

An Adaptive Local Trajectory Planning Method for DWA Based on the ACT-R Cognitive Mechanism

Liwen Wang¹, Aijuan Li^{1*}, Máté Zöldy², Xibo Wang¹, Chuanyan Xu¹, Yuansheng Cheng¹

¹ School of Automotive Engineering, Shandong Jiaotong University, Jinan 250357, China;

² Department of Environmental Economics and Sustainability, Faculty of Economics and Social Sciences, Budapest University of Technology and Economics, Műegyetem rkp 3-5, H-1111 Budapest, Hungary

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* Corresponding Author: Author Name (liaijuan@sdjtu.edu.cn)

Abstract. To address the issues of fixed evaluation weights and the lack of historical experience utilization in the traditional Dynamic Window Approach (DWA) for autonomous vehicles in complex dynamic environments, this paper proposes an adaptive local trajectory planning method based on the ACT-R cognitive mechanism. First, the system constructs an environmental perception based on obstacle clearance, predicted risks from dynamic obstacles, and target progress, and establishes three cognitive planning strategies: Normal, Avoid, and Recover. Second, the memory activation mechanism of ACT-R is utilized to describe the historical usage characteristics of different strategies, and utility feedback learning is employed to reflect the long-term effectiveness of strategies under different environmental states. This allows the results of strategic decisions to be mapped in real time to the multi-objective evaluation function of DWA, thereby achieving adaptive and dynamic adjustment of planning weights. Finally, simulation results show that in mixed static and dynamic obstacle scenarios, while ensuring 100% collision-free arrival, this method achieves an average speed 30.17% higher than traditional DWA, reduces travel time by 18.48%, and improves trajectory smoothness by 46.34%, effectively balancing safety and travel efficiency.

Keywords: *Dynamic Window Approach (DWA); ACT-R Cognitive Mechanisms; Local Path Planning; Unmanned Ground Vehicle*

1. Introduction

With the rapid development of intelligent perception, automatic control, and artificial

intelligence technologies, autonomous vehicles—equipped with autonomous perception, environmental understanding, and motion control capabilities—are increasingly being applied in scenarios such as logistics and transportation, field inspections, agricultural operations, and autonomous operations in complex environments[1]. During actual operation, autonomous vehicles must adjust their speed and direction in real time based on the distribution of surrounding obstacles, the vehicle's own motion state, and the target location. As the core link between environmental perception and motion control, local trajectory planning directly determines the safety, efficiency, and trajectory smoothness of unmanned vehicle operation[2]. However, traditional local trajectory planning algorithms struggle to simultaneously address real-time obstacle avoidance, motion constraints, and environmental adaptability when dealing with complex obstacles[3]; therefore, targeted improvements to these algorithms are of great significance.

The Dynamic Window Approach (DWA) predicts short-term motion trajectories by sampling candidate velocities within the dynamically feasible velocity space and evaluating their corresponding trajectories under motion and safety constraints. By directly incorporating the vehicle's kinematic and dynamic limitations into the local planning process, DWA can generate executable control commands while maintaining relatively low computational complexity and good real-time performance[4]. Therefore, it has been widely applied to local trajectory planning for unmanned vehicles operating in environments with obstacles. However, conventional DWA relies heavily on predefined velocity sampling strategies and fixed evaluation-function weights, which may limit its adaptability when the surrounding obstacle distribution and risk level vary significantly. In particular, in complex obstacle environments, fixed evaluation preferences can make it difficult to simultaneously balance trajectory safety, obstacle avoidance efficiency, motion smoothness, and forward progress.

To address these limitations, previous studies have introduced improvements to DWA from several aspects, including velocity sampling, evaluation functions, attraction-repulsion mechanisms, and dynamic obstacle modeling [5]. These studies aim to improve the adaptability of local trajectory planning by incorporating more environmental information into the trajectory generation and evaluation process. For example, Xu et al. dynamically adjusted the evaluation weights according to environmental complexity and the distance between the vehicle and obstacles, thereby improving the adaptability of DWA under different obstacle conditions [6]. Gong et al. introduced fuzzy control to realize adaptive adjustment of evaluation-function weights, allowing the relative importance of different

evaluation factors to vary with the current environmental state [7]. Liu et al. further developed a fuzzy-control-based local planning method, enabling DWA to dynamically regulate the influence of different evaluation factors according to changes in the surrounding environment [8]. These studies demonstrate that introducing adaptive decision mechanisms into the DWA evaluation process can effectively alleviate the limitations associated with fixed parameters and improve its adaptability to complex obstacle environments.

In environments with dynamic obstacles, local path planning must also take into account the future motion of obstacles, rather than relying solely on the current instantaneous distance. Hossain et al. combined an improved DWA with a gap-following method to enhance the local obstacle avoidance capabilities of a mobile platform when facing both static and moving obstacles [9]; Kobayashi and Motoi improved the safety of DWA candidate trajectories by introducing a virtual manipulator to handle dynamic obstacles [10]; Yang et al. combined an improved particle swarm optimization with DWA and introduced the concept of velocity obstacles to enhance trajectory planning capabilities in dynamic obstacle environments [11]; Sarkis et al. further employed online particle swarm optimization to dynamically adjust the weights of the DWA objective function, enabling the planner to modify the trade-offs between different evaluation metrics based on environmental feedback [12].

Existing research indicates that adaptively adjusting the DWA evaluation weights can effectively enhance environmental adaptability; however, most methods rely solely on the current state to adjust parameters, failing to account for historical experience and long-term benefits. For example, methods based on fuzzy rules or online optimization tend to focus on numerical solutions, making it difficult to capture the continuous evolutionary process of “current environment — historical experience — strategy selection — feedback learning.” Therefore, determining how to enable a local planner to incorporate historical experience into a dependency mechanism is a key issue for further enhancing the adaptability of DWA.

Cognitive architectures offer new approaches to addressing the aforementioned issues. ACT-R (Adaptive Control of Thought-Rational), as a cognitive architecture equipped with memory, learning, and decision-making mechanisms, can simulate human behavioral choices through activation, retrieval, and utility mechanisms. In recent years, it has been widely applied in cognitive decision-making and the modeling of autonomous driving behavior. For example, Cina and Rad noted that ACT-R can provide a unified framework for vehicle environmental understanding and decision-making [13]; Oh et al. used it to establish a model for predicting driving behavior and cognitive load in takeover scenarios, validating its ability

to describe the dynamic response of cognitive states in driving decision-making [14].

