2024 IEEE International Conference on Robotics and Automation (ICRA 2024)
May 13-17, 2024. Yokohama, Japan

Adaptive Pedestrian Agent Modeling for Scenario-based Testing of Autonomous Vehicles through Behavior Retargeting

Golam Md Muktadir
Computer Science and Engineering
University of California, Santa Cruz
muktadir@ucsc.edu

Jim Whitehead
Computational Media
University of California, Santa Cruz
ejw@ucsc.edu

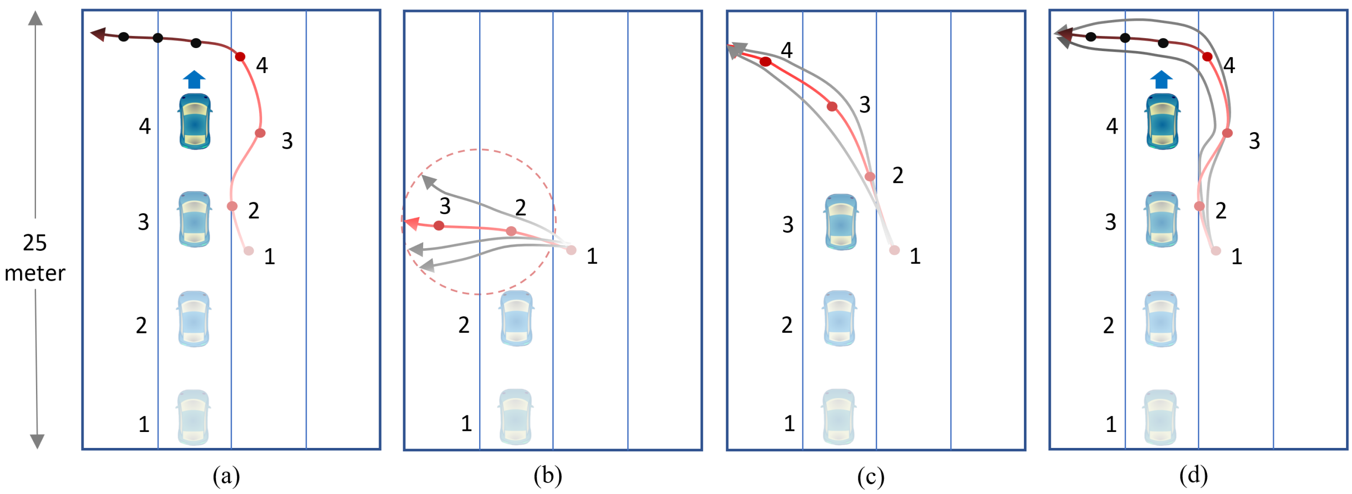


Fig. 1: A real-world scenario and three modeling approaches. (a) In a 4-lane unidirectional road, the vehicle drives at 20 mph, shown at four interesting time steps (1-4). The pedestrian walks in a wavering fashion and suddenly crosses in front of the vehicle (dots at the same time steps). (b) Existing simulation models have low expressiveness and limited spatial and temporal variance, yielding simple behaviors. (c) Goal-based planners and Social-Force-based methods do not allow controllability and reproducibility of events. (d) Our modeling approach captures the original behavior and allows adaptability.

***Abstract*—This work proposes a new representation of pedestrian crossing scenarios and a hybrid modeling approach, RePed, that facilitates transferring microscopic behavior models from behavior research to higher-level trajectories. With this, real-world trajectory-based scenarios can be augmented with a diverse set of human crossing maneuvers, producing a wealth of new scenarios and addressing the scarcity of rare case data that existing works struggle to deal with. Leveraging the controllability of this modeling approach, perturbation-based augmentation can be applied to enrich scenarios further. In addition, the representation is rooted in the Ego vehicle's coordinate system with a logical representation of roads. This design enables scenario retargeting to various road structures, traffic conditions, and ego vehicle behaviors. Thus, it strongly supports scenario-based testing by forcing pedestrians to produce certain situations in simulation even when the Ego Vehicle tries to evade them.**

***Index Terms*—Pedestrian Behavior Modeling, Jaywalker Modeling, Scenario-based Testing of Autonomous Vehicles, Pedestrian Simulation, Pedestrian Scenario Modeling, Midblock Crossing**

I. Introduction

Pedestrians do the darndest things. Consider the jaywalking pedestrian in the leftmost panel of Figure 1, from the Pedestrian Situated Intent (PSI) 2.0 dataset [1]. In this scenario, a vehicle is cruising along the second lane in a four-lane one-way road. The pedestrian is in the lane immediately to its right. The scenario starts at *step 1* with the pedestrian approximately 15 meters away and walking towards the vehicle's lane, showing crossing intent by *step 2*. However, they change their decision and start to move away, leading the driver to think they will not cross the road. The cautious human driver slows down a tiny bit, anticipating the potential for a dangerous situation (*step 3*). Suddenly, the pedestrian changes direction, approaches the vehicle's lane, and starts crossing (*step 4*) within a fraction of a second. Luckily, the pedestrian safely crosses the road without getting hit or making the vehicle stop.

