Approaches to Predict Pedestrian Dynamics

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Identifying the factors that control the dynamics of pedestrians is a crucial step toward modeling and building various pedestrian-oriented simulation systems. Several approaches have been proposed by researchers to predict pedestrians' movement characteristics using different methods and techniques. Based solely on experimental evidence, researchers isolate the factors that influence the interactions between pedestrians in single-file movement. With artificial neural networks, one can approximate the fitting function that describes pedestrians' movement without having modeling bias. The analysis is focused on the distances and range of interactions across neighboring pedestrians.

Keywords: artificial neural networks ; pedestrian dynamics ; modeling ; simulation ; traffic and crowd dynamics ; single-file movement

1. Introduction

For the sake of safe mass events, comfortable and efficient transport infrastructures, for example, airports, much work is dedicated to understanding the laws governing crowd dynamics. In recent years, the number of empirical studies increased significantly, which led to more insights into the movement of people. Additionally, these insights often offer useful criteria that validate models and evaluate the simulacrum of reality they create.

Trustworthy models are valuable tools that shed light on unknown aspects of crowds and allow for assessing and investigating new design and planning measures. There are several approaches to model pedestrian dynamics, as will be discussed in the following sections.

The focus here is to apply feed-forward neural networks (FFNN) to investigate and empirically analyze the impact of distance interaction range on the dynamics of pedestrians without modeling bias. Unlike most current research, the aim is to analyze single-file movement in different homogeneous and heterogeneous gender flows to predict the pedestrian's speed. **Figure 1** below shows the methodology followed in developing the algorithms for speed prediction using FFNN.

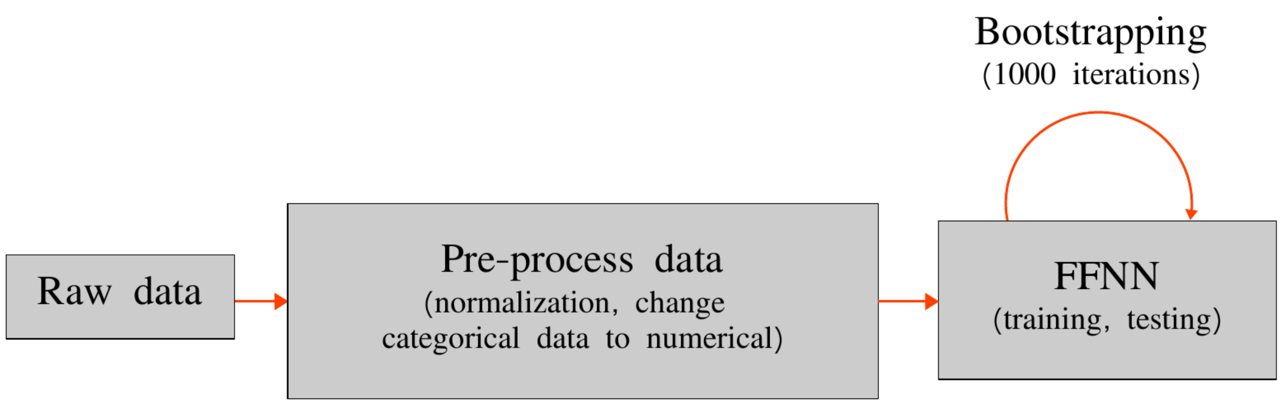

Figure 1. The methodology followed in developing the algorithms for speed prediction. In the pre-processing step, researchers change the categorical to numerical values and normalize the data between [0, 1] to have the same scale of values (an important step before training for artificial neural networks).

2. Approaches to Model Pedestrian Dynamics

2.1. Physics-based approaches

More attention has been given to studying the influential factors that control the dynamics of pedestrians in closed and open environments [1][2][3][4][5][6]. Understanding such factors can help in modeling complex pedestrian movement. When dealing with complex systems, such as pedestrian dynamics, scientists generate numerous models based on different approaches, variables, and parameters [7]. For instance, force-based models (see [8] for a review) assume that pedestrians' deviation from their intended trajectories can be explained by external forces. Another ansatz by Karamouzas et al. [9] follows a statistical–mechanical approach to measure the interaction energy between pedestrians based on the time to a potential future collision (time-to-collision). Tordeux et al. [10] introduce the walking time-gap as a parameter to model pedestrian movement. Van den Berg et al. [11] propose a model based on optimal collision-avoidance techniques to describe the movement of pedestrians in two-dimensional space. Another model, the Linear Trajectory Avoidance (LTA) model, introduced by Pellegrini et al. [12], takes into account both simple scene information in the form of destinations or desired directions and interactions between different pedestrians. Cellular automaton model proposed by Schadschneider et al. [13] is inspired by the chemotaxis process, which ants use for communication. This discrete on-space model assumes that pedestrian transition to neighbor cell probability varies dynamically and is not constant. Thus, this model modifies the transition probabilities by considering the nearest-neighbor interactions to determine pedestrians' transition to the next state.

2.2 Data-based approaches

Recently, many researchers have proposed human trajectory prediction algorithms [14], arguing that neural networks have high flexibility and are devoid of any modeling bias. For example, Alahi et al. [15] develop the Social LSTM (S-LSTM) algorithm to predict the future trajectories of pedestrians depending on their past positions and the interactions with their neighbors. To model the social interaction, Alahi uses a social-pooling layer to allow sharing of each neighboring pedestrian's LSTM hidden state to predict the subject pedestrian's future positions. The Alahi et al. algorithm improved the prediction of the next position by approximately 21% compared to the force-based model (SF) [16]. Xue et al. [17] developed a trajectory-prediction algorithm, called the Bi-prediction algorithm, based on the S-LSTM and considering the importance of pedestrians' intended destinations in predicting their future trajectories. This two-stage prediction model employs bidirectional LSTM architecture to forecast multiple possible trajectories with different probabilities in the scene. In other research [18], the authors propose the MX-LSTM model, which adds to the previous models a new variable (direction of the pedestrian head) to improve the trajectory predictions (the model improves the prediction by approximately 19% compared to the SF classical model). All the aforementioned data-based approaches have been used to describe low-density situations using specific datasets (UCY [19], ETH [12], etc.) where social interaction techniques for collision avoidance take up to several meters.