The memory and learning mechanisms of the ACT-R are equally applicable to describing decision-making processes that involve historical dependencies. van der Velde et al. studied the dynamic changes in the declarative memory parameters of the ACT-R, demonstrating that memory activation can reflect the influence of experiential information as it changes over time [15]; Yang et al. incorporated motivational mechanisms into the ACT-R, using cost-benefit relationships to influence behavioral choices, thereby providing a new modeling approach for utility-based dynamic decision-making [16]; Fisher et al. further utilized system factor techniques to analyze the core architectural assumptions of ACT-R, verifying that its memory, perception, and processing mechanisms have a theoretically grounded basis that can be quantitatively analyzed [17].

To address the issues of fixed weights and high-frequency oscillations in traditional DWA strategies, this paper proposes an adaptive local path planning method for DWA based on the ACT-R cognitive mechanism. By deeply integrating the human cognitive decision-making framework with path planning, this method comprehensively enhances the adaptive obstacle avoidance capabilities, safety, and motion continuity of autonomous vehicles in environments with complex dynamic and static obstacles. The specific research content is as follows:

(1) Develop a foundational DWA trajectory planning system based on kinematic constraints and multi-objective evaluation: To address the issues of insufficient dynamic response to moving and stationary obstacles and a tendency to get stuck in local optima in complex environments—common in traditional DWA—we have established a candidate trajectory prediction mechanism based on kinematic constraints and velocity-space sampling; We introduced spatiotemporal collision prediction and spatial short-term memory revisit penalties to establish a multi-objective comprehensive evaluation function that integrates heading, clearance, speed, progress, smoothness, and safety risks; supplemented by hard constraint arbitration and a safety escape mechanism, we achieved reliable trajectory generation.

(2) Designing a strategy decision-making and adaptive weight adjustment algorithm based on the ACT-R cognitive mechanism: To overcome the limitation of traditional adaptive parameter tuning methods—namely, their lack of historical dependence—we construct an ACT-R cognitive decision-making architecture comprising three planning strategies: Normal, Avoid, and Recover. We utilize environmental risk context and memory activation to represent historical features, and employ feedback-driven utility learning to drive the continuous evolution of strategies. By leveraging cooling and hysteresis mechanisms to

suppress high-frequency oscillations in strategies, we achieve an adaptive dynamic mapping from cognitive decisions to DWA evaluation weights.

(3) Carry out algorithm simulation comparisons and ablation analyses: Under a unified test scenario, conduct horizontal comparison simulations of the traditional DWA, Fuzzy-DWA, and the Full ACT-R-DWA algorithm proposed in this paper. Through ablation experiments, separate the core modules related to memory retrieval and utility learning, quantitatively analyze the impact of each module on the algorithm performance, and clarify the intrinsic evolutionary mechanism of memory retrieval and utility learning within the ACT-R framework.

The remainder of this paper is organized as follows: Chapter 2 introduces the DWA local trajectory planning method, including the principles of DWA trajectory generation and multi-objective trajectory evaluation methods; Chapter 3 presents DWA local trajectory planning based on ACT-R cognitive decision-making, covering the overall architecture and strategy definition, the construction of the ACT-R cognitive decision-making model, cognitive decision-making based on memory retrieval and utility, and ACT-R-driven dynamic weight adjustment and feedback updates for DWA; Chapter 4 validates the effectiveness of the proposed method through simulation comparison experiments; Chapter 5 summarizes the research findings.

2. Methodology

2.1. DWA Local Path Planning Method

2.1.1. Principles of DWA Trajectory Generation

The Dynamic Window Approach (DWA) is a real-time planning method that performs local trajectory search in velocity space. Unlike methods that search for geometric paths directly in Cartesian space, the DWA samples candidate control inputs within a finite velocity space based on the autonomous vehicle's current motion state, velocity constraints, and acceleration constraints, and predicts its motion trajectory over a short time horizon.

In this paper, the state of an autonomous vehicle is defined as:

Here, x and y represent the planar position of the autonomous vehicle, θ represents the

$$\mathbf{S} = [x, y, \theta, v, \omega]^T \quad (1)$$

heading angle, v represents the linear velocity, and ω represents the angular velocity. Considering the kinematic characteristics of the autonomous vehicle, this paper adopts a

single-wheeled vehicle kinematic model to describe its local motion state, and the discrete simulation time step is set to:

$$\Delta t = 0.10s \quad (2)$$

For a given control input $\mathbf{u} = [v, \omega]^T$, the state of the autonomous vehicle is updated according to the following equation:

$$\begin{aligned} x_{k+1} &= x_k + v_k \cos(\theta_k) \Delta t \\ y_{k+1} &= y_k + v_k \sin(\theta_k) \Delta t \\ \theta_{k+1} &= \theta_k + \omega_k \Delta t \end{aligned} \quad (3)$$

Within a single prediction time step, the candidate linear and angular velocities remain constant, and local trajectories are generated through discrete integration. In the experiments

$$T_{\text{pred}} = 2.0s \quad (4)$$

in this paper, the prediction time step is set to:

Therefore, each candidate trajectory consists of $N_{\text{pred}} = \frac{T_{\text{pred}}}{\Delta t} + 1$ discrete state points.

To ensure that the candidate control commands comply with the physical motion constraints of the autonomous vehicle, the system's maximum linear velocity, maximum angular velocity, maximum linear acceleration, and maximum angular acceleration are set as

$$\begin{aligned} v_{\max} &= 1.45\text{m/s} \\ \omega_{\max} &= 1.35\text{rad/s} \\ a_v &= 1.0\text{m/s}^2 \\ a_\omega &= 1.8\text{rad/s}^2 \end{aligned} \quad (5)$$

follows:

During the current control cycle, the linear velocity dynamic window and the angular velocity dynamic window are expressed as follows:

$$\begin{aligned} V_d &= \{v | \max(0, v_t - a_v \Delta t) \leq v \leq \min(v_{\max}, v_t + a_v \Delta t)\} \\ W_d &= \{\omega | \max(-\omega_{\max}, \omega_t - a_\omega \Delta t) \leq \omega \leq \min(a_{\max}, \omega_t + a_\omega \Delta t)\} \end{aligned} \quad (6)$$

Within the dynamic window, linear velocity and angular velocity are sampled discretely, with sampling resolutions set at 0.08 m/s and 0.12 rad/s, respectively. At the same time, zero-velocity samples and exploration velocities constrained by safety clearance are introduced to

increase the diversity of the candidate velocity space. The exploration velocity is defined as:

$$v_{explore} = \min(v_{high}, \max(v_{low}, 0.55v_{safe})) \quad (7)$$

In this context, v_{safe} is the maximum safe speed calculated based on the current obstacle clearance.