Though this kind of pedestrian scenario is rare, it does happen, and most human drivers have had to handle unexpected pedestrian behavior. Hence, autonomous vehicles must also safely handle these rare pedestrian scenarios. Now, imagine an ego vehicle is driving instead of the human one. Different ways of handling this situation can lead to varying outcomes. In the first variation, at step 3, the ego vehicle might speed up, assuming the pedestrian will not cross, leading to a dangerous situation at step 4. In the second variation, the ego vehicle moves much faster to pass the pedestrian before they begin crossing, avoiding any collision. In the third, the ego vehicle moves to the empty left-most lane, where the pedestrian might never challenge them. As we can see, due to possible variations in the ego vehicle's driving strategy, it is hard to ensure that they experience the near-miss event at step 4 like the human driver. From this, we identify *two different problems* in achieving the goal of testing the scenario against the ego vehicle at the *target situations in steps 3 and 4*: (a) reproducing the scenario and (b) adapting the scenario.

Existing literature addresses these two problems separately, resulting in either suboptimal performance in reproduction or limited adaptation capability. Figure 1.b illustrates a machine learning-based approach that takes past trajectories of all the actors around the pedestrian and generates the future trajectory of the pedestrian. However, these methods cannot express dramatic long-term spatial and temporal variance due to the scarcity of rare scenario training data. In addition, it is hard to control the behavior of such models, making reproducibility harder to achieve. Figure 1.c shows potential solutions to both problems involving Goal-based planners and Social-Force-Based behaviors, which can produce a simplified version of the pedestrian trajectories towards the destination point. However, they overlook the exciting events in between. An alternative approach involves creating a trajectory follower model that compels pedestrians to replicate the exact trajectory from a rare scenario. Nevertheless, this approach precludes the adaptability of the pedestrian against any change in the scenario, such as vehicle speed, vehicle lane, lane width, and the presence of other traffic participants.

We introduce a pedestrian scenario retargeting method, **RePed**, that can represent rare pedestrian scenarios and systematically adapt them to various test situations. This adaptation includes adjustments for varying vehicle speed, lane changes, and differences in lane count and width (*depicted in Figure 1.d*). Our approach overcomes the expressivity limitations of current methods via a hybrid modeling approach that can utilize the best parts of the existing approaches. It allows reproducibility, adaptability, and controllability of the pedestrian behavior model.

The adaptability of our model ensures that ego vehicles are challenged by the target situations even when the ego vehicle's trajectory changes and the scenario tries to drift away during testing. The adaptability is achieved through a set of retargeting methods, which has a broader application to other types of traffic participants. The controllability of our model yields more advantages in addition to ensuring reproducibility and further variability using perturbation techniques. Search-based methods in scenario-based testing can use our proposed control parameters to create a search space to cover the possible range of variety, such as the minimum and maximum speed range of the vehicle under test.

We review relevant literature in Section II and outline our methods in Section III. The simulation results of our behavior retargeting methods are presented in Section IV, while Section V explores the limitations and outlines future research prospects.

II. RELATED WORK

Testing of autonomous driving in simulation involves creating a set of agents such as vehicles, pedestrians, and bicycles that mimic the real-world behavior of human road users. The testing process aims to identify critical scenarios (see [2]) where the ego vehicle behaves unexpectedly. On one end, testing methods replay real-world scenarios where the behavior of all the traffic participants is pre-determined except for the vehicle under test (the ego vehicle) [3]–[5]. However, it's often desirable to create variations of a scenario to stress-test the ego vehicle or adapt the behavior of other actors to the changing behavior of the ego vehicle [6]. On the opposite end, some methods have actors show completely random behavior by sampling from a set of predefined actions, and testing methods search for critical scenarios over a huge search space [7], [8], which can lead to unrealistic scenarios [9]. Realistic behaviors exhibit structured inter-dependencies, significantly reducing the search space. The exploration of this trade-off between extremes is an active area of research in scenario generation methods (*see comprehensive surveys in [9]–[13]*).

With realistic behavior models of traffic participants including pedestrians, scenario-generation methods get more freedom in creating random valid situations. Unfortunately, extensive exploration of pedestrian behavior is hindered by the complexity of human behavior and the scarcity of recorded data on rare events. Refer to [14] for a comprehensive literature review of pedestrian behavior modeling for AV testing. On another note, crowd behavior literature does not address individual-level diversity and richness and does not aim to capture rare behavior in road crossings, [15]–[18].

This work is closely related to individual-level pedestrian crossing modeling, a crucial source of test scenarios for AV testing, [19]. The modeling problems during road-crossing can be categorized into three areas: (a) physical constraints, (b) maneuvers, and (c) crossing trajectory. Physical constraints define the boundaries of pedestrian movement such as speed, direction change, and reaction time. Maneuvers include speeding up, avoiding collision, retreating, and hand-signaling. Crossing trajectories involve movement plans using physical constraints and maneuvers. Some methods are good at modeling physical constraints [20]–[24], some at maneuvers [25]–[32], and some at producing long-term trajectories, [33]–[44].

Physical constraint-based models require high-level trajectory and maneuver planners to be used as simulation models. Manuever-based models require high-level trajectory planners. Methods adept at modeling maneuvers are often employed in generating long-term trajectories, but they tend to produce less diverse trajectories due to tight coupling with interaction modeling. For instance, in the Social-Force-based approach, [25], high-level trajectory is generated by an attractive destination force. However, it is easy to model physical constraints and maneuvers with a limited amount of data and transfer the behavior enabling existing work outputs directly reusable. This motivates us to improve their trajectory generation process.

Various trajectory generation methods exist. Supervised learning and sequence modeling can create long trajectories but aren't suitable for road crossing scenarios, [45]. Another approach focuses on pedestrian pose trajectories using Generative AI, [34]. However, these machine learning-based methods struggle to model rare trajectories, transfer behaviors across settings, and are challenging to control for scenario search. Reinforcement learning-based methods such as [43], [46]–[48] learn specific outcomes defined by reward functions, limiting diversity and rare scenarios. Non-machine learning-based methods use path search in free areas, [33].

