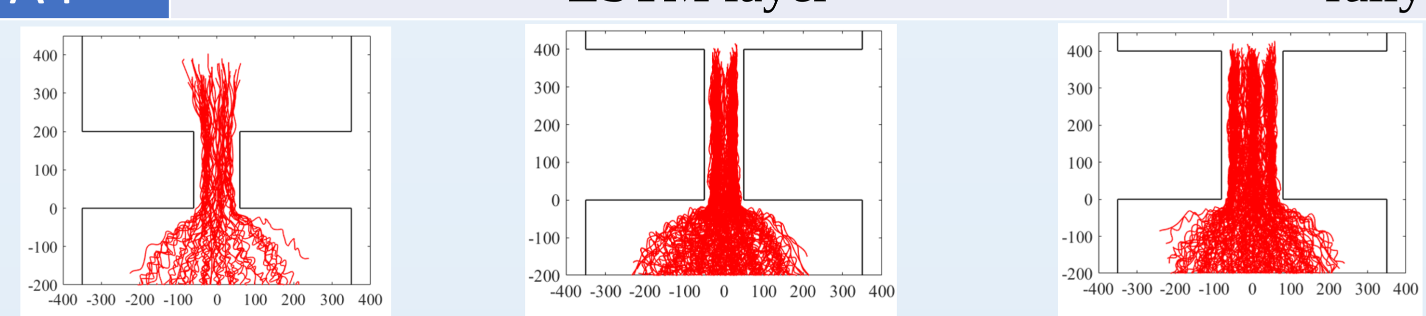
Fig.6 Topological network structure of the LSTM

Results

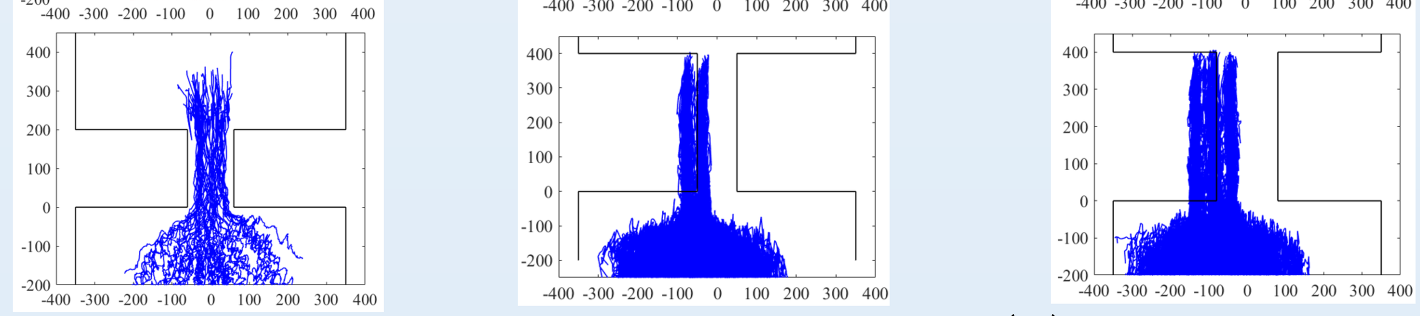
In order to improve the generalization ability of the LSTM model for micro-simulation of pedestrian flow at the bottleneck, this paper uses transfer learning to improve it. this paper sets up four combination strategies of transfer learning tuning layers, as shown in Tab.4. The training method of the LSTM model based on transfer learning is as follows: Firstly, the LSTM model trained by the data of experiment S1 (b=1.2m,l=2m), then freeze different network layer parameters according to the transfer learning strategies, and randomly select 20% of the data from S2 and S3 new scenarios to train the fine-tuning layer. Finally, obtain a pedestrian flow microscopic simulation LSTM model suitable for the new scene.

Tab.1 The training strategies for fine-tuning layer of transfer learning

Strategy	Freezing layer	Fine-tuning layer
A1	LSTM layer、fully connected layers 1, 2	fully connected layer 0
A2	LSTM layer、fully connected layers 0, 2	fully connected layer 1
A3	LSTM layer、fully connected layers 0, 1	fully connected layer 2
A4	LSTM layer	fully connected layer



Real trajectories



Model-simulated trajectories

(a) Experiment S1 (b=1.2m,l=2m)　(b) Experiment S2 (b=1m,l=4m)　(c) Experiment S3 (b=1.6m,l=4m)

Fig.7 Comparison of the real and simulated trajectories by applying the LSTM model trained by S1 data only to the S2 and S3 scenarios

Conclusions

The results show that the best performance of the model can be obtained by using the input data of one backward time step and two hidden layers, and using transfer learning can increase the generalizing ability of the model greatly. The model using transfer learning can adapt different modeling scenarios with only 20% data from new scenarios and performs best with the training strategy of freezing the LSTM layer and tuning the three fully connected layers.

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