After the candidate trajectories are generated, calculate the minimum clearance distance between each trajectory point and the static rectangular obstacles, static circular obstacles, and dynamic circular obstacles, and determine feasibility based on the hard safety boundaries. If the clearance distance to any obstacle corresponding to a trajectory point does not exceed the hard safety boundary, the candidate trajectory is deemed infeasible.

$$d_{hard} = 0.05m \quad (8)$$

A time-varying motion model for dynamic obstacles is constructed based on their initial position, radius, velocity, and active time period. Spatio-temporal collision detection is performed by calculating the predicted positions at each discrete time step, thereby enabling the assessment of the spatio-temporal feasibility of local trajectories.

When there is no feasible trajectory that meets the safety constraints within the conventional dynamic window, it indicates that it is difficult for the conventional speed sampling to generate an effective trajectory that simultaneously satisfies the motion constraints and the safety distance requirements for obstacles in the current local environment. In response to this situation, this paper introduces a safety escape mechanism in the local planning execution stage. By constructing low-speed left and right turning trajectories and candidate trajectories for small radius turns, the search range for local feasible trajectories in the restricted state is expanded. For the generated candidate trajectories, safety checks are conducted point by point within the short-term prediction range, and the minimum obstacle clearance of each candidate trajectory is compared. When there is an escape trajectory that meets the safety boundary constraints, the candidate trajectory with a larger safety margin is prioritized for execution, enabling the unmanned vehicle to promptly leave the current restricted area and reducing the risk of stalling or falling into a locally unsolvable state due to the absence of feasible trajectories in the local area. This mechanism is mainly used to handle the special situation where no feasible trajectory can be obtained within the conventional dynamic window, thereby improving the continuity and executability of the local planning process.

2.1.2. Multi-Objective Trajectory Evaluation Methods

In order to precisely select the optimal motion trajectory that is safe, stable and suitable for the task, a multi-dimensional comprehensive evaluation of the feasible candidate trajectories is required. This evaluation focuses on the core characteristics of trajectory operation, the environment and task constraints, covering seven key evaluation dimensions such as heading consistency, obstacle clearance, movement speed, target progress, control smoothness, historical revisit and safety risks. It comprehensively considers the safety, stability, efficiency and rationality of the trajectory in terms of passage, movement, task execution and path. The evaluation function is defined as:

$$J(\mathbf{u}) = w_H H_n + w_C C_n + w_V V_n + w_G G_n - w_{SM} SM - w_{loop} LP - w_{safe} SAFE \quad (9)$$

Among them, H_n 、 C_n 、 V_n 、 G_n represent the normalized heading evaluation, normalized clearance evaluation, normalized speed evaluation and normalized target progress evaluation respectively; SM is the angular velocity change penalty term, which is used to characterize the loss of trajectory control smoothness, LP is the historical revisit penalty term, which is used to constrain the problem of repeated circling of the path, and $SAFE$ is the safety risk penalty term, which is used to quantify the potential hazards of trajectory passage. The heading evaluation item is calculated based on the angle between the heading at the predicted trajectory end and the direction from the end to the target.

$$H_n = 1 - \frac{|\text{wrapToPi}(\theta_{\text{goal}} - \theta_{\text{end}})|}{\pi} \quad (10)$$

The heading evaluation item is used to measure the degree of closeness between the predicted trajectory's destination heading and the target direction. When the destination heading of the predicted trajectory points towards the target direction, it indicates that the robot's movement direction at the trajectory's end is consistent with the target direction, and a larger value can be taken; if the destination heading has a significant deviation from the target direction, this item should be appropriately set to a smaller value to guide the planner to preferentially select candidate trajectories with the final state facing the target. The clearance evaluation item is determined by the minimum obstacle clearance distance on the candidate trajectory:

$$C_n = \text{clip}\left(\frac{d_{\min}}{d_{\text{clrCap}}}, 0, 1\right) \quad (11)$$

When calculating obstacle distances, the safety cutoff distance is set to $d_{\text{clrCap}} = 4.0\text{m}$, and

both dynamic and static obstacles are included in the calculation of the minimum obstacle distance $d_{\min}$.

The overall evaluation function of DWA is composed of the speed evaluation item, the smoothness penalty item, the target progress item, the revisit penalty item, and the safety risk penalty item. Each evaluation item comprehensively scores the candidate trajectory from perspectives such as driving efficiency, motion smoothness, task achievement degree, state diversity, and safety. Then, the weighted sum is calculated based on the weights, and the candidate with the highest total score is the optimal trajectory for the current cycle. Among them, the speed evaluation item V_n is used to encourage the vehicle to maintain a higher driving speed: under the premise of meeting the safety constraints, the higher the speed corresponding to the candidate trajectory, the larger the value of this item, which is more conducive to shortening the task duration and improving the traffic efficiency. In practical applications, the weight of this item can be dynamically adjusted according to the road speed limit and task timeliness requirements. The smoothness penalty item SM is used to suppress the sudden change in angular velocity between adjacent cycles.

A target progress item is defined as:

$$G = \|\mathbf{p}_t - \mathbf{p}_{goal}\| - \|\mathbf{p}_{end} - \mathbf{p}_{goal}\| \quad (12)$$

Here, P_t represents the current position of the autonomous vehicle, and P_{end} represents the end point of the candidate trajectory. The larger the value of G , the more significant the reduction in distance to the target that the candidate trajectory can achieve.

Furthermore, to prevent the unmanned vehicle from getting stuck locally or repeatedly circling in complex obstacle areas, a revisit penalty term LP based on spatial short-term memory is introduced into the evaluation function. The environment is rasterized at a certain resolution, and the vehicle's recent driving trajectory is recorded using a sliding time window. The frequency of access to each grid cell and its time decay weight are statistically calculated in real time. When the end point of the candidate trajectory coincides with a spatial area with high recent frequency of access, it indicates that this trajectory is likely to guide the vehicle to re-enter the traversed area. At this time, the LP penalty value is dynamically increased to reduce the comprehensive score of this trajectory, prompting the planner to preferentially select areas with low access frequency and high freshness of time, thereby effectively avoiding getting stuck in a local optimal solution. At the same time, the access memory decays exponentially over time, taking into account the accessibility requirements of narrow passages and other necessary visiting areas, avoiding blocking necessary revisit paths due to

excessive penalties, and achieving a balance between suppressing repetitive circling and ensuring continuous passage.

