Incorporating Physics Prior for Data-Driven Indoor Crowd Flow Forecasting

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1 Introduction

1.1 Background and Related Work

Crowd management is an essential aspect of urban planning and emergency. One of the important realizations is to predict the crowd. Precise crowd prediction holds significance for venue operators, enabling effective responses to large gatherings.

In order to understand pedestrian behavior and manage pedestrian infrastructures more optimally, simulation models have been developed that simulate the behavior or dynamics of the crowd. In general, existing pedestrian movement models could be summarized as microscopic, macroscopic, and mesoscopic (Dong et al., 2019; Duives et al., 2013). Amongst the wide variety of microscopic models, the Social Force Model (SFM) (Helbing and Molnar, 1995) is one of the most used models. It is based on the principles of social interactions and the forces that influence individuals' movement in a crowd. Also the grid-based Cellular Automata (CA) (Blue and Adler, 1998) and the continuous velocity-obstacle models are often used microscopic model types. In contrast, the continuum models (Hughes, 2000) describe the behavior of a system as a continuous field or distribution rather than individual entities or particles. The network flow model (Chalmet et al., 1982) is another type of macroscopic crowd movement model. The facilities in an infrastructure are represented by the nodes in a static network, with this we can study the spatial characteristics of the crowds.

Even though these pedestrian modeling approaches are knowledge-driven, they all feature formal models with strict physical assumptions. In many cases, calibrating the parameters of the model from data is a daunting task (Rasouli, 2021). With the emergence of machine learning and deep learning, researchers can now also apply data-driven models to simulate pedestrian dynamics, which requires less assumption and less expert knowledge (Song et al., 2018). Tordeux et al. (Tordeux et al., 2020) use artificial neural network (ANN) to predict crowd dynamics in complex spatial structures, highlighting the advantage of data-assisted methods without making specific mathematical assumptions.

The aforementioned research focuses on offline simulation for the what-if analysis (Makinoshima and Oishi, 2022). On the other hand, a lot of research studies how to apply data-driven models to forecast or estimate the movement patterns and behaviors of individuals or vehicles across an entire network or transportation system in real-time (Manibardo et al., 2022). It involves analyzing historical data, current conditions, and various factors influencing future mobility patterns. Compared to simulation, these methods make it easier to realize online prediction in an end-to-end way.

Traditional statistical models such as history average (HA), auto-regressive-moving-average (ARIMA) (Levin and Tsao, 1980), and vector auto-regression (VAR) have been widely used for traffic flow time series data prediction. These models are limited to single target point prediction and are not suitable for network-wide mobility prediction. With the advent of complex model structures, e.g. convolutional neural network and graph neural network, researchers have developed different deep learning models to capture the complex dynamics of vehicular mobility (Li et al., 2023, 2018; Wu et al., 2019) and human mobility (Lin et al., 2019; Simini et al., 2021; Sun et al., 2020). These models aim to approximate the intricate dynamics function involved in predicting network-wide mobility patterns, mostly are in the city level.

In indoor spaces, there are lot of work trying to predict the movement of the crowd with data-driven approaches. Generally, they can also be categorized as microscopic and macroscopic levels. At the microscopic level, researchers in (Alahi et al., 2016; Gupta et al., 2018) try to use the trajectory data to predict the individual motion of the pedestrian. Martani et al. (Martani et al., 2017) study monitoring techniques and apply them to pedestrian microsimulations to predict crowd flow. Such research contributes valuable micro-level insights into understanding individual actions, behaviors, route preferences, and various motion patterns within crowds.

On the other hand, at the macroscopic level, some studies focus on using video datasets (Zhang et al., 2016) for tasks like crowd counting and density estimation. Zhang et al. (Zhang et al., 2017) have developed a crowd management system based on crowd density estimation, including a risk rating system and an early warning mechanism to manage crowd dynamics. Sudo et al. (Sudo et al., 2017) leverage deep learning techniques to predict crowd density using Wi-Fi data collected in various indoor venues. Macroscopic models provide insights into system-level dynamics, which can guide high-level policy and infrastructure decisions. In this study, our primary focus is on macroscopic level crowd flow prediction.

Despite all these progressive works mentioned above for either traffic prediction or indoor crowd prediction, there remains a research gap concerning the macroscopic level of crowd movement prediction within the whole building (most of them focusing on a specific place). One example thereof is the short-term forecasting of the state in large pedestrian infrastructures. Furthermore, there's a lack of research about the reliability of data-driven prediction models in scenarios where obtaining data is challenging, such as evacuation scenarios. Therefore, the prediction accuracy of the data-driven model in these out-of-distribution data cannot be guaranteed.

In this research, we aim to use modern data-driven state-estimation and forecasting methods to establish a trustworthy and robust short-term crowd prediction model that can be generalized to incorporate unseen scenarios. This model will serve to anticipate crowd movements and facilitate crowd management, thus mitigating the risk of overcrowding. Through accurate prediction and effective crowd control measures, venue operators can proactively safeguard the safety and well-being of visitors.

