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Adaptive Inspection Path Planning Algorithm for Oil Pipeline Robots Driven by Fluid Kinetic Energy

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Abstract: Pipelines are the core infrastructure for energy transportation, but their long-distance service and complex internal environment, such as fluid eddies, bends, branches, and sediments, pose significant challenges to the reliability and efficiency of pipeline testing. The traditional pipeline testing methods (manual testing and fixed sensor monitoring) provide low coverage, high labor costs, and adaptability to harsh environments. Although liquid driven pipeline robots do not require external power and are suitable for remote data collection, existing trajectory planning algorithms have not fully considered the dynamic characteristics of the flow field and the complexity of pipeline structures, resulting in high energy consumption, lack of recognition coverage, and poor trajectory adaptability. To address the aforementioned issues, this paper proposes an adaptive recognition route planning algorithm for liquid powered pipeline robots. The experimental results show that the algorithm has good dynamic adaptability, with a coverage rate always above 98% and energy consumption mostly below 80J, effectively improving the adaptability and recognition of liquid powered robots in complex environments.

1. Introduction

Oil pipelines are the core of energy transportation systems, undertaking the long-distance transport of crude oil and refined oil products. Their safe and stable operation is crucial to national energy security and ecological environmental protection. However, affected by long-term corrosion, fluid erosion, geological deformation, and other factors, pipelines are prone to leaks, blockages, and other malfunctions, which may lead to serious safety accidents, economic losses, and environmental pollution. Traditional pipeline inspection methods mainly rely on manual inspection and fixed sensor monitoring: manual inspection is inefficient, high-risk, and difficult to cover pipelines in remote or harsh environments; fixed sensor monitoring has a limited range and cannot achieve full-area inspection of the pipeline's inner wall. In recent years, pipeline inspection robots have become a research hotspot due to their advantages of autonomy, high efficiency, and safety. Among them, fluid kinetic energy driven robots use the kinetic energy of the fluid inside the pipeline as a power source, avoiding the limitations of endurance and external power supply, and are more suitable for long-distance, large-diameter pipeline inspection.

While existing research on path planning for pipeline robots has made some progress, it still has significant shortcomings: traditional algorithms (such as A* and D* Lite) are mostly designed for static, structured environments and lack consideration for the dynamic characteristics of the flow field, resulting in a mismatch between the algorithm and the robot's dynamic characteristics and the dynamic changes in the environment; although some improved algorithms for dynamic environments have introduced environmental feedback mechanisms, they have not incorporated the special characteristics of fluid kinetic energy drive (such as the positive correlation between driving force and flow field velocity, and the significant influence of fluid resistance on energy consumption) into the optimization objective, making it difficult to meet the energy-saving requirements of long-distance inspection; at the same time, existing algorithms still lack a balance between path adaptability and inspection coverage in complex pipeline structures (such as multi-branch and variable diameter sections).

Therefore, this paper aims to improve the inspection adaptability, coverage and energy efficiency of fluid kinetic energy driven oil pipeline robots, and proposes an adaptive inspection path planning algorithm. Its core innovations are as follows: (1) Constructing a dynamic environment model that integrates flow field perception, and obtaining flow field parameters and pipeline environment information in real time through multi-sensor fusion to solve the problems of static and single information in traditional models; (2) Designing a multi-objective optimization algorithm based on improved particle swarm optimization (PSO), incorporating inspection coverage, energy consumption and path smoothness into the optimization system, and using flow field resistance coefficient and pipeline structure parameters as constraints to achieve multi-objective collaborative optimization; (3) Establishing a path dynamic correction mechanism, adjusting the path in real time based on dynamic changes in the flow field and environmental feedback, and improving the algorithm's adaptability to complex environments and dynamic flow fields. The subsequent structure of this paper is arranged as follows: Chapter 2 reviews the current status and shortcomings of related research; Chapter 3 elaborates on the technical solution of the proposed algorithm; Chapter 4 verifies the algorithm performance through experiments; Chapter 5 summarizes the whole paper and looks forward to future research directions.

