TRACEABILITY METHOD OF ACTIVE AND PASSIVE FUSION FOR POLLUTANT EMISSIONS IN WATERSHEDS

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To swiftly and accurately trace water pollution incidents, a hybrid tracing method combining active and passive approaches is proposed. Active tracing algorithms serve as the primary pollutant source tracking strategy, complemented by passive tracing algorithms for adjusting search parameters. Validation through pollution tracing simulations confirms the feasibility and robustness of the fused active-passive tracing method. Additionally, a mobile water pollution tracing platform and a ground management platform were designed and developed, incorporating the proposed tracing algorithm. These platforms enable real-time water quality monitoring and pollutant source tracking, improving overall response efficiency.

Keywords: Water pollution tracing, Active and passive fusion, Simulation experiment, Mobile traceability platform

1. Introduction

Water resources play an indispensable role in human society and are crucial for economic development [1]. However, frequent sudden water pollution incidents in China exacerbate water scarcity, characterized by high frequency, severe destructiveness, diverse forms, rapid spread, and long-lasting environmental impacts [2]. The inability to promptly identify pollutant sources, often due to human-induced illegal discharges, has resulted in environmental regulatory agencies witnessing the gradual spread of pollution across watersheds. Therefore, swiftly and accurately locating pollutant sources during sudden water pollution

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incidents is the primary focus of this study. Water pollution tracing methods fall into two main categories: passive tracing algorithms and active tracing algorithms [3]. Passive tracing involves retroactively deducing pollutant sources based on water quality data from monitoring stations, providing information on source location, emission intensity, and leakage time. Different types of passive tracing algorithms include analytical methods [4-5], regularization techniques [6-7], intelligent optimization algorithms [8-9], and probabilistic approaches [10].

Active tracing algorithms primarily utilize mobile devices equipped with corresponding sensors to conduct active searches within polluted river zones according to predefined rules until emission sources are located. Currently, proposed active tracing algorithms include machine vision-assisted methods [11], biomimetic olfaction methods [12-13], and information-oriented approaches [14]. Russell [15] developed a mobile platform equipped with concentration and obstacle avoidance sensors. They analyzed the strengths and weaknesses of four active tracing algorithms: Escherichia coli algorithm [16], moth algorithm [17], cockroach algorithm [18], and concentration gradient algorithm—by comparing their performance in controlling the mobile platform during the tracing process. Both passive and active tracing algorithms have certain limitations. For passive tracing algorithms, limitations in source inversion include the uneven distribution of monitoring stations, which hinders effective water pollution tracing, and an over-reliance on the accuracy of pollution diffusion models, even though real-world water pollution environments are often complex and variable. Active tracing algorithms face challenges such as: in the early stages of tracing, when downstream pollutant concentrations are too low, sensors on the mobile platform may fail to detect significant differences in pollutant concentrations, hindering effective active tracing; additionally, the mobile platform can easily become trapped in local optima due to overly small search step sizes. Therefore, this paper integrates the global search capability of passive tracing algorithms with the local search capability of active tracing algorithms, fully leveraging water quality information from both fixed and mobile monitoring stations. A hybrid tracing method is proposed, and a water pollution traceability platform is designed to include functionalities such as water quality monitoring, pollutant source tracking, and remote viewing of water quality information. This platform aims to provide references and assistance to relevant authorities in pollution source tracking efforts.

2. Research on hybrid tracing method of river pollution sources

2.1. Design concept of active and passive fusion method

The design concept of the hybrid tracing method is illustrated in Fig.1. Initially, an unmanned boat utilizes monitoring information from fixed monitoring stations. It employs passive tracing algorithms to infer and estimate the approximate location of the pollutant source, providing movement directional and step lengths for pollutant source tracking until entering areas of high pollution. During the tracing phase in high-pollution areas, the unmanned boat switches to active tracing algorithms for pollutant source tracking.

