Journal of Management and Planning Research
2024, 1(1), 17-30

SELF-PARKING FOR INTELLIGENT CONNECTED VEHICLES IN GATED RESIDENTIAL COMMUNITIES: MULTI-SENSOR FUSION LOCALIZATION AND PATH-PLANNING ALGORITHM DESIGN

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As cities continue to densify, intelligent connected vehicles increasingly encounter practical challenges in parking—especially in gated residential communities where tight layouts and diverse obstacles demand higher-performing autonomous parking solutions. To address autonomous parking in narrow residential parking bays, this study presents a path-planning approach built on multi-sensor fusion localization. An environmental sensing platform is developed using 12 ultrasonic sensors and four high-definition cameras, and a fusion framework is constructed by combining a camera model, an IMU measurement model, and a wheel-speed (tachometer) kinematic model. An enhanced inverse-expansion Hybrid A planning method is introduced to boost efficiency by swapping the start and goal positions, allowing node expansion to proceed from the constrained interior space toward a more open area. Simulation results indicate that planning completes within 1.4 seconds across scenarios, with a best-case runtime of 0.75 seconds. Parking-space feasibility tests show that at 3 km/h the minimum required space is 6.821 m × 2.164 m, increasing to 7.058 m × 2.205 m at 6 km/h. The method achieves safe planning for both perpendicular and parallel parking, while keeping the vehicle's intersection-position error relative to the parking boundary within 12 cm. Overall, the proposed approach offers a practical and effective technical pathway for autonomous parking in complex residential settings.*

Index Terms — intelligent connected vehicle, multi-sensor fusion, autonomous parking, path planning, Hybrid algorithm, localization

INTRODUCTION

Throughout the course of urban growth, the planning and construction of residential districts has remained a central concern. Among the prevailing development patterns, *closed residential areas* are especially common and exert long-lasting influence on urban spatial structure, residents' daily routines, and broader social development [1, 2, 3, 4]. A closed residential area typically refers to a neighborhood with clearly defined boundaries—often delineated by walls or fences—that limits unrestricted entry by non-residents while providing internal property management and supporting services [5, 6, 7]. Historically, this community form has addressed demands for security, privacy, and environmental quality for extended periods [8, 9]. Nevertheless, closed residential areas also introduce notable drawbacks. In societies with high car ownership, perimeter barriers can fragment the urban road network, reduce network permeability, intensify parking pressure, and lower overall traffic efficiency. In this context, intelligent connected vehicle (ICV) autonomous parking systems offer a promising way to mitigate these constraints [10, 11, 12, 13].

Intelligent connected vehicles integrate advanced onboard sensing, control, and actuation technologies with modern communication and networking capabilities. By enabling V2X information exchange and shared situational awareness, such vehicles can support complex environment perception, intelligent decision-making, cooperative control, and reliable execution, with the long-term aim of achieving safe, comfortable, energy-efficient, and highly efficient mobility that can partially or fully replace human driving operations [14, 15, 16, 17]. Within this broader ICV ecosystem, autonomous parking has progressed relatively quickly and is often considered one of the more mature application domains. For instance, BenQ Electronics has proposed an unmanned parking solution that addresses parking constraints through a vehicle handling approach described as whole-vehicle suspension during the parking process [18, 19, 20]. Likewise, Bosch's VoiceParkSystem explores driver-assist intelligent parking technology that allows users to specify a desired parking location by voice, after which the system searches for an available space, performs the parking maneuver automatically, and records the process using an onboard recording device [21, 22, 23, 24].