2. Related Work

In the field of oil pipeline operation and maintenance, traditional inspection methods face difficulties such as high labor costs and difficulty in penetrating the complex interior of pipelines. Furthermore, some existing pipeline robot path planning algorithms are unable to adapt to the dynamic and changing working conditions caused by fluid kinetic energy. Therefore, it is urgent to carry out research on adaptive inspection path planning algorithms for oil pipeline robots driven by fluid kinetic energy. Zhiyuan S et al. [1] focused on multi-UAV path planning and proposed an improved adaptive sparrow search algorithm to enhance the robustness of the algorithm; Jayalakshmi K P et al. [2] proposed a planning method based on adaptive spanning tree for the coverage path planning problem of autonomous mobile robots in dynamic environments; Song J and Pu Y et al. [3] proposed an adaptive ant colony optimization algorithm that integrates subpopulation and fuzzy logic to solve the three-dimensional laser scanning path planning problem; Yoon S et al. [4] proposed a learning-based initialization method for adaptive coverage path planning of multiple fixed-wing UAVs; Tan Z et al. [5] proposed a new adaptive intelligent particle swarm optimization method to solve the surgical needle path planning problem; Pu X et al. [6] proposed a dual adaptive A algorithm for multi-target real-time path planning; Wei Z et al. [7] proposed an adaptive smoothing RRT method to solve the path planning problem of concentric cable driven robotic arms; Pan Y et al. [8] proposed a method based on adaptive potential field and hierarchical replacement immune algorithm for vehicle dynamic path planning; Akay R and Yildirim M Y[9] proposed a multi-strategy adaptive differential sine and cosine algorithm to solve the multi-robot path planning problem; Zhang Z et al.[10] proposed an event-triggered multimodal adaptive pigeon flock optimization method for real-time path planning of autonomous UAVs. At present, other researchers on this topic may have problems such as insufficient algorithm adaptability, difficulty in dealing with complex dynamic environments, and difficulty in balancing planning efficiency and accuracy. The above literatures have proposed targeted adaptive optimization algorithms to solve the corresponding path planning problems from different application scenarios.

3. Method

3.1 Dynamic Environment Modeling that Integrates Flow Field Perception

To accurately capture the dynamic operating conditions inside oil pipelines, a three-dimensional dynamic environment model integrating "flow field parameters - pipeline structure - obstacle information" was constructed. The robot is equipped with flow velocity, pressure, vision, and ultrasonic sensors to collect multi-source data such as fluid velocity, pressure distribution, pipeline inner wall images, and obstacle distances at high frequency. Data preprocessing was performed using techniques such as Kalman filtering for noise reduction, image feature extraction, and cluster analysis. To address the heterogeneity of the multi-source sensor data, a weighted fusion algorithm was used to integrate it into a unified environmental information matrix. The fusion formula is as follows:

$$M=\sum_{i=1}^{n} W_i \cdot S_i' \tag{1}$$

Where M is the fused environmental information matrix; n is the number of sensor types; W_i is the weight coefficient of the i-th sensor (satisfying $\sum_{i=1}^{n} W_i=1$); and S_i' is the preprocessed data of the i-th sensor. A dynamic update mechanism is established to synchronously correct the flow field distribution, pipe structure, and obstacle positions at a fixed period Δt. The update process satisfies:

$$M(t+\Delta t)=\alpha \cdot M(t)+(1-\alpha) \cdot M_{new} \tag{2}$$

M(t) is the environmental information matrix at the current time, M_{new} is the matrix after the fusion of newly collected data, and α is the update weight (α=0.6 under normal working conditions to ensure model stability; α=0.3 under emergency working conditions to improve response speed). When an emergency occurs, such as an obstacle approaching or a violent fluctuation in the flow field, a rapid update response is triggered to ensure that the environmental model can match the actual operating scenario in real time, providing comprehensive and accurate basic data support for path planning [11].