A security risk penalty is defined as:

$$SAFE = \left[\frac{\max(0, d_{\text{safe}} - d_{\text{min}})}{d_{\text{safe}}} \right]^2 \quad (13)$$

In particular, the safety distance is used to characterize the minimum distance that should be maintained between an autonomous vehicle and an obstacle, and is set as follows:

$$d_{\text{safe}} = 0.90\text{m} \quad (14)$$

This measure expands the trajectory evaluation from a simple assessment of collision feasibility to a comprehensive evaluation of safety margin: The evaluation is no longer limited to determining whether the candidate trajectory will collide with obstacles, but further measures the minimum clearance distance from obstacles during the entire driving process and the change in safety margin over time, thereby distinguishing the safer ones among the feasible trajectory set, providing a continuous and comparable safety basis for subsequent comprehensive decision-making. Among the candidate control inputs that meet the safety constraints, the control input with the highest comprehensive evaluation value of $J(u)$ is selected as the local planning result for the current control cycle. This control input is obtained by weighted and comprehensive calculation of the speed evaluation item, smooth penalty item, task progress item, revisit penalty item and safety risk penalty item, taking into account driving efficiency, motion smoothness, task achievement and obstacle avoidance safety, and is updated in real time based on the latest environmental information within each control cycle, enabling timely response to the dynamic obstacle environment.

2.2. DWA Local Trajectory Planning Based on ACT-R Cognitive Decision-Making

2.2.1. Overall Architecture and Strategy Definition

Traditional DWA uses fixed evaluation function weights, with each evaluation metric having a constant weight parameter throughout the planning process. To address the varying requirements of autonomous vehicles for path following, obstacle avoidance safety, and dynamic performance under different operating conditions, a dynamic weight adjustment mechanism is introduced. This mechanism adaptively adjusts the weights of each evaluation metric based on the vehicle's current motion state, thereby enhancing the adaptability of local trajectory planning to different scenarios.

The “Normal” strategy is primarily used in open environments and emphasizes goal progress and speed; the ‘Avoid’ strategy is primarily used in situations where the risk of obstacles is elevated, and it increases the clearance from obstacles, dynamic risk, and safety weight; the “Recover” strategy is primarily used in high-risk situations or when goal progress is obstructed, and it increases heading, clearance, smoothness, and safety weight, while reducing the speed weight.

The mapping from strategies to DWA weights can be written as:

$$w_t = F(s_t, w_{base}) \quad (15)$$

Here, s_t represents the current policy, and w_{base} represents the base weight vector.

To achieve multi-objective coordinated optimization, the basic weight vector of the evaluation model is defined as follows:

$$\mathbf{w}_{base} = [0.25, 0.48, 0.24, 0.42, 0.16, 0.12] \quad (16)$$

These correspond to heading, clearance, speed, progress, smoothness, and safety, respectively.

It is important to emphasize that the fallback mechanism used by DWA when no feasible trajectory is available and the “Recover” strategy generated by ACT-R are two distinct decision-making mechanisms. The former is used to handle exceptional situations where no feasible solution is found during local trajectory planning, while the latter involves the ACT-R cognitive decision-making mechanism selecting a strategy based on the autonomous vehicle’s current operating state. Therefore, the “Recover” state refers solely to the recovery strategy generated by the ACT-R cognitive decision-making layer; it does not indicate a failure of the underlying DWA local planning. The two should not be equated or confused.

During actual operation, the system employs an arbitration mechanism that prioritizes low-level hard constraints. Regardless of the strategy currently output by the ACT-R cognitive layer, once the underlying DWA determines that the set of feasible trajectories is empty, the system will immediately halt the transmission of top-level weights and forcibly trigger the low-level safety escape mechanism (low-speed steering or in-place rotation). In contrast, the Recover strategy generated by ACT-R constitutes a proactive risk intervention. Its purpose is to guide the vehicle away from high-risk areas by preemptively tightening the safety and clearance weights before the DWA reaches a completely unsolvable state, thereby reducing the probability of triggering the lower-level forced escape mechanism.

2.2.2. Development of the ACT-R Cognitive Decision-Making Model

This paper introduces the ACT-R cognitive architecture into the DWA local trajectory planner to enable environmental risk perception, retrieval of historical experience, policy utility learning, and adaptive adjustment of planning weights. The system employs three cognitive strategies: “Normal” indicates a relatively open environment, where the autonomous vehicle prioritizes progress toward its goal and operating speed; “Avoid” indicates that an obstacle has entered the local risk zone, prompting the vehicle to increase clearance and safety; and “Recover” indicates a high level of dynamic risk or a significant impediment to the vehicle’s progress toward its goal, requiring the implementation of stronger safety and recovery strategies.

Each strategy corresponds to a memory block. A memory block contains features associated with the distance to obstacles and the target state, and also records the history of when that strategy was used.

In the ACT-R mechanism, the baseline activation level of a memory chunk is determined jointly by its historical usage frequency and the corresponding time interval, and can be

$$B_i(t) = \ln \left[\max \left(0.15, \sum_j \exp[-d(t - t_{ij})] \right) \right] \quad (17)$$

expressed as:

Here, $d = 0.45$ is the memory decay parameter, and t_{ij} represents the time at which strategy i is triggered or maintained for the j th time beyond the time threshold. Given that the local planner operates at a high frequency, this paper adopts an event-driven approach to record the timing of strategy usage. Specifically, an event is recorded as a distinct historical experience only when a cognitive strategy switches, or when the same strategy remains active continuously for longer than a set time threshold (e.g., 1.0 s). This approach prevents abnormal saturation of activation levels caused by high-frequency sampling.

Compared to the initial constant activation model, the current implementation accounts for real-time decay and the influence of usage history, resulting in a dynamically changing activation curve. Environmental risk is primarily determined by the current minimum obstacle clearance and the predicted dynamic obstacle clearance. Static risk is defined as:

$$r_o = \text{clip} \left(\frac{1.9 - \max(0, d_{obs})}{1.9}, 0, 1 \right) \quad (18)$$

Dynamic risk is defined as:

$$r_d = clip\left(\frac{1.45 - \max(0, d_{dyn}^{pred})}{1.45}, 0, 1\right) \quad (19)$$

Here, d_{obs} represents the current clearance around all obstacles, and d_{dyn}^{pred} represents the minimum predicted clearance between the autonomous vehicle and dynamic obstacles within the short-term prediction window.

2.2.3. Cognitive Decision-Making Based on Memory Retrieval and Utility

Building upon the basic activation model, we further consider the degree of alignment between the current environmental state and strategy memory, as well as the impact of different risk scenarios on strategy selection. We construct a strategy activation model that incorporates environmental alignment information and risk context information, which is expressed mathematically as:

$$A_i = 0.28B_i + 0.18M_i + 0.42C_i \quad (20)$$

Here, M_i represents the match between the current obstacle distance and the target state and the policy memory block, and C_i represents the risk context term.