Traffic congestion and shortages of parking resources are becoming increasingly severe in modern cities, and the problem is particularly acute in densely populated residential districts where parking difficulty has become a key determinant of residents' quality of life. The spatial characteristics of closed residential areas—including narrow passages, intricate geometric layouts, and tightly arranged parking spaces—pose substantial challenges for conventional manual parking. Drivers must execute precise maneuvers within constrained spaces, which not only demands high driving skill but also raises collision risk. Moreover, repeated reversing and incremental adjustments extend parking duration and reduce overall parking throughput. Against this background, intelligent autonomous parking technology provides a compelling pathway for improvement. By combining advanced sensing with intelligent algorithms, an autonomous parking system can complete parking maneuvers without continuous driver intervention, reducing driver burden while improving both accuracy and efficiency. However, the complex environments typical of closed residential areas impose higher technical requirements on autonomous parking systems, notably in high-precision environment perception, robust vehicle localization, and efficient path planning.

Motivated by these challenges, this study proposes an integrated technical solution. First, a multi-sensor fusion localization framework is developed by combining measurements from ultrasonic sensors, high-definition cameras, inertial measurement units (IMUs), and wheel tachometers to obtain accurate estimates of vehicle state and surrounding environmental features. Next, a complete set of sensor and motion models is established—including a camera projection model, an IMU error model, and a vehicle kinematic model—to provide the theoretical foundation for subsequent data fusion. Then, to address narrow-space characteristics in closed residential environments, an improved inverse extended Hybrid A* path-planning algorithm is designed; planning efficiency and path quality in complex scenarios are enhanced through an optimized

Figure 1: Image-data processing flow for localization and mapping (schematic).

search strategy and a refined cost-function formulation. Finally, simulation experiments across multiple parking scenarios are conducted to validate the effectiveness and robustness of the proposed approach, thereby providing technical support for real-world deployment.

AUTONOMOUS PARKING PATH PLANNING BASED ON MULTI-SENSOR FUSION LOCALIZATION

This section models the parking task using the environmental data acquisition framework and sensor models, and then develops a path-planning method built upon multi-sensor fusion localization. The proposed approach is intended to support the autonomous parking system design for intelligent connected vehicles operating in closed residential areas.

Environmental Data Acquisition System

Accurate autonomous parking requires reliable perception of the near-field environment, correct identification of vacant parking spaces, and verification that the detected space satisfies the constraints needed for automated maneuvers. The environmental data acquisition system considered here integrates short-range ultrasonic sensors, long-range ultrasonic sensors, and high-definition cameras distributed around the vehicle body. These sensors estimate distances to surrounding vehicles and obstacles, while ABS wheel-speed sensors provide velocity signals that are used to infer traveled distance. By combining distance observations with motion information, the system constructs an environmental model of the parking space and evaluates whether its dimensions are sufficient for parking.

Using ultrasonic scanning, the distance between the vehicle and nearby obstacles can be measured in real time. With the ABS wheel-speed signal, the system estimates the vehicle's incremental displacement and uses this information to infer candidate parking-space boundaries.

Because an ultrasonic beam typically covers a sector-shaped region, a single ultrasonic measurement cannot directly determine the orientation of a detected object. During forward motion, variations in speed and lateral offset change echo timing and can introduce measurement ambiguity. Therefore, in the automated parking assist (APA) process, the vehicle tracks its trajectory and continuously corrects observations using real-time data from the full sensor set (e.g., 12 ultrasonic sensors), enabling robust space detection and parking execution.

Figure 1 illustrates the image-data processing pipeline. Based on the imaging characteristics of spatial scanning, a camera-based ranging model is established by constructing a visual projection relationship and computing distances from camera to corresponding feature points in real space. A comprehensive evaluation model is then used to estimate final parking-space length and width, as well as the relative distance between the entering vehicle and the parking space. In practice, the fusion scheme combines ultrasonic sensing with AVM (around-view monitoring) fusion technology to support parking-space detection, path planning, vehicle localization, and steering-control tracking, thereby enabling automatic parking into the target slot. The APA controller is integrated into the AVM panoramic controller. The sensing configuration includes six ultrasonic sensors and one HD camera at both the front and rear of the vehicle, plus one HD camera at each of the left and right rearview mirrors, yielding a total of twelve ultrasonic sensors and four HD camera modules.

