

RESEARCH ARTICLE

Multi-learning strategy particle swarm optimization for agricultural machinery path optimization

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Agricultural machinery path planning is gradually shifting from single shortest-path solutions to comprehensive path optimization. However, current path optimization methods struggle to balance path smoothness, energy consumption, and rapid replanning amid environmental changes in fragmented, sloped, and irregular fields. To address these challenges, this study proposed a 3D path-cost model for agricultural machinery operating in hilly and mountainous regions. The proposed path cost model included path length, turning cost, slope risk, trafficability constraints, and unit energy consumption. Furthermore, a Multi-learning Fusion Particle Swarm Optimization algorithm was introduced. The results indicated that, in hilly fields with dynamic obstacles, the average number of convergence iterations decreased from 126.00 to 79.00, and the repeated positioning accuracy error decreased from 0.31 m to 0.13 m. In real-world fields with dense obstacles, the obstacle-avoidance success rate reached 98.00%, and the task completion rate reached 95.90%. These findings demonstrated that the proposed algorithm enhanced optimization stability, path-execution consistency, and obstacle-avoidance capability in complex hilly terrains. This study provided a reference for engineering applications involving intelligent path planning, risk-constrained modeling, and dynamic path adjustment for agricultural machinery in hilly and mountainous regions.

Keywords: hilly and mountainous areas; agricultural machinery; path planning; multi-learning strategy; particle swarm optimization; energy consumption optimization.

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Introduction

The continuous advancement of agricultural mechanization and intelligent technologies has made operational path optimization a key factor affecting the efficiency, energy consumption, and safety of agricultural machinery [1]. Unlike regular plots on flat terrain, hilly and mountainous fields are characterized by considerable elevation variations, fragmented boundaries, steep slopes, and irregular operating areas. Therefore, path planning in these

environments cannot be limited to minimizing travel distance in two-dimensional space, but must also account for three-dimensional terrain, machinery motion constraints, and operational risks under uncertain conditions [2]. Without coordinated consideration of path smoothness, turning constraints, slope risk, trafficability, and energy consumption, the planned path may contain frequent turns, locally stagnant segments, or high-risk passages.

Existing research has gradually extended agricultural machinery path planning from isolated route generation to system-level integration of environmental perception, planning, and execution. Zahidi *et al.* showed that 5G communication and edge computing could improve the online processing and response capabilities of agricultural robots, providing technical support for the integration of perception, decision-making, and execution [3]. Donat *et al.* incorporated plot boundaries, working width, headland space, and turning constraints into field-path optimization, demonstrating that agricultural operation paths could not be determined solely according to geometric distance [4]. Fujinaga further validated a LiDAR-supported hybrid navigation strategy in both virtual environments and real strawberry fields, indicating a transition from static offline planning to perception-driven dynamic optimization [5]. Research on hilly and mountainous fields has increasingly incorporated three-dimensional terrain and farmland-boundary information into path generation. Li *et al.* constructed three-dimensional models of hilly tea gardens using low-altitude remote sensing and oblique photography and generated global paths for working and headland areas [6]. Vahdanjoo *et al.* developed a three-dimensional coverage-planning model based on energy-consumption criteria by jointly considering terrain variation, vehicle travel direction, and operating load [7]. PourArab *et al.* further introduced slope cost into a three-dimensional farmland coverage-planning framework, improving solution efficiency while maintaining coverage quality [8]. These studies have established the basis for integrating terrain characteristics, operational constraints, and energy consumption into agricultural machinery path planning. At the algorithmic level, existing methods generally separate global path generation from local dynamic adjustment. Peng *et al.* developed an optimization-based motion-planning method for autonomous agricultural vehicles operating in constrained headlands [9]. Yang *et al.* used RGB-D perception to guide online path correction for a crop-phenotyping robot

[10]. Kulathunga *et al.* combined elastic-band replanning with Hybrid A* to repair local trajectories in unknown environments [11]. Particle Swarm Optimization (PSO) has also been applied to candidate-path optimization because of its relatively simple implementation and adaptability to multidimensional nonlinear problems [12]. However, conventional PSO remains susceptible to premature convergence, insufficient population diversity, and parameter sensitivity in complex search spaces [13]. Despite these advances, major challenges remain in agricultural machinery path planning for hilly and mountainous fields. The path length, turning smoothness, slope safety, trafficability, and energy consumption are often evaluated in isolation, and their interactions lack adequate representation within a unified quantitative model. Consequently, a geometrically short path may not provide favorable safety or energy performance under complex terrain conditions. Further, the connection between global planning and local real-time replanning remains insufficient. Liu *et al.* integrated laser simultaneous localization and mapping, A*, and the Dynamic Window Approach into a greenhouse picking-robot navigation system, but the validation mainly involved structured environments [14]. Ambuj and Machavaram also showed that global planning was effective in using prior environmental information, whereas local planning depended on real-time perception for dynamic correction [15]. Efficiently coordinating these two processes amid changing slopes, sudden obstacles, and deteriorated trafficability remains a practical challenge. Furthermore, the standard PSO mechanism has limited adaptability to high-dimensional agricultural path optimization. Its search process may provide insufficient exploration during the early iterations, lose population diversity, and converge prematurely toward local optima. These limitations become more pronounced in fragmented hilly fields containing multiple feasible corridors, obstacle belts, and locally low-cost terrain regions.