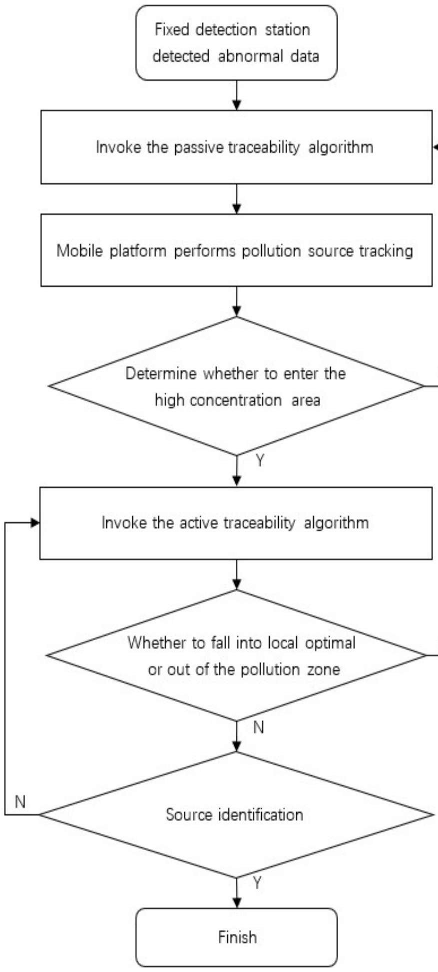


Fig.1. Flow chart of active and passive fusion method

If situations arise where the boat becomes trapped in local optima or deviates from the pollution zone, it utilizes information obtained from passive tracing algorithms to infer and estimate the pollutant source location, thereby providing movement directional and step lengths for active tracing, aiming to escape local optima or return to the pollution zone.

2.2. Construction of active and passive fusion method

2.2.1 Passive tracing algorithm module

The passive tracing algorithm module in this study employs a genetic algorithm. Genetic algorithms simulate natural selection and genetic mechanisms in optimization search. By simulating processes such as genetic inheritance, crossover, and mutation, they evolve from an initial set of solutions to progressively form better sets of solutions, addressing various optimization and search problems. Using a genetic algorithm for inverse estimation of water pollution sources provides the most realistic pollutant source location, emission intensity, and emission time. The steps are as follows:(1) Determination of Genetic Algorithm Parameters.(2) Determination of Pollution Source Parameters range.(3) Generation of Initial Population.(4) Construction of the Fitness Function.(5) Implementation of Genetic Algorithm.(6) Iterative Optimization.

2.2.2 Active tracing algorithm module

The active source tracking algorithm module in this paper adopts the Beetle Antennae Search Algorithm (BAS)[19]. The core idea of the BAS is to mimic a beetle's perception of the environment using its two antennae and adjust its movement direction based on differences in environmental information, ultimately leading it to locate food sources. The steps of the pollution source tracking method based on the BAS Algorithm are as follows:

Step 1: The parameters of the Beetle Antennae are initialized.

Step 2: The unmanned boat undergoes a random rotation by any angle.

Step 3: The unmanned boat is moved towards the side with higher pollutant concentration.

2.2.3 Active tracing algorithm module

Combining the passive traceback algorithm module based on the genetic algorithm with the active traceback algorithm module based on the beetle antenna search algorithm, detailed steps for the integration of active and passive traceback methods are proposed under the global search strategy, information interaction strategy, and local search strategy.

(1) Integration Strategy

To address the issue of unmanned boats blindly tracing pollution sources upstream in the initial stage, fixed monitoring stations deployed along the river are utilized. These stations provide water quality information to invoke the passive traceback algorithm module, inferring approximate pollution source locations. This information serves as a global search strategy to guide the movement direction and step size for the active traceback module until the unmanned boat enters a low pollution concentration area. To overcome the problem of the unmanned boat becoming trapped in a local optimum or deviating from the pollution plume, the passive traceback algorithm module is re-invoked to provide movement direction and step size for the active traceback module, facilitating escape from local optima and return to the pollution plume.