Recognizing the limitations of existing methods, we propose a hybrid approach that blends high-level pedestrian trajectories with low-level microscopic maneuvers. This approach has the potential to inject variability and diversity at both levels. By enabling the transfer of behavior across different scenarios, adapting to the ego vehicle's actions, and exposing control parameters, our proposed method empowers scenario generation techniques to craft novel yet realistic scenarios with a greater degree of flexibility.

III. METHODOLOGY

Our approach represents pedestrian trajectories using two main techniques. At a coarse level, the path of a pedestrian is modeled as a navigation path (NavPath) moving from one navigation point (NavPoint) to another in order. Fine-grained behavior is determined by a Behavior Primitive, which controls the pedestrian position from second to second. The process of creating a test scenario from a pedestrian behavior video involves (a) determining a set of NavPoints consistent with the observed pedestrian locations and (b) determining one or more Behavior Primitives that match observed pedestrian behaviors. We describe the representation of the Navigation Path, Behavior Primitives, the role of the Behavior Matcher in augmenting the Navigation Path, retargeting during the test, and how scenarios are adapted in simulation.

A. Navigation Path (NavPath)

A **NavPath**, comprised of **NavPoint**s, is a sparse pedestrian trajectory in the ego vehicle's coordinate system. Each pedestrian in a scenario is described as a NavPath. Key NavPath characteristics include:

- Represents only coarse directional movement, abstracting away micro-level behavioral variation.
- Tied to the vehicle coordinate system, so, if the vehicle reference frame moves, it also moves.
- Can be somewhat imprecise, allowing for flexibility in scenario crafting.

The Navpath's goal is to record behavior changes (which occur at NavPoints) and travel direction in pedestrian movement. These elements challenge ego vehicle prediction models. This representation plays the central role in representing diversity in pedestrian paths and behavior, whether manually crafted or automatically derived from real-world data or trained models.

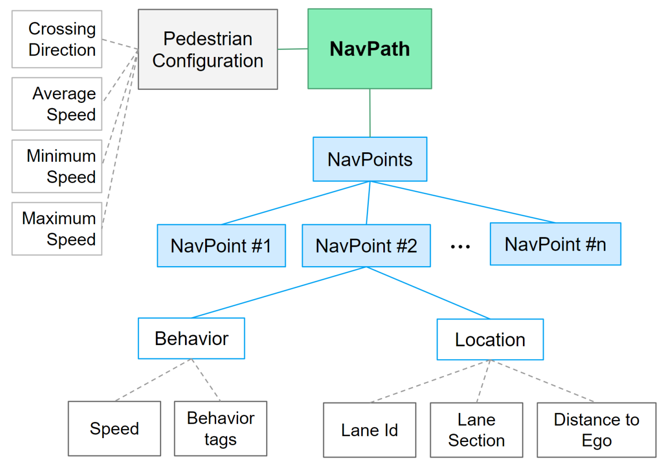


Fig. 2: Structure of the Navigation Path

Figure 2 illustrates the structure of a NavPath. A NavPath contains a set of NavPoints, each with associated behavioral and location properties. The NavPath itself also contains properties for pedestrian information, such as crossing direction (left-to-right or right-to-left) relative to the ego vehicle's travel axis (see Figure 3).

A NavPoint defines a pedestrian's state concerning the vehicle at a specific time. Key properties are *LaneId* (0 for ego lane, negative/positive for left/right lanes), *Lane Section* (LEFT (L), MIDDLE (M), RIGHT (R)), *Distance to Ego* (on ego vehicle's axis), and *Original Speed. For details, refer to Appendix 5.*

NavPoint properties achieve three goals: (1) retargeting for diverse road structures and ego vehicle locations, (2) translating behaviorally significant locations based on ego

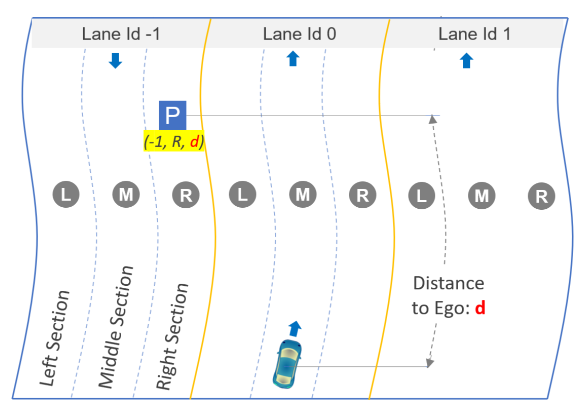


Fig. 3: In this three-driving-lane road, NavPoint *P* has Lane Id: -1, Lane Section: R (right), and distance: d.

vehicle behavior, and (3) allowing fuzzing techniques while retaining the link to the ego vehicle's behavior.

B. Behavior Primitives (Behavior Tags)

Behavior primitives represent unique microscopic pedestrian behaviors (maneuvers) that happen sequentially on a trajectory. Each primitive has microscopic spatial and temporal variation based on pedestrian age, background, mental state, weather, road structure, and other traffic participants. This work proposes a few fundamental behavior primitives, emphasizing the unpredictability observed in the PSI 2.0 dataset, [1]:

- **Evasive Stop:** A complete halt within a roadway while crossing (*see Figure 5*).
- **Evasive Flinch:** Resembling Evasive Stop, this maneuver includes a brief backward movement, occurring involuntarily and rapidly creating two situations (*see Figure 4*).
- **Evasive Retreat:** The pedestrian voluntarily steps back to safety from an approaching vehicle, a process that can take seconds (*see Figure 4*).
- **Evasive Speedup:** The pedestrian increases speed to avoid the approaching vehicle. (*see Figure 5*)
- **Evasive Slowdown:** The pedestrian reduces speed to let the vehicle pass, often leading to near-collision scenarios (*see Figure 5*).