This study developed a path-optimization method that coordinated operational safety, path continuity, planning efficiency, and energy consumption for agricultural machinery working in complex hilly and mountainous fields. A three-dimensional path-cost model was first constructed by integrating path length, turning cost, slope risk, trafficability constraints, and unit energy consumption. On this basis, a Multi-learning Fusion Particle Swarm Optimization (MF-PSO) algorithm was developed. The algorithm combined a Sigmoid-like inertia weight, adaptive learning factors, and K-means subgroup learning to coordinate individual experience, subgroup information, and global-best information during particle updates. Cauchy perturbation was introduced to escape search stagnation, while a rolling-window replanning mechanism used real-time environmental information to update local path segments. The method was evaluated through ablation experiments under four simulated scenarios and comparative field experiments involving improved A*, A*-DWA, and MF-PSO in three hilly citrus plots. By incorporating terrain-aware cost modeling, multilevel population learning, global optimization, and local replanning into a unified framework, this study provided a quantitative approach for examining the relationships among path geometry, terrain risk, operational continuity, and energy consumption. The proposed framework could also provide methodological support for risk-constrained path planning and adaptive operation control of autonomous agricultural machinery in complex farmland environments.

Materials and methods

MF-PSO algorithm design for hilly agricultural machinery operation

To balance operational safety, path continuity, and energy consumption in complex hilly fields, the proposed MF-PSO framework integrated comprehensive path-cost modeling, multi-learning global search, and rolling-window local replanning. The environmental inputs comprised

digital elevation model (DEM) data, parcel boundaries, obstacles or impassable areas, soil-resistance data, start and goal locations, and machinery kinematic constraints. Each candidate path was represented by a fixed sequence of three-dimensional control nodes. The corresponding path segments were assigned as slope, soil-resistance, and obstacle-clearance attributes and evaluated in terms of path length, turning cost, energy consumption, and operational risk. The weighted sum of these components defined the MF-PSO fitness function. The path-length term was shown as follows.

$$L = \sum_{k=1}^{m-1} \|\mathbf{p}_{k+1} - \mathbf{p}_k\|_2 \quad (1)$$

where L was the total length of the entire operation path. $\mathbf{p}_k$ was the 3D position vector of the k -th path node. The term "node" here referred to a key control point of the agricultural machinery from the start point to the end point. However, path length alone could not adequately define path quality as frequent turns and narrow maneuvers often compromised operational continuity in hilly fields. Therefore, this study modeled turning smoothness separately as shown below.

$$T = \sum_{k=2}^{m-1} \arccos \frac{(\mathbf{p}_k - \mathbf{p}_{k-1}) \cdot (\mathbf{p}_{k+1} - \mathbf{p}_k)}{\|\mathbf{p}_k - \mathbf{p}_{k-1}\|_2 \|\mathbf{p}_{k+1} - \mathbf{p}_k\|_2 + \varepsilon} \quad (2)$$

where T was the cumulative turning cost. ε was a small value used to avoid division by zero. Furthermore, slope and soil-bearing conditions directly influenced trafficability and stability. Accordingly, this study considered energy consumption as a key parameter and employed a segment distance-weighted energy consumption model. The energy consumption model for slope operation was described below.

$$E = \sum_{k=1}^{m-1} d_k (a_0 + a_1 \tan^2 \theta_k + a_2 \rho_k) + a_3 T \quad (3)$$

where E was the total energy consumption cost of the entire path. $d_k = \|\mathbf{p}_{k+1} - \mathbf{p}_k\|_2$ was the length of the k -th path segment. θ_k was the average slope of that segment. ρ_k was the soil resistance or surface impedance coefficient. a_0 , a_1 , a_2 , and a_3 were parameters to be calibrated. In addition, safety risks were modeled separately in this study. In hilly regions, beyond the collision hazards posed by obstacles, there was a rollover risk caused by the combined effects of slope and clearance [16, 17]. The risk term was given as follows.