2 Research Gap, Questions, Motivations and Approaches

In this section, we detail the research gap, motivation, and approach for the research question.

2.1 How to model the movement of the crowd so as to generalize the data-driven predictive model to data-scarce scenarios?

- **Research Gap and Motivation:** Data-driven models especially deep learning models often require large amounts of data to learn an implicit representation of raw data for a better understanding of the process to be modeled to achieve a good prediction accuracy. However, we couldn't retrieve enough data to train the model in some real-world application. This challenge can be dissected into two critical obstacles:

  (1) Scarcity of comprehensive training data: Obtaining a complete and extensive historical dataset is difficult, as recent studies (Li et al., 2022) (Manibardo et al., 2022) have pointed out. This scarcity of data can cause deep learning models to overfit.

(2) Rarity of data with extreme events: Gathering data that encompasses extreme events is often a formidable task. These rare instances are inherently challenging to collect, and this scarcity hinders the models' ability to generalize to such abnormal scenarios.

In most existing endeavors where data-driven models are employed for prediction, the emphasis is placed on utilizing a significant amount of data rather than initially exploring the dynamics of the crowd. To bridge this gap, we are going to incorporate prior knowledge about crowd movement that could potentially reduce the amount of data required for the model to learn the inherent dynamics of the crowd, enabling better generalization across various situations.

- **Sub-questions:**
  - What's the correlation between crowd movement and the flow data? What kind of physics model can reflect this correlation?
  - To what extent can we enhance the generalizability if we inject this physics prior into the data-driven model?
- **Challenges and Approaches:**
  - **Simulation:** To understand how the flow data reflects the underneath crowd movement, simulation techniques will be employed to replicate crowd motion under various scenarios. These collected data would be used for exploratory data analysis, e.g., summarizing the main characteristics of different scenarios and employing visualization methods for the data. On the other hand, simulation provides us a way to study the correlations of the flow data the the crowd dynamics, make it possible to model the motion of the crowd.
  - **Physics prior:** The famous Navier-Stokes equation has been applied to describe crowd fluids dynamic (Ivancevic and Reid, 2012). This physical model will provide a foundation for understanding and predicting crowd movements. In Liu et al. (2015), the authors adopted the diffusion equation to model the unidirectional pedestrian movement, the the flow could be infer by the equation directly. However, the parameters in the equation could only be estimated and calibrated by accurate data such as road width, road grade, pedestrian flow volume, and pedestrian types. These data are not easy to acquire in real-time prediction.

    Leveraging the concept of physics-informed machine learning (Lu et al., 2021), a particular focus will be placed on the second category of prediction models depicted in Figure 1. For example, the parameters in the physics model can be inferred directly from the crowd flow data and we can design a neural network to represent these latent variables. This approach seeks to strike a balance between available data and the underlying physics principles. This approach bridges the gap between data-driven and physics-driven methods.
  - **Online Learning:** Online learning encompasses a range of machine learning techniques wherein a learner endeavors to address predictive or decision-making tasks by sequentially learning from individual data instances. The primary objective of online learning is to optimize the accuracy or correctness of a sequence of predictions or decisions made by the learner (Hoi et al., 2021). In the context of crowd prediction, the dynamic nature of crowd movement patterns necessitates the consideration of online learning as a promising approach. Online learning holds potential in adapting the model to accommodate evolving patterns through the incorporation of new data.

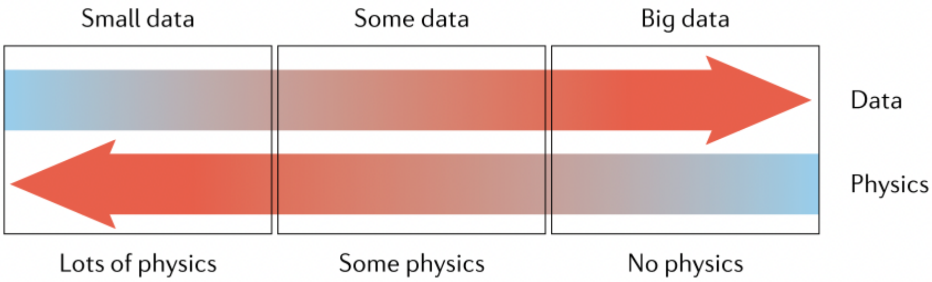

Figure 1: Paradigm of physics-driven and data-driven.

- **Limitation:** The current strategy involves using a simulator to produce synthetic data for subsequent analysis. However, a discrepancy exists between the simulated and real-world crowd dynamics due to limitations inherent in the algorithm employed for crowd simulation. Moreover, differences in data formats are expected between the real-world data collected and the simulator-generated data. These disparities could introduce uncertainties and potential challenges in the accuracy and applicability of the results we gain from the experiment. Moreover, the mathematical model data-driven model is also based on prior knowledge, therefore there still exists inductive bias.

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