Each behavior primitive is defined based on existing literature (*see Section II*) and is characterized by its own set of controllable parameters.

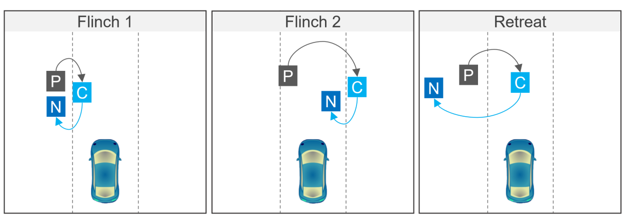


Fig. 4: Flinch maneuver can place the pedestrian out of the way or in front of the ego vehicle. Retreat follows a longer path with voluntary movement. *P, C, and N* are previous, current, and next pedestrian locations respectively.

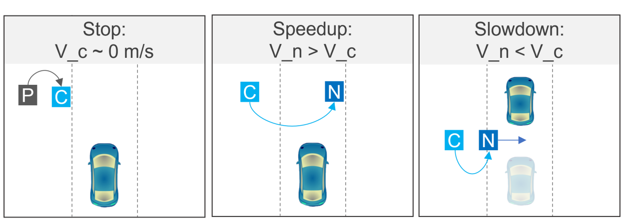


Fig. 5: Evasive stop happens when the pedestrian speed is nearly 0. Speedup or Slowdown is characterized by acceleration/deceleration to avoid accidents.

C. Behavior Matcher

The Behavior Matcher matches a portion of the NavPath with a Behavior Primitive representing observed behaviors in the video. It augments the sparse trajectory defined by a NavPath with possible maneuvers. We have developed constraint-based pattern-matching methods for each behavior primitive, where each NavPoint is evaluated against all the matcher methods. *Detailed current set of constraints available at the link in Appendix 4*.

Given the current NavPoint N_{curr}, previous NavPoint N_{prev}, next NavPoint N_{next}, a future NavPoint N_{future}, distance between X, Y on ego travel axis $dLon(X, Y)$ in meters and on the lateral axis $dLat(X, Y)$ in lane sections, lateral side of Y with respect to X $side(X, Y)$, the summary of the constraints for each primitive is set forth below :

- **Evasive Stop:** speed(N_{curr})<Evastive Stop Threshold (defaults to 0.1 m/s).
- **Evasive Flinch:** N_{prev} and N_{next} are on the same side of N_{curr} and
  - $dLat(N_{next}, N_{curr})$<Lateral Threshold (defaults to one lane section width)
  - $dLon(N_{prev}, Ego)$<Longitudinal Threshold (defaults to 0.5 meters).
- **Evasive Retreat:** There exists a N_{future} such that $dLat(N_{curr}, N_{future}) >$ Lateral Threshold (defaults to two-lane section width) and :
  - N_{prev} and N_{future} are on the same side of N_{curr}.
  - $dLon(N_{future}, N_{prev}) <$ Longitudinal Threshold (defaults to 0.5 meters).
- **Evasive Speedup:** There N_{future} in front of the ego such that $speed(N_{future}) < speed(N_{curr})$ and
  - $side(Ego, N_{curr}) <> side(Ego, N_{future})$
  - Angle between $direction(N_{curr}, N_{future})$ and $direction(N_{first}, N_{last}) < 90°$
  - There is no NavPoint between N_{curr} and N_{future}
- **Evasive Slowdown:** There exists N_{future} such that $speed(N_{future})$ <$speed(N_{curr})$ and
  - $side(Ego, N_{curr}) == side(Ego, N_{future})$
  - Angle between $direction(N_{curr}, N_{future})$ and $direction(N_{first}, N_{last}) < 90°$

D. Retargeting

Our current retargeting methods accommodate some key changes in ego behavior and road structure:

- **Lane Count:** We can retarget a m-lane scenario to a n-lane one using relative NavPaths.
- **Lane Width:** NavPoints handle lane width variations seamlessly (*due to logical lane sections*).
- **Ego Lane Change:** During simulation, ego vehicle lane changes are accommodated by re-planning.
- **Ego Speed Change:** Pedestrian speed is adjusted to meet the relative *distanceToEgo* constraint during ego vehicle speed changes.

E. Simulation Process

See Figure 6 for an overview of the scenario realization process in simulation. The pedestrian is reactive and adaptive.
Steps in Simulation:

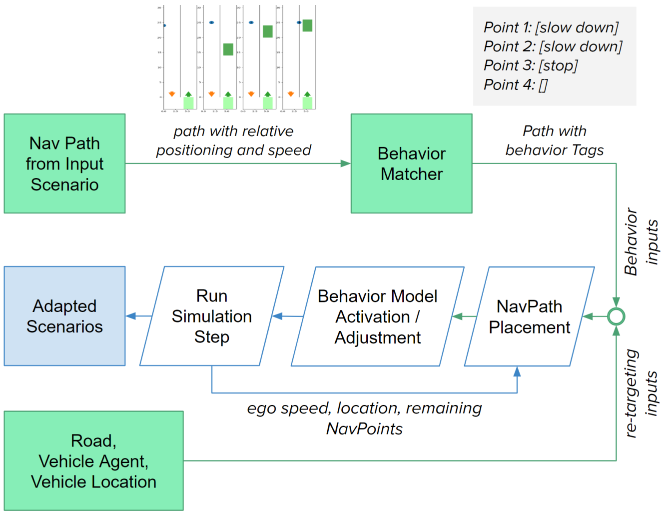


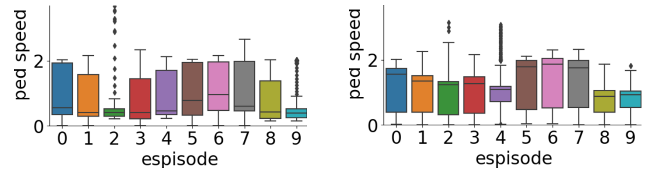
Fig. 6: The test simulator takes two sets of inputs: Pedestrian navigation paths with behavior tags and vehicle agent, location, and road maps. Before the testing begins, the Behavior Matcher (III-C) tags the navigation points with Behavior Primitive Types (III-B). During a simulation loop, models for different primitives are activated or deactivated based on the proximity to specific NavPoints and NavPoints are translated based on ego-vehicles location, and road structure.

1) The Behavior Matcher (BM) consumes a NavPath and tags each NavPoint with Behavior Primitives (BP).
2) The tagged NavPath, Road, Ego vehicle, and its spawn location are given to the simulator as the inputs.
3) An *initial trajectory plan* for pedestrians is made based on road structure and ego vehicle's position and lane, with lateral perturbations in NavPoint locations.
4) As pedestrians approach NavPoints, activated BPs guide their movement, estimating time to the next destination while preserving spatial constraints with respect to the ego. Previous NavPoints are discarded.
5) If the ego changes lanes, then the pedestrian's *trajectory is re-planned* based on the remaining NavPoints.

The implementation architecture is available in Appendix 1, and the process and mathematical models of NavPoint realization are available in Appendix 5.

IV. Evaluation

The validity of retargeting is explored by (a) examining the range of generated pedestrian velocities to ensure they are within plausible ranges, and (b) examining the distribution of pedestrian speeds vs. ego vehicle speeds. We explore scenarios that were generated via the translation of *PSI 2.0 Video #0015* into a NavPath with the stopping behavior modeled using Evasive Stop. The video shows a pedestrian coming to a stop in the middle of the road, allowing a vehicle (avg. speed 19 km/hr) to pass. To explore different scenarios, we *retargeted this video to two different road configurations*: a 2-lane road and a 4-lane road where the ego vehicle changes lanes. In both cases, the pedestrian starts crossing from the left sidewalk, and the ego vehicle



(a) 2-lane road (b) 4-lane road + lane change

Fig. 7: Pedestrian speed (in ms^{-1}) distribution of first ten episodes (trajectories) in each retargeting settings.

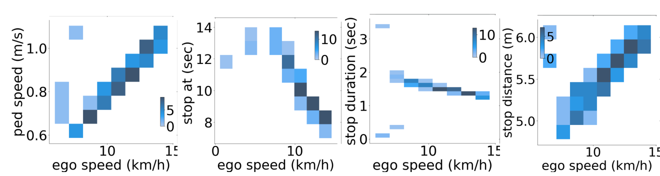
starts in the right lane closest to the center of the road. In the four-lane configuration, the ego vehicle makes a lane change to the right-most lane, thereby moving away from the pedestrian. Each configuration was run in simulation for 100 episodes, with *ego vehicle speed varying in each run*, uniformly sampled in the range of [10, 30] km/h. NavPoint locations are also *laterally perturbed* by adding a noise value to their location. *We skipped the detailed evaluation of variability and diversity of maneuver models as retargeting is our main contribution.*

A. Pedestrian Speed Distribution

Figure 7 shows pedestrian speed data (sampled 25 times a second) for the first 10 (of 100) simulation runs for each road configuration. The median pedestrian speed is moderate and speed distribution resembles real-world after retargeting, (*see [49]*). However, several runs in the 2-lane road have moments exceeding 2 m/s, and the 4-lane road has moments exceeding 2.5 m/s, which is a running speed. The fast speeds in the 4-lane scenario are due to the pedestrian needing to quickly catch up to the ego vehicle which has switched lanes away from the pedestrian.

B. Retargeting against Ego Speed

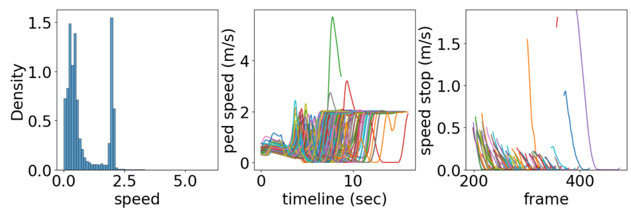
Figure 8a shows a series of joint distributions of vehicle speed vs. pedestrian speed. *Pedestrian successfully adapts to vehicle speed changes*. As pedestrian speed increases, the distance required to stop increases, and the pedestrian starts stop maneuver earlier, figure 8b. *The y-axis variation is due to lateral perturbation in NavPoint location in lane sections and destination force model* by Helbing, [25]. Figure 8c shows the stop duration. The variation happens due to the vehicle's speed trajectory, which impacts the Evasive Stop's duration. Figure 8d shows the variation in distance between