During the traceback stage in low-pollution areas, the unmanned boat utilizes the pollution source location information obtained from the passive traceback module to guide movement direction and step size for pollution source tracking. Upon reaching a new position, monitoring information is fed back to the passive traceback module. This continual exchange of information between active and passive traceback allows for ongoing pollution source tracking.

During the traceback stage in high-pollution areas, the unmanned boat employs the active traceback algorithm module based on differences in concentration detected by sensors on both sides. It utilizes a local search strategy to track pollution sources.

(2) Detailed Steps of the Integrated Tracing Method

Based on the Genetic Algorithm and the BAS algorithm, the detailed steps of the integrated traceback method are as follows:

Step 1: When the fixed monitoring station detects abnormal concentrations of the target pollutant, the traceback program of the unmanned boat is activated. The unmanned boat is equipped with symmetric sensors for the target pollutant on both sides, positioned at a distance L from the boat's center (X, Y).

Step 2: Record the changes in concentration of the target pollutant detected by the fixed monitoring station. Invoke the genetic algorithm to infer the position of the pollution source, and the unmanned boat moves toward this position by a step length.

Step 3: Check if the sensors on both sides of the unmanned boat detect a change in the concentration of the target pollutant. If an abnormal concentration is detected, proceed to Step 4; otherwise, return to Step 2.

Step 4: Utilizing the position information and detected concentration of the target pollutant from both the monitoring station and the unmanned boat, invoke the genetic algorithm to infer a new pollution source position. The unmanned boat is moved toward this position by a step length.

Step 5: Check if the difference in pollutant concentration detected by the sensors on both sides of the unmanned boat is greater than a threshold value. If the concentration difference exceeds the threshold, proceed to Step 6; otherwise, return to Step 4.

Step 6: Based on the concentration of the target pollutant detected by the sensors on both sides, invoke the BAS algorithm to output the coordinates of the next position for the mobile platform and move towards it.

Step 7: If the unmanned boat repeatedly hovers around a position, it is considered trapped in a local optimum. Return to Step 4; otherwise, proceed to Step 8.

Step 8: Check if the unmanned boat has deviated from the pollution plume. If so, return to Step 4; otherwise, proceed to Step 9.

Step 9: Check if the concentration of the target pollutant measured by the sensors on the unmanned boat exceeds a threshold value. If it does, the pollutant source is considered found. If not, proceed to Step 10.

Step 10: Check if the maximum iteration count has been reached. If so, it is determined that the pollutant source cannot be found; otherwise, return to Step 7.

In Steps 2 and 4 mentioned above, invoking the genetic algorithm to infer the pollution source location involves a calculation process similar to the step of the passive traceback algorithm module based on the genetic algorithm mentioned. The optimization objective function is modified to:

$$F = \sum_{t=1}^{T}\sum_{i=1}^{n}\left[\frac{\left(C_{th}^{t,i}-C_{me1}^{t.i}\right)^2+\left(C_{th}^{t,i}-C_{me2}^{t.i}\right)^2}{2}\right]$$

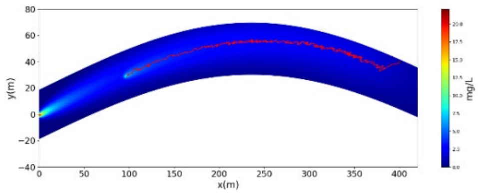
In the equations: $C_{th}^{t,i}$ represents theoretical monitoring data; $C_{me1}^{t.i}$ represents actual data detected by fixed monitoring platforms; $C_{me2}^{t.i}$ represents actual data detected by the unmanned boat; T denotes the total monitoring time; and n is the number of observation points. The step length mentioned in the above steps 2 and 4 is determined by the formula:

$$step = \frac{\sqrt{(\hat{X}_0 - X)^2 + (\hat{Y}_0 - Y)^2}}{20}$$

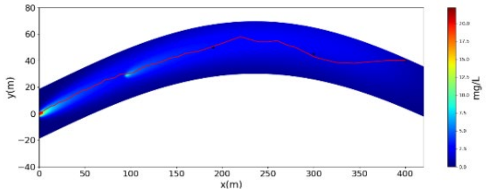
The procedure mentioned in step 6, where the BA search algorithm is invoked to obtain the next position coordinates of the mobile platform, follows the same steps as outlined in the previous section on the active traceback algorithm based on the BA search algorithm.