In the full ACT-R model, the system integrates memory activation and decision utility to select a strategy. The basic form of decision utility is defined as:

$$U_i^d = 0.55(U_i - \bar{U}) + 0.65A_i + U_i^{context} \quad (21)$$

Here, U_i represents the long-term utility of a strategy, $\bar{U}$ is the average utility of the three strategies, and $U_i^{context}$ is the environmental context term calculated based on the current static risk, dynamic risk, and progress risk.

Use target progress, clearance changes, and dynamic risks as feedback signals. Let the change in target distance be:

$$\Delta g = g_t - g_{t+1} \quad (22)$$

The changes in obstacle clearance are as follows:

$$\Delta d = d_{t+1} - d_t \quad (23)$$

$$\begin{aligned}
 R_1 &= 3.5\Delta g - 1.5r_o \\
 R_2 &= 2.4\Delta d + 1.0r_o - 0.7(1-r_o) + 0.4\Delta g \\
 R_3 &= 1.5\Delta d + 2.8r_d - 1.1(1-r_d) + 0.5\Delta g
 \end{aligned} \tag{24}$$

The reward vectors corresponding to the three strategies are:

To curb the unbounded growth in utility caused by abnormal feedback, the reward function incorporates a bound that limits it to:

$$R_i \in [-2.5, 2.5] \tag{25}$$

This paper proposes a feedback-driven mechanism for incrementally updating the utility of a strategy:

$$U_i^{new} = (1 - \alpha_i)U_i + \alpha_i(U_i^0 + R_i) \tag{26}$$

$$\alpha_i = 0.10(0.35 + 0.65 I[i = s]) \tag{27}$$

Furthermore, to ensure the stability of utility values during the dynamic update process, we introduce a weak constraint from the prior utility on the current utility, causing the current

$$U_i \leftarrow 0.975U_i + 0.025U_i^0 \tag{28}$$

utility to regress toward the prior utility at a modest rate. Specifically, this is expressed as:

This design prevents any single strategy from becoming permanently locked in and ensures that the accumulation of Recover utility does not permanently suppress Normal and Avoid.

Given that environmental risks exhibit a certain degree of temporal continuity, to prevent sudden changes in risk states from causing significant fluctuations in Activation and Utility within a single control cycle, a first-order finite-response filtering mechanism is introduced to smooth the updates of relevant state variables, thereby reducing the impact of instantaneous

$$\begin{aligned}
 A_{i,t}^f &= 0.82A_{i,t-1}^f + 0.18A_{i,t} \\
 U_{i,t}^f &= 0.78U_{i,t-1}^f + 0.22U_{i,t}
 \end{aligned} \tag{29}$$

risk changes on policy decisions. The computational form is as follows:

Therefore, Activation and Decision Utility still respond to changes in dynamic obstacles and target progress, but the curves exhibit continuous transitions, which better align with the nature of limited responses in cognitive processes.

2.2.4. ACT-R-Driven Dynamic Weight Adjustment and Feedback Updates in DWA

$$s_t = \arg \max_i U_{i,t}^f \quad (30)$$

Strategy selection follows the principle of maximum decision utility:

To prevent the strategy from oscillating frequently between adjacent control cycles, a cooling time and a hysteresis threshold are set. When the utility difference between the candidate strategy and the current strategy is less than the hysteresis threshold, or when the duration of the current strategy is less than the cooling time, the system maintains the original

$$s_t = s_{t-1}, \quad \text{if } U_{\max} - U_{\text{current}} \leq h \text{ or } \tau_{\text{current}} < T_{\text{cool}} \quad (31)$$

strategy:

Specifically, when $\frac{h}{T_{\text{cool}}} = \frac{0.20}{0.70\text{s}}$, the system allows a strategy switch only if the utility advantage exceeds the hysteresis threshold and the cooling time meets the requirements.

After the strategy switch is complete, the weights of the DWA evaluation function are adaptively adjusted based on the current cognitive strategy state. Specifically, the “Normal” state emphasizes progress and speed; the “Avoid” state emphasizes clearance and risk; and the “Recover” state emphasizes heading, clearance, smoothness, and safety, while appropriately reducing the weight assigned to speed.

$$\begin{aligned} w_C &\leftarrow 1.04w_C \\ w_{SM} &\leftarrow 1.06w_{SM} \\ w_G &\leftarrow 1.24w_G \\ w_V &\leftarrow 1.18w_V \\ w_{safe} &\leftarrow 1.03w_{safe} \end{aligned} \quad (32)$$

The complete ACT-R model further couples the patterns based on the strategy mapping:

This setting reflects the comprehensive balance of Full ACT-R-DWA in terms of safety, trajectory smoothness, and target progress, rather than simply focusing on improving any single evaluation item. The weights of each item and the intensity of penalties are adaptively adjusted according to the current environmental conditions and the vehicle's operating status. In open areas, a greater emphasis is placed on speed and target progress to improve traffic efficiency. In complex obstacle areas, safety risks and recall penalties are strengthened to ensure the margin for obstacle avoidance and path diversity. Thus, the algorithm can maintain

the coordination and unity of safety, smoothness, and task completion in various scenarios. Therefore, the method proposed in this paper forms the following closed loop. The algorithm flowchart is shown in Figure 1:

