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УСОВЕРШЕНСТВОВАННЫЙ МЕТОД ДИНАМИЧЕСКОГО ОКНА ДЛЯ ЛОКАЛЬНОЙ НАВИГАЦИИ В УСЛОВИЯХ МНОЖЕСТВА ПРЕПЯТСТВИЙ

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Аннотация. Рассматриваются ограничения классического метода динамического окна в задачах локального планирования траектории: отсутствие плавности траектории, неустойчивость состояния, недостаточная адаптация к глобальной навигации. В качестве решения предлагается усовершенствованный метод динамического окна, работающий в условиях множества препятствий. Данный метод оптимизирует оценку траектории за счет

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введения нескольких дополнительных параметров: двустороннего отклонения от курса, соблюдения общей траектории, контроля изменения кривизны и подавления рывков при движении. Они интегрированы в единую функцию оценки, которая способствует более плавному, обоснованному и динамически повторяемому созданию траектории. Для проверки эффективности предлагаемого метода проводится серия экспериментов с применением различных карт, включающих как простое, так и сложное окружение. Усовершенствованный метод сравнивается с классическим методом динамического окна и несколькими его улучшенными вариантами. Устанавливается, что предлагаемый метод достигает более высоких характеристик с точки зрения качества пути, безопасности и общей надежности планирования, демонстрируя улучшенную адаптивность и надежность при решении сложных навигационных задач.

Ключевые слова: метод динамического окна; планирование местного пути; оптимизация для множества препятствий; глобальная и локальная координация; плавность траектории; автономный обход препятствий.

Вклад авторов. И Тан выполнил основную часть исследовательской работы, включая разработку дизайна проекта, проведение экспериментов, анализ данных и подготовку чернового варианта рукописи. Д. Ю. Перцев осуществлял научное руководство исследованием, давал ценные рекомендации на всех этапах работы и тщательно отредактировал рукопись, повысив ее научный уровень и логическую стройность. Д. В. Куприянова внесла ряд правок в черновой вариант статьи и участвовала в разработке дизайна исследования.

MULTI-CONSTRAINT ENHANCED DYNAMIC WINDOW APPROACH FOR ROBUST AND SMOOTH LOCAL NAVIGATION

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Abstract. The limitations of the traditional dynamic window approach in local path planning, including poor trajectory smoothness, unstable control performance and insufficient global navigation guidance, are examined. An improved multi-constraint dynamic window approach is proposed as a solution. This method enhances the trajectory evaluation by introducing several refined constraint metrics: dual-angle heading deviation, global path adherence, curvature variation control and jerk suppression. They are integrated into a unified multi-objective scoring function that promotes smoother, more reasonable and dynamically feasible trajectory generation. To verify the effectiveness of the proposed approach, a series of experiments is conducted across various representative map scenarios, including both standard and complex environments. The enhanced algorithm is compared with the classical dynamic window approach and several of its improved variants. It is established that the proposed approach achieves superior performance in terms of path quality, safety and overall planning robustness, demonstrating improved adaptability and reliability in solving complex navigation tasks.

Keywords: dynamic window approach; local path planning; multi-constraint optimisation; global-local coordination; trajectory smoothness; autonomous obstacle avoidance.

Author's contribution. Yi Tang carried out the majority of the research work, including project design, experimental execution, data analysis and manuscript drafting. D. Yu. Pertsau supervised the study, provided valuable guidance throughout the research process and carefully revised the manuscript to enhance its scientific quality and coherence. D. V. Kupriyanava made some corrections to the draft version and worked on the design of the work.

Introduction

Due to the continuous development of intelligent and automation tools, mobile robots are being increasingly applied in various fields such as industry, healthcare and logistics. As a core component of autonomous navigation, path planning has become one of the most critical research topics in the field of robotics. The goal of path planning is to generate an optimal path from the robot's starting position to its target destination that is safe, collision-free and meets performance requirements. It concerns not only the safety of robot motion,

but also addresses the challenge of optimising navigation in complex and dynamically changing environments to ensure efficient and reliable task execution [1].

Path planning algorithms are usually divided into global path planning and local path planning. Global path planning assumes complete knowledge of the environment and generates a globally optimal path based on a pre-constructed map. Classical algorithms such as A^* and Dijkstra are widely used and are well-suited for static and well-structured environments [2]. In contrast, local path planning relies on real-time perception of the environment, enabling the robot to dynamically adjust its motion strategy during execution in response to environmental uncertainties and obstacle changes. In practice, mobile robots are often encountering dynamically changing environments and incomplete sensor information. In such conditions the flexibility and real-time adaptability of local path planning are particularly crucial, especially in tasks involving dynamic obstacle avoidance and path reconfiguration [1]. As a result, local path planning serves as an essential foundation for ensuring safe navigation and successful task completion for mobile robots.

The dynamic window approach (DWA) is a classic local path planning algorithm, first proposed by D. Fox, W. Burgard and S. Thrun in 1997 [3]. This method generates possible short-term trajectories by simulating the robot's motion in the velocity space in real time and selects the optimal trajectory to execute based on a scoring function applied to the possible trajectories. However, the traditional DWA algorithm has limited consideration of the robot's kinematic and dynamic characteristics during trajectory generation. At the same time, factors such as trajectory smoothness, stability and curvature variation are not properly taken into account. As a result, the robot may experience abrupt turns or sudden velocity changes during motion, which can negatively affect the stability of the control system and reduce the reliability of trajectory. To this end, the researchers have proposed various improvements from different perspectives. As for the target guideline, X. Gong and his colleagues [4] introduced a fuzzy control mechanism based on the distances to the target and surrounding obstacles, which allows to dynamically adjust the velocity and heading weights within the DWA. This approach has improved the adaptability of the algorithm to various environments. However, because it is based on manually developed fuzzy rules, it lacks a systematic mechanism to guide the path shape effectively, especially in dynamic and time-varying scenarios. To solve the problem of deviation from the global path, A.-Z. Liu, C. Liu, L. Li, R.-C. Wang and Z. Lu [5] proposed a function for estimating the similarity of trajectories based on dynamic time warping to enforce shape consistency between local trajectories and the global path. However, this method aligns the trajectories only geometrically, without considering motion smoothness or control continuity, which can lead to unstable execution in high-curvature regions. To improve control stability, Z. Wang and G. Li [6] introduced constraints on trajectory curvature variation and jerk (i. e., the derivative of linear and angular velocities), enabling more continuous and stable command outputs. However, their approach embeds these constraints as additional cost terms without unified coordination within the evaluation framework, which can lead to conflicts with other objectives and degrade the overall quality of planning. In addition, Y. Lu and C. Da [7] combined an improved ant colony optimisation algorithm with DWA, incorporating a direction angle cost function and velocity sampling optimisation to improve obstacle avoidance and simultaneously improve directional attraction to the target. However, due to the slow convergence of search based on the ant colony optimisation algorithm, this method remains limited in highly dynamic environments. Integrated strategies combining global and local planning have recently attracted increasing attention. W. Sang, Y. Yue, K. Zhai and M. Lin [8] proposed a two-stage planning framework that integrates an improved A^* algorithm for global path generation and DWA for local execution. The nodes of the global path are used as dynamic sub-goals for the DWA, and the cubic B-spline is used to smooth the global trajectory. Although this method works well in structured static environments, it suffers from fixed parameter settings that can lead to delayed responses and trajectory deviation in complex and dynamic scenarios.