$$R = \sum_{k=1}^{m-1} \left[b_1 \max(0, \theta_k - \theta_{\text{safe}})^2 + b_2 \frac{1}{o_k + \varepsilon} \right] \quad (4)$$

where R was the operation risk cost. θ_{safe} was the safety slope threshold, which was set to 15° as a basic boundary. o_k was the clearance distance from the path segment to the nearest obstacle or impassable boundary. b_1 and b_2 were risk weights. By integrating length, turning, energy consumption, and risk, this study constructed a comprehensive fitness function for agricultural machinery path optimization in hilly terrains as follows.

$$J = \lambda_1 L + \lambda_2 T + \lambda_3 E + \lambda_4 R \quad (5)$$

where J was the total path cost, which was also the fitness objective. λ_1 , λ_2 , λ_3 , and λ_4 were the weights of the four types of costs. To prioritize operational safety, λ_4 could be increased. Conversely, to emphasize efficiency and energy balance, λ_1 and λ_3 were coordinated.

Global optimization mechanism with multi-learning strategy fusion

The comprehensive cost function evaluated the geometric, energetic, and operational characteristics of each candidate path. During optimization, each particle represented a complete three-dimensional operation path rather than an individual scalar parameter. Particle updates drew on three sources of

information including the historical best path of the particle, the best path within its subgroup, and the global-best path of the entire population. A Sigmoid-like inertia weight regulated the balance between exploration and exploitation, while adaptive learning factors and K-means subgroup learning controlled the relative contributions of the three information sources. The candidate path was expressed as below.

$$\mathbf{X}_i^t = [\mathbf{p}_{i1}^t, \mathbf{p}_{i2}^t, \dots, \mathbf{p}_{im}^t] \quad (6)$$

where $\mathbf{X}_i^t$ was the complete candidate path represented by the i -th particle at the t -th iteration. $\mathbf{p}_{ik}^t$ was the k -th three-dimensional control node of that path. At each iteration, K-means clustering divided geometrically similar candidate paths into subgroups $C_1^t, \dots, C_K^t$. The velocity of each particle was then updated using its historical best path, the best path within its subgroup, and the global-best path. This structure preserved population diversity by allowing particles to learn from locally similar paths while retaining guidance from the global-best solution. Therefore, a Sigmoid-like form was utilized, which better supported broad exploration in the early stages and rapid convergence in the later stages [18]. The inertia weight was shown as follows.

$$\omega^t = \begin{cases} 0.9, & t \leq \alpha T_{\max} \\ \frac{1}{1 + \exp(\frac{10t - 2T}{T_{\max}})} + 0.4, & t > \alpha T_{\max} \end{cases} \quad (7)$$

where ω^t was the inertia weight. α was a parameter that controlled the length of the high-inertia interval in the early stage. Furthermore, rather than using fixed individual and social learning factors, this study applied adaptive learning factors to the path particles, decreasing individual learning and increasing social learning over iterations. The learning factors were shown below.

$$c_1^t = c_{\max} - (c_{\max} - c_{\min}) \frac{t}{T_{\max}}, \quad c_2^t = c_{\min} - (c_{\max} - c_{\min}) \frac{t}{T_{\max}} \quad (8)$$

where c_1^t was the individual learning factor. c_2^t was the social learning factor. A larger c_1^t in the early stage helped particles explore different feasible paths. A larger c_2^t in the later stage helped guide the population toward a better global path. However, relying solely on global and individual learning was insufficient due to the distinct local terrain features in hilly farmlands. Therefore, the particle swarm was divided into several subgroups, and each subgroup evolved independently in a local feasible space. K-means clustering was shown below.

$$C_j^t = \left\{ i : j = \arg \min_q \left\| \mathbf{X}_i^t - \mathbf{M}_q^t \right\|_2^2 \right\}, \quad \mathbf{M}_j^t = \frac{1}{|C_j^t|} \sum_{i \in C_j^t} \mathbf{X}_i^t \quad (9)$$

where C_j^t was the j -th subgroup. $\mathbf{M}_j^t$ was the corresponding cluster center. Candidate paths with similar geometric structures were assigned to the same subgroup, allowing different regions of the feasible search space to be explored in parallel [19]. After clustering, the particle with the lowest fitness value in each subgroup was selected as the subgroup-best path. The velocity and position updates that integrated the individual-best, subgroup-best, and global-best paths were defined below.

$$\begin{cases} \mathbf{Q}_j^t = \arg \min_{i \in C_j^t} J(\mathbf{X}_i^t) \\ \mathbf{V}_i^{t+1} = \omega^t \mathbf{V}_i^t + c_1^t r_1 (\mathbf{P}_i^t - \mathbf{X}_i^t) + c_2^t r_2 (\mathbf{Q}_{g(i)}^t - \mathbf{X}_i^t) + c_3^t r_3 (\mathbf{G}^t - \mathbf{X}_i^t) \\ \mathbf{X}_i^{t+1} = \mathbf{X}_i^t + \mathbf{V}_i^{t+1} \end{cases} \quad (10)$$

where $\mathbf{Q}_j^t$ was the optimal path of the j -th subgroup, $\mathbf{P}_i^t$ was the historical best path of the particle. $\mathbf{G}^t$ was the global optimal path. $g(i)$ was the subgroup index to which particle i belonged. Each particle retained its historical experience, learned from locally similar paths, and was guided by the global optimum, thereby establishing a comprehensive multi-learning strategy.