3. Simulation environment setup and experimental design

To construct a simulated concentration field that better reflects real river conditions, a segment of a meandering river is selected as the computational domain. Python is used to create a simulation environment for the continuous discharge of sewage from a single-point source based on a two-dimensional diffusion model. Simulations and analyses are then performed on the pollution source tracking and positioning methods, utilizing both the BA search algorithm and the integrated active-passive fusion tracing method within this concentration field. The pollution source is located at (0, 0), and the initial position of the mobile platform is (400, 40). To further compare the anti-interference capabilities of these two algorithms, a concentration interference point is introduced at position (100, 25) in the pollution diffusion concentration field, creating a local concentration peak. Simulations and analyses are conducted on the pollution source tracking and localization methods based on the BAS algorithm and the integrated active-passive fusion tracing method under this interference concentration field. The trajectory of the mobile platform is illustrated in Fig.2.



(a) the BAS



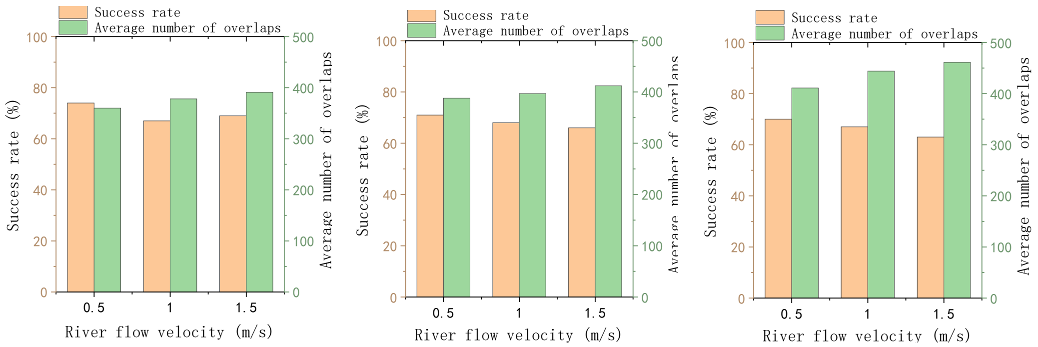
(b) active and passive fusion method

Fig.2. Traceability trajectories of pollution sources using different methods in interference concentration fields

From the trajectories of the two pollutant tracking methods shown in Fig. 2, it is clear that the pollutant tracking and localization method based on the BAS algorithm gets stuck at a local interference point during the tracking process, which leads to tracking failure. In contrast, during the traceability process of the active and passive fusion method (from 400m to 200m), a genetic algorithm is employed. The algorithm dynamically adjusts the estimated pollutant source location in response to concentration variations detected by the monitoring stations, resulting in significant fluctuations in the unmanned boat's trajectory due to the relatively large search step size. At 200m, the method transitions to the BAS algorithm. When the active and passive fusion method encounters a local interference point, it calls the passive tracking algorithm to modify the search step length and direction, allowing it to escape the local optimum. This results in stronger resistance to interference, making the method more effective at solving tracking problems in complex water pollution environments.