In summary, although the existing studies have proposed various improvements to the DWA, several limitations remain. These include insufficient consistency of local and global paths, which can cause the robot to get stuck in local minima during navigation; insufficient consideration of trajectory smoothness and dynamic stability, which can lead to sudden motions and reduced task performance; simplified mechanisms for attracting targets, which are often ineffective over long distances, resulting in detours or reduced navigation efficiency. To address these issues, this paper proposes an improved multi-constraint dynamic window approach (MC-DWA). The proposed method introduces multiple evaluation dimensions and constraint mechanisms, constructs a unified multi-objective scoring model to enhance the global rationality, local smoothness and control stability of the planned path. The key improvements are the following.

1. Enhanced heading guidance and target alignment. A dual-angle deviation evaluation mechanism is introduced to assess the angular deviation between the predicted trajectory endpoint and both the target direction and the global path orientation. Then a weighted course evaluation function is created. This mechanism enhances

the robot's directional alignment toward the goal and its coordination with the global path, reducing deviations from the intended navigation route.

2. Global path adherence constraint. During local planning, a segment of the global path near the robot's current position is dynamically extracted. The average minimum distance between predicted trajectory points and this local path segment is computed and used as a path adherence score. This design ensures spatial consistency between local and global paths, prevents the robot from entering densely obstructed regions and improves the overall rationality and safety of path planning.

3. Trajectory smoothness and dynamic stability control. To ensure continuity and dynamic feasibility, MC-DWA includes constraints on trajectory curvature variation and jerk (i. e., the rate of change of linear and angular velocity). Curvature variation reflects the geometric smoothness of the path, while jerk quantifies the smoothness of control commands. The combined control of these two indicators effectively suppresses trajectory fluctuations and sudden speed changes, thereby improving path stability and control robustness.

4. Unified trajectory scoring model. MC-DWA establishes a comprehensive trajectory-scoring model that combines multiple evaluation indicators (heading consistency, path adherence, smoothness and stability, target attraction) using weighted fusion. This enables multi-dimensional assessment and quality control of the trajectory within a unified decision-making system.

With these enhancements, the MC-DWA algorithm significantly improves global-local coordination, trajectory smoothness control and adaptability to difficult obstacles, while retaining the real-time performance advantages of the original DWA. As a result, it provides a more robust and efficient path planning solution for autonomous navigation of mobile robots in difficult conditions.

Multi-constraint dynamic window approach

Basic principles of the classical DWA algorithm. The classical DWA algorithm is a real-time local path planning algorithm. Its core concept is to sample multiple pairs of linear and angular velocities within the velocity space based on the robot's current state. By evaluating the predicted short-term trajectories corresponding to these velocity combinations, the method selects the optimal control command to effectively avoid obstacles and direct the robot to the goal. The set of selected velocity pairs in the velocity space must satisfy kinematic constraints, dynamic constraints and safety constraints [3].

1. Kinematic constraints V_{kin} . The robot's velocities must comply hardware limits, including the allowable ranges of linear velocity v and angular velocity ω . Assume that the minimum and maximum values of the linear velocity are $v_{\min}$ and $v_{\max}$, and the minimum and maximum values of the angular velocity are $\omega_{\min}$ and $\omega_{\max}$, respectively. Then the set of velocities that satisfy the kinematic constraints can be calculated as follows:

$$V_{\text{kin}} = \{(v, \omega) | v \in [v_{\min}, v_{\max}], \omega \in [\omega_{\min}, \omega_{\max}]\}.$$

Typically, the robot is unable to move in the opposite direction ($v_{\min} \geq 0$), and the allowable angular velocity is symmetrical in both directions, i. e., $\omega_{\min} = -\omega_{\max}$.

2. Dynamic constraints V_{dyn} . Due to the robot's limited acceleration capabilities, the change in velocity within a single control time step Δt is also limited. Let the current linear and angular velocities be v_0 and ω_0 , respectively, and let the maximum allowable linear and angular accelerations be $a_v^{\max}$ and $a_\omega^{\max}$. Then the set of velocities satisfying the dynamic constraints can be expressed in equation:

$$V_{\text{dyn}} = \left\{ (v, \omega) \left| \begin{array}{l} v \in [v_0 - a_v^{\max} \Delta t, v_0 + a_v^{\max} \Delta t] \\ \omega \in [\omega_0 - a_\omega^{\max} \Delta t, \omega_0 + a_\omega^{\max} \Delta t] \end{array} \right. \right\}.$$

3. Safety constraints V_{safe} . The robot must ensure that it does not collide with any obstacles. Assume that the robot is moving at the current velocity v_c and applies the maximum deceleration of braking a_{brake} (here $a_{\text{brake}} = -a_v^{\max}$), the required braking distance d_{brake} can be calculated using $d_{\text{brake}} = \frac{v_c^2}{2|a_{\text{brake}}|}$. A possible velocity is considered safe only if the minimum distance to obstacles $d_{\min}$ along the predicted trajectory, is bigger than the sum of d_{brake} and safe margin d_{sm} . Thus, V_{safe} is calculated as follows:

$$V_{\text{safe}} = \{(v, \omega) | v_c \leq \sqrt{2|a_{\text{brake}}|(d_{\min} - d_{\text{sm}})}\}.$$