Cauchy perturbation escape and rolling window replanning mechanism

A path generated through a single global optimization process could not respond to newly detected obstacles, slope changes, or deterioration in surface trafficability. To couple global planning with real-time environmental updates, the proposed method combined stagnation detection and Cauchy perturbation with rolling-window local replanning. Search stagnation was first identified from the relative change in the global-best fitness value as defined below.

$$S(t) = \frac{|J(\mathbf{G}^{t-\tau}) - J(\mathbf{G}^t)|}{J(\mathbf{G}^{t-\tau}) + \varepsilon} \quad (11)$$

where $S(t)$ was the stagnation indicator. τ was the observation window length. When $S(t)$ remained below the prescribed threshold for W consecutive iterations, regular global search was suspended, and Cauchy perturbation was applied to generate long-tail escape candidates around the current global-best path. The feasibility and fitness of each candidate were then reevaluated. A better feasible candidate replaced the global best. Otherwise, the original global best was retained, and the perturbation scale was adjusted before global search resumed. The long-tailed Cauchy distribution was selected because it could jump beyond local low-cost basins formed by slopes, obstacle belts, and narrow passages in hilly fields [20]. The perturbed path was shown below.

$$\mathbf{G}^{t+1} = \mathbf{G}^t + \beta^t \zeta^t, \quad \zeta^t \sim \text{Caychy}(0,1) \quad (12)$$

where ζ^t was the standard Cauchy random vector. β^t was the perturbation scale. However, global escape alone was insufficient because agricultural machinery also encountered real-time local changes such as increased mud, sudden obstacles, or slope variations. Therefore, this study defined replanning trigger conditions. The replanning trigger indicator was shown as follows.

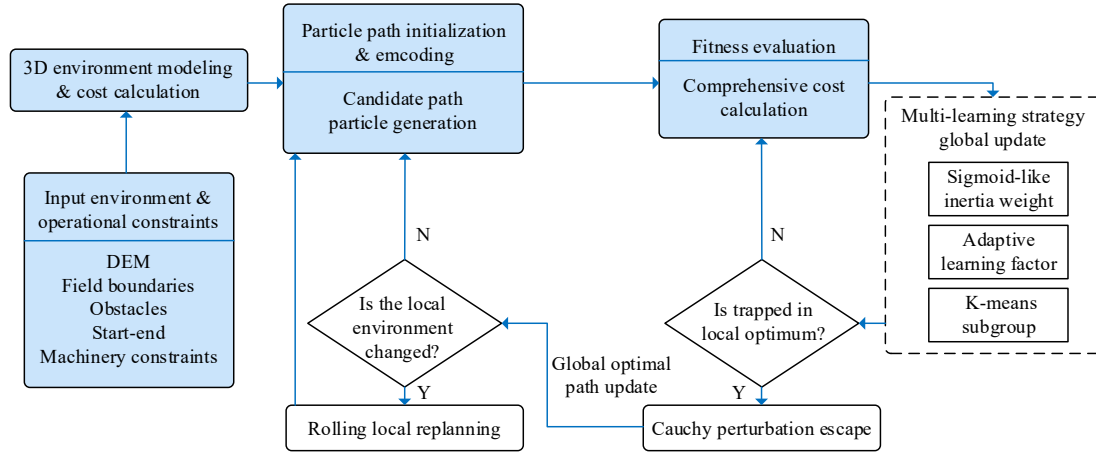


Figure 1. MF-PSO algorithm workflow.

$$\chi_k = I(o_k < o_{\min}) + I(|\theta_k - \theta_{k-1}| > \delta_\theta) + I(\rho_k > \rho_{\max}) \quad (13)$$

where χ_k was the replanning trigger indicator of the k -th local window. δ_θ was the slope variation threshold. Once $\chi_k > 0$ occurred, the current local segment was no longer suitable to follow the original global path. Upon triggering local replanning, randomly initializing particles from scratch would result in an unacceptably slow response. A more effective approach utilized the current global-best window segment and its velocity as a warm start and expressed as follows.

