

A Review of Path Planning Research Based on the Optimisation of the A* Algorithm Using Multi-Source Heterogeneous Data

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ABSTRACT

Path planning is a core technology in the fields of intelligent transport, autonomous driving and mobile robotics. The traditional A* algorithm is suited to static environments, but suffers from shortcomings in terms of real-time performance and adaptability in highly dynamic, highly constrained scenarios. With the development of multi-source, heterogeneous perception technologies, the deep integration of data with the A* algorithm has become a key area of research aimed at overcoming this bottleneck. Based on the end-to-end process of ‘data processing—fusion modelling—algorithm optimisation—scenario application’, this paper systematically reviews methods for fusing multi-source heterogeneous data. It constructs a four-dimensional analytical framework encompassing heuristics, cost functions, search strategies and dynamic updates, and provides an in-depth analysis of the optimisation mechanisms of the A* algorithm driven by data. By comparing typical application scenarios such as intelligent urban transport, drone obstacle avoidance and construction site navigation, this paper summarises existing bottlenecks—including low data fusion efficiency and weak cross-scenario transferability—and outlines future development directions such as lightweight data collection, adaptive intelligent decision-making and multi-agent collaboration. This research provides a systematic reference for the theoretical iteration and engineering implementation of path planning technologies.

Keywords: Multi-Source Heterogeneous Data; A* Algorithm; Path Planning; Literature Review

1. INTRODUCTION

With the acceleration of urbanisation and the widespread adoption of Intelligent Transport Systems (ITS), route planning faces increasingly complex challenges posed by dynamic environments. As a classic heuristic search algorithm, the A* algorithm has become the mainstream method in the field of route planning due to its high search efficiency and guarantee of global optimality [1]. However, the traditional A* algorithm relies heavily on static road network models, and its heuristic and cost functions are designed in a simplistic manner, making it difficult to effectively quantify real-world constraints such as traffic congestion, dynamic obstacles and complex terrain.

In recent years, the proliferation of multi-source heterogeneous data—including LiDAR, visual sensors, V2X communications and crowdsourced geospatial data—has made it possible to characterise environments with high precision and fine granularity. By integrating multi-source heterogeneous data with the A* algorithm—through improvements to the heuristic function, the introduction of multi-objective cost functions, the optimisation of search strategies and the incorporation of deep reinforcement learning (DRL)—the algorithm’s robustness and real-time performance in complex dynamic environments can be significantly enhanced [2].

However, current research in this field remains fragmented, with a lack of systematic synthesis regarding data fusion methods and algorithmic optimisation dimensions. Against this backdrop, this paper transcends the limitations of traditional single-dimensional analysis by constructing a multi-dimensional theoretical analytical framework, with the aim of distilling common patterns and predicting future development trends.

2. MULTI-SOURCE HETEROGENEOUS DATA SYSTEMS AND INTEGRATED MODELLING

2.1 Classification System for Multi-source Heterogeneous Data

In route planning scenarios, multi-source heterogeneous data exhibit significant differences in terms of data structure, spatio-temporal resolution and semantics. This paper categorises them into three main types: static geographical data, dynamic traffic flow data and multimodal sensor data (Table 1).

Table 1. Classification and Feature Comparison of Multi-source Heterogeneous Data in Path Planning Scenarios.

Data categories	Origin and Characteristics	Applications and Functions
Static geographical data	OSM road network, ASTER GDEM, etc.	Global planning, terrain awareness
Real-time traffic flow data	GPS, traffic congestion and traffic light data; flow field characteristics, updated in real time at high frequency	Dynamic route optimisation; calculating road impedance and updating route weights
Multimodal sensor data	Visual and radar sensors; multi-dimensional space, real-time data acquisition at millisecond intervals	Local obstacle avoidance, target recognition

2.2 Methods for the fusion of multi-source heterogeneous data

The fusion of multi-source data aims to eliminate spatio-temporal misalignment and semantic conflicts, thereby generating a unified environmental representation. Mathematically, a transport network can be abstracted as a directed graph $G=(N,R,f)$, where N is the set of nodes, R is the set of edges, and f is the weight function. For different data sources, the main fusion methods are as follows:

1. Fusion using probabilistic models and filtering

To address sensor measurement noise and data uncertainty, Bayesian estimation or Kalman filtering is commonly employed for fusion. For example, in dynamic obstacle avoidance using unmanned aerial vehicles (UAVs), Kalman filtering is utilised to fuse data from event cameras and depth cameras, thereby enabling precise estimation of the position and velocity of dynamic obstacles [5]:

$$X_{k|k} = X_{k|k-1} + X_k(Z_k - HX_{k|k-1}) \quad (1)$$

In Equation (1), $X_{k|k}$ denotes the posterior state estimate, X_k denotes the Kalman gain, and Z_k denotes the multi-source observations.