Then the final dynamic window is defined as the intersection of three sets of constraints:

$$V_{dw} = V_{kin} \cap V_{dyn} \cap V_{safe}.$$

Each velocity pair $(v, \omega) \in V_{dw}$ is forward-simulated over a short time horizon T , generating a corresponding trajectory. The quality of each trajectory is then evaluated using a weighted evaluation function:

$$G = \alpha \cdot \text{heading} + \beta \cdot \text{clearance} + \gamma \cdot \text{velocity}.$$

In this formula, the heading term measures the angular alignment between the trajectory endpoint and the target direction, promoting goal-oriented motion. The clearance term is the shortest distance between the predicted trajectory and nearby obstacles, which provides safer paths. The velocity term prefers trajectories with higher speeds, which contributes to the efficient use of time. The weights α, β, γ are tuning parameters used to balance these three objectives according to the task requirements. The detailed formula is given in paper [3].

Multi-constraint enhanced DWA. Although DWA has significant advantages in terms of real-time performance and dynamic obstacle avoidance, it still faces significant challenges in complex or highly dynamic environments. Firstly, its evaluation function is relatively simple and usually takes into account only basic factors such as goal direction, velocity and obstacle proximity, while lacking effective integration of global path information. As a result, the robot may deviate from the planned global path during local planning and become trapped in local minima. Secondly, in densely cluttered environments, improper weighting of the obstacle distance term may result in excessive deviation from the route or unnatural avoidance behaviours, deteriorating the quality of the path and travel efficiency. Furthermore, the conventional DWA does not sufficiently take into account the smoothness of the trajectory or dynamic controllability; it lacks restrictions on acceleration, curvature variation and other dynamic characteristics, which can lead to movement jitter, increased energy consumption or even control instability during execution.

To effectively eliminate these limitations in trajectory generation, this paper proposes a redesigned trajectory evaluation function, resulting in MC-DWA. By introducing constraint terms with clear physical meaning and engineering applicability, MC-DWA enhances global consistency, control stability and dynamic adaptability in difficult environmental conditions, while maintaining the real-time benefits of the original algorithm. Specific improvements are described in details below.

Enhanced heading guidance and target alignment. To improve the robot's directional control capabilities during navigation, MC-DWA implements a dual orientation consistency evaluation mechanism, including target orientation consistency and global path orientation consistency. In particular, let the terminal orientation of the predicted trajectory be θ_{pred} , the orientation of the target point be θ_{goal} , and the terminal orientation of the global path be θ_{final} . Figure 1 shows a diagram of orientation angles in MC-DWA. In addition, the orientation deviations between them are calculated using the following expression:

$$\Delta\theta_{goal} = |\theta_{pred} - \theta_{goal}|,$$

$$\Delta\theta_{final} = |\theta_{pred} - \theta_{final}|.$$

Based on this, the heading consistency score is calculated by the formula

$$H(v, \omega) = \lambda_1 \frac{\pi - \Delta\theta_{goal}}{\pi} + \lambda_2 \frac{\pi - \Delta\theta_{final}}{\pi},$$

where λ_1 and λ_2 are weighting factors to balance the contributions of goal direction and path direction alignment, respectively (here we set $\lambda_1 = \lambda_2 = 0.5$).

However, when the robot is far from the target, heading-based scoring alone may be insufficient to provide strong attraction toward the goal [9]. To solve this problem, a goal distance factor is included in the evaluation function. The exponential attraction function is used to introduce a non-linear response to distance variations:

$$G_{att}(v, \omega) = -\exp(\alpha d_g(v, \omega)),$$

where $d_g(v, \omega)$ represents the Euclidean distance between the predicted trajectory endpoint and the goal, and $\alpha = 0.5$ is a configurable parameter to control the strength of the attractive force. Therefore, the heading guidance and target alignment evaluation function is denoted as $O(v, \omega)$:

$$O(v, \omega) = H(v, \omega) + G_{att}(v, \omega).$$

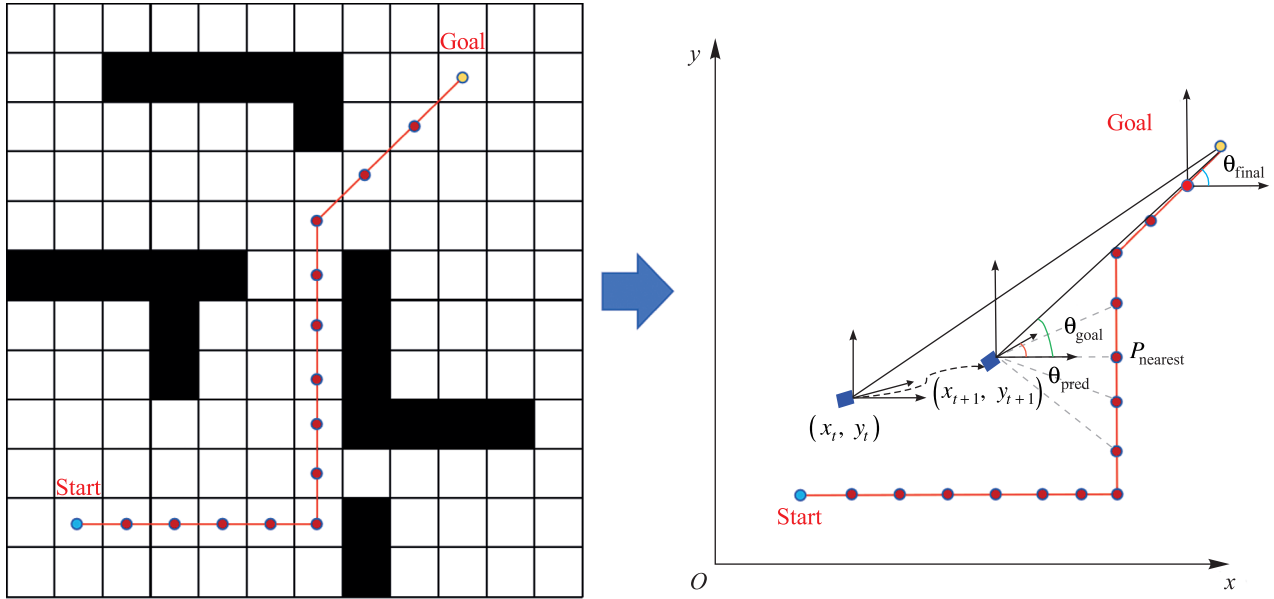


Fig. 1. Illustration of orientation consistency angles

Global path adherence constraint. To solve the problem in classical DWA, where local path planning may deviate significantly from the global reference path, which causes the robot to fall into local minima, we are introducing a global path adherence constraint. Specifically, let the global path generated by a global planner (e. g., A^*) be denoted as $P_{\text{global}} = \{P_1, P_2, \dots, P_L\}$, where each $P_i = (x_i, y_i)$ represents a waypoint on the global path. At each control cycle the algorithm first identifies the index i^* of the global path point closest to the robot's current position $X_c = (x_c, y_c)$. A local segment P_{local} of the global path is selected, consisting of M consecutive nodes starting from P_{global} . Then given the predicted trajectory consisting of T points, denoted as $T_{\text{pred}} = \{t_1, t_2, \dots, t_N\}$, the path adherence metric is defined as the maximum deviation between the predicted trajectory and the selected local global path segment. The calculation process is described in equations

$$i^* = \arg \min_{1 \leq i \leq L} \|P_i - X_c\|_2,$$

$$P_{\text{local}} = \{P_{i^*}, P_{i^*+1}, \dots, P_{i^*+M-1}\},$$

$$D(v, \omega) = -\max_{1 \leq i \leq N} \min_{p \in P_{\text{local}}} \|t_i - p\|_2.$$

Here $\|\cdot\|_2$ indicates L_2 distance (Euclidean distance). By focusing on path consistency within the local range and avoiding interference of distant path points in the local evaluation, the accuracy and stability of the local trajectory can be significantly improved.

Trajectory smoothness and dynamic stability control. In classical DWA the lack of temporal continuity in decision-making often leads to abrupt changes in velocity and steering, resulting in trajectories intermittent and unstable robot motion [4]. To solve this problem, MC-DWA introduces a penalty term based on the variation in motion state from the previous time step during candidate velocity selection. In addition, MC-DWA enhances the trajectory evaluation function by incorporating constraints on trajectory curvature variation and jerk (i. e., the rate of change of acceleration), optimising trajectory smoothness and dynamic stability from both spatial and dynamic perspectives. Specifically, the curvature variation is defined as the average absolute second-order difference of consecutive trajectory points in the lateral direction, serves as a lightweight yet highly effective heuristic proxy for lateral oscillation:

$$C_{\text{var}}(v, \omega) = -\frac{1}{N-2} \sum_{i=1}^{N-2} \left| \frac{y_{i+2} - 2y_{i+1} + y_i}{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + \varepsilon} \right|,$$

where ε is a small constant to prevent division by zero. This expression captures the local bending intensity of the trajectory. Furthermore, jerk metrics, which are introduced for both linear and angular velocities to suppress control shocks during execution, can be calculated as follows:

$$J_v(v, \omega) = -\frac{1}{N-2} \sum_{i=1}^{N-2} \left| \frac{a_{v,i+1} - a_{v,i}}{\Delta t} \right|,$$

$$J_{\omega}(v, \omega) = -\frac{1}{N-2} \sum_{i=1}^{N-2} \left| \frac{a_{\omega, i+1} - a_{\omega, i}}{\Delta t} \right|.$$

Its design limits sudden changes in velocity commands, improving trajectory control and smooth execution, especially for mobile platforms that require high trajectory continuity. The overall smoothness and stability evaluation function is denoted as $S(v, \omega)$:

$$S(v, \omega) = C_{\text{var}}(v, \omega) + J_v(v, \omega) + J_{\omega}(v, \omega).$$

At the same time, dynamic stability control is especially important during high-speed cornering. For mobile platforms with significant velocity or centre of mass height (e. g., differential-drive robots or automated forklifts), a sharp turn at high speed can cause skidding or even rollover. To mitigate this, MC-DWA includes restrictions on the radius of curvature and lateral acceleration during the velocity space filtering stage. Specifically, the maximum allowable angular velocity at a given linear velocity is limited based on the lateral acceleration threshold a_{lat} , as formulated in equation

$$V_{\text{lat}} = \{(v, \omega) | v\omega < a_{\text{lat}}\}.$$

This constraint ensures that the resulting centrifugal force during turning does not exceed the platform's stability limit, thereby enhancing dynamic controllability and operational safety. Accordingly, in MC-DWA the admissible velocity space of the dynamic window is defined as

$$V_{\text{dw}} = V_{\text{kin}} \cap V_{\text{dyn}} \cap V_{\text{safe}} \cap V_{\text{lat}}.$$

Unified trajectory scoring model. In order to effectively integrate the aforementioned constraints, MC-DWA creates a complex trajectory evaluation function:

$$\text{score}(v, \omega) = w_O O(v, \omega) + w_D D(v, \omega) + w_S S(v, \omega).$$

Here w_O , w_D and w_S are weighting factors that can be changed to adapt to specific applications. In this paper, all values are 1. The final scoring function with multiple metrics acting synergistically, allows the robot to generate smooth, robust and goal-oriented feasible paths in complex environments.

Experiments and results

Experimental environment and parameter settings. The improved DWA algorithm framework was implemented on the *MATLAB R2024a* platform. To systematically evaluate the effectiveness of path planning performance and control stability, 50 two-dimensional grid maps were designed, covering typical navigation tasks such as dense obstacle regions and long corridor intersections. Each map includes a defined start and goal point with a guaranteed feasible global reference path.

All evaluation metrics were obtained statistically based on these 50 representative test scenarios, which are characterised by different map structures, obstacle densities and dynamic obstacle patterns. This diverse task setup ensures strong generalisation and a realistic level of complexity, thereby providing a more objective and comprehensive verification of the proposed method's robustness and adaptability in difficult dynamic conditions. The robot's control and physical parameters used in the simulation are shown in table 1.