$$\mathbf{X}_{i,\text{win}}^0 = \mathbf{G}_{\text{win}} + \sigma_i \mathbf{V}_{i,\text{win}}^t, \sigma_i \sim U(-1,1) \quad (14)$$

where $\mathbf{X}_{i,\text{win}}^0$ was the initial particles for local window replanning. $\mathbf{G}_{\text{win}}$ was the segment of the original global best path within the current window. $\mathbf{V}_{i,\text{win}}^t$ was the corresponding velocity vector. When a new obstacle, an excessive slope change, or deteriorated trafficability was detected, the affected segment of the global path was extracted for local MF-PSO optimization. The optimized segment was connected to the reference path through an endpoint-reconnection penalty, after which the executable path was updated. If no replanning condition was triggered, the machinery continued to follow the current global path. This mechanism reduced the

occurrence of sharp turns, backtracking, and high-slope discontinuities at the end of the replanning window. The local optimization objective was defined as below.

$$\begin{cases} J_{\text{loc}} = \lambda_1 L_{\text{win}} + \lambda_2 T_{\text{win}} + \lambda_3 E_{\text{win}} + \lambda_4 R_{\text{win}} + \lambda_5 D_{\text{end}} \\ D_{\text{end}} = \|\mathbf{p}_{\text{win,end}} - \mathbf{p}_{\text{ref}}\|_2 \end{cases} \quad (15)$$

where J_{loc} was the optimization objective of the local window replanning. D_{end} was the distance between the end of the local path and the reference reconnection point. The whole workflow of the proposed algorithm from hilly farmland data input to executable operation paths output based on the three-level mechanism was shown in Figure 1. After the terrain, boundary, obstacle, and machinery-constraint data were loaded, the comprehensive path-cost function was constructed, and the particle population was initialized. Global optimization was then performed through fitness evaluation and multi-learning particle updates. Cauchy perturbation was activated when search stagnation was detected. During path execution, newly detected obstacles, excessive slope changes, or deteriorated trafficability triggered rolling-window local replanning. The resulting local segment was reconnected to the unaffected portion of the global path to produce the updated executable path.

Experimental platform and validation protocol

A two-level validation protocol was adopted to connect simulation ablation with field application. The simulation stage evaluated the contributions of the Sigmoid-like inertia weight, adaptive learning factors, K-means clustering, Cauchy perturbation to convergence, path quality, and turning control. The field stage evaluated execution performance in three types of hilly plots using obstacle-avoidance success rate, task completion rate, cumulative path length, number of turns, and fuel consumption rate. The same three-dimensional cost model, machinery kinematic constraints, start/end rules, and obstacle-clearance criteria were applied to all methods. Simulation experiments were conducted on Windows 11 64-bit (Microsoft Corporation, Redmond, WA, USA) and MATLAB R2022b (<https://www.mathworks.com/products/matlab.html>) using a workstation equipped with an Intel Core i7-12700F processor, 32 GB RAM, and an NVIDIA GeForce RTX 4060 GPU. Field deployment used an NVIDIA Jetson AGX Orin 32 GB edge computer (NVIDIA Corporation, Santa Clara, CA, USA) running Ubuntu 22.04 LTS (<https://ubuntu.com/>) and ROS 2 Humble (<https://docs.ros.org/en/humble/>). MF-PSO, improved A*, and A*-DWA were implemented as unified ROS 2 nodes using Python 3.10 (<https://www.python.org/>) and C++17 compiled with GCC 11.4 (<https://gcc.gnu.org/>). The perception unit comprised a ZED-F9P RTK-GNSS module (u-blox AG, Thalwil, Zurich, Switzerland), an MTi-300 inertial measurement unit (Xsens Technologies B.V./Movella, Enschede, Overijssel, the Netherlands), an RS-LiDAR-16 LiDAR (RoboSense Technology Co., Ltd., Shenzhen, Guangdong, China), and an Intel RealSense D455 RGB-D camera (Intel Corporation, Santa Clara, CA, USA). RTK-GNSS, IMU, LiDAR, and RGB-D data were acquired at 10 Hz, 100 Hz, 10 Hz, and 30 frames/s, respectively, and synchronized using ROS 2 timestamps. The experimental data consisted of simulation maps created by the authors and operation records collected from field tests. The simulation data included four categories of three-layer maps including regular parcels, parcels with