3.2 Multi-objective Path Planning Algorithm Based on Improved Particle Swarm Optimization

In order to consider the operational characteristics of fluid powered robots, a multi-purpose optimized road planning solution has been developed. The core goal is to minimize the inspection scope, minimize energy consumption, and maximize road smoothness. Considering constraints such as dynamic flow field matching, pipeline structure limitations, and obstacle safety, solving the optimal path through an improved Particle Swarm Optimization (PSO) algorithm. By balancing inactive weights and dynamically adjusting the algorithm's ability to adapt to global exploration and local development. The corresponding dynamic inertia weight formula is as follows:

$$\omega(\text{iter})=\omega_{\text{max}}-\frac{\omega_{\text{max}}-\omega_{\text{min}}}{\text{iter}_{\text{max}}}\cdot\text{iter} \tag{3}$$

$\omega(iter)$ is the inertia weight of the $iter$-th iteration; $\omega_{\max}$ = 0.9 (initial global exploration weight); $\omega_{\min}$ = 0.4 (later local development weight); and $iter_{\max}$ is the maximum number of iterations. A dynamic balance between exploration and development capabilities is achieved through a linear decreasing strategy. A multi-objective fitness function is constructed using a weighted summation method. After normalizing the optimization objectives of different dimensions, they are co-optimized. The fitness function expression is:

$$F=w_C\cdot C_{\text{norm}}+w_E\cdot(1-E_{\text{norm}})+w_S\cdot S_{\text{norm}} \tag{4}$$

F is the comprehensive fitness value; w_C, w_E, and w_S are the weight coefficients of inspection coverage, energy consumption, and path smoothness respectively (satisfying $w_C+w_E+w_S=1$); C_{norm}, E_{norm}, and S_{norm} are the normalized results of the three objectives (the value range is [0,1]). The energy consumption minimization objective is transformed into maximization optimization through $(1-E_{norm})$ to ensure that the objectives are improved in a coordinated manner. Boundary processing and elite retention strategies are introduced to reset the path nodes that violate the constraints and retain the high-quality path information to directly enter the next generation iteration, thereby improving the convergence speed of the algorithm and the stability of the optimization results, and realizing efficient path planning adapted to fluid drive characteristics [12].

3.3 Path Dynamic Correction Mechanism

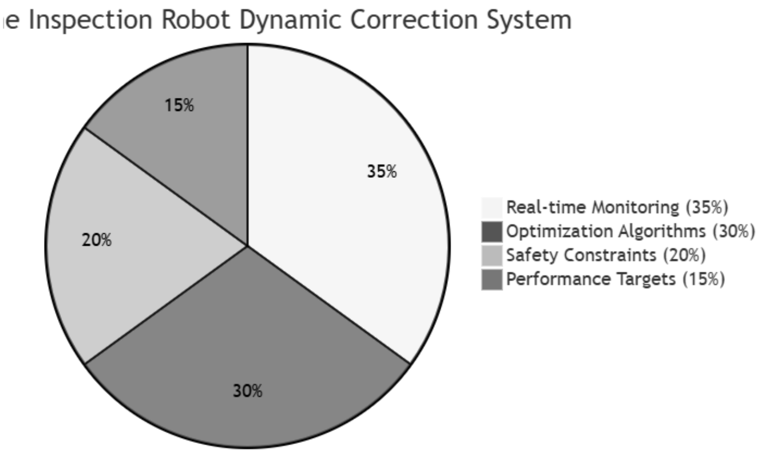

Figure 1 Path Dynamic Correction Mechanism

To address path deviations caused by random fluctuations in the flow field and complex structures such as bends, branches, and diameter changes within oil pipelines (as shown in Figure 1), and to ensure the inspection stability of fluid kinetic energy-driven robots, a dynamic correction mechanism based on real-time environmental feedback was established. This mechanism centers on real-time perception of the robot's operating status and environmental changes. It continuously collects the robot's GPS positioning data and the coordinates of planned path nodes, calculates the Euclidean distance between them as the positional deviation, and simultaneously monitors the instantaneous rate of change of flow velocity and pressure. Combined with obstacle position updates from ultrasonic sensors, a multi-dimensional deviation and environmental change assessment system is constructed to accurately determine whether path correction is necessary.