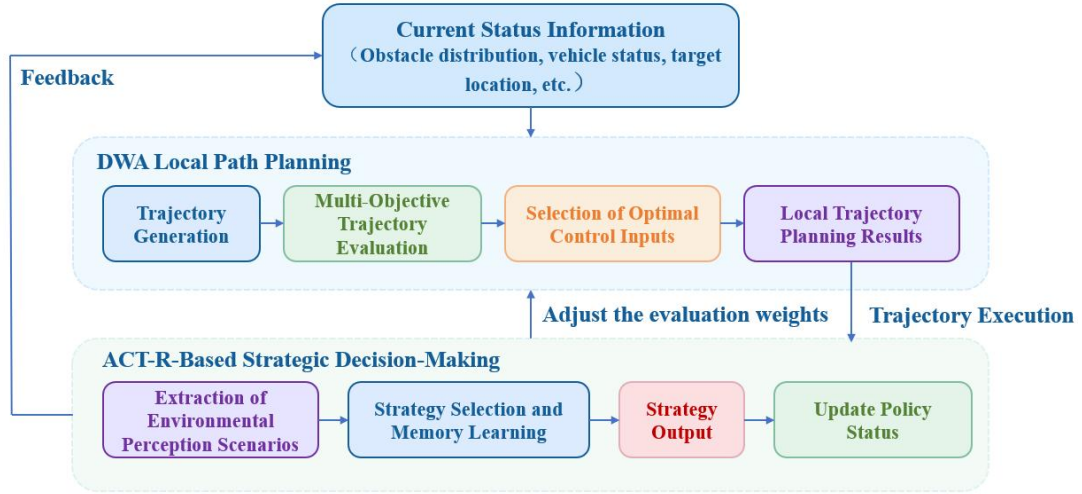
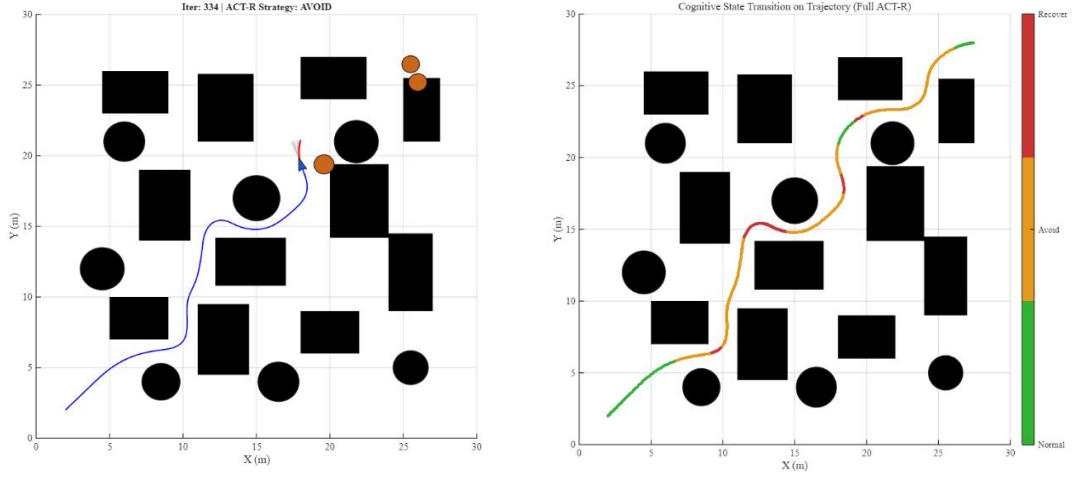


Figure 1. Algorithm Flowchart

3. Results

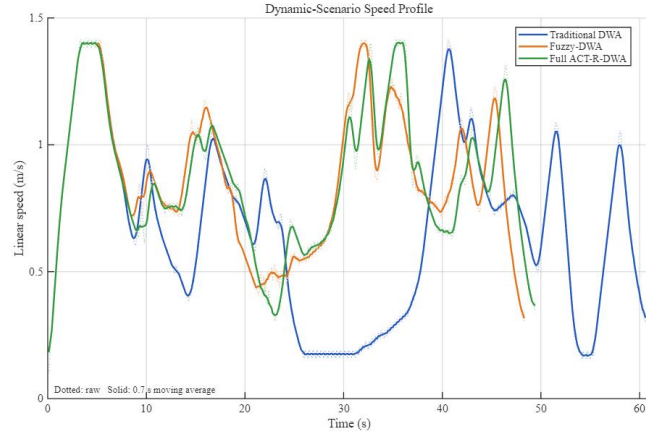
3.1. Comparative Analysis of Local Trajectory Planning Results

The experiment was conducted in a two-dimensional plane of 30m×30m. The starting point and the ending point of the unmanned vehicle were set as (2.0, 2.0) and (28.0, 28.0), respectively. A total of two scenarios were set for the test: the static scenario (Static Only), which only contained stationary obstacles, and the dynamic scenario (Static + Dynamic), which additionally introduced three dynamic obstacles. The positions of the dynamic obstacles were updated in real time according to their movement attributes and were incorporated into the collision prediction model of the candidate trajectories. To verify the performance of the algorithm, this paper compared three traditional algorithms: DWA, Fuzzy-DWA, and Full ACT-R-DWA. The planning process and state transition of Full ACT-R-DWA are shown in Figure 2. The motion responses and safety clearances of different local planning algorithms in the dynamic obstacle scenario are compared in Figure 3, and the performance comparison table of the three algorithms is shown in Table 1.

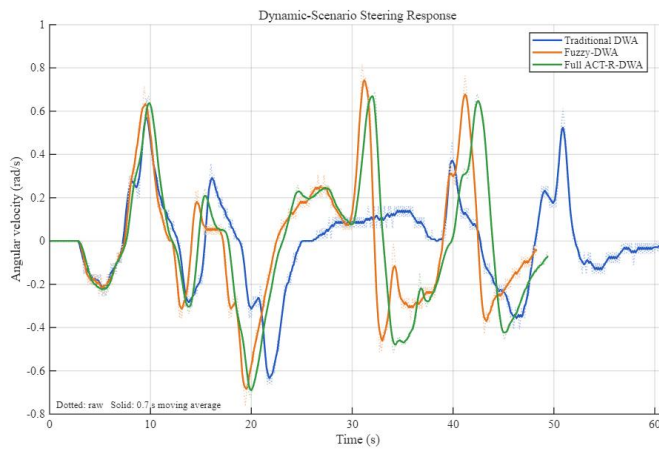


(a) Diagram of the Full ACT-R-DWA Planning Process (b) Cognitive strategy state transitions along the full ACT-R-DWA trajectory

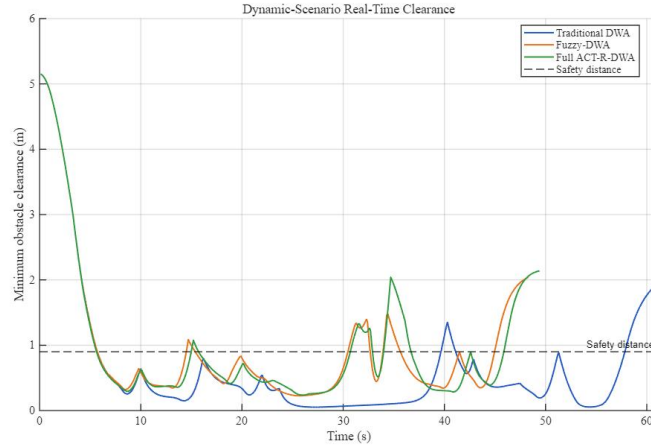
Figure 2: The Full ACT-R-DWA Planning Process and State Transitions in Cognitive Strategies



(a) Linear velocity response in scenarios with moving obstacles



(b) Angular Velocity Response in Scenarios with Moving Obstacles



(c) Real-time minimum obstacle distance in dynamic obstacle scenarios

Figure 3: Comparison of Motion Responses and Safety Margins for Different Local Planning Algorithms in a Dynamic Obstacle Scenario