irregular boundaries, hilly parcels containing static obstacles, and hilly parcels containing dynamic obstacles. Each map integrated digital elevation model raster data, parcel boundary vector data, and obstacle raster data. The relevant data were derived from real-time dynamic differential GNSS and LiDAR measurements conducted during the pre-experimental phase, and the obstacle samples were manually verified. Field data included ROS 2 mission logs, real-time dynamic differential GNSS trajectories, real-time dynamic differential GNSS and inertial measurement unit (IMU) fused heading data, and calibrated onboard fuel consumption records, all collected during repeated operations across the three types of hilly citrus plots. Field tests were conducted in three hilly citrus plots in Wanzhou District, Chongqing, China, representing gentle-slope, fragmented-boundary, and obstacle-dense conditions. Improved A*, A*-DWA, and MF-PSO were each tested in ten 25-min runs in every plot, producing 90 ROS 2 bag files and 37.5 h of field-operation data. The improved A* method added slope, turning, and obstacle-clearance penalties to the conventional A* heuristic. A*-DWA used improved A* for global planning and the Dynamic Window Approach for local velocity selection and obstacle avoidance. The baseline implementations were adapted from public A* (https://atsushisakai.github.io/PythonRobotics/modules/5_path_planning/grid_base_search/grid_base_search.html) and DWA (https://atsushisakai.github.io/PythonRobotics/modules/5_path_planning/dynamic_window_approach/dynamic_window_approach.html) descriptions in PythonRobotics whereas MF-PSO was developed. Obstacle-avoidance success and task completion were obtained from ROS 2 event logs, while cumulative path length was from RTK-GNSS trajectories, turns from fused RTK-GNSS/IMU headings, and fuel consumption rate from the platform's calibrated onboard fuel-use channel.

Results and discussion

Simulation ablation experiment validation

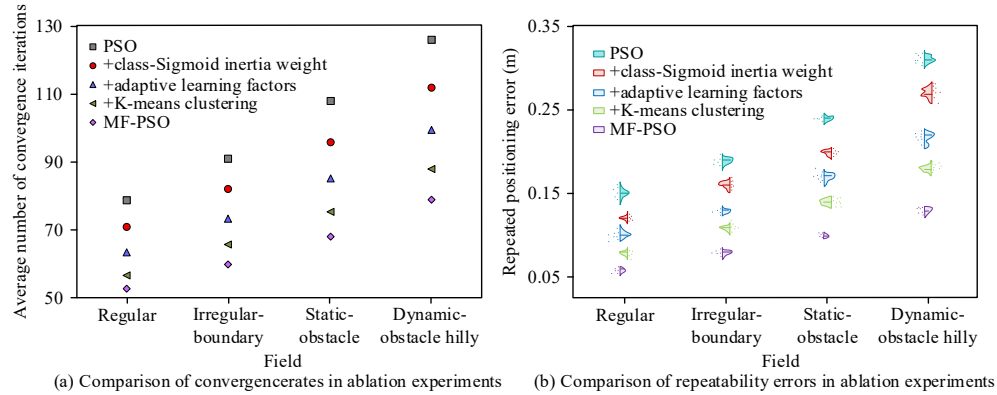


Figure 2. Convergence performance and repeated positioning accuracy.

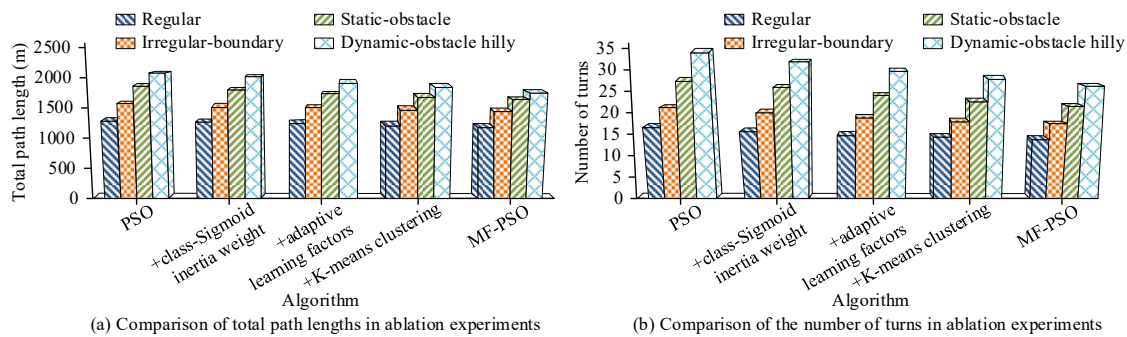


Figure 3. Path length and turning control.

