SG-LSTM Dataset: A Comprehensive Dataset for Analyzing Pedestrian Behavior in Real-World Environments

Rashmi Bhaskara, Maurice Chiu, Avi Patel, Yashvardhan Khaitan and Aniket Bera
Department of Computer Science, Purdue University, USA

***Abstract*—The SG-LSTM dataset is a valuable resource for researchers in computer vision, robotics, and pedestrian behavior studies, collected at Purdue University's West Lafayette campus. This dataset focuses on annotated pedestrian groups in crowded scenes, meticulously labeled using RGB frames and depth data. It encompasses defaced color frames, precise depth frames, and annotated bounding boxes for pedestrian groups and individuals. Covering diverse scenarios from busy thoroughfares to serene plazas, crosswalks, and even inclement weather and nighttime situations, this dataset captures the dynamic outdoor environment. The data collection was carried out autonomously by the GO1 Edu robot by Unitree Robotics, ensuring minimal disruption to pedestrians. Researchers can explore pedestrian behavior, group dynamics, and interactions within real-world settings using this dataset. It also provides essential metrics for in-depth analysis, including group size, individual walking speeds, and pedestrian proximity. The SG-LSTM dataset significantly contributes to the study of pedestrian-centric research and human-robot interactions.**

***Index Terms*—Pedestrian Behavior, Dataset, Robot Data Collection, Computer Vision, Human-Robot Interaction, Campus Environments.**

I. Introduction

Understanding pedestrian behavior in real-world outdoor environments is pivotal for various applications, including urban planning, autonomous navigation systems, and human-robot interaction. Pedestrian movements in dynamic outdoor settings are complex, and influenced by a multitude of factors, such as social interactions, environmental conditions, and individual preferences. This intricate behavior presents both challenges and opportunities for researchers and engineers seeking to design safer and more efficient urban spaces and develop advanced robotic systems capable of seamlessly interacting with pedestrians.

The study of pedestrian behavior has traditionally relied on theoretical models and controlled experiments, which, while valuable, may not fully capture the intricacies of real-world scenarios. Recognizing the need for comprehensive datasets that reflect the complexities of outdoor pedestrian dynamics, we introduce the SG-LSTM dataset.

All authors are with the Department of Computer Science, Purdue University, USA, {bhaskarr, chiu93, patel313, ykhaita aniketbera}@purdue.edu

Fig. 1. *Demonstration of FlowMNO integrated with GVO, deployed on a Robot.*

The motivation behind creating the SG-LSTM dataset stems from the increasing demand for authentic data to enhance our understanding of pedestrian behavior in outdoor settings. Urban environments are dynamic and unpredictable, and pedestrian interactions within them are influenced by a myriad of factors, from the layout of walkways to the presence of other individuals. Therefore, a realistic and diverse dataset like SG-LSTM is essential to bridge the gap between theory and practice in the field of pedestrian behavior analysis.

The SG-LSTM dataset addresses the need for high-quality, real-world data on pedestrian behavior by providing a comprehensive collection of scenarios observed within Purdue University's West Lafayette campus. This dataset meticulously records the actions, interactions, and group formations of pedestrians as they navigate this vibrant outdoor environment. It serves as a valuable resource for researchers, engineers, and urban planners seeking to develop safer and more efficient urban spaces, as well as for those working on autonomous navigation systems and human-robot interaction technologies.

This paper presents an in-depth exploration of the SG-LSTM dataset, detailing its collection process, dataset context, and the scenarios it covers within the Purdue University campus. We delve into the robot platform used for data collection and how it seamlessly captured pedestrian behavior while minimizing disruptions. Furthermore, we highlight the meticulous annotation of the dataset, showcasing its rich potential for studying pedestrian dynamics.

In subsequent sections, we discuss related work in the field of pedestrian behavior analysis and the significance of SG-LSTM in filling the existing gaps. We provide insights into the data collection process, emphasizing the methods employed to capture real-world pedestrian behavior. Additionally, we explore the diverse scenarios covered within the dataset and the relevance of each scenario for research inquiries.

The paper continues with a discussion of the roles of the robot platform and human behavior annotation in data collection. We detail the sensors used to capture RGB-D data, which is essential for comprehending pedestrian movements and interactions. We then dive deep into the metrics and parameters included in the SG-LSTM dataset, which provide a foundation for in-depth analysis of pedestrian behavior.

In the subsequent sections, we present experiments and analyses conducted using the SG-LSTM dataset, highlight potential applications, and conclude by summarizing the significance of this resource for advancing our understanding of pedestrian behavior in real-world outdoor environments.