Sensor Models

Camera Model

The mapping from a three-dimensional point to a two-dimensional image can be described by a geometric camera model, typically decomposed into a projection model and a distortion model. Common projection models include the pinhole model, omnidirectional models, and uniform projection models; among these, the pinhole camera model is most widely used. It idealizes imaging as projection through a virtual pinhole, with the imaging plane located opposite the pinhole. Due to inversion through the pinhole, the formed image is flipped relative to the real scene. Under the pinhole model, the relationship between a 3D point and its image projection follows from similar triangles. For a point $P(X,Y,Z)$ and its pixel coordinate $p(u,v)$ on the image plane:

$$\begin{aligned} u &= f_x \frac{X}{Z} + c_x, \\ v &= f_y \frac{Y}{Z} + c_y, \end{aligned} \tag{1}$$

where f_x and f_y denote focal lengths in pixel units along the horizontal and vertical directions, respectively, and (c_x, c_y) is the principal point (the intersection of the optical axis with the image plane in pixel coordinates).

To improve imaging quality, cameras employ lens modules; lens geometry alters light propagation so that straight lines in the environment may appear curved on the image plane. This effect is commonly modeled as radial distortion (e.g., barrel or pincushion distortion). Additionally, slight angular misalignment between the lens and the image plane can introduce tangential distortion. A common approach is to model distortion with a polynomial form. Considering a normalized-plane point $p(x,y)$ with radius r, radial distortion may be expressed as:

$$\begin{aligned} x_{\text{distorted}} &= x\left(1 + k_1 r^2 + k_2 r^4 + k_3 r^6\right), \\ y_{\text{distorted}} &= y\left(1 + k_1 r^2 + k_2 r^4 + k_3 r^6\right), \end{aligned} \tag{2}$$

and tangential distortion can be corrected using coefficients p_1, p_2:

$$\begin{aligned} x_{\text{distorted}} &= x + 2p_1 xy + p_2(r^2 + 2x^2), \\ y_{\text{distorted}} &= y + p_1(r^2 + 2y^2) + 2p_2 xy. \end{aligned} \tag{3}$$

Combining radial and tangential terms yields:

$$\begin{aligned} x_{\text{distorted}} &= x\left(1 + k_1 r^2 + k_2 r^4 + k_3 r^6\right) + 2p_1 xy + p_2(r^2 + 2x^2), \\ y_{\text{distorted}} &= y\left(1 + k_1 r^2 + k_2 r^4 + k_3 r^6\right) + p_1(r^2 + 2y^2) + 2p_2 xy. \end{aligned} \tag{4}$$

Finally, distorted normalized coordinates are mapped back to pixel coordinates using intrinsic parameters:

$$\begin{aligned} u &= f_x x_{\text{distorted}} + c_x, \\ v &= f_y y_{\text{distorted}} + c_y. \end{aligned} \tag{5}$$

IMU Measurement and Motion Modeling

An IMU typically contains three-axis accelerometers and three-axis gyroscopes (six degrees of freedom), which measure linear acceleration and angular velocity along three orthogonal directions. Attitude estimation often requires time integration of these measurements, which can accumulate error; therefore, IMU error sources must be modeled.

IMU errors are commonly separated into deterministic components (e.g., bias, scale factor, and non-orthogonality) that can be estimated via calibration, and stochastic components (e.g., measurement noise and bias random walk), typically modeled as Gaussian noise. A standard IMU measurement model is:

$$\begin{aligned} \mathbf{a}^B &= \mathbf{R}_W^B(\mathbf{a}^W - \mathbf{g}^W) + \mathbf{b}_a + \mathbf{n}_a, \\ \omega^B &= \omega_{\text{true}}^B + \mathbf{b}_\omega + \mathbf{n}_\omega, \end{aligned} \tag{6}$$

where $\mathbf{a}^B$ and ω^B denote accelerometer and gyroscope measurements, $\mathbf{a}^W$ is the true acceleration in the world frame $\{W\}$, $\mathbf{g}^W$ is gravity, $\mathbf{R}_W^B$ is the rotation from $\{W\}$ to the body frame $\{B\}$, $\mathbf{b}_a$ and $\mathbf{b}_\omega$ are biases, and $\mathbf{n}_a$ and $\mathbf{n}_\omega$ are measurement noises.