The average convergence iterations and repeated positioning accuracy error of each algorithm by scenario showed that, as the scenario complexity gradually increased from regular plots to hilly plots with dynamic obstacles, the average number of convergence iterations of all algorithms increased, but MF-PSO consistently maintained the lowest level. In the most complex scenario, it decreased from 126.00 iterations for standard PSO to 79.00 iterations, and in regular plots, it decreased from 79.00 iterations to 53.00 iterations, which demonstrated stable convergence advantages (Figure 2a). Further, the repeated positioning accuracy error increased with environmental complexity. The error of standard PSO in the hilly plots with dynamic obstacles reached 0.31 m, whereas the error of MF-PSO was limited to 0.13 m. In regular plots, these values were 0.15 m and 0.06 m, respectively (Figure 2b). The results demonstrated that the proposed approach not

only reduced optimization time but also ensured path-positioning consistency. In addition, based on the convergence rate, the ablation effect of the proposed approach on path quality was quantified by two criteria including the total length of the path and the number of turns. MF-PSO achieved the shortest path in all four scenarios. In regular plots, the total path length decreased from 1,308.42 m for standard PSO to 1,228.91 m, and in hilly plots with dynamic obstacles, it decreased from 2,089.64 m to 1,791.86 m, exhibiting a more significant reduction in complex scenarios (Figure 3a). The number of turns for the standard PSO in the most complex scenario was 33.80. For MF-PSO, the number of turns decreased to 26.40. In regular plots, it was reduced from 16.80 to 14.20 (Figure 3b). The results demonstrated that the improvements were not limited to high-difficulty scenarios.

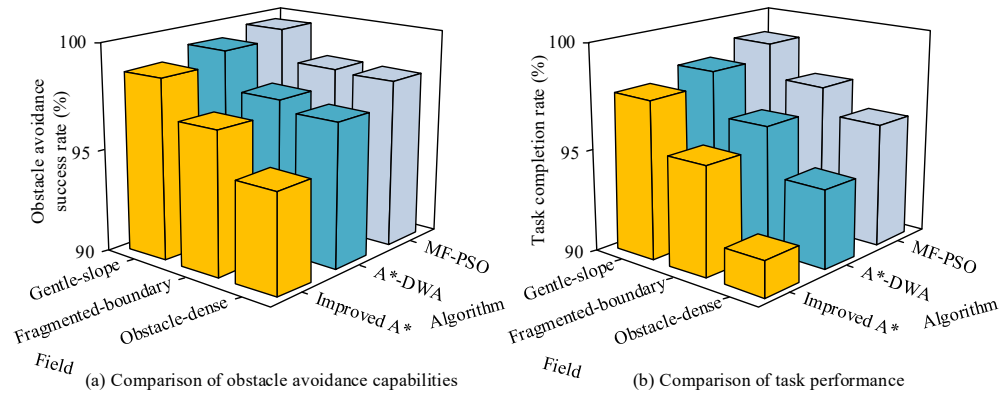


Figure 4. Comparison of obstacle avoidance capability and task completion effect.

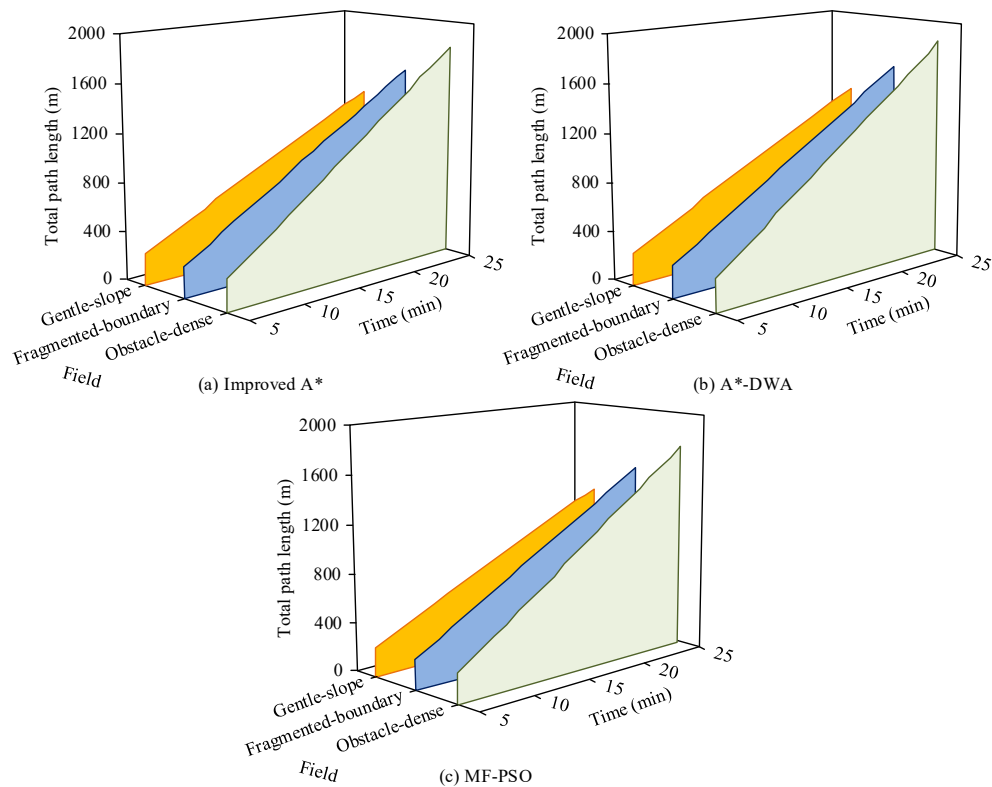


Figure 5. Cumulative path length changes over time.