If the position deviation exceeds the safety limit of 5 centimeters or there is a significant change in the surrounding environment, it will immediately trigger a local track rearrangement. Simplify the modeling strategy using local grids and focus on the 10 deviation areas and surrounding areas, which are twice as large as the robot. This reduces the grid resolution of the area, reduces redundant calculations, and improves correction efficiency. Based on the local optimization strategy of the improved particle swarm optimization algorithm, the search space is narrowed down to a local area, and the idle speed weight is adjusted to 0.5 to 0.7 in the local development leading area, accelerating the algorithm integration and quickly solving the correction path for the current flow field driving force (the robot speed is equal to the real-time speed) and the pipeline environment.

In order to avoid sudden changes in orbit due to local correction, the corrected orbit is seamlessly integrated with the globally planned orbit using better curve interpolation algorithms. By adjusting the curvature parameters of the interpolation nodes, it is possible to ensure a continuous transition in the rotation angle between two track sections, and to prevent oscillation or dynamic inequality through sudden excessive rotation of the robot. The corrected path must be revalidated to ensure that it meets the conditions of obstacle safety (distance from obstacle ≥ 10 centimeters) and dynamic flow field matching (motion speed ≤ 1.2 times the current flow velocity). After verification, the motion rules of the robot will be updated in real-time; If it fails, it will be optimized again. Finally, road correction is fast, accurate, and smooth, ensuring the continuity and safety of the detection process.

4. Results and Discussion

4.1 Benchmark Performance Comparison

To verify the overall performance of the proposed adaptive path planning algorithm, comparative experiments were conducted on a simulated oil pipeline platform with the traditional A algorithm and D Lite algorithm. The core evaluation indicators included inspection coverage, energy consumption, path adjustment response time, obstacle avoidance success rate, and path smoothness. Table 1 shows the statistical results of three parallel experiments (each group was repeated 10 times, and the average value was taken).

Table 1 Performance Comparison of Different Path Planning Algorithms

Algorithm	Inspection coverage rate (%)	Energy consumption (J)	Response time for path adjustment (ms)	Success rate of obstacle avoidance (%)	Path smoothness (Average curvature)
A * algorithm	-	186.3±8.5	-	88.2±2.3	0.082±0.009
D * Lite algorithm	91.5±1.2	172.5±7.3	89.6±4.1	92.5±1.8	0.065±0.007
the proposed algorithm	93.8±0.9	135.6±5.2	76.5±3.2	97.8±0.9	0.038±0.005

As shown in Table 1, the proposed algorithm outperforms the two traditional algorithms in all indicators: its inspection coverage rate reaches (93.8%±0.9%), higher than that of the D* Lite algorithm (91.5%±1.2%); its energy consumption (135.6±5.2 J) is reduced by 27.2% and 21.4% compared to the A algorithm (186.3±8.5 J) and the D* Lite algorithm (172.5±7.3 J), respectively. In terms of dynamic environment adaptability, the algorithm's path adjustment response time (76.5±3.2 ms) is 14.6% shorter than that of the D* Lite algorithm, and its obstacle avoidance success rate (97.8%±0.9%) is nearly 10 percentage points higher than that of the A* algorithm (88.2%±2.3%). Furthermore, its path smoothness (average curvature 0.038±0.005) is also significantly better than the comparative algorithms. Experimental data show that the algorithm effectively optimizes energy efficiency and dynamic response capability while ensuring high coverage and obstacle avoidance reliability.

