Deep Learning Approach to Force-Based Modeling of Pedestrian Flow in Bottleneck Scenarios

František Koutenský*[1,2], Daniel Vašata[1], and Pavel Hrabák[1]

[1]Faculty of Information Technology, Czech Technical University in Prague, Czechia
[2]Czech Institute of Informatics, Robotics and Cybernetics, Czech Technical University in Prague, Czechia

Abstract This work introduces a hybrid force-based concept for modeling pedestrian flow through bottlenecks, integrating Graph Neural Networks with the Social Force Model. While the model dynamics is driven by the social-force based equation of motion, the goal-directed, interaction, and environmental forces are learned from trajectory data in the Bottleneck Caserne dataset [3] using a neural network. Through data-driven simulations, this approach has been shown to be applicable to bottleneck flow modeling, accurately predicting pedestrian dynamics even in unseen scenarios.

Keywords pedestrian modeling, neural networks, bottleneck flow, crowd dynamics, force prediction.

Introduction and Model Architecture

Due to the increasing popularity of artificial intelligence, machine learning (ML) methods find applications in various scientific fields, including pedestrian flow modeling. Recent studies focus on the possibility of using ML methods as an alternative or supplement to classical knowledge-based (KB) models such as the Social Force Model (SFM) [2]. While deep learning models excel at capturing complex patterns, knowledge-based models offer interpretability and physical realism. Hybrid models aim to combine these strengths by embedding neural networks within KB frameworks [1].

This work proposes a novel hybrid approach, integrating a graph neural network based deep learning model into the SFM. The idea is to drive the dynamics by the social-force equation of motion

$$\ddot{\boldsymbol{x}}_t = \boldsymbol{F}_{\text{total}}\left(\boldsymbol{x}_t, \dot{\boldsymbol{x}}_t\right) = \boldsymbol{F}_{\text{goal}}\left(\boldsymbol{x}_t, \dot{\boldsymbol{x}}_t\right) + \boldsymbol{F}_{\text{int}}\left(\boldsymbol{x}_t, \dot{\boldsymbol{x}}_t\right) + \boldsymbol{F}_{\text{obs}}\left(\boldsymbol{x}_t, \dot{\boldsymbol{x}}_t\right), \tag{1}$$

letting the neural network learn the goal-directed, interaction, and environmental forces from trajectory data. The model is designed as Markovian, i.e., only current pedestrian positions, velocities, obstacles, and goals are used to predict the acting force. The model consists of three force modules, as shown in Figure 1.

Force Modules The goal-directed module uses *individual features* ($\mathbf{X}_{\text{ind}} \in \mathbb{R}^6$): current velocity (v_x, v_y), distance to goal (d_{goal}), direction vector to goal (d_x, d_y), and velocity toward goal (v_{goal}). Interaction module processes *interaction features* ($\mathbf{X}_{\text{int}} \in \mathbb{R}^{k\times 5}$) for k pedestrians including distance to pedestrian, direction vector, relative velocity, and alignment. Obstacle module processes *obstacle features* ($\mathbf{X}_{\text{obs}} \in \mathbb{R}^{m\times 9}$) for m obstacles including distances and direction vectors to obstacle endpoints and the closest point.

Feature Transformation and Core Network Interaction and obstacle features are projected to a higher-dimensional space to enhance their representation before being aggregated via summation in a graph neural network way. The core network processes individual and aggregated interaction/obstacle features through feedforward blocks. The final force is the sum of the outputs from each force module analogous to (1).