Table 1

Simulation parameters

Name	Symbol	Value
Time step	Δt	0.1 s
Horizon	T	2.0 s
Max step	—	500
Maximum linear velocity	v_{max}	2.0 m/s
Minimum linear velocity	v_{min}	0 m/s
Maximum linear acceleration	a_v^{max}	0.4 m/s ²
Minimum linear acceleration	a_v^{min}	−0.4 m/s ²

Ending of the table 1

Name	Symbol	Value
Robot radius	—	0.4
Safe margin	d_{sm}	0.2
Maximum lateral acceleration	a_{lat}	$1.0 \text{ m} \cdot \text{rad/s}^2$
Maximum angular velocity	ω_{max}	1.57 rad/s
Minimum angular velocity	ω_{min}	-1.57 rad/s
Maximum angular acceleration	a_{ω}^{max}	0.78 rad/s^2
Minimum angular acceleration	a_{ω}^{min}	-0.78 rad/s^2

Comparison of the proposed MC-DWA algorithm with other improved DWA algorithms. To comprehensively evaluate the practical performance of the proposed MC-DWA algorithm, we conducted a systematic comparison with the classical DWA algorithm as well as three representative improved variants: energy efficient DWA (EDWA) [10], fuzzy adaptive DWA (fuzzy-DWA) [11] and predictive DWA (pred-DWA) [12].

To ensure fairness, all algorithms were tested under the same initial conditions and map configurations, and a unified evaluation framework was adopted to quantify performance across multiple dimensions. Specifically, the evaluation metrics include minimum safe distance (MSD), which measures the minimum distance between the robot and obstacles along the path and reflects the safety margin; time step (TS), which denotes the total number of control cycles required to achieve the goal and indicates the efficiency of time use; path length (PL), which evaluates the overall compactness and rationality of the planned trajectory; path curvature (PC), which quantifies trajectory smoothness and dynamic controllability based on the average curvature variation. Taken together, these metrics provide a comprehensive overview of each algorithm's performance in terms of path safety, efficiency, smoothness and control stability. Table 2 provides a comparative analysis of the proposed MC-DWA against the classical DWA and three representative improved variants for four key performance metrics.

Table 2

**Comparison of the proposed MC-DWA algorithm
with other DWA algorithms**

Method	MSD	PL	PC	TS
Classical DWA	0.20	35.67	0.706	357
EDWA	0.19	30.41	0.513	304
Fuzzy-DWA	0.16	35.15	0.792	352
Pred-DWA	0.22	33.04	0.763	330
MC-DWA	0.53	37.97	0.323	380

Overall, the MC-DWA demonstrates excellent performance in terms of path safety, trajectory smoothness and control stability, which confirms the effectiveness of its multi-constraint fusion mechanism.

As for MSD, MC-DWA provides a minimum obstacle clearance of 0.53, which is significantly higher than other algorithms, indicating improved obstacle avoidance safety and greater navigational redundancy. This improvement is mainly due to the introduction of restrictions on compliance with the global path, which ensures that local trajectories remain closely aligned with global navigation goals and allows you to effectively bypass areas with dense obstacles. For PC, MC-DWA gives an average change in curvature equal to 0.323, which indicates a high degree of trajectory smoothness. In contrast, classical DWA, pred-DWA and fuzzy-DWA have curvature values exceeding 0.7, suggesting more pronounced oscillations in their paths. This result directly reflects the effectiveness of the curvature variation constraint and jerk suppression mechanisms used in MC-DWA, which

help to soften sharp turns and sudden velocity changes, thereby improving trajectory executability and control system stability. As for PL, MC-DWA produces a trajectory length of 37.97, which is slightly longer than some other methods such as EDWA and pred-DWA, but comparable to classical DWA and fuzzy-DWA. This result is closely related to the dual heading guidance mechanism implemented in MC-DWA, which improves the stability of the robot's directional consistency and goal orientation, while reducing oscillations and heading deviations. Although the path is a bit longer, this compromise is acceptable, given the substantial gains in safety and controllability. In terms of TS, MC-DWA completes the navigation in 380 control cycles, which is slightly higher than classical DWA and fuzzy-DWA, while EDWA is the most time-efficient. Although MC-DWA is slightly behind in time efficiency, the smoother and safer trajectories it generates make it more suitable for dynamic or high-risk environments, emphasising the balance between control stability and trajectory quality.

Thus, MC-DWA surpasses existing algorithms in several key performance metrics, in particular, in trajectory smoothness and obstacle avoidance safety. These improvements stem from its trajectory evaluation mechanism, which integrates multi-dimensional control constraints and global guidance strategies. This design effectively eliminates the limitations of traditional DWA in trajectory continuity and dynamic feasibility, significantly improving the algorithm's robustness and adaptability in complex dynamic environments and providing a more practical and reliable solution for high-quality path planning in real-world applications for mobile robots.

Visualisation. To further provide an intuitive comparison of the path planning performance across different environments, the experimental results were visualised. Figure 2, *a*, and figure 2, *b*, illustrate the paths generated using the proposed MC-DWA algorithm, classical DWA and improved A^* algorithm under normal and dense obstructed environments, respectively. To avoid visual clutter, only these three representative algorithms were selected for comparison.