Table 1: Performance Comparison of the Three Algorithms

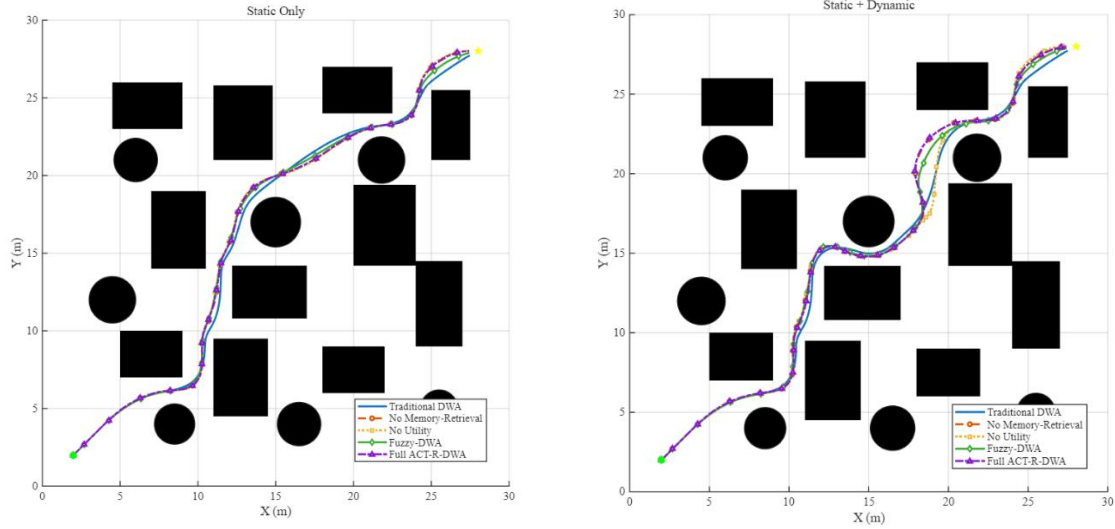
Algorithm	Success Rate (%)	Number of collisions	Minimum Distance (m)	Path Length (m)	Average Speed (m/s)	Arrival Time (s)	Smoothness	Scheduled Time (ms)
Traditional DWA	100	0	0.052	40.180	0.663	60.6	0.451	4.295
Fuzzy-DWA	100	0	0.226	41.764	0.865	48.3	0.496	4.634
Full ACT-R-DWA	100	0	0.237	42.610	0.863	49.4	0.242	4.586

Combining the simulation trajectories and kinematic responses shown in Figures 2 and 3, it can be seen that Full ACT-R-DWA is capable of smoothly switching between three cognitive strategies — “ Normal, ” “ Obstacle Avoidance, ” and “ Recovery ” — based on local environmental risks, demonstrating dynamic decision-making and situational awareness capabilities. At the same time, it maintains a high average operating speed, smooth angular velocity changes, and sufficient real-time safety clearance, thereby avoiding the issue of approaching collision limits inherent in traditional methods. As shown in Table 1, while both methods achieved 100% zero collisions, Full ACT-R-DWA demonstrated significant advantages in terms of safety, operational efficiency, and trajectory quality. Compared to Traditional DWA: the minimum obstacle distance increased from 0.052 m to 0.237 m; the average speed increased from 0.663 m/s to 0.863 m/s, representing a 30.17% improvement; the arrival time decreased from 60.6 s to 49.4 s, a reduction of 18.48%; and the smoothness

decreased from 0.451 to 0.242, representing a 46.34% improvement. Compared to Fuzzy-DWA: the minimum obstacle distance increased from 0.226 m to 0.237 m, a 4.87% improvement; smoothness decreased from 0.496 to 0.242, a significant improvement of 51.21%; and the average single-step planning time decreased from 4.634 ms to 4.586 ms, a reduction of 1.04%.

3.2. Experiment on the Ablation of ACT-R Cognitive Mechanisms and Performance Analysis

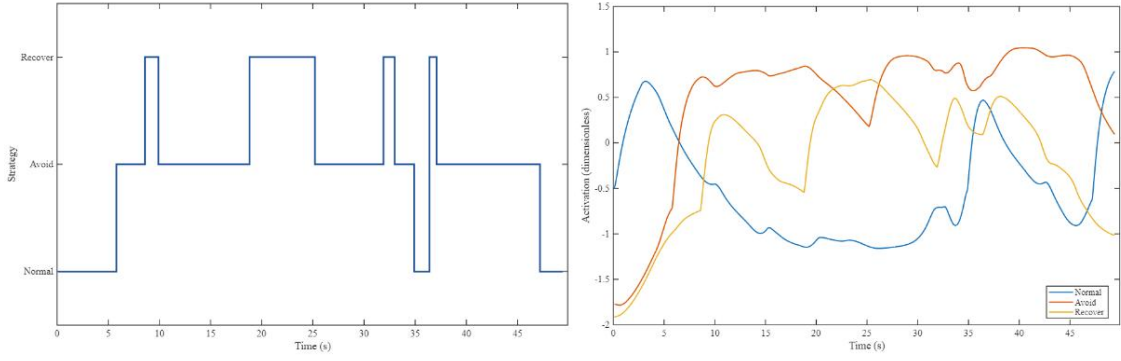
To validate the roles of each component module of ACT-R, four ablation scenarios were set up: Traditional DWA, No Memory-Retrieval, No Utility, and Full ACT-R-DWA. Additionally, Fuzzy-DWA—which does not rely on ACT-R—was included as a side-by-side baseline.



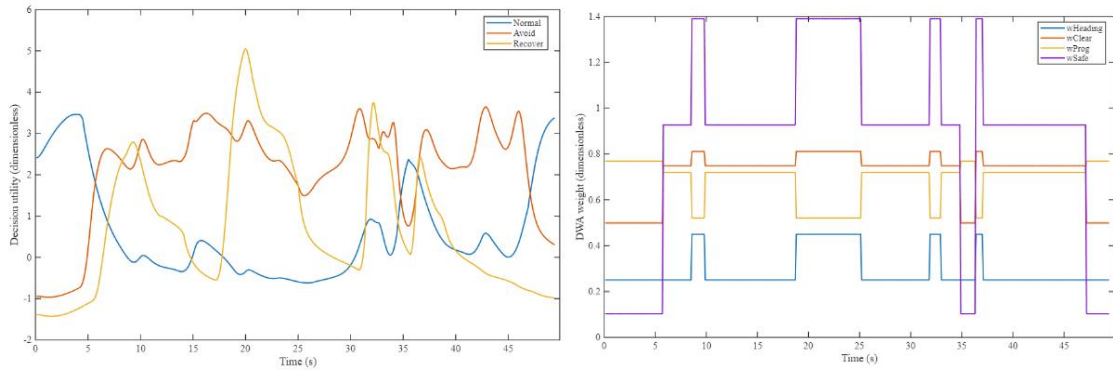
(a) Trajectory Comparison in Scenarios with Static Obstacles (b) Trajectory Comparison in Static–Dynamic Mixed Obstacle Scenarios

Figure 4: Comparison of Planned Trajectories Under Different Ablation Strategies

A comparison of planning trajectories under different strategies is shown in Figure 4. Based on this, a hybrid static-dynamic scenario was selected to analyze the operation of Full ACT-R-DWA. Figure 5 illustrates the process of ACT-R cognitive decision-making and the dynamic adjustment of DWA evaluation weights. The system achieves strategy competition and switching through memory retrieval activation and utility feedback, which are ultimately mapped to DWA’s multiple evaluation weights to enable adaptive adjustment.



