GEP-RRT*: Smooth and Predictable Vehicle Trajectory Planning for Pedestrian-Vehicle Interaction in Shared Environments

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Abstract— **Accurate pedestrian behavior prediction in pedestrian-vehicle interaction (PVI) scenarios depends critically on the quality of surrounding vehicle motion as a contextual input. However, standard sampling-based planners such as RRT* produce jagged, erratic trajectories due to uninformed random sampling, introducing noise into the vehicle motion context and degrading prediction reliability. We propose GEP-RRT*, a two-stage framework that generates smooth, consistent vehicle trajectories suitable for PVI scenarios. An improved RRT* with flexible boundary re-parameterization, global-path target tracking, and a task-oriented metric rapidly produces a kinematically compliant initial path; a corridor-constrained genetic algorithm then jointly optimizes path length, smoothness, safety margins, and global consistency. Validated across 90 simulation trials and 240 real-vehicle experiments on a pedestrian-shared campus road, GEP-RRT* achieves 0.19 s average planning time (91.8% faster than RRT*), reduces steering angle variation by up to 73.5%, and maintains 100% planning success across all tested speed conditions.**

I. INTRODUCTION

Pedestrian behavior prediction in pedestrian-vehicle mixed environments relies not only on modeling pedestrian dynamics but also on accurately characterizing the motion of surrounding vehicles [1]. Prediction models in such scenarios must jointly reason over vehicle trajectories and pedestrian states: the vehicle's future position, heading, and motion consistency directly condition a pedestrian's crossing decision and serve as a primary contextual input to prediction frameworks [2]. Despite this coupling, the quality of the vehicle trajectory output by the onboard planner is rarely treated as a factor affecting downstream prediction performance.

Standard sampling-based planners such as RRT* [3] are widely deployed for autonomous vehicle motion planning, but uninformed random sampling produces jagged, oscillatory paths. Such erratic trajectories introduce temporal inconsistency into the vehicle motion signal, reducing the reliability of vehicle intent estimation in pedestrian prediction models. Post-processing smoothing partially mitigates this, but adds latency incompatible with real-time PVI systems and decouples trajectory quality from the planner's optimization objectives.

We propose **GEP-RRT***, a two-stage planner that (i) accelerates RRT* convergence through directional, intent-aware sampling and (ii) refines trajectory quality within a safety corridor via multi-objective evolutionary optimization—producing smooth, consistent vehicle motion that provides a reliable context for pedestrian behavior prediction in shared environments.

II. METHOD

A. Stage 1: Improved RRT* with Directional Guidance

Standard RRT* is augmented with three enhancements that collectively embed directional intent into tree growth.

Flexible Boundary Re-parameterization. Virtual lane boundaries are constructed by laterally offsetting the global path, and a virtual obstacle is inserted at a speed-dependent safety distance

$$D_{\mathrm{vir}} = D_0 + \frac{v^2}{2a_{\mathrm{brake}}} + t_{\mathrm{rec}}\, v, \tag{1}$$

to confine the feasible sampling region and suppress invalid node generation.

Global-Path Target Tracking (GPTT). A goal-bias probability p_{goal} directs tree expansion toward a look-ahead target on the global path, reducing the iterations required to establish the first feasible connection.

Task-Oriented Metric. Nearest-neighbor selection uses a composite metric weighting spatial distance and heading deviation jointly, promoting kinematically smooth tree growth and reducing steering discontinuities in the resulting path. Together, these three enhancements produce smooth, temporally consistent trajectories that directly reduce motion signal noise for downstream pedestrian prediction models operating in PVI scenarios.

B. Stage 2: Corridor-Constrained Genetic Optimization

Given the initial path $\mathcal{P}_0 = \{S_i\}_{i=1}^{n}$ from Stage 1, a safety corridor is constructed by expanding each node perpendicular to the local path direction by

$$D_{\mathrm{ep}} = 0.5\, W_d + d_{\mathrm{safe}}, \tag{2}$$

where W_d is the vehicle width. A genetic algorithm (GA) refines $\mathcal{P}_0$ within this corridor using a multi-objective fitness function

$$f_{\mathrm{total}} = w_l\, f_{\mathrm{length}} + w_s\, f_{\mathrm{smooth}} + w_d\, f_{\mathrm{deviation}} + w_o\, f_{\mathrm{obstacle}}, \tag{3}$$

jointly optimizing path length, curvature smoothness, global-path adherence, and collision clearance. Two adaptive operators are employed: *ASAC-GPTT* crossover, which segments genes by global-path deviation with fitness-adaptive crossover probability, and *Adaptive Mutation*, which adjusts mutation rate per individual to preserve high-quality solutions while maintaining population diversity.

The complete two-stage pipeline is illustrated in Fig. 1.

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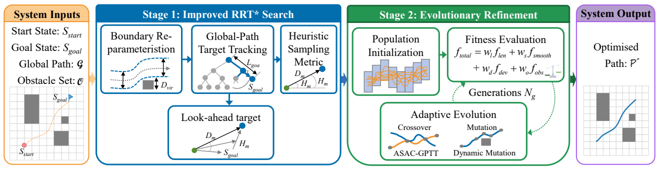


Fig. 1. System overview of GEP-RRT*. Stage 1 produces an initial path via improved RRT*; Stage 2 refines it through corridor-constrained GA optimization.