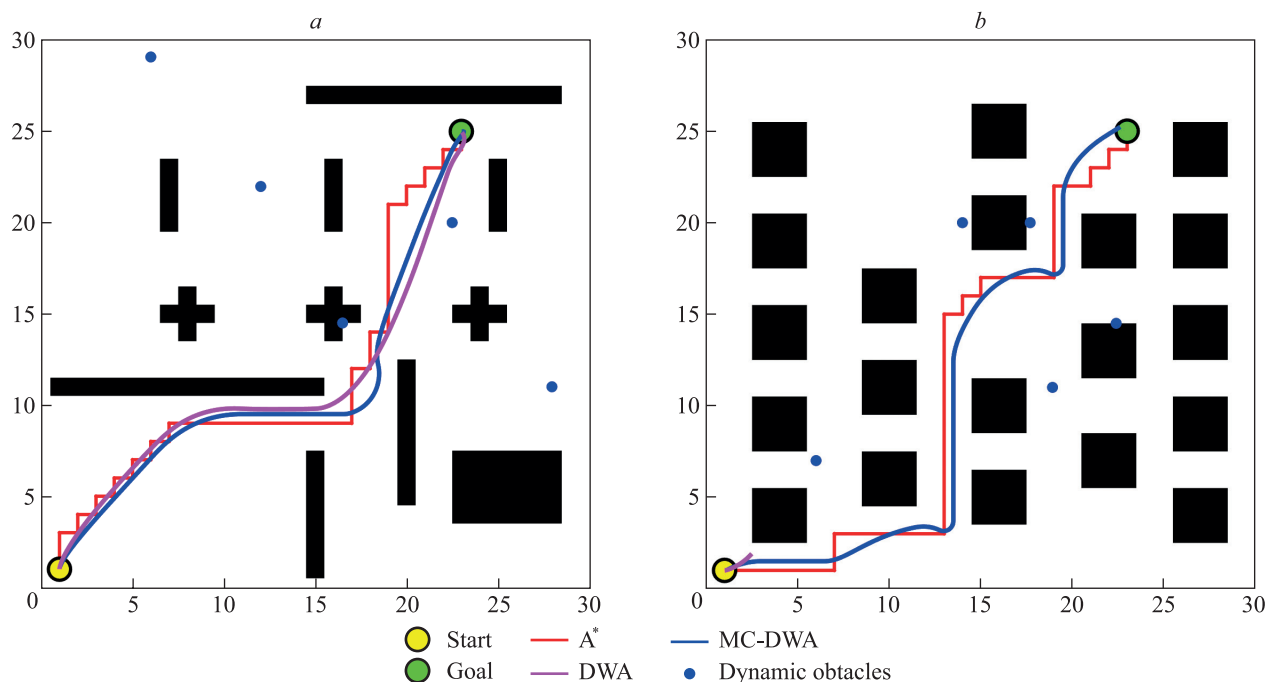


Fig. 2. Visual comparison using classical DWA algorithms and the global A^* algorithm on different maps:
a – normal environment; *b* – dense obstructed environment

From the visualisation, it can be seen that under normal conditions, although the classical DWA is able to successfully reach the target, its generated path tends to closely follow the boundaries of static obstacles, which creates a higher risk of collision. In more difficult environment with dense obstacles the classical DWA often fails to complete navigation, which often leads to an interruption of the path or a complete stop of the robot due to the lack of effective global guidance and dynamic obstacle avoidance strategies.

In contrast, the proposed MC-DWA successfully completes the navigation task in both environments. Its generated trajectories ensure good adherence to the global path and constant maintenance of a safe distance from surrounding obstacles throughout the motion process (greater than the predefined minimum safety distance), demonstrating excellent adaptability to difficult environmental conditions and increased path safety.

Furthermore, figure 3 shows a visual comparison of the proposed algorithm and several representative algorithms in two typical complex environments. The purpose of this experiment is to evaluate the robustness and planning capability of each algorithm when solving problems such as long-distance obstacle interference and densely cluttered obstacle fields.

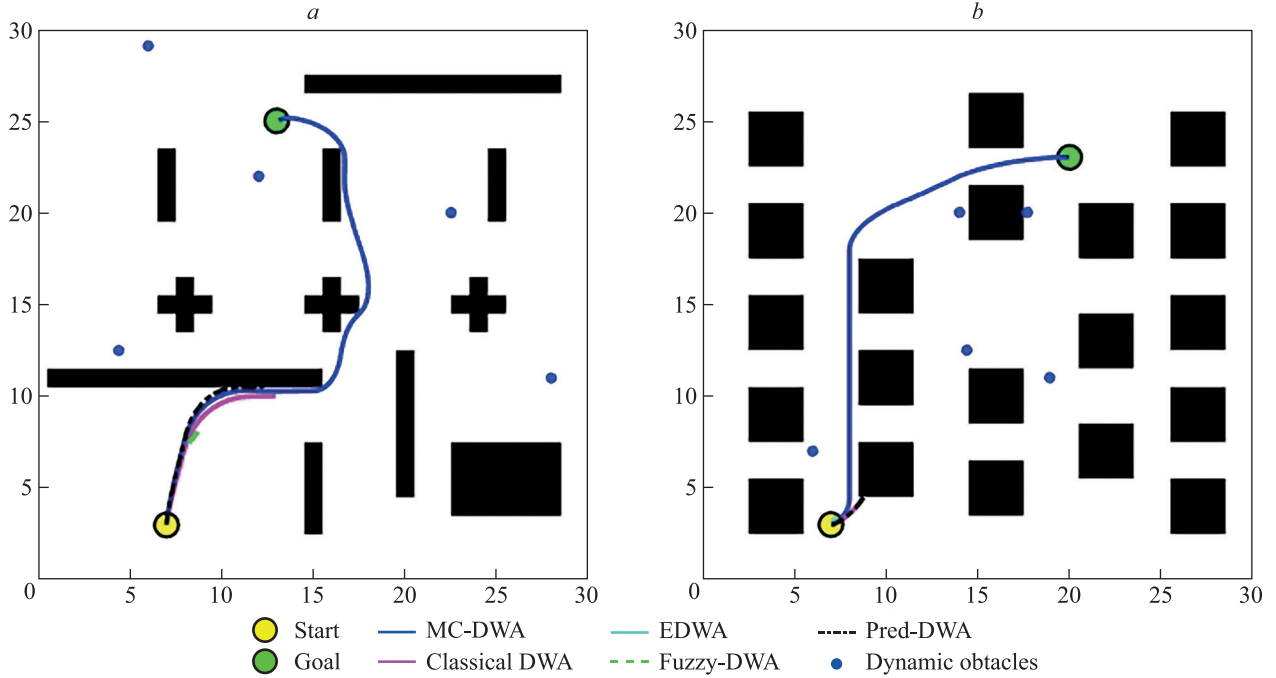


Fig. 3. Visual comparison using different DWA algorithms in complex environments:
a – environment with a distant obstacle; b – environment with densely distributed obstacles

As shown in fig. 3, *a*, the scenario involves a distant obstacle that creates a critical impediment to the planned path. The results demonstrate that, except MC-DWA, all other algorithms fail to navigate around the obstacle and eventually become stuck. Further analysis reveals that this problem is primarily related to the lack of effective target-oriented guidance, causing traditional algorithms to lose directional cues near the obstacle. In contrast, MC-DWA uses an exponential attraction mechanism in trajectory estimation, which enhances the goal-directed driving force while maintaining safety, allowing the robot to traverse complex terrain and move smoothly toward the target. Figure 3, *b*, shows an extremely complex environment consisting of densely distributed obstacles. In this scenario classical DWA and other improved methods are generally limited by local information and tend to fall into local minima, halting progress. However, MC-DWA introduces a global path keeping constraint, which allows for better alignment of local planning with global navigation objectives. This mechanism allows the robot to avoid local traps and successfully reach the goal. Throughout the entire process, the generated path maintains safe distances from obstacles, while demonstrating good continuity and dynamic stability.