Through the presentation of the SG-LSTM dataset and its diverse applications, this paper aims to contribute to the growing body of research on pedestrian behavior analysis and its practical implications in various fields.

II. Related Work

Understanding pedestrian behavior, human-robot interaction, and developing efficient navigation algorithms are critical research areas with a reliance on datasets. Notable datasets, like "3D point cloud and RGBD of pedestrians in robot crowd navigation" by Paez-Granados et al. [33], and "Pedestrian-Robot Interactions on Autonomous Crowd Navigation" [34], have contributed to this field. Additionally, datasets like "Depth and Appearance for Mobile Scene Analysis" by Ess et al. [35] and "MOTChallenge 2015" [36] have advanced pedestrian tracking and analysis. However, these datasets primarily focus on individual tracking and lack detailed group behavior annotations in crowded scenarios, limiting research on social interactions and group dynamics in outdoor environments.

The SG-LSTM dataset addresses gaps in pedestrian behavior analysis by meticulously annotating visible pedestrian groups in bustling scenes. This unique dataset encompasses a wide range of scenarios, capturing individual pedestrian movements and the complexities of group dynamics in Purdue University's dynamic outdoor environment. SG-LSTM empowers researchers to delve into the intricacies of pedestrian group behavior, advancing human-robot interaction, navigation algorithms, and urban planning. Its diverse scenarios provide a solid foundation for exploring various pedestrian phenomena, enhancing safety, efficiency, and innovation in urban spaces and autonomous navigation systems. SG-LSTM represents a significant contribution to the evolving field of pedestrian behavior research.

In the subsequent sections, we will delve into the data collection process of the SG-LSTM dataset, highlighting its significance in addressing the need for comprehensive pedestrian behavior data in real-world outdoor environments.

III. SG-LSTM Dataset

A. Dataset Context and Scope

The SG-LSTM dataset offers a comprehensive perspective on pedestrian behavior within the dynamic environment of Purdue University's West Lafayette campus. This dataset was meticulously curated to address the need for in-depth insights into pedestrian behavior in real-world outdoor environments, focusing specifically on perceptually visible pedestrian groups. Purdue University's West Lafayette campus was chosen as the data collection environment due to its vibrant and bustling surroundings, providing a rich source of data for understanding how individuals interact and navigate in a dynamic outdoor setting.

B. Environment

The SG-LSTM dataset captures a diverse range of outdoor settings on Purdue University's West Lafayette campus. These settings encompass various pedestrian pathways, expansive quads, lively plazas, and other areas frequently traversed by students, faculty, and visitors. The choice of this environment was strategic, as it mirrors the complexity of real-world urban spaces and facilitates the study of pedestrian behavior within a bustling educational campus.

C. Data Collected

SG-LSTM is a multifaceted dataset that includes a rich array of data types crucial for comprehensive pedestrian behavior analysis. It comprises defaced color frames, precise depth frames, and meticulously annotated bounding boxes encapsulating both pedestrian groups and individual pedestrians. This diverse data collection empowers researchers to explore the intricate dynamics of pedestrian interactions, group formations, and individual behaviors within a real-world outdoor context.

D. Scenarios

The SG-LSTM dataset covers a wide spectrum of scenarios representing real-world pedestrian interactions within the Purdue University campus. These scenarios are essential for gaining insights into various facets of pedestrian behavior, human-robot interaction, and navigation algorithms. Some of the key scenarios include:

- **Campus Thoroughfare during Class Transitions:** This scenario captures the bustling thoroughfares of the Purdue University campus during class transitions, providing valuable insights into a high-density pedestrian flow, group formations, and navigational dynamics.
- **Campus Plaza Gatherings:** SG-LSTM meticulously documents scenarios where pedestrians congregate in campus plazas, offering opportunities to study pedestrian interactions in relaxed and social contexts. Researchers

can delve into group formations, stationary behavior, and social dynamics within these settings.