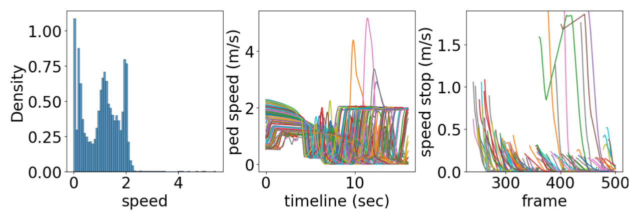
(a) (b) (c) (d)

Fig. 8: Joint distribution of pedestrian (a) speed and vehicle (ego) average speeds, (b) stop-start time and vehicle speed at that time, (c) stop distance and vehicle average speed, and (d) stop duration and vehicle average speed, in 2-lane scenarios.

the pedestrian and the vehicle when the pedestrian makes a stop. The variation along the y-axis occurs due to the pedestrian agent's time-gap estimation, *which exemplifies the variability introduced by maneuver models*.



(a) 2-lane road with speed change only.



(b) 4-lane road with speed and lane change.

Fig. 9: Distribution of pedestrian speed *(left)*, speed trajectories *(middle)*, speed and frame at the moment of Evasive Stop activation *(right)*.

C. Retargeting against Roads and Ego Lane Change

Figure 9 shows, for both 2-lane and 4-lane configurations, the distribution of pedestrian speeds, the variation of pedestrian speed over time, and the pedestrian speed at the moment the pedestrian decided to begin stopping for Evasive Stop. *The stopping statistics in figure 9b show that the pedestrian model successfully adapts when the vehicle makes a lane change*. Due to the lane change, the Evasive Stop tends to activate later (most stop activation times are greater than 300 frames). To accommodate the lane change, we can see an increase in pedestrian speed in general as they have to travel further. As this re-planning is done while the simulation is in progress, the pedestrian sometimes runs to catch up, (*see Figure 7*). The pedestrian failed to catch up in 1 episode.

D. Scenario Expressiveness

In the current implementation of the simulator, we have successfully represented all scenarios within the PSI 2.0 dataset with single pedestrians on straight and curved roads. However, since this dataset has midblock crossings only, additional work is required to represent intersection scenarios because inside intersections the notion of lanes changes.

V. Limitations and Future Work

This study focused on Behavior Primitives and the Behavior Matcher using PSI 2.0 data. Future research could enhance scenario expressiveness by utilizing alternative datasets such as the Waymo Open Dataset [50], NuScenes [51], or *behaviorally rich YouTube Dashcam Videos* such as [52]. Future expressiveness tasks:

- Expanding Behavior Primitives with new ones such as *dropping and picking up items while crossing and gestures perceivable by drivers [31], [32]*.
- Implementing vehicle collision avoidance models for near-collision situations. However, the vehicle repulsive force model such as [28] performs poorly in out-of-distribution situations. We suggest a set of models based on reachability sets, [33], or rules, [53].

Another direction would be automatic NavPath extraction from dense trajectories or videos. Interestingly, NavPath works smoothly even when the trajectories are broken, which is common in trajectory extraction from videos (*see [54]*). Future work should explore it more.

Lastly, future work should explore retargeting methods for road structures not addressed in this work such as intersections, where nearly fifty percent of accidents happen [55]. incorporating various traffic participants, occlusions, and obstacles by extending the NavPath representation.

VI. Conclusions

In conclusion, this paper introduces a novel hybrid modeling approach for addressing the challenges in pedestrian behavior modeling and scenario-based testing against pedestrians for autonomous vehicles. It offers a unique contribution to the field by combining the strengths of existing pedestrian behavior modeling approaches to achieve scenario reproduction, adaptability, and controllability.

Our approach excels in reproducing real-world pedestrian crossing scenarios, ensuring the rigorous testing of autonomous systems against rare and complex events. Furthermore, its adaptability allows for modifying pedestrian behavior in response to changing scenarios, making it a valuable tool for testing under diverse conditions. The controllable nature of our model provides the added benefit of introducing variability through perturbation techniques, enabling a wide range of test scenarios. Future research can explore its application to various traffic participants and further refine its implementation, offering a promising avenue for continued advancements in autonomous vehicle development and testing.

Appendix

1) https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model.md - Model Architecture
2) https://github.com/adhocmaster/carla-jaywalker-experiments - Python Implementation for CARLA
3) https://github.com/adhocmaster/carla-jaywalker-experiments/tree/main/data/navpath - NavPath Dataset
4) https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model-behavior.md - Behavior Primitives & Matcher
5) https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model-navpath.md - NavPath & Navpoint

References

[1] PSI 2.0. Pedestrian Situated Intent (PSI) Bencharmark. [Online]. Available https://github.com/PSI-Intention2022/PSI-Dataset, last accessed on 09/08/2023.

[2] ISO/PAS 21448:2019. Road vehicles — Safety of the intended functionality. [Online]. Available https://www.iso.org/standard/70939.html, last accessed on 09/08/2023.

[3] F. Montanari, C. Stadler, J. Sichermann, R. German, and A. Djanatliev, "Maneuver-based resimulation of driving scenarios based on real driving data," *2021 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1124–1131, 2021.

[4] F. Hauer, I. Gerostathopoulos, T. Schmidt, and A. Pretschner, "Clustering traffic scenarios using mental models as little as possible," *2020 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1007–1012, 2020.

[5] J. J. So, I. Park, J. Wee, S. Park, and I. Yun, "Generating traffic safety test scenarios for automated vehicles using a big data technique," *KSCE Journal of Civil Engineering*, vol. 23, pp. 2702–2712, 2019.