Figure 4 illustrates the dynamic behaviour of various path planning algorithms during execution. The left part of the fig. 4 shows the trajectory followed by each method, demonstrating their obstacle avoidance performance and convergence behaviour near the goal. The right part depicts the time-series variations of linear and angular velocities throughout the planning process, which serve to assess motion continuity and control smoothness.

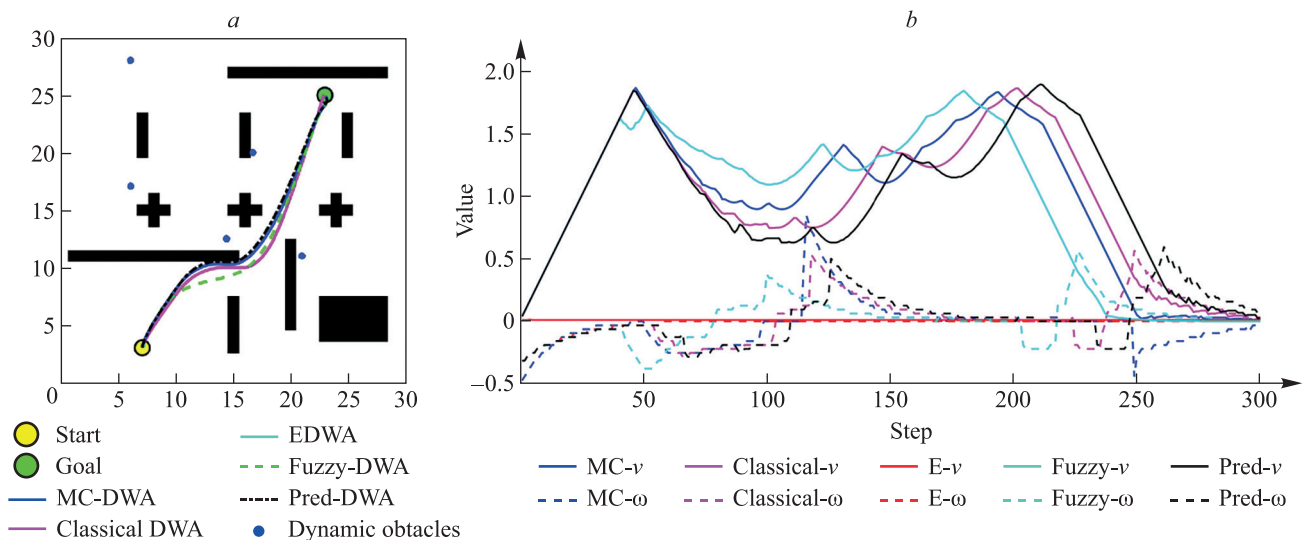


Fig. 4. Dynamic behaviour of various path planning algorithms during execution: *a* – comparison of path planning algorithms; *b* – visualisation of changes in linear and angular speed during the planning process

Among the compared methods, all algorithms except EDWA successfully completed the navigation task. Notably, fuzzy-DWA achieved the fastest arrival by taking advantage of the flexibility provided by fuzzy rules. However, it exhibited frequent and irregular fluctuations in both linear and angular velocities, indicating the absence of effective constraints on control smoothness and revealing limitations in the fuzzy rule base's tuning capability. This unstable velocity jumps the reliability of the movement. Classical DWA and pred-DWA suffered from pronounced oscillations, particularly during the deceleration phase near the goal, where significant jitter was observed in both velocity profiles. This instability suggests that these methods are unable to provide smooth braking and precise goal alignment, which may negatively impact docking precision and overall control robustness. In contrast, the proposed MC-DWA exhibits significantly smoother transitions in both velocity and steering control. The performance improvement is primarily due to the inclusion of jerk penalties (for linear and angular accelerations) in the evaluation function, which effectively suppresses abrupt control variations. As a result, MC-DWA provides improved motion continuity and system stability during trajectory execution. In addition, MC-DWA has become the second fastest method to reach the goal, which indicates a good balance between efficiency and control quality. Also the trajectory visualisation on the left side of fig. 4 shows that MC-DWA consistently maintains a safe distance from both static and dynamic obstacles throughout the entire execution process, without any incidents of near-collision or critical proximity. This highlights the method's reliability in ensuring safety, especially in complex environments.

Discussion

The experimental results demonstrate that the proposed MC-DWA is superior to classical DWA and its typical variants across multiple key performance metrics. Whether in terms of trajectory smoothness, minimum obstacle distance or overall path length, MC-DWA has greater robustness and environmental adaptability. This performance gain is primarily due to the integration of several fine-grained constraint designs within the trajectory evaluation mechanism, dual-angle heading deviation, global path adherence assessment, curvature variation control and jerk suppression. Collectively, these improvements significantly enhance the rationality, continuity and feasibility of planned trajectories, while maintaining the real-time responsiveness inherent in the original DWA framework.

Despite promising results in rule design and trajectory quality, MC-DWA remains, in fact, a manually developed heuristic method. Its evaluation function and weighting parameters are set manually, which makes it impossible to dynamically adjust in various environments and task scenarios. In practical applications, this often requires manual parameter settings for each new context, which limits the algorithm's generalisability and deployment efficiency. Moreover, heuristic methods are inherently difficult to model complex, multi-dimensional and temporally dynamic features of real-world environments. In particular, in conditions associated with numerous dynamic obstacles or high-dimensional state input data, the performance limit of traditional methods becomes obvious [13].