Wheel Tachometer Kinematic Modeling

Real vehicles generally follow Ackermann steering geometry, where steering is controlled by the front-wheel mechanism and a differential distributes torque across the rear wheels, enabling different wheel speeds during turns. For simplified modeling, the Ackermann model is often reduced to a bicycle model. Under this simplification, the vehicle motion is treated as planar, and the left and right wheels on the same axle are assumed to share an equivalent speed and steering angle.

Given the average front-wheel steering angle θ_H and rear-wheel speed v_R, the velocity components of the vehicle's center of mass in the x and y directions, and the yaw rate, can be expressed as:

$$\begin{aligned} \dot{\psi} &= \frac{v_R}{L}\tan\theta_H, \\ \dot{X} &= v_R\cos\psi, \\ \dot{Y} &= v_R\sin\psi, \end{aligned} \tag{7}$$

where L is the wheelbase and ψ is the vehicle yaw angle.

GNSS/RTK Positioning Considerations

GNSS estimates receiver position via trilateration using satellite signal time-of-flight and ephemeris data. In practice, positioning accuracy is degraded by long propagation distances and environmental effects such as ionospheric and tropospheric delays, weather conditions, and Doppler effects due to satellite motion, leading to non-negligible errors.

To reduce these errors, RTK (Real-Time Kinematic) techniques apply real-time differential corrections between a fixed reference station and a mobile receiver, enabling centimeter-level accuracy. The reference station, knowing its precise coordinates, estimates propagation errors and transmits correction information to the mobile receiver, which uses the differential data to correct its measurements.

Despite its high accuracy, RTK can become unreliable in underground garages or heavily occluded scenes where satellite signals are blocked. Therefore, for high-precision and high-robustness positioning in autonomous parking, GNSS/RTK must be fused with additional onboard sensors.

Parking-Problem Modeling

Vehicle Kinematic Model

In autonomous valet parking, vehicle speeds are typically limited to no more than 15 km/h on internal roads and about 5 km/h during the parking maneuver. Under these low-speed, non-extreme conditions, the following assumptions are reasonable:

1. Tire lateral slip is negligible; wheel velocity directions align with steering directions.
2. Only planar motion on the XOY plane is considered.
3. Front wheels (and rear wheels) can be approximated by a single equivalent wheel, enabling a bicycle-model representation.
4. The vehicle body and suspension are treated as rigid.

Accordingly, the vehicle can be modeled as a rigid body moving in 2D, with the vehicle coordinate origin at the rear-axle center. Let v be the velocity at the rear axle center, δ the front-wheel steering angle, L the wheelbase, L_f the front overhang, L_r the rear overhang, vehicle width $2b$, and heading angle θ relative to the world x-axis. The rear-axle center is $O_b(x,y)$. A simplified kinematic model is:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v\cos\theta \\ v\sin\theta \\ \frac{v}{L}\tan\delta \end{bmatrix}. \tag{8}$$

More generally,

$$\dot{\psi} = f(\psi, u), \tag{9}$$

with state and control defined as:

$$\psi = [x,\ y,\ \theta]^T, \tag{10}$$

$$u = [v,\ \delta]^T. \tag{11}$$

Parking-Lot Map Models

A parking-lot environment is constructed in the Gazebo simulation platform. The simulated lot includes a smart-parking capability that can identify the number of vacant spaces, space coordinates, lane geometry, and congestion indicators. To support autonomous valet parking, two complementary representations are built for the structured parking-lot scene: a topological map and a raster map.

(1) Topological map. The topological map abstracts the environment into nodes and connecting edges. Nodes represent key locations such as corners, entrances, elevators, or intersections, while edges represent traversable connections such as lanes or corridors. Compared with metric maps, topological maps are compact and easier to update, which supports route planning and obstacle avoidance. Following common smart-parking descriptions, the model adopts these conventions:

- Parking nodes record spatial coordinates and occupancy status. The system can query space location and whether it is idle or occupied via node identifiers.