- **Cafeteria and Dining Areas:** The dataset includes observations within cafeteria and dining areas, where pedestrians engage in queueing, seating, and mealtime activities. This scenario is particularly relevant for understanding pedestrian behavior in semi-confined spaces, including queue dynamics, seating preferences, and dining interactions.
- **Pedestrian Crosswalks and Intersection Points:** SG-LSTM captures scenarios at pedestrian crosswalks and intersections within the campus, pivotal for investigating pedestrian-vehicle interactions, adherence to traffic rules, and pedestrian decision-making when navigating complex crossing scenarios.
- **Outdoor Study Spaces:** Researchers can explore scenarios in outdoor study spaces, where students engage in academic activities such as studying, group discussions or working on laptops. This setting provides insights into stationary behavior, outdoor furniture use, and environmental factors influencing pedestrian choices.
- **Green Spaces and Leisure Areas:** The dataset offers a glimpse into scenarios within green spaces and leisure areas on campus, facilitating the study of pedestrian behavior in recreational contexts, including leisurely walks, picnics, and social interactions in open environments.
- **Campus Events and Gatherings:** SG-LSTM covers scenarios during campus events and gatherings, such as sports events, rallies, or performances. These scenarios involve unique crowd dynamics, including crowd density, directional flow, and the effects of event-specific factors on pedestrian behavior.
- **Building Entrances and Exits:** Detailed observations are available for scenarios at building entrances and exits, crucial points for pedestrian ingress and egress. Researchers can investigate the efficiency of entry/exit processes, congestion patterns, and the impact of building architecture on pedestrian flow.
- **Inclement Weather Situations:** The dataset includes instances of inclement weather scenarios, allowing for the study of how adverse weather conditions influence pedestrian behavior, including shelter-seeking, altered walking speeds, and the use of indoor pathways.
- **Nighttime Scenarios:** SG-LSTM extends its coverage to nighttime scenarios on campus. These observations offer insights into pedestrian behavior under reduced visibility conditions, including lighting effects, altered routes, and safety considerations.

These diverse scenarios within the SG-LSTM dataset provide a robust foundation for research inquiries, enabling investigations into pedestrian-centric phenomena across various real-world, dynamic environments.

IV. Data Collection Process

A. Robot Platform and Behavior

The GO1 Edu robot, a creation by Unitree Robotics, expertly facilitated the data collection process for SG-LSTM. This innovative robot played a pivotal role in capturing data as it autonomously navigated through the dynamic environment of Purdue's West Lafayette campus. The key features of the robot's behavior during data collection included precision and minimal disruption to pedestrians. This methodology ensured that the dataset accurately represents the natural behavior of individuals on campus.

B. Human Behavior

In the SG-LSTM Dataset, manual annotation tracked pedestrian groups using data from Purdue Campus and a 3D point cloud, alongside a publicly available RGB-D pedestrian dataset [33]. A reference algorithm processed RGB frames to outline pedestrians accurately, while also extrapolating their positions relative to the robot's coordinates based on [4]. Key metrics, like group size, walking speed, and spatial proximity, were computed to assess group cohesiveness. Pedestrians were classified into groups per [4], and CVAT.ai was used for precise bounding box generation. This robust methodology establishes SG-LSTM as a valuable resource for research in pedestrian behavior analysis, human-robot interaction, and urban planning.

C. Sensors

SG-LSTM relies on state-of-the-art RGB-D cameras for data capture. These cameras are proficient in capturing vibrant color frames and precise depth data. The combination of RGB and depth information is instrumental in comprehending the intricacies of spatial relationships and the nuanced movements of pedestrians within the Purdue campus. This sensor setup ensures that the dataset contains rich and detailed data, enabling in-depth analysis of pedestrian behavior in real-world outdoor environments.

V. Tasks and Metrics

SG-LSTM provides researchers with comprehensive metrics tailored for in-depth analysis of pedestrian behavior. These metrics encompass essential parameters, including group size, individual pedestrian walking speeds, and proximity between pedestrians. The meticulous collection of these metrics serves as a strong foundation for modeling and scrutinizing pedestrian behavior, particularly elucidating the cohesiveness and interactions within pedestrian groups. Researchers can leverage these metrics to gain valuable insights into various aspects of pedestrian behavior, furthering the understanding of real-world outdoor interactions and contributing to advancements in related fields.

VI. Experiments and Analysis

In the SG-LSTM dataset, extensive experiments were conducted to analyze pedestrian behavior, group cohesiveness, and interactions across various real-world scenarios. These experiments provided valuable insights into the complexities

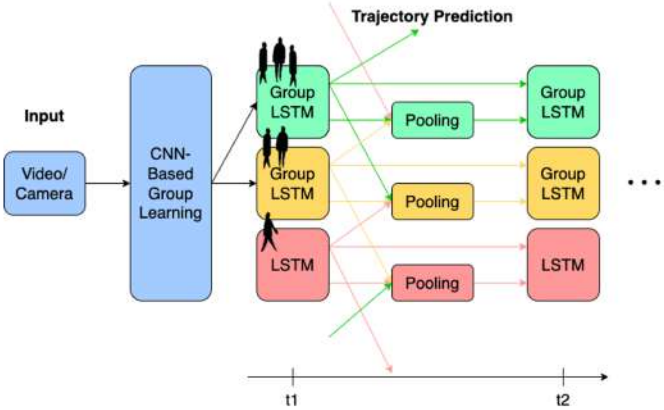

Fig. 2. Overview of SG-LSTM model. RGB frames captured from the camera will go through group detection so that spatial coordinates can be extrapolated and fed as input to the architecture.