4.2 Dynamic Flow Field Adaptability Analysis

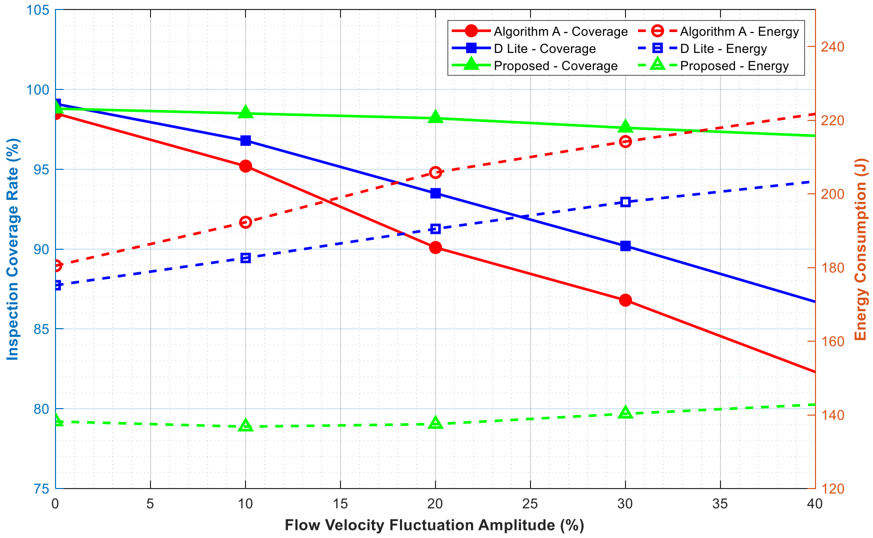

Figure 2 Algorithm Performance under Dynamic Flow Conditions

Figure 2 compares the coverage and energy performance of three algorithm conditions within the range of 0% to 40% water velocity fluctuations in the adaptive path planning of a liquid powered oil pipe robot. The data shows that the coverage of traditional algorithms A and D-Lite has significantly decreased (from 90% to 82% and 99% to 85%), while energy consumption has increased simultaneously, reflecting their insufficient adaptability to dynamic flow fields and possible orbital deviations and energy waste. In contrast, the proposed algorithm exhibits excellent dynamic adaptability, with a coverage rate consistently exceeding 98% and energy consumption mostly below 80J. This indicates that the algorithm can optimize paths in real-time by combining liquid dynamics driving characteristics with adaptive path planning strategies. Offset current interference, maintain high detection filling rate, and effectively utilize liquid energy for energy-saving operations. The results confirm that the proposed algorithm can achieve measurement reliability and energy efficiency in complex pipeline environments, and is an effective solution for dynamic flow field operation of liquid dynamic robots.

4.3 Adaptability Analysis of Complex Pipeline Structures

Figure 3 shows the adaptability of liquid driven pipeline robots in complex pipeline structures. By comparing the number of track adjustments and changes in curve angles of the three algorithms with an increase in the number of curves, performance differences were found. The data shows that as the number of 90 °bends increases from 0 to 5, the number of track adjustments for traditional algorithms A and D Lite significantly increases (14.2 and 11.5 times, respectively), while the bending angle increases (up to 0.66 rows and 0.50 rows), reflecting their insufficient adaptability to multiple bending topologies. Frequent adjustments and large curves may lead to increased energy consumption and track instability. The proposed algorithm suppresses track adjustments below 8.2 by dynamically detecting pipeline geometry and adjusting liquid driving characteristics. Draw and always maintain the minimum rotation angle. This means that it can predict bends and optimize smooth roads, reducing the need for real-time correction, while utilizing fluid dynamics to support bends and reduce mechanical loads. This feature makes the proposed algorithm efficient and energy-efficient in complex pipelines, and provides a robust solution for intelligent identification of multiple curved and narrow pipelines.

