Graph-based pedestrian locomotion model

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Abstract We propose a data-driven approach to pedestrian locomotion modeling by combining ideas from traditional knowledge-based models and machine learning. Our approach considers a human crowd as a locally connected graph of neighbors. The data-driven algorithm incorporates this neighborhood information to predict the next step of individual pedestrians. Unlike most machine learning approaches, our model is based on random features and thus can be trained rapidly, making real-world applications and rapid prototyping viable.

Keywords pedestrian modeling, crowd modeling, machine learning, graph neural network

Motivation

The progress made in the field of machine learning (ML) in recent decades has brought novel approaches also in the field of crowd modeling. Today there are hundreds of different ML models that have been developed and employed with the aim of modeling the trajectory of pedestrians (e.g., Social LSTM [1]). However, it is not always clear what is the best choice among existing ML models, and what performance should be expected for a particular scenario. Our approach uses ideas from graph neural networks to represent the local environment of an agent to learn how a single individual takes their next step. This allows us to use established validation tools for classical agent-based models (in particular emergent behavior formation for fundamental diagrams, lane formation behavior) to evaluate our model and compare it to established knowledge-based approaches.

Graph-based locomotion model

A locomotion model requires the knowledge of the geometry and tactical information (e.g., target choice), and with this knowledge it is possible to find a suitable path. Algorithms that perform pathfinding already exist and are computationally efficient [2]. Figure 1 illustrates the main idea of our approach. Once the intended path is known, the interactions in the local neighborhood remain to be considered. These interactions can be situation-dependent and lead to patterns in data, motivating the use of machine learning. In a global coordinate system (with coordinates x, y) five agents are illustrated as blue circles, with a spike indicating their orientation. The target of all agents is towards the right, and a floorfield is depicted as a background color gradient from light red to darker red. One pedestrian is marked with a star, as this pedestrian is currently about to take a step. In this situation we want to learn how to consider the influence of neighbors to inform the agent's step. We start by considering a useful representation of a neighborhood of a pedestrian in motion. The key influencing factors are the other nearby pedestrians, and their distance from the moving pedestrian. We model the neighborhood with a graph (a collection of nodes connected by edges), since this structure allows for flexibility in the number of neigbhouring agents (graph nodes), which should be allowed to vary. We illustrate this graph in Figure 1 with a green color, and the resulting prediction is indicated as an arrow, in fact we aim to learn a change in position of the moving pedestrian. For

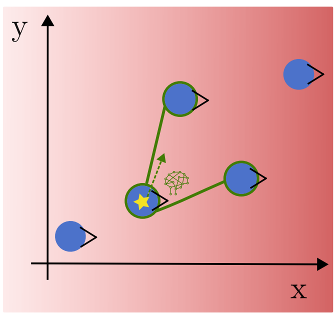

Figure 1: Illustration of a data-driven prediction for a step.

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supervised learning, we prepare a dataset by collecting simulation outputs and processing the data into graphs which predict a change in position appropriately. For our initial experiment we use the optimal steps model in Vadere to simulate data [3, 4]. The graph is constructed such that the node features contain the position of a pedestrian and the desired speed. We convert the representation from global coordinates (such as those shown in Figure 1) into local coordinates centered at the moving pedestrian with an orientation that matches the x-axis with the spike of the moving pedestrian. This leads to a translation and rotation invariant representation. Once the graph is constructed it is transformed with a trainable function that first applies the same transformation to all nodes, then averages the obtained features and transforms this to predict the change in position for the moving pedestrian. To be competitive with existing algorithms, we train our model with an efficient sampling method [5], and for the results shown in Figure 2 training took 0.04 seconds, on a common laptop.

Initial results

Our initial investigation has focused on simple scenarios such as a crowd moving through a corridor. We found that our graph model trained on corridor data readily generalizes to a bottleneck scenario fairly well. As an investigation of the suitability of our model we use the speed-density and speed-velocity relationship, and in Figure 2 we show the fundamental diagram obtained for the training data (labeld as OSM) and the predictions from our graph-based locomotion model (labeled as ours). The predictions look reasonable, and typically in favor slower movement. Further investigations need to be done for the suitability of our model for higher crowd densities.

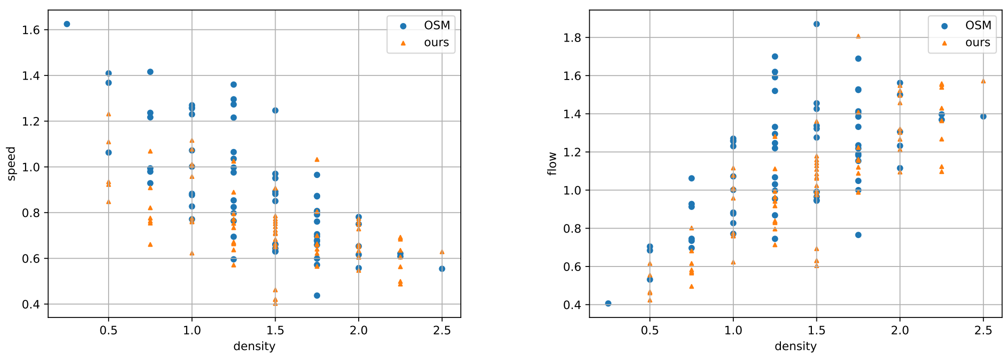

Figure 2: Fundamental diagram shown for training data (OSM) and our graph-based locomotion model.

We intend to better align the novel trends in ML with the existing practice in pedestrian modeling. Our current approach is promising but further experimentation will likely reveal the strengths and weaknesses of the proposed approach.

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