- Lanes and intersections store geometric extent and congestion information, retrievable via lane and intersection identifiers.

(2) Raster map. Because the path planner must consider obstacle positions and contours, a grid-based raster map is also constructed. Raster maps store environmental occupancy in a 2D matrix, enabling simple storage and fast random access. Grid resolution can be selected based on application needs. Two raster maps are used: a global static occupancy grid for all static obstacles (without inflation, storing only occupancy), and a local dynamic grid centered on the rear-axle center that updates in real time as the vehicle moves. The local replanning stage uses inflated-grid surrogate values to generate safe, feasible local trajectories.

Vehicle Collision Detection

Collision avoidance is required throughout autonomous valet parking, making collision constraints essential. Common vehicle-contour approximations include single-circle, double-circle, and rectangular models. This work adopts a rectangular model because it closely matches the vehicle outline, reduces redundant safety margins, and improves planning precision in narrow environments. However, a rectangle is not rotation-invariant in the world frame, so its vertices must be updated based on the current vehicle state.

Let the rear-axle center be $O_b(x_r, y_r)$. Denote the rectangle vertices as $A(x_a, y_a)$ (left-rear), $B(x_b, y_b)$ (right-rear), $C(x_c, y_c)$ (right-front), and $D(x_d, y_d)$ (left-front). Using the vehicle geometry and heading θ, vertex coordinates can be computed (as in Eqs. (12)–(15) of the original formulation). Collision checking is performed by sampling points along the rectangle boundary at equal intervals and testing whether any sample lies inside an obstacle region; if so, a collision is declared.

Autonomous Parking Path-Planning Algorithm Design

To improve planning efficiency in narrow parking spaces typical of closed residential areas, this section proposes enhancements to a Hybrid A* path-planning method [25].

Cost Maps and Collision Detection

(1) Rasterized cost map. The search space is represented by a rasterized cost map storing information about traversable areas, obstacles, and non-crossable regions. Each grid cell is assigned a value in $[0, 1]$ representing traversal cost. Grid states include *Free*, *Occupied*, and *Unknown*. The *Occupied* state may further include true obstacles and inflated (buffer) regions. Classification is determined using an occupied threshold and a passable threshold.

(2) Inflated (expansion) collision detection. An expansion-based collision detection strategy is used to determine whether a vehicle pose is in collision:

1. Compute an inflation radius from vehicle parameters. Initially, the radius corresponds to the smallest set of overlapping circles that fully covers the vehicle, with circle centers placed along the vehicle longitudinal axis. Increasing the number of circles reduces the required radius and can improve detection accuracy.

2. Inflate obstacle grids outward by the inflation radius. If the radius is not an integer multiple of grid size, it is rounded up to the nearest multiple.

3. Mark all grids within the inflated obstacle region as occupied and thus non-traversable.
4. Check whether the centers of the overlapping circles lie inside inflated grids. Outcomes include: (a) collision if any center is inside the inflated region; (b) no collision if no center is inside and the grid surrogate value is below the passable threshold; (c) indeterminate if no center is inside but the surrogate value exceeds the passable threshold, in which case traversal is disallowed.

Hybrid A* Path Planning

(1) Hybrid state-space representation. Hybrid A* maintains both continuous and discretized (grid-indexed) representations of the vehicle state. The continuous state (x, y, θ) ensures smooth, drivable trajectories, where (x, y) is the rear-axle center position and θ is heading. For efficient grid search, the continuous state is discretized into $(\tilde{x}, \tilde{y}, \tilde{\theta})$ using:

$$\tilde{x} = \frac{x - O_x}{\sigma}, \qquad \tilde{y} = \frac{y - O_y}{\sigma}, \qquad \tilde{\theta} = \frac{\theta}{\sigma_\theta}, \tag{12}$$

where (O_x, O_y) is the cost-map origin, σ is grid-cell side length, and σ_θ is the discrete heading increment.