(a) The ACT-R Strategy State Transition Process (b) Changes in memory retrieval activation across the three types of strategies



(c) The Evolution of Utility in ACT-R Strategy Decision-Making (d) The process of dynamically adjusting DWA evaluation weights driven by ACT-R

Figure 5: Dynamic Adjustment Process of Evaluation Weights in ACT-R Cognitive Decision-Making and DWA

As shown in Figure 4, compared with the trajectory deviation and stagnation phenomenon that occur in traditional DWA in complex mixed scenarios, Full ACT-R-DWA can generate smoother obstacle avoidance trajectories and effectively suppress the speed changes in adjacent cycles, indicating that the cognitive-driven evaluation adjustment significantly improves the trajectory continuity and driving smoothness while ensuring the safety margin. Figure 5 (a) shows that the system strategy can dynamically switch according to the environmental state, and the hysteresis mechanism effectively suppresses the high-frequency oscillations during the strategy switching process, avoiding the control command jitter caused by environmental perception disturbances. Figure 5 (b) shows that the activation level of memory retrieval evolves continuously based on historical experience and environmental matching degree, accurately reflecting the degree of correlation between the environmental state and historical calls, providing empirical support corresponding to the scenarios for strategy selection. Figure 5 (c) demonstrates the utility competition process, where the

strategy switching is determined by the maximum value of the utilities of each cognitive module rather than a preset fixed rule, reflecting the system's adaptive decision-making ability for different scenarios. Figure 5 (d) indicates that the cognitive strategy can adjust the weights of each evaluation item of DWA in real time, verifying the effective driving of the ACT-R cognitive layer for local planning, and thereby achieving the comprehensive achievement of safety, smoothness and efficiency goals.

4. Discussion

In dynamic local trajectory planning, the traditional DWA usually adopts fixed evaluation weights and relies only on current perceptual information, which makes it difficult to adapt to time-varying obstacle distributions, cannot utilize historical decision-making experience, and tends to cause strategy oscillation when the environment changes rapidly. To address issues such as fixed evaluation weights, lack of historical experience utilization, and strategy oscillation in dynamic local trajectory planning, this study proposes an adaptive dynamic window approach (DWA) based on the ACT-R cognitive mechanism. By introducing a cognitive decision layer into the local planner, the proposed method transforms the static weight configuration of the conventional DWA into a cognition-driven adaptive adjustment process, enabling the evaluation function to be dynamically matched with the current environmental state.

The proposed "memory-utility-mapping" architecture overcomes traditional rule-based or numerical optimization methods by integrating historical dependence into real-time decision-making. Specifically, the event-driven memory activation model retrieves the most relevant historical experience according to the similarity between the current environment and past scenarios, while the feedback-driven utility learning model updates the preference strength of each candidate strategy based on the planning results. By combining the event-driven memory activation model with the feedback-driven utility learning, the system can capture the "environment-experience-strategy-feedback" loop, forming a closed loop in which historical experience continuously informs strategy selection and the selection results in turn revise the accumulated experience. Additionally, introducing cooling time and lag threshold, this system suppresses high-frequency strategy switching, thereby achieving a smooth real-time mapping from cognitive decision-making to multi-objective DWA weights, which effectively avoids the control jitter and trajectory oscillation caused by frequent switching.

The comparison of simulation results shows that even when the success rate is as high as 100%, the complete ACT-R-DWA still outperforms the traditional DWA and the fuzzy

DWA. Compared to traditional DWA, its minimum obstacle spacing increases from 0.052 meters to 0.237 meters, the average speed increases by 30.17% (0.863 m/s), and the trajectory smoothness improves by 46.34% (0.242), indicating that the proposed method substantially enlarges the safety margin while improving both driving efficiency and trajectory quality. Compared to Fuzzy-DWA, this method improves the smoothness by 51.21% while maintaining the average single-step planning time of only 4.586 milliseconds, meeting the real-time requirements. These results demonstrate that the ACT-R-driven adaptive DWA achieves a favorable trade-off among safety, efficiency, and smoothness in complex dynamic environments.

5. Conclusion

This paper addresses the issues of fixed evaluation weights, insufficient utilization of historical experience, and frequent oscillations in the strategy of the traditional Dynamic Window Approach (DWA) for unmanned vehicles in complex dynamic environments. To address these problems, a DWA adaptive local trajectory planning method based on the ACT-R cognitive mechanism is proposed. The main research conclusions are as follows:

(1) At the levels of trajectory generation and multi-objective evaluation: The trajectory generation and evaluation system based on DWA has been improved. By introducing spatial-temporal collision prediction and revisit penalty mechanisms, a multi-objective comprehensive evaluation function and a safety escape arbitration mechanism have been designed, providing a reliable underlying execution framework for the trajectory optimization in cognitive decision-making.

(2) At the cognitive decision-making and adaptive mapping level: An integrated ACT-R cognitive architecture of "memory - utility - mapping" was constructed. Through an event-driven mechanism, historical memories were activated, and combined with feedback-driven utility updates, the smooth evolution of three types of cognitive strategies was achieved; at the same time, cooling time and hysteresis mechanisms were introduced to inhibit frequent switching of strategies, ultimately realizing the adaptive real-time mapping of cognitive decisions to DWA evaluation weights.

(3) At the levels of simulation comparison : System simulation indicates that, under the condition of 100% zero collision arrival, Full ACT-R-DWA will increase the minimum obstacle distance from 0.052 m to 0.237 m, shorten the arrival time by 18.48%, and improve the smoothness index by 46.34% compared with Traditional DWA; compared with Fuzzy-

DWA, it improves the minimum obstacle distance by 4.87% and the smoothness index by 51.21%, and the average single-step planning time is only 4.586 ms, fully meeting the real-time control requirements.

In conclusion, the DWA adaptive local trajectory planning method based on the ACT-R cognitive mechanism proposed in this paper takes into account the safety of local obstacle avoidance, motion efficiency, control smoothness, and the ability to utilize historical experience, providing a feasible solution for the autonomous smooth maneuver of unmanned vehicles in complex dynamic environments.

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