2. Cross-modal integration of attention mechanisms

To address the issue of inconsistent coordinate spaces among multi-modal sensors, the Transformer architecture utilises a cross-attention mechanism to facilitate cross-modal feature interaction [6]. In the bird's-eye-view (BEV) space, the fusion of camera features F_{cam} and F_{lidar} can be expressed as:

$$F_{fused} = \text{Softmax}\left(\frac{Q_{cam}K_{lidar}^T}{\sqrt{d_k}}\right)V_{lidar} \quad (2)$$

In Equation (2), Q_{cam} denotes the query matrix for camera features, whilst K_{lidar} and V_{lidar} denote the key-value matrices for LiDAR features.

3. Spatio-temporal topological hierarchical fusion

In scenarios such as complex construction sites, a dynamic network topology is constructed by fusing BIM, GIS and oblique photogrammetry models [7]. The elements of its adjacency matrix A_{con} are defined as follows:

$$a_{ij}^{(t)} \begin{cases} 1, & \text{Road (i,j) Connected at time t} \\ 0, & \text{Road closure} \end{cases} \quad (3)$$

3. OPTIMISATION MECHANISMS FOR THE A* ALGORITHM DRIVEN BY MULTI-SOURCE HETEROGENEOUS DATA

The core of the A* algorithm lies in guiding the search direction via the evaluation function $f(n) = g(n) + h(n)$. The introduction of multi-source heterogeneous data enables the algorithm to be deeply optimised across four dimensions: the heuristic function, the cost function, the search strategy, and dynamic updates.

3.1 Optimisation of the Heuristic Function

Traditional heuristic functions $h(n)$ typically use Euclidean or Manhattan distance, without taking into account terrain elevation or road attributes. By integrating ASTER GDEM and OSM data, an anisotropic heuristic function can be constructed [8]:

$$h_{opt}(n) = \lambda_1 D_{euc}(n, goal) + \lambda_2 \Delta H(n, goal) + \lambda_3 R_{road}(n, goal) \quad (4)$$

In Equation (4), D_{euc} represents the Euclidean distance, ΔH represents the energy cost resulting from the elevation difference, and R_{road} represents the road-class resistance coefficient. This mechanism enables the heuristic function to more closely reflect actual travel energy consumption, thereby effectively reducing the number of invalid search nodes.

3.2 Multi-objective Optimisation of the Cost Function

Following the integration of dynamic traffic flow data, the cost function shifts from single-objective distance optimisation to multi-objective weighted optimisation. Based on the weighted sum method (WSM), a comprehensive cost function $F_{total}(p)$ is constructed as follows [8]:

$$\min_p F_{total}(p) = \alpha(t)f_{length}(p) + \beta(t)f_{congestion}(p) + \gamma(t)f_{time}(p) + \epsilon(t)f_{risk}(p) + \eta(t)f_{avoidance}(p) \quad (5)$$

The constraints are as follows:

$$\begin{cases} f_{time}(p) \leq T_{max} \\ f_{congestion}(p) \leq C_{max} \\ f_{risk}(p) \leq R_{max} \end{cases} \quad (6)$$

In Equation (6), the weight parameters $\alpha, \beta, \gamma, \epsilon, \eta$ are dynamically adjusted according to the scenario. For example, in a night-time delivery scenario, the weights for safety and obstacle avoidance are significantly increased (Table 2) [8].

Table 2. Dynamic Weighting of Urban Transport Demand Across Multiple Scenarios.

Use Cases	Time weight γ	Congestion weight β	Distance weight α	Security weight ϵ	Obstacle avoidance weight η
Daily commute	0.30	0.30	0.25	0.10	0.05
Long-distance travel	0.25	0.15	0.30	0.15	0.15
Night-time deliveries	0.25	0.10	0.10	0.35	0.20

Furthermore, by combining traffic information with the road flow function, it is possible to calculate the lane-specific road impedance T_r [9]:

$$T_r = t_0 \left[1 + \left(\frac{V}{C} \right)^{\beta} \right]^{\alpha} \quad (7)$$

In the equation, t_0 represents the travel time under zero traffic conditions, V represents traffic volume, C represents road capacity, and α and β are regression coefficients.

3.3 Optimisation of Search Strategies

In the context of complex road network structures, the incorporation of multi-source data has driven innovation in search strategies (Table 3).

Table 3. A Comparative Analysis of Representative Studies on the Optimisation of Search Strategies in the A* Algorithm.

Optimisation strategies	Core Mechanism	Advantages	Applicable scenarios
Bidirectional Alternating Search	Search simultaneously from the start and end points until the paths coincide	Significantly reduce search time	Large-scale static road network
Quick queries on detail and summary levels	Identify key nodes in the high-level road network, then refine the local routes	Avoids double counting and is highly efficient	Tiered Map Navigation
Extend the search depth	Considering the impact of the lane type at the subsequent junction on journey time	Accurately calculate the time required for turning and exiting	Urban junctions with multiple traffic lights

3.4 Dynamic Updates and Hybrid Decision-Making Mechanisms

In the face of sudden obstacles and local disturbances, the global re-planning in Algorithm A* incurs significant computational overhead. Current research predominantly adopts a hybrid architecture comprising ‘global A’ combined with ‘local DRL/DP’ [8][11]. For example, by combining a Deep Q-Network (DQN) to construct the state-action value function $Q(s, \alpha; \theta)$:

$$Q(s, \alpha; \theta) \leftarrow Q(s, \alpha; \theta) + \alpha \left[r + \gamma \max_a Q(s', \alpha'; \theta^-) - Q(s, \alpha; \theta) \right] \quad (8)$$

Under this mechanism, the A* algorithm generates a global initial path, whilst the DQN uses experience replay and an ϵ -greedy policy to generate local obstacle-avoidance actions in real time. Experiments show that this hybrid algorithm increases the success rate of dynamic obstacle avoidance from 10% to 95% and reduces planning time by 61.9% [8].