(2) Node-expansion constraints. Node expansion is realized by forward/backward motion primitives with a step length and steering constraints:

- The number of sub-steps in one expansion is a positive odd integer, and the expansion length l must exit the current grid:
$$l > 2\sigma. \tag{13}$$
- Steering is bounded by the maximum front-wheel angle $\delta_{\max}$:
$$-\delta_{\max} \leq \delta \leq \delta_{\max}. \tag{14}$$
- Steering change $\Delta\delta$ is quantized as an integer multiple of σ_θ:
$$\Delta\delta = k\sigma_\theta, \quad k \in \mathbb{Z}. \tag{15}$$

(3) Cost-function formulation. Nodes are evaluated using a cost function $f(n)$ to select the best candidate for expansion:

$$f(n) = \lambda_n g(n) + h(n) + c_n, \tag{16}$$

where $g(n)$ is the accumulated cost from the start node to the current node:

$$g(n) = \sum_{i=1}^{n} l_i, \tag{17}$$

$h(n)$ is a heuristic estimate of the remaining cost to the goal (guiding search toward the target), λ_n is a penalty coefficient controlling preference for forward vs. reverse expansion:

$$\lambda_n = \begin{cases} c_{\text{forward}}, & \text{if the expansion step is forward,} \\ c_{\text{reverse}}, & \text{if the expansion step is backward,} \end{cases} \tag{18}$$

and c_n penalizes switching direction to reduce frequent alternation between forward and reverse:

$$c_n = \begin{cases} 0, & \text{if the expansion direction is unchanged,} \\ c_{\text{direction}}, & \text{if the expansion direction changes.} \end{cases} \tag{19}$$

(4) Stepwise Reeds–Shepp connection. During node expansion, at intervals of l_{RS} the algorithm attempts to connect the current best node to the goal using a Reeds–Shepp (RS) curve. If the RS connection is collision-free, node expansion stops and the RS segment is appended to form the final path. If the RS connection collides, normal expansion continues. This strategy can reduce computation in relatively open regions but may be inefficient in cluttered spaces where most RS connections are invalid, increasing overall search time.

Reverse-Expansion Strategy for Confined Parking Spaces

For vertical and diagonal parking in tight spaces, this work modifies conventional Hybrid A* via a reverse-expansion design. The key idea is to swap the start and goal states when the goal lies inside a confined region, so that node expansion begins within the narrow slot and progresses outward into more open space. This can substantially improve planning efficiency for constrained maneuvers.

SIMULATION EXPERIMENTS FOR AUTONOMOUS PARKING PATH PLANNING

This section evaluates the proposed Hybrid A* path-planning method through autonomous parking simulations, with the aim of verifying feasibility, efficiency, and robustness under representative parking-lot conditions.

Simulation Setup and Result Analysis

Global Path Planning

To examine the applicability of the reverse-expansion Hybrid A* strategy for global parking-lot navigation, a set of simulations is conducted in a structured environment. The parking lot is modeled as an $80\,\text{m} \times 60\,\text{m}$ area, with the lower-left corner defined as the coordinate origin. The lot contains five rows of available parking spaces. The vehicle starts near the upper-left region of the map and navigates toward the vicinity of the parking rows, providing an initial approach trajectory prior to executing the final parking maneuver.

For routes that include constrained segments, the planner is combined with Reeds–Shepp connections so that both forward and reverse motion primitives are considered under vehicle kinematic constraints. In complex passages, the planned trajectory may include direction switches (forward/reverse alternation) in order to satisfy feasibility requirements while maintaining collision-free motion through narrow regions.

When the terminal parking pose is changed (i.e., different end configurations are specified), the reverse-expansion Hybrid A* method generates correspondingly different global approach paths. Across several representative scenarios, planning times remain low and the algorithm consistently produces complete, feasible trajectories within a short computation window. Table 1 summarizes the planning-time results for four tested global-planning cases; all scenarios finish within 1.4 s, demonstrating that the planner can generate global parking routes efficiently.