of human group dynamics within crowded environments. Specifically, the dataset was employed in the development and evaluation of the Social Group Long Short-term Memory (SG-LSTM) model [1], designed to predict pedestrian movements and interactions effectively. The SG-LSTM model integrates social group awareness into the Social-LSTM architecture, resulting in significantly enhanced trajectory predictions. This innovation empowers navigation algorithms to compute collision-free paths with increased speed and accuracy, particularly in complex and crowded scenarios.

The performance of the SG-LSTM model was rigorously evaluated through extensive experiments on multiple datasets, including ETH, Hotel, and MOT15. Various prediction approaches, such as Linear, LSTM, O-LSTM [2], and S-LSTM [2], were compared. The findings are summarized in Tab. I and Tab. II:

TABLE I
QUANTITATIVE RESULTS OF ALL THE METHODS ON DIFFERENT DATASETS.

Metric and Methods	Datasets		
Avg. Displacement Error	**ETH**	**MOT15**	**Our Dataset**
Linear	0.80	0.93	0.65
LSTM	0.60	0.67	0.43
O-LSTM	0.49	0.59	0.32
S-LSTM	0.50	0.57	0.38
SG-LSTM (Ours)	**0.35**	**0.40**	**0.23**
Final Displacement Error	**ETH**	**MOT15**	**Our Dataset**
Linear	1.31	1.01	0.91
LSTM	1.31	0.70	0.58
O-LSTM	1.06	0.66	0.41
S-LSTM	1.07	0.69	0.42
SG-LSTM (Ours)	**0.68**	**0.48**	**0.27**

VII. APPLICATIONS

The SG-LSTM dataset presents a versatile resource with numerous potential applications spanning various domains. These applications capitalize on the rich insights into pedestrian behavior and group dynamics offered by SG-LSTM.

One key avenue of application lies in **Dynamic Group Formation Prediction**, where SG-LSTM data serves as the foundation for developing predictive models. These models anticipate the emergence of social groups within crowded environments, enabling robots to adapt their navigation strategies accordingly. Techniques encompass object detection, tracking, social group identification through clustering, behavioral analysis of historical data, and machine learning, including Long Short-Term Memory (LSTM) networks. The inclusion of real-time data integration ensures the models remain adaptive during robot navigation.

TABLE II
AVERAGE RUNTIME FOR EACH MODEL TO COMPUTE A TRAJECTORY MEASURED ON A DENSELY-CROWDED SCENE

Methods	Average Runtime (ms)
Linear	8.4
S-LSTM	101
O-LSTM	63
Vanilla-LSTM	57
SG-LSTM (**Ours**)	**45**

Another promising application pertains to **Human-Robot Team Formation** in public spaces. SG-LSTM facilitates the investigation of methods for autonomous robots to form ephemeral teams with social groups. These ad-hoc teams collaborate on tasks like information dissemination and crowd management. Strategies encompass behavioral analysis of natural group coordination, reinforcement learning for robotic engagement with groups, Natural Language Processing (NLP) for communication, creation of simulation environments for training, and task allocation algorithms for efficient cooperation.

Furthermore, the dataset supports **Cross-Cultural Social Navigation** research. This area explores how social navigation systems can adapt to diverse cultural norms and group behaviors, enhancing the global applicability of robot navigation. Cultural patterns in group dynamics preferred interpersonal distances, communication styles, and common group formations can be identified through SG-LSTM analysis. Cultural semiotics modeling, integrating natural language processing and computer vision, interprets cultural symbols and signs related to group interactions. Adaptive navigation policies that align with cultural norms are implemented, while user feedback loops from diverse cultural backgrounds validate system adaptability.

These applications underscore the dataset's immense potential, not only in advancing research but also in fostering innovation in human-robot interaction, pedestrian simulation, urban planning, and related fields. Researchers, practitioners, and developers stand to benefit significantly from the wealth of data and insights offered by SG-LSTM.

VIII. CONCLUSION

In summary, the SG-LSTM dataset stands as a pivotal resource for advancing our knowledge of pedestrian dynamics, driving innovation in diverse fields, and shaping the future of human-robot interactions in bustling outdoor environments. Researchers and practitioners alike will find immense value in this comprehensive dataset for years to come.

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