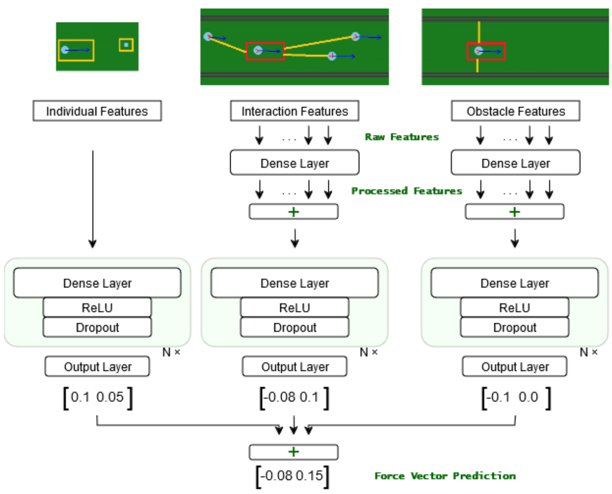


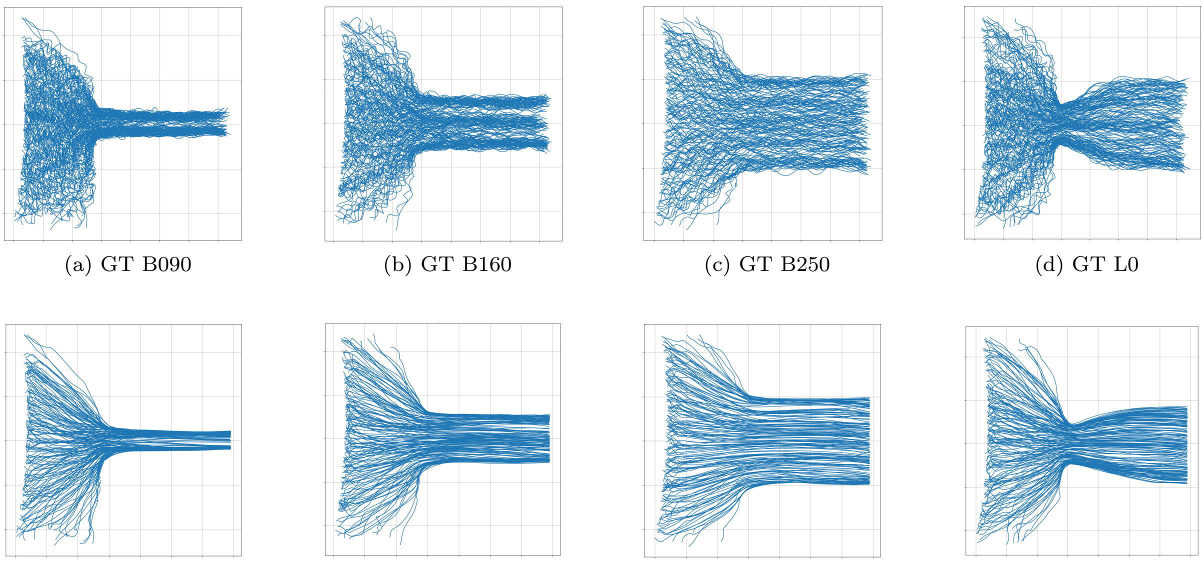
Figure 1: Model architecture.

*Email of the corresponding author: koutefra@gmail.com

Results and Conclusion

The network has hidden layer dimensions of 512, 1024, 512, 256, and 128. The first of these layers, with 512 dimensions, handles the pre-aggregation projection. Velocities are approximated using backward finite differences. The model is trained by minimizing the L_2 loss between predicted and true positions over 32 frames, using the ADAM optimizer (learning rate 0.001, dropout 0.5, batch size 64). We evaluate our model on the Bottleneck Caserne dataset [3], which provides diverse scenarios of pedestrian flow through bottlenecks. Scene `b160` was excluded from training for generalization testing. The training lasted 5 epochs.

Figure 2 shows predicted and true trajectories across scenes, including the unseen `B160` scene, demonstrating strong generalization. A video showcasing our model's performance, including the unseen `B160` scene, is available on YouTube: `https://youtu.be/E4YjcGl7qtw?si=zmSZiT57Dxf2-aix`. The model-generated trajectories qualitatively align with the true trajectories, validating our approach. However, the predicted trajectories exhibit higher speeds in the corridor after the bottleneck.



(a) GT B090 (b) GT B160 (c) GT B250 (d) GT L0

(e) Model B090 (f) Model B160 (g) Model B250 (h) Model L0

Figure 2: Comparison of ground truth (GT) and model-predicted trajectories across different scenes.

To summarize, the introduced data-driven neural network approach is capable to effectively capture pedestrian dynamics in bottleneck scenarios and even generalizes well to unseen scenes. However, this conclusion is limited only to the Caserne dataset [3], yet, the presented results promise that the concept can be applicable in more general layouts as well, which is the aim of our future work.

The source code will be released upon acceptance.

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