The weighting terms in the reverse-expansion Hybrid A* cost function have a pronounced influence on vertical-parking trajectories, particularly with respect to steering effort and the frequency of switching between forward

Table 1: Global path-planning time for representative scenarios.

Scenario	Case 1	Case 2	Case 3	Case 4
Planning time (s)	0.75	1.32	1.01	1.05

and reverse motion. To illustrate this sensitivity, three configurations are compared under identical start and goal states but with different cost weights. In *Case 1*, the penalty for switching driving direction is set high, so the planner tends to accept larger reverse-clearance requirements in exchange for fewer direction changes. In *Case 2*, the steering penalty is reduced, producing shorter paths that may require larger steering angles. In *Case 3*, the steering penalty is increased while the direction-switch penalty is reduced; the resulting trajectories are more consistent with practical parking behavior and typically yield improved driving comfort and maneuver smoothness.

Parking-Entry Path Planning

To validate reverse-expansion Hybrid $A^{\star}$ performance in the local parking-entry stage, a simulation environment consistent with the global setup is constructed ($80\,\mathrm{m} \times 60\,\mathrm{m}$), abstracted as five rows with twelve parking spaces per row.

For *vertical parking entry*, if direction switching is not allowed and the vehicle must enter head-first, the planned trajectory may initially move away from the slot to create sufficient maneuvering room, which implies a larger required free space. When reverse motion is permitted, the vehicle can complete the maneuver within a tighter slot by switching driving direction, thereby reducing the minimum spatial requirement for successful parking.

For *parallel parking*, after specifying slot parameters and the initial pose, the planner outputs a time-indexed sequence of vehicle states along the maneuver. The resulting trajectory can be interpreted as a combination of two tangent-arc segments (a gyratory-curve style maneuver). The planned motion remains kinematically feasible and yields a safe approach into the designated parking pose.

Nearby *obstacles* around the slot can alter the geometry of the planned path. Under otherwise fixed slot geometry and vehicle dimensions, adding obstacles typically increases the turning radii of the arc segments and results in a more conservative trajectory. In these obstacle-present scenarios, the vehicle remains collision-free while maintaining feasibility, at the cost of a larger maneuver envelope relative to obstacle-free conditions. In simulation-based measurements at the slot boundary, the intersection deviation remains small (e.g., on the order of centimeters), and the residual error is acceptable given vehicle curvature and the clearance maintained between the vehicle body and the slot boundaries.

Parking-Scenario Verification

To further test the proposed reverse-expansion Hybrid $A^{\star}$ method, additional simulations are carried out across varying parking-space dimensions and parking speeds, focusing on how these factors affect the gyratory-curve (two-arc) parking behavior.

Different Parking-Space Sizes

Two parallel-parking slot sizes are tested to evaluate sensitivity to space dimensions. The terminal position is fixed at $(1.163, -0.975)$, the longitudinal coordinate of the start pose is set to $y_0 = 2.1$, and the vehicle speed is held constant at $3\,\mathrm{km/h}$. The two slots are:

- $7.2\,\mathrm{m} \times 2.6\,\mathrm{m}$ (length $\times$ width),
- $7.4\,\mathrm{m} \times 2.4\,\mathrm{m}$.

The simulation shows that the planned trajectories under the two slot sizes nearly overlap: the rear-axle-center paths coincide, the vehicle pose evolution is essentially identical, and both the heading-angle profile and curvature profile match closely. This indicates that once the slot satisfies the minimum feasibility requirement and the end pose, start longitudinal coordinate, and speed are fixed, moderate increases in slot dimensions do not materially change the planned path. However, increasing *slot length* improves safety margins by increasing clearance to the outer upper corner during the maneuver, while increasing *slot width* provides comparatively less noticeable safety benefit in this setup.