4. COMPARATIVE ANALYSIS OF TYPICAL APPLICATION SCENARIOS

The optimised A* algorithm for multi-source heterogeneous data has been implemented in a number of fields, with its data source matching and optimisation strategies exhibiting marked differences across different scenarios (Table 4).

Table 4. Algorithm Fusion Architectures and Performance Evaluation in Typical Application Scenarios.

Use Cases	Data and Optimization Direction	Representative algorithms	Performance Improvement
Urban intelligent transportation	OSM, signal lights, GPS tracking; multi-objective cost function, extended search depth	Dynamic Weighted A*, Time-Optimised A*	By avoiding traffic congestion, traffic efficiency has improved by 6.24 per cent
Drone obstacle avoidance	Event camera, RGB, depth information; dynamic updates, optimisation of heuristic functions	Improvements to the Speed Barrier Method and A*+DQN	95% success rate in avoiding high-speed moving obstacles
Smart Navigation on Construction Sites	BIM, GIS, oblique photography, UWB; topological layering, dynamic weighting	Stigmergy-coordinated A*, Prospect Theory A*	Travel time reduced by 22.5 per cent; response time to incidents reduced by 67 per cent

In urban transport, the focus is on integrating macro-level traffic flow data to optimise journey times; in drone obstacle avoidance, the focus is on integrating microsecond-level sensor data to achieve local dynamic responses; and in construction site navigation, the focus is on integrating high-precision BIM models to address frequent changes in the topology of temporary road networks and human-machine conflicts.

5. RESEARCH BOTTLENECKS AND FUTURE PROSPECTS

5.1 Bottlenecks in Existing Research

1. Balancing fusion efficiency and accuracy

Deep learning fusion models for high-dimensional multimodal data (such as LiDAR point clouds and video streams) incur significant computational overhead, making it difficult to achieve millisecond-level real-time responses on computationally constrained edge devices [6].

2. Insufficient cross-scenario transferability

Existing algorithms rely heavily on scenario-specific prior knowledge and weight calibration (such as hazard level coefficients in construction site navigation), making it difficult to generalise directly to open roads or unstructured outdoor environments [7].

3. Weak robustness under extreme operating conditions

In the event of sensor degradation (e.g. rain, snow or fog, or loss of GPS signal) or in highly unstructured environments, the quality of data fusion deteriorates sharply, leading to planning failures.

5.2 Future Research Trends

1. Lightweight data acquisition and edge computing

Explore low-cost solutions based on crowdsourced mobile phone data and video from small drones, combined with model pruning and edge computing, to reduce the burden on cloud-based communication and computation.

2. Adaptive decision-making using meta-heuristic algorithms

Introduce meta-heuristic strategies such as genetic algorithms (GA) and ant colony optimisation (ACO) to achieve adaptive tuning of weight parameters α , β and γ in dynamic scenarios, thereby enhancing robustness under extremely complex operating conditions.

3. Multi-agent Coordination and Interaction

Extending single-agent A* to multi-agent scenarios and combining it with Markov game theory to resolve collaborative path planning and resource competition conflicts among multiple vehicles or drones.

4. End-to-End Planning and Control Integration

Breaking down the barriers between high-precision localisation, path planning and MPC dynamic control to construct an end-to-end autonomous driving framework, thereby reducing communication latency between modules.

6. CONCLUSIONS

Based on the four-dimensional analytical framework of ‘data—fusion—optimisation—application’, this paper provides a systematic review of research progress on the optimisation of the A* algorithm using multi-source heterogeneous data. The synthesis of existing literature indicates that the introduction of multi-source heterogeneous data has driven notable advancements in the A* algorithm with respect to the physical credibility of the heuristic function, the multi-objective balance of the cost function, the macro-level acceleration of search strategies, and the local adaptability of dynamic updates. Through comparative analysis across typical scenarios such as urban intelligent transportation, UAV obstacle avoidance and construction site navigation, data-driven optimisation approaches show distinct advantages in enhancing the algorithm’s adaptability and performance in complex dynamic environments.

As a systematic review based exclusively on published studies, this work does not include original experimental verification or comprehensive quantitative statistical comparison, meaning the generalisability of the synthesised findings remains to be further validated by empirical research. Meanwhile, current research in this field still faces prevailing bottlenecks, including the trade-off between fusion efficiency and accuracy, limited cross-scenario transferability, and weak robustness under extreme operating conditions. Looking ahead, alongside advances in lightweight perception technologies, adaptive decision-making models and multi-agent collaboration mechanisms, multi-source heterogeneous data-driven path planning techniques are expected to achieve deeper engineering implementation and wider practical deployment in complex dynamic environments.

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