Real-world application results comparison

In obstacle-dense plots, the obstacle-avoidance success rate of improved A* was 94.80%, whereas A*-DWA increased to 96.90%, and MF-PSO reached 98.00%, which indicated that MF-PSO had greater superiority in obstacle-dense plots (Figure 4a). The change in task completion rate was consistent with the success rate of

obstacle avoidance. MF-PSO was able to achieve 98.90% in regular plots with gentle slopes, 97.20% in plots with fragmented boundaries, and still maintain 95.90% in obstacle-dense plots (Figure 4b). The results showed that MF-PSO not only improved the probability of successful single-obstacle avoidance but also enhanced the continuity and final task-completion capability

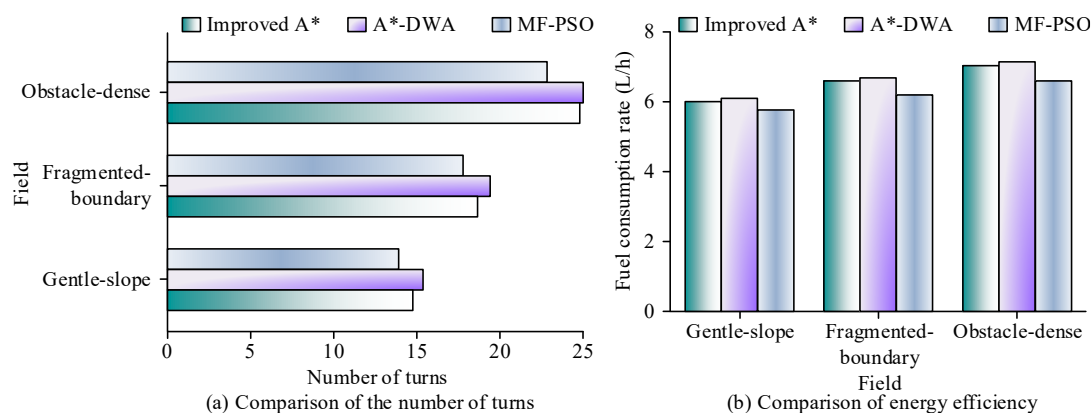


Figure 6. Comparison of turning control and fuel consumption rate.

during complex hilly operations. Because the proposed algorithm unified terrain risk, path length, turning cost, and dynamic adjustment into a single optimization process, it maintained a strong overall coordination capability even when local conflicts increased. The cumulative path length of the agricultural machinery continued to rise as the operation time increased from 5 min to 25 min. All three algorithms showed that the cumulative path length was the lowest in gentle-slope plots, intermediate in fragmented-boundary plots, and the highest in obstacle-dense plots. A horizontal comparison revealed that MF-PSO yielded the lowest values overall at 25 min, while the cumulative path lengths for the three plot types were 1,246.19 m, 1,481.35 m, and 1,719.48 m, respectively (Figure 5). Under the common task definition used in the field tests, these results indicated that MF-PSO reduced unnecessary detours during global path execution and local replanning. In regular plots with gentle slopes, the number of turns for improved A*, A*-DWA, and MF-PSO were 14.80, 15.30, and 13.90, respectively. In obstacle-dense plots, MF-PSO maintained the lowest number of turns at 22.80, and the gap with comparison algorithms widened (Figure 6a). The fuel consumption rate also increased with plot complexity, but the algorithms still maintained stable hierarchical differences. The fuel consumption rates of MF-PSO in three types of plots were 5.78 L/h, 6.22 L/h, and 6.63 L/h, all being the lowest among the same type. The fuel

consumption rates of A*-DWA across the three scenarios were slightly higher than those of improved A*, which suggested that, although local dynamic correction improved environmental adaptability, it also incurred additional energy costs (Figure 6b). Overall, the results demonstrated that MF-PSO provided the best balance of path compactness, turning control, obstacle avoidance, task completion, and fuel consumption across the tested hilly-field conditions. Its advantage could be attributed to the coordinated use of multilevel learning for global exploration, Cauchy perturbation for escaping stagnation, and rolling-window replanning for local environmental changes. The present evidence was limited to single-machine operation in three plots. Multi-machine coordination, cross-regional parameter transfer, and robustness under longer-term seasonal changes remained to be validated.

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