TABLE I

REAL-VEHICLE RESULTS (20 RANDOMIZED TRIALS PER SPEED PER METHOD)

Method & Metric	**5 km/h**	**15 km/h**	**25 km/h**	**35 km/h**
GEP-RRT* t_{avg} (s)	**0.190**	**0.185**	**0.190**	**0.188**
GEP-RRT* r_{steer} (rad)	**0.040**	**0.041**	**0.077**	**0.234**
GEP-RRT* s_{rate} (%)	**100**	**100**	**100**	**100**
RRT* t_{avg} (s)	2.320	1.553	1.293	0.849
RRT* r_{steer} (rad)	0.165	0.188	0.225	0.985
RRT* s_{rate} (%)	100	100	100	95
Inf. RRT* t_{avg} (s)	1.135	0.335	0.325	0.349
Inf. RRT* r_{steer} (rad)	0.184	0.222	0.290	0.238
Inf. RRT* s_{rate} (%)	100	100	95	90

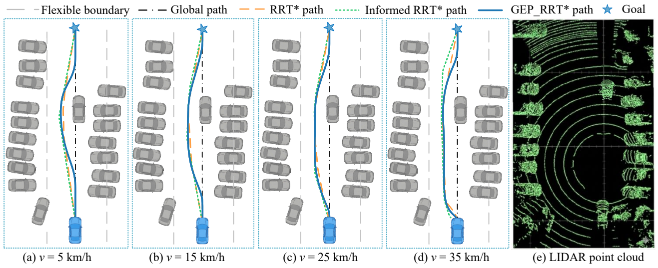
III. EXPERIMENTAL VALIDATION

A. Setup and Baselines

Simulation experiments were conducted in MATLAB on a cluttered static environment over 30 independent randomized trials per method (start $[25, 25]$, goal $[381, 381]$, theoretical optimum $C_{\text{opt}} = 506$). Real-vehicle experiments were performed on a campus road with pedestrians present, featuring narrow passages formed by parked vehicles on both sides and a static obstacle within the driving corridor, using a JAC "Yiwei 3" platform (Intel Core i7-10700; 128-line LiDAR; 0.2 m grid resolution) over 20 trials per speed per method, totaling 240 planning instances across four speed profiles (5, 15, 25, 35 km/h). This scenario is representative of low-speed PVI environments where pedestrian presence constrains the feasible corridor and demands temporally stable vehicle motion. All methods were compared against **RRT*** [3] and **Informed RRT*** [4].

B. Results

Table I reports the aggregate real-vehicle results. GEP-RRT* maintains a stable planning time of $\approx$0.19 s across all speeds, improving efficiency by up to **91.8%** and **83.3%** over RRT* and Informed RRT* at 5 km/h. Steering angle variation (r_{steer}) is reduced by up to **73.5%** at 25 km/h, yielding a low-noise, temporally consistent vehicle motion signal well suited for use as input to pedestrian prediction models. The 100% planning success rate is maintained at all speeds, while both baselines degrade at higher velocities. All comparisons are statistically validated via Wilcoxon signed-rank tests ($p < 0.01$) over 240 planning instances.



(a) v = 5 km/h (b) v = 15 km/h (c) v = 25 km/h (d) v = 35 km/h (e) LIDAR point cloud

Fig. 2. Real-vehicle planning results at 5–35 km/h in a constrained campus scenario. GEP-RRT* (blue) produces smooth, consistent trajectories; baselines exhibit jagged paths and failure at higher speeds.

Qualitative trajectory comparisons are shown in Fig. 2. GEP-RRT* consistently produces smooth, globally coherent paths across all speed conditions, whereas RRT* and Informed RRT* exhibit oscillatory trajectories and late-stage convergence failure in the narrowed passage.

In simulation, GEP-RRT* deviates only **0.3%** from the theoretical optimum (vs. 0.8% for RRT*; 0.4% for Informed RRT*) with 15–33% lower computation time. Under a reduced iteration budget (2000 vs. 5000), path cost remains nearly constant while computation time drops 75.4%, confirming robustness under limited resources.

IV. CONCLUSION

We present GEP-RRT*, a two-stage motion planner combining guided heuristic sampling with corridor-constrained evolutionary refinement. The framework achieves real-time performance (0.19 s average), substantially reduced steering variation, and 100% planning success without offline training or post-processing.

Beyond planning efficiency, this work addresses a PVI-level problem: pedestrian behavior prediction models depend on vehicle motion as a contextual input [1], and trajectory noise from planners such as RRT* directly degrades this context. GEP-RRT* provides a smooth, temporally stable vehicle motion signal that reduces input noise for downstream pedestrian prediction modules. Future work will couple GEP-RRT* with pedestrian intention prediction frameworks to evaluate whether planning-layer smoothness yields measurable gains in prediction accuracy under realistic PVI conditions.

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