[6] F. Hauer, A. Pretschner, and B. Holzmüller, "Re-using concrete test scenarios generally is a bad idea," *2020 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1305–1310, 2020.

[7] S. Feng, X. Yan, H. Sun, Y. Feng, and H. X. Liu, "Intelligent driving intelligence test for autonomous vehicles with naturalistic and adversarial environment," *Nature Communications*, vol. 12, 2021.

[8] S. Kuutti, S. Fallah, and R. Bowden, "Training adversarial agents to exploit weaknesses in deep control policies," *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 108–114, 2020.

[9] W. Ding, C. Xu, M. Arief, H. ming Lin, B. Li, and D. Zhao, "A survey on safety-critical driving scenario generation—a methodological perspective," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, pp. 6971–6988, 2022.

[10] L. Birkemeyer, C. King, and I. Schaefer, "Is scenario generation ready for sotif? a systematic literature review," *ArXiv*, vol. abs/2308.02273, 2023.

[11] T. Menzel, G. Bagschik, and M. Maurer, "Scenarios for development, test and validation of automated vehicles," *2018 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1821–1827, 2018.

[12] S. Riedmaier, T. Ponn, D. Ludwig, B. Schick, and F. Diermeyer, "Survey on scenario-based safety assessment of automated vehicles," *IEEE Access*, vol. 8, pp. 87 456–87 477, 2020.

[13] Z. Zhong, Y. Tang, Y. Zhou, V. de Oliveira Neves, Y. Liu, and B. Ray, "A survey on scenario-based testing for automated driving systems in high-fidelity simulation," *ArXiv*, vol. abs/2112.00964, 2021.

[14] G. M. Muktadir, "Adversarial testing for autonomous vehicle trajectory prediction algorithms using pcg - research proposal," 12 2021.

[15] S. Curtis, A. Best, and D. Manocha, "Menge: A modular framework for simulating crowd movement," *Collective Dynamics*, vol. 1, pp. 1–40, 2016.

[16] D. C. Duives, W. Daamen, and S. P. Hoogendoorn, "State-of-the-art crowd motion simulation models," *Transportation research part C: emerging technologies*, vol. 37, pp. 193–209, 2013.

[17] S. Paris, J. Pettré, and S. Donikian, "Pedestrian reactive navigation for crowd simulation: a predictive approach," in *Computer Graphics Forum*, vol. 26, no. 3. Wiley Online Library, 2007, pp. 665–674.

[18] S. Yang, T. Li, X. Gong, B. Peng, and J. Hu, "A review on crowd simulation and modeling," *Graphical Models*, vol. 111, p. 101081, 2020.

[19] P. Chen, W. Zeng, and G. Yu, "Assessing right-turning vehicle-pedestrian conflicts at intersections using an integrated microscopic simulation model." *ACCIDENT ANAL PREV*, pp. 211–224, 2019.

[20] A. Sobhani, B. Farooq, and Z. Zhong, "Distracted pedestrians crossing behaviour: Application of immersive head mounted virtual reality," in *2017 IEEE 20th ITSC*. IEEE, 2017, pp. 1–6.

[21] H. A. Mohammed, "Assessment of distracted pedestrian crossing behavior at midblock crosswalks," *IATSS Research*, 2021.

[22] X. Zhang, P. Chen, H. Nakamura, and M. Asano, "Modeling pedestrian walking speed at signalized crosswalks considering crosswalk length and signal timing," 2013.

[23] W. J. Yu, R. Chen, L. Y. Dong, and S. Dai, "Centrifugal force model for pedestrian dynamics." *Physical review. E, Statistical, nonlinear, and soft matter physics*, vol. 72 2 Pt 2, p. 026112, 2005.

[24] M. Chraibi, A. Seyfried, and A. Schadschneider, "Generalized centrifugal-force model for pedestrian dynamics." *Physical review. E, Statistical, nonlinear, and soft matter physics*, vol. 82 4 Pt 2, p. 046111, 2010.

[25] Helbing and Molnár, "Social force model for pedestrian dynamics." *Physical review. E, Statistical physics, plasmas, fluids, and related interdisciplinary topics*, pp. 4282–4286, 1995.

[26] M. Liu, W. Zeng, P. Chen, and X. Wu, "A microscopic simulation model for pedestrian-pedestrian and pedestrian-vehicle interactions at crosswalks," *PLoS ONE*, vol. 12, 2017.

[27] D. Yang, Ü. Özgüner, and K. A. Redmill, "A social force based pedestrian motion model considering multi-pedestrian interaction with a vehicle," *ACM Transactions on Spatial Algorithms and Systems (TSAS)*, vol. 6, pp. 1 – 27, 2020.

[28] W. Zeng, P. Chen, H. Nakamura, and M. Iryo-Asano, "Application of social force model to pedestrian behavior analysis at signalized crosswalk," *TRANSPORT RES C-EMER*, pp. 143–159, 2014.

[29] C. Burstedde, K. Klauck, A. Schadschneider, and J. Zittartz, "Simulation of pedestrian dynamics using a two dimensional cellular automaton," *Physica A-statistical Mechanics and Its Applications*, vol. 295, pp. 507–525, 2001.

[30] D. Kim and A. Quaini, "A kinetic theory approach to model pedestrian dynamics in bounded domains with obstacles," *Kinetic & Related Models*, 2019.

