Empirical analysis on external factors affecting pedestrian dynamics in high-density situations

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Motivation

- In **high-density scenarios**, the increased number of neighbors leads to more interactions among pedestrians.
- Existing approaches primarily model pedestrian interactions using either **relative positions, velocities**, or both with respect to neighbors.
- Predicting pedestrian dynamics in **crowded environments** is a complex task as pedestrian speed is influenced by multiple **external factors**.

Objectives

- Propose a set of **perspective variables** and extract data of these features from **Jülich experiment** [1].
- Investigate the impact of the proposed variables on **pedestrian walking speed**, and subsequently **identify** the **key factors** affecting pedestrian walking speed in the high-density situations.

Data preparation

Proposed variables are extracted for **K nearest neighbors**:

- Fundamental Information (**FI**): FI $= \{||v_i||, \Delta x_{ij}, \Delta y_{ij}, \Delta v_{x_{ij}}, \Delta v_{y_{ij}} | 1 \leq j \leq K\}$
- Environmental Effect (**EE**): $d_W = \sqrt{(x_i - x_W)^2 + (y_i - y_W)^2}$
- Time-to-Collision (**TTC**) [2]: TTC $= \min_{1 \leq j \leq K} \tau_{ij}$
- Mean Distance (**MD**): $d = \frac{1}{K} \sum_{j=1}^{K} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
- Frontal Effect (**FE**): FI_{Front}

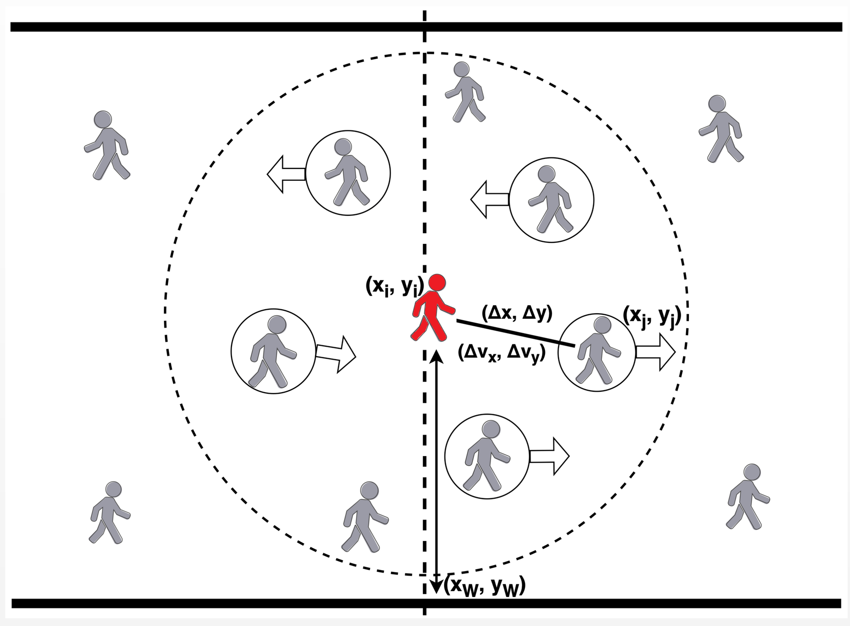

Fig. 1: Data preparation for K = 5.

Method

- Neural network (NN): a Multilayer Perceptron (**MLP**) with hidden layers $h = (6, 3)$
- Different types of input are fed into the neural network:
  $\mathrm{I}_0 = \mathrm{FI}, \mathrm{I}_1 = (\mathrm{FI}, d_W), \mathrm{I}_2 = (\mathrm{FI}, \mathrm{TTC}), \mathrm{I}_3 = (\mathrm{FI}, d), \mathrm{I}_4 = \mathrm{FI}_{Front}$
- Training and testing: $s(t + \Delta t) = \mathrm{NN}(\mathrm{I}_i(t))$
- Evaluation metric: Mean Absolute Error (**MAE**)