A study proposed by Tordeux et al. [17] applies feed-forward neural networks (FFNN) to predict the speed of pedestrians walking on different types of facilities (corridors and bottlenecks). Several FFNNs are presented to approximate the fitting function with different input features (relative positions, relative velocities, and mean distance to the nearest ten neighbors in front), hidden layers, and hidden neurons. The results of FFNN show an improvement of 20% compared to the classical approach (Weidmann fitting model [20]) evaluated with mixed data (corridor and bottleneck). In another study by Tkachuk et al. [18], the authors develop a system that simulates pedestrians' behavior during the evacuation process. The proposed system uses FFNN to predict how people act during evacuations. The acceleration and average velocity are used to predict each pedestrian's horizontal and vertical speeds. Another study by Yi Ma et al. [19] proposes an approach based on a multilayer perceptron artificial neural network for simulating pedestrians' behavior. The authors train the artificial neural network using pedestrians' actual movement data to encapsulate and predict their future behaviors. To verify the correctness of the proposed simulation system, the authors compared the simulation results of pedestrian counter-flow in a road-crossing situation and pedestrian collision avoidance with the actual experiments. The simulation results in both studies show that the proposed models based on artificial neural networks provide greater prediction accuracy by learning from actual experimental data rather than other models.

3. Single-file Movement Experiments

Single-file movement experiments are a simple setup that allows easily controlling of the influential factors to investigate pedestrian movement. Figure 2 below illustrates single-file experiments performed at the Arab American University in Palestine [21]:

Figure 2. Snapshots from Palestine experiments. Left: UM experiment,N=20. Right: UX experiment, N=24.

4. Results and Analysis

The research aims to investigate the influence of the follower, predecessor, and second predecessor pedestrians' headway distances on the speed behavior of a pedestrian. The investigation examines the isotropic nature of the interaction behavior, considering that a pedestrian interacts not only with pedestrians in their field of vision to regulate the speed but also with the pedestrians behind.

Interestingly, in Figure 3 readers can see that the combination of distance with the pedestrian in front and right behind improves the speed prediction compared to the combination of headway distances in front. From observing experiments' videos, one can notice that the pedestrians in relatively high densities start to adjust their speed when they approach the nearest neighbors to avoid colliding. This result demonstrates that the interaction behavior is not strictly anisotropic in single-file movement, contrary to classical modeling approaches assuming that the front distances only influence the speed.

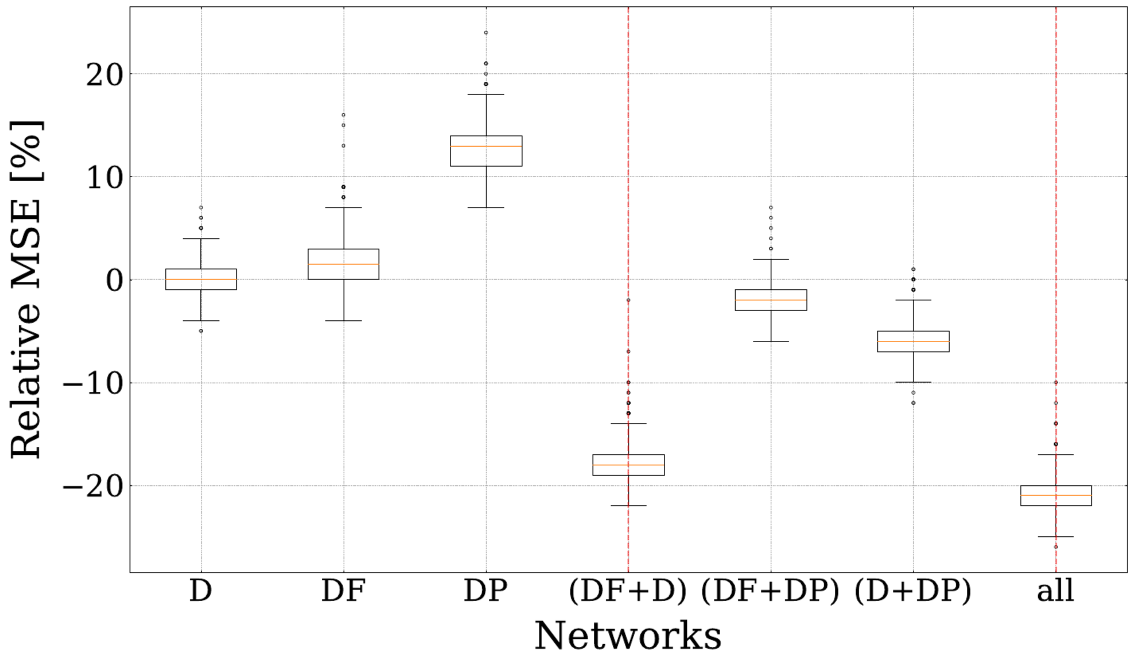

Figure 3. Boxplots represent the training MSE results of the algorithms using UX, N=20, 24, 30 samples with complexity (3,2). The x-axis represents the algorithm inputs applied, and the y-axis denotes the relative MSE calculated with D-input algorithms as a reference case.

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