[31] C. Myers, T. Zane, R. V. Houten, and V. T. Francisco, "The effects of pedestrian gestures on driver yielding at crosswalks: A systematic replication." *Journal of applied behavior analysis*, 2022. [Online]. Available: https://api.semanticscholar.org/CorpusID:246475211

[32] X. Zhuang and C. Wu, "Pedestrian gestures increase driver yielding at uncontrolled mid-block road crossings," *Accident Analysis & Prevention*, vol. 70, pp. 235–244, 2014.

[33] M. Hartmann and D. Watzenig, "Pedestrians walking on reachable sets and manifolds," in *2019 IEEE International Conference on Mechatronics (ICM)*, vol. 1, 2019, pp. 562–569.

[34] J. Spooner, V. Palade, M. Cheah, S. Kanarachos, and A. Daneshkhah, "Generation of pedestrian crossing scenarios using ped-cross generative adversarial network," *Applied Sciences*, no. 2, 2021.

[35] Y. Huang, H. Bi, Z. Li, T. Mao, and Z. Wang, "Stgat: Modeling spatial-temporal interactions for human trajectory prediction," *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 6271–6280, 2019.

[36] A. Alahi, K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese, "Social lstm: Human trajectory prediction in crowded spaces," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 961–971, 2016.

[37] P. Xu, J.-B. Hayet, and I. Karamouzas, "Socialvae: Human trajectory prediction using timewise latents," in *European Conference on Computer Vision*, 2022.

[38] P. Zhang, W. Ouyang, P. Zhang, J. Xue, and N. Zheng, "Sr-lstm: State refinement for lstm towards pedestrian trajectory prediction," *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 12 077–12 086, 2019.

[39] M. Lisotto, P. Coscia, and L. Ballan, "Social and scene-aware trajectory prediction in crowded spaces," *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, pp. 2567–2574, 2019.

[40] B. F. de Brito, H. Zhu, W. Pan, and J. Alonso-Mora, "Social-vrnn: One-shot multi-modal trajectory prediction for interacting pedestrians," in *Conference on Robot Learning*, 2020.

[41] B. Cheng, X. Xu, Y. Zeng, J. Ren, and S. Jung, "Pedestrian trajectory prediction via the social-grid lstm model," *The Journal of Engineering*, 2018.

[42] A. Postnikov, A. Gamayunov, and G. Ferrer, "Conditioned human trajectory prediction using iterative attention blocks," *2022 International Conference on Robotics and Automation (ICRA)*, pp. 4599–4604, 2022.

[43] P. Nasernejad, T. Sayed, and R. Alsaleh, "Modeling pedestrian behavior in pedestrian-vehicle near misses: A continuous gaussian process inverse reinforcement learning (gp-irl) approach." *ACCIDENT ANAL PREV*, p. 106355, 2021.

[44] P. Kothari, S. Kreiss, and A. Alahi, "Human trajectory forecasting in crowds: A deep learning perspective," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, pp. 7386–7400, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:220381085

[45] W. Ding, J. Chen, and S. Shen, "Predicting vehicle behaviors over an extended horizon using behavior interaction network," *2019 International Conference on Robotics and Automation (ICRA)*, pp. 8634–8640, 2019.

[46] D. Chen, E. Yurtsever, K. A. Redmill, and U. Ozguner, "Using collision momentum in deep reinforcement learning based adversarial pedestrian

modeling," *2023 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1–6, 2023.

[47] A. Rafiei, A. O. Fasakhodi, and F. Hajati, "Pedestrian collision avoidance using deep reinforcement learning," *International Journal of Automotive Technology*, vol. 23, pp. 613 – 622, 2022.

[48] G. Vizzari and T. Cecconello, "Pedestrian simulation with reinforcement learning: A curriculum-based approach," *Future Internet*, vol. 15, p. 12, 2022.

[49] Parth Kothari and Sven Kreiss and Alexandre Alahi. Trajnet++ Tools. [Online]. Available https://github.com/vita-epfl/trajnetplusplustools, last accessed on 09/13/2023.

[50] P. Sun, H. Kretzschmar, X. Dotiwalla, A. Chouard, V. Patnaik, P. Tsui, J. Guo, Y. Zhou, Y. Chai, B. Caine, V. Vasudevan, W. Han, J. Ngiam, H. Zhao, A. Timofeev, S. Ettinger, M. Krivokon, A. Gao, A. Joshi, Y. Zhang, J. Shlens, Z. Chen, and D. Anguelov, "Scalability in perception for autonomous driving: Waymo open dataset," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

[51] H. Caesar, V. Bankiti, A. H. Lang, S. Vora, V. E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan, and O. Beijbom, "nuscenes: A multimodal dataset for autonomous driving," *arXiv preprint arXiv:1903.11027*, 2019.

[52] Polish Roads. PEDESTRIAN ACCIDENTS #1. [Online]. Available https://www.youtube.com/watch?v=eu4QqwsfXFE, last accessed on 09/14/2023.

[53] C. Ningbo, W. Wei, Q. Zhaowei, Z. Li-ying, and B. Qiaowen, "Simulation of pedestrian crossing behaviors at unmarked roadways based on social force model," *Discrete Dynamics in Nature and Society*, vol. 2017, pp. 1–15, 2017.

[54] Z. Zhang, J. Gao, J. Mao, Y. Liu, D. Anguelov, and C. Li, "Stinet: Spatio-temporal-interactive network for pedestrian detection and trajectory prediction," *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 11 343–11 352, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:218581874

[55] FHWA. Intersection Safety. [Online]. Available https://highways.dot.gov/research/research-programs/safety/intersection-safety, last accessed on 09/14/2023.