To address these challenges, recent advances in deep reinforcement learning (DRL) have provided new perspectives for path planning. DRL offers end-to-end learning capability, allowing agents to autonomously learn optimal navigation strategies through continuous interaction with the environment, thereby eliminating the need for explicit modeling and hand-written rules [14]. Compared to traditional methods, DRL-based planning approaches have superior adaptability, policy expressiveness and cross-task transferability, making them particularly suitable for dynamic, uncertain or frequently changing environments.

Based on this understanding, future research may explore the possibility of using the MC-DWA heuristic framework as an initial policy or hybrid guidance model for DRL-based navigation systems. By integrating the experience of creating rule-based paths into the training process of deep neural networks, it is possible to effectively combine heuristic knowledge with data-driven learning. This hybrid approach potentially preserves the interpretability and stability of traditional methods, while increasing the intelligence and generalising capabilities of path planning algorithms. This could pave the way for the development of highly reliable and robust intelligent mobile robotic systems capable of navigating complex real-world scenarios.

Conclusions

This article proposes an improved MC-DWA to address several limitations of the traditional DWA in local path planning. By introducing multi-dimensional trajectory constraints and a fused estimation mechanism, the proposed method comprehensively optimises trajectory evaluation in terms of heading consistency, global path adherence, trajectory smoothness and control stability. Specifically, MC-DWA includes a dual-heading guidance strategy to improve goal alignment, uses a path adherence constraint to increase consistency between local planning and global navigation intent and integrates curvature variation and jerk constraints to improve trajectory

smoothness and dynamic feasibility. A unified weighted estimation model has been developed to support multi-objective trajectory decision making.

To confirm the effectiveness of the proposed method, comparative experiments were conducted on a series of simulation maps with varying environmental complexity. Three representative improved DWA algorithms were selected as baselines. All experiments were performed on a unified simulation platform using evaluation metrics such as navigation time, path length, curvature smoothness and minimum obstacle distance. The results show that MC-DWA outperforms both classical DWA and several improved variants in planning efficiency, trajectory quality and obstacle avoidance safety, demonstrating excellent robustness and practical applicability.

The source code for the MC-DWA function and the maps used for the simulation is published and available for free non-commercial use¹.

Future work will focus on extending MC-DWA to the ROS2 and Gazebo simulation platforms to further evaluate its generalisation ability and engineering adaptability in dynamically modeled environments. Furthermore, we plan to deploy the proven MC-DWA algorithm on a real mobile robotic platform to conduct physical experiments in real-world scenarios, facilitating its practical application in industrial and service robotics.

References

1. Yang L, Li P, Qian S, Quan H, Miao J, Liu M, et al. Path planning technique for mobile robots: a review. *Machines*. 2023; 11(10):980. DOI: 10.3390/machines11100980.
2. Sánchez-Ibáñez JR, Pérez-del-Pulgar CJ, García-Cerezo A. Path planning for autonomous mobile robots: a review. *Sensors*. 2021;21(23):7898. DOI: 10.3390/s21237898.
3. Fox D, Burgard W, Thrun S. The dynamic window approach to collision avoidance. *IEEE Robotics & Automation Magazine*. 1997;4(1):23–33. DOI: 10.1109/100.580977.
4. Gong X, Gao Y-F, Wang F-B, Zhu D-R, Zhao W, Wang F, et al. A local path planning algorithm for robots based on improved DWA. *Electronics*. 2024;13(15):2965. DOI: 10.3390/electronics13152965.
5. Liu A-Z, Liu C, Li L, Wang R-C, Lu Z. An improved fuzzy-controlled local path planning algorithm based on dynamic window approach. *Journal of Field Robotics*. 2024;42(2):430–454. DOI: 10.1002/rob.22419.
6. Wang Z, Li G. Research on path planning algorithm of driverless ferry vehicles combining improved A* and DWA. *Sensors*. 2024;24(13):4041. DOI: 10.3390/s24134041.
7. Lu Y, Da C. Global and local path planning of robots combining ACO and dynamic window algorithm. *Nature: Scientific Reports*. 2025;15:9452. DOI: 10.1038/s41598-025-93571-8.
8. Sang W, Yue Y, Zhai K, Lin M. Research on AGV path planning integrating an improved A* algorithm and DWA algorithm. *Applied Sciences*. 2024;14(17):7551. DOI: 10.3390/app14177551.
9. Zhang Z, Xue Y, Figueroa N, Åkesson K. Gradient field-based dynamic window approach for collision avoidance in complex environments. arXiv:2504.03260v2 [Preprint]. 2025 [cited 2025 October 12]: [6 p.]. Available from: <https://arxiv.org/abs/2504.03260v2>.
10. Henkel C, Bubeck A, Xu W. Energy efficient dynamic window approach for local path planning in mobile service robotics. *IFAC-Papers Online*. 2016;49(15):32–37. DOI: 10.1016/j.ifacol.2016.07.610.
11. Liu A-Z, Liu C, Li L, Wang R-C, Lu Z. An improved fuzzy-controlled local path planning algorithm based on dynamic window approach. *Journal of Field Robotics*. 2025;42(2):430–454. DOI: 10.1002/rob.22419.
12. Missura M, Bennewitz M. Predictive collision avoidance for the dynamic window approach. In: Institute of Electrical and Electronics Engineers. *2019 International conference on robotics and automation; 2019 May 20–24; Montreal, Canada*. Montreal: Institute of Electrical and Electronics Engineers; 2019. p. 8620–8626. DOI: 10.1109/ICRA.2019.8794386.
13. Abubakr OA, Jaradat MA, Abdel-Hafez MF. Intelligent optimization of adaptive dynamic window approach for mobile robot motion control using fuzzy logic. *IEEE Access*. 2022;10:119368–119378. DOI: 10.1109/ACCESS.2022.3220703.
14. Wu C, Yu W, Li G, Liao W. Deep reinforcement learning with dynamic window approach based collision avoidance path planning for maritime autonomous surface ships. *Ocean Engineering*. 2023;284:115208. DOI: 10.1016/j.oceaneng.2023.115208.

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¹MC_DWA: multi-constraint enhanced DWA for robust and smooth local navigation // GitHub : website. URL: https://github.com/tjyjbzd/MC_DWA (date of access: 12.10.2025).