Different Parking Speeds

To examine the effect of speed, two constant-speed conditions are compared using a $7.4\,\mathrm{m} \times 2.4\,\mathrm{m}$ parallel-parking slot. The terminal position is fixed at $(1.163, -0.975)$, the start longitudinal coordinate is set to $y_0 = 1.6$, and speeds are $3\,\mathrm{km/h}$ and $6\,\mathrm{km/h}$.

The planned paths differ between the two speeds even with the same end pose and the same start longitudinal coordinate. A key change is that the required aisle (approach) length increases at higher speed: the $6\,\mathrm{km/h}$ condition begins from a start pose with a larger horizontal coordinate, implying a longer maneuver corridor to satisfy curvature and feasibility constraints. Both speed conditions still allow the vehicle to park safely into the target position, but the lower-speed case exhibits larger body-orientation variation during the maneuver.

The heading-angle profiles for both speeds show a bell-shaped trend with respect to horizontal progression, but the slower-speed trajectory typically reaches a larger maximum heading angle earlier (i.e., at a smaller horizontal coordinate), reflecting a more rearward and upward maneuver relative to the higher-speed case. Similarly, curvature evolves more rapidly at the lower speed, reaching maximum curvature over a shorter horizontal distance, whereas the higher-speed condition spreads the curvature change over a longer arc length. This implies that increasing speed enlarges the gyratory-curve segment and increases the space required for a feasible maneuver.

Simulation-based minimum-slot calculations indicate that the $6\,\mathrm{km/h}$ condition requires approximately $7.058\,\mathrm{m} \times 2.205\,\mathrm{m}$, while the $3\,\mathrm{km/h}$ condition requires about $6.821\,\mathrm{m} \times 2.164\,\mathrm{m}$, corresponding to an increase of roughly $0.207\,\mathrm{m}$ in required length and $0.041\,\mathrm{m}$ in required width for the higher-speed case. Therefore, minimum feasible space depends on parking speed: larger speeds demand slightly larger slots. Since autonomous parking typically operates at low speeds, the increase in minimum required space remains modest within the tested speed range, and standard residential parking dimensions can generally satisfy the planner's feasibility constraints.

CONCLUSION

This paper addressed the autonomous parking challenge in closed residential areas, where constrained geometry, narrow passages, and dense parking layouts make manual parking inefficient and risky. To respond to these conditions, an autonomous parking framework was developed around multi-sensor fusion localization and an improved path-planning strategy tailored to tight environments. The proposed system integrates complementary sensing modalities—including ultrasonic sensors, high-definition cameras, IMU measurements, and wheel-speed information (with GNSS/RTK considered where available)—to enhance environmental perception and vehicle-state estimation, thereby providing reliable inputs for planning and control.

On the planning side, a reverse-expansion Hybrid A* method was designed to improve search efficiency when the goal lies inside confined parking spaces. By expanding nodes from the narrow target region toward a more open area and leveraging collision-aware cost mapping and stepwise Reeds–Shepp connections, the planner produces kinematically feasible, collision-free trajectories while reducing unnecessary exploration. Simulation studies in representative parking-lot environments validated that the approach can generate complete global approach paths and local parking-entry maneuvers with low computation time. The experiments further demonstrated that cost-function weighting significantly influences maneuver comfort and direction-switch frequency, and that the proposed tuning strategy yields trajectories that are more consistent with practical parking behavior. Additional scenario tests confirmed that, once minimum geometric feasibility is satisfied, moderate increases in parking-space size have limited effect on the planned path, whereas higher parking speeds modestly increase the minimum space required for safe execution.

Overall, the results indicate that combining multi-sensor fusion localization with the reverse-expansion Hybrid A* planner offers an effective and practical solution for autonomous parking in closed residential settings. Future work will focus on extending the approach to real-vehicle deployment, incorporating dynamic obstacle prediction and uncertainty-aware fusion, improving planning performance in highly cluttered scenes, and integrating learning-based components and V2X information to further enhance robustness, safety, and user comfort in complex residential parking environments.

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Manuscript Published; 15 August 2024.