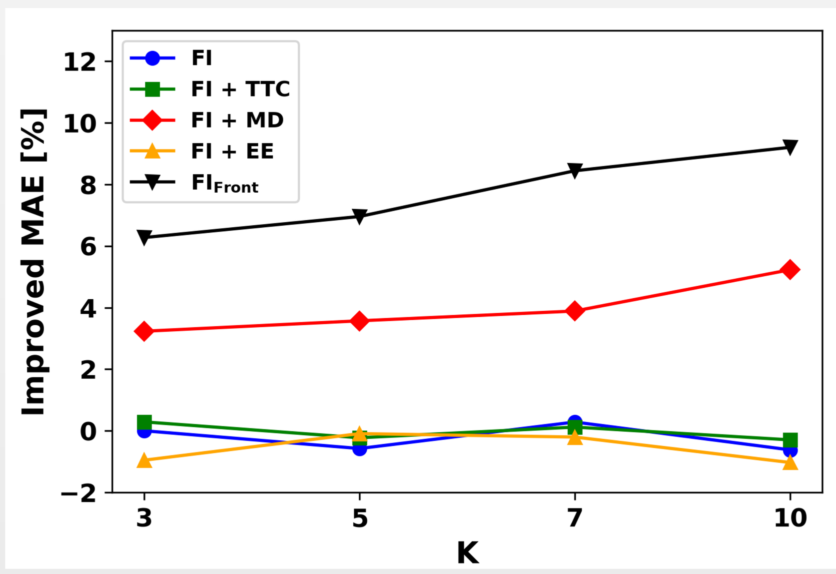

Fig. 2: Unidirectional flow, $\Delta t = 0.4\ s$.

Results

- **Frontal Effect** and **Mean Distance** exhibit a noticeable improvement in accuracy in both unidirectional and bidirectional scenarios in the Jülich datasets.
- **Better accuracy improvement** is observed in the **unidirectional** dataset, which has less complex interactions compared to the bidirectional dataset.
- In high-density scenarios, neural networks are unable to achieve improved accuracy by incorporating **Time-to-Collision**.

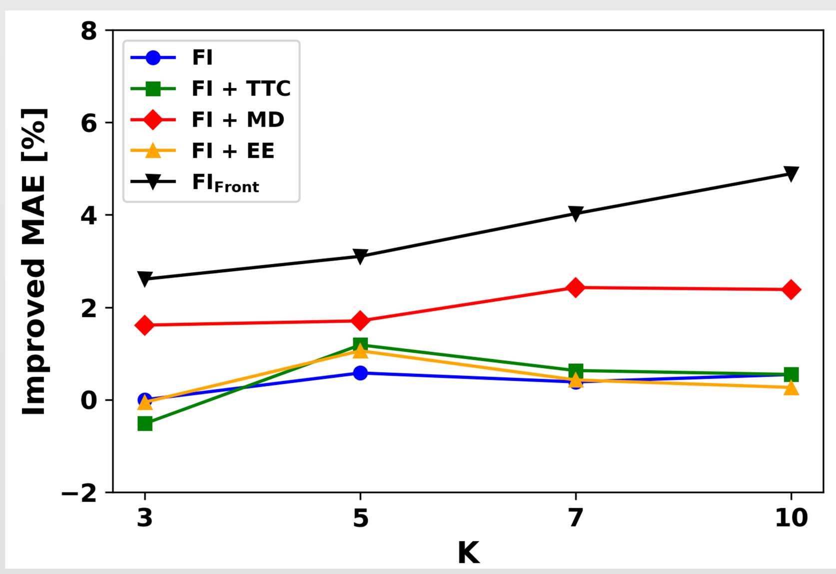

Fig. 3: Bidirectional flow, $\Delta t = 0.375\ s$.

Future works

- Conducting a **sensitivity analysis** to determine the relative importance of the key variables.
- Comparing results with those from **low-density datasets**.
- Incorporating useful variables as **additional features** in pedestrian simulation models.

References

[1] Cao, S., Seyfried, A., Zhang, J., Holl, S. & Song, W. Fundamental diagrams for multidirectional pedestrian flows. *Journal Of Statistical Mechanics: Theory And Experiment*. **2017**, 033404 (2017)

[2] Karamouzas, I., Skinner, B. & Guy, S. Universal power law governing pedestrian interactions. *Physical Review Letters*. **113**, 238701 (2014)

The MADRAS project is funded by