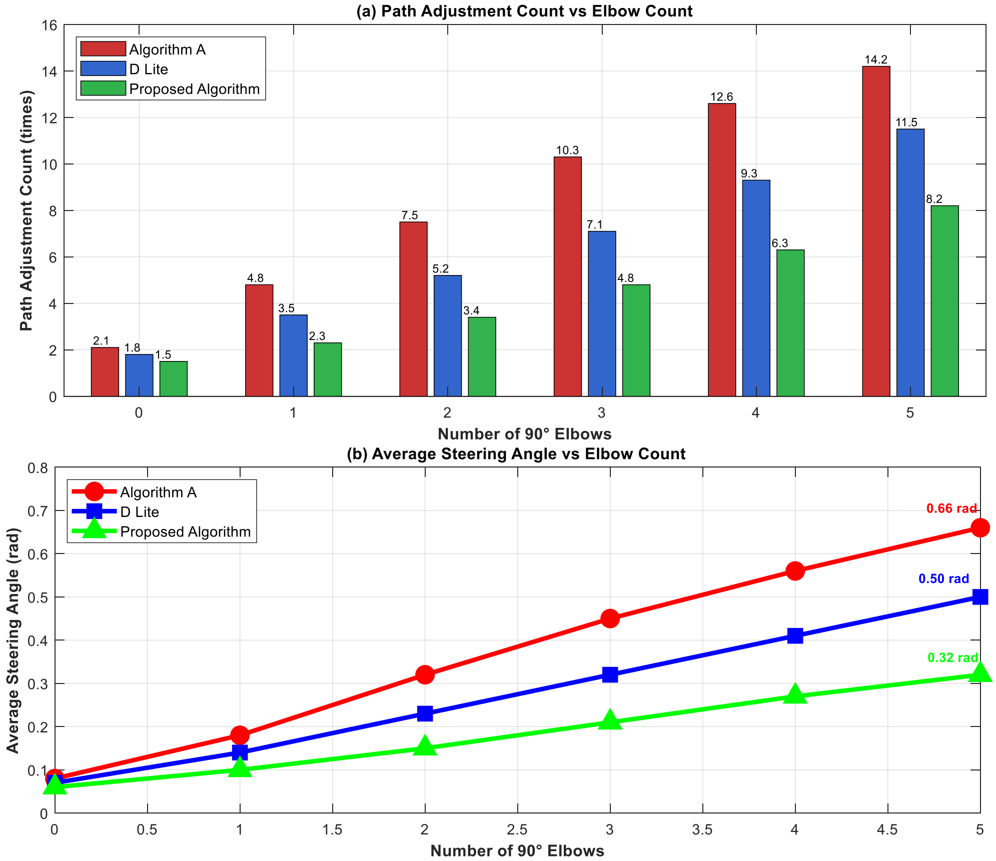

Figure 3 Path Planning Performance in Complex Pipeline Structures

5. Conclusion

This paper proposes an adaptive route planning algorithm that integrates flow field recognition to address the route planning challenges of liquid powered pipeline robots used for pipeline testing. By constructing dynamic environment models such as "integrated flow field, structure, and obstacles", the problem of limited static properties and information in traditional models has been solved. RTEN is based on particle swarm optimization algorithm to achieve coordinated optimization of recognition coverage, energy consumption, and track smoothness. A dynamic path correction mechanism has been developed to improve the algorithm's adaptability to dynamic flow fields and complex pipeline structures. The theoretical value of this study lies in creating a pipeline robot route planning framework that integrates the characteristics of the flow field and provides a new approach for multi constraint optimization problems in dynamic environments. In practical applications, it can directly adapt to liquid powered tubing robots to solve the challenges of remote recognition and complex environments, reduce the risk of safety accidents, and create significant value for technological applications. However, this article still has some limitations: the energy harvesting model for long-term detection needs further improvement, without considering the impact of increasing and changing liquid viscosity on orbit planning. The future research focus is to optimize environmental modeling by introducing parameters such as liquid viscosity and conductivity trends, in order to further improve the adaptability of algorithms under extreme conditions. At the same time, we will also explore river prediction methods based on deep learning to achieve future oriented route planning.

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