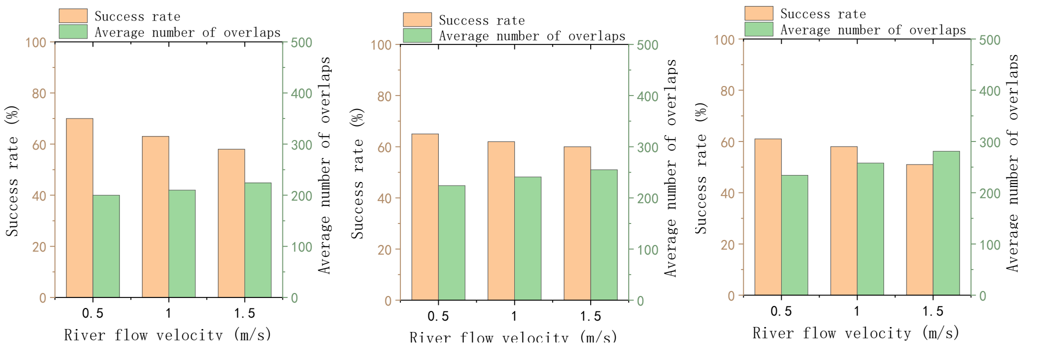
To further analyze the advantages of the intelligent step adjustment method proposed in this paper over the approach of using a fixed scaling factor for step adjustment, success rate, and average iteration count are employed as evaluation metrics. River flow velocity and pollutant emission intensity are selected as experimental variables. The BAS Algorithm, the Improved BAS Algorithm with fixed scaling factor adjustment, and the integrated active-passive fusion tracing method are subjected to tracing simulations under various conditions. The Improved BAS Algorithm utilizes a fixed scaling factor to adjust the search step. Tracing is deemed successful if the search reaches within a radius of 15m from the pollution source. Nine sets of experiments are designed under different operating conditions, with pollutant emission intensities of 200g/s, 150g/s, and 100g/s, and river flow velocities of 0.5m/s, 1.0m/s, and 1.5m/s, respectively. Each tracing algorithm is executed 100 times under each condition, and the results are presented in Figs. 3, 4, and 5.

Comparing Figs. 3, 4, and 5, it is evident that under different discharge intensities and flow velocities, the main-passive fusion tracing method can achieve a success rate of over 80%, with significantly fewer average iterations compared to other search algorithms, all within fewer than 100 iterations.



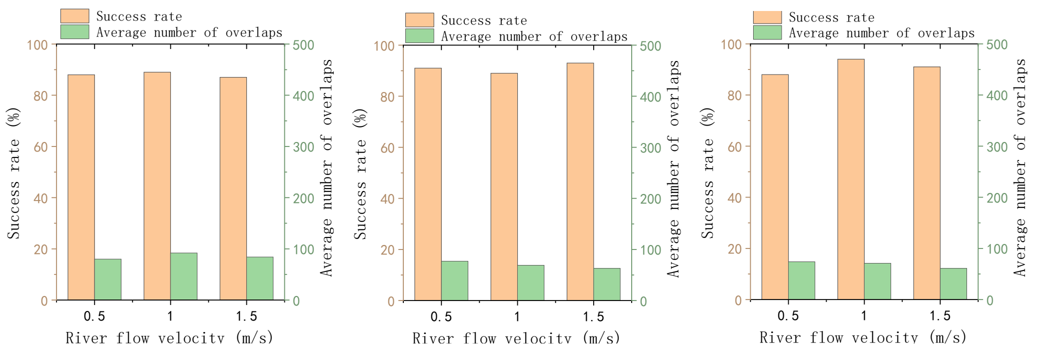
(a) Emission intensity of 200g/s （b） Emission intensity of 150g/s (c) Emission intensity of 100g/s

Fig.3. Simulation results of The BAS Algorithm under different conditions.



(a) Emission intensity of 200g/s （b） Emission intensity of 150g/s (c) Emission intensity of 100g/s

Fig.4. Simulation results of The Improved BAS Algorithm under different conditions.



(a) Emission intensity of 200g/s （b） Emission intensity of 150g/s (c) Emission intensity of 100g/s

Fig.5. Simulation results of the passive-active fusion tracing method under different conditions

When changes occur in pollutant discharge intensity and river flow velocity, noticeable fluctuations are observed in the performance of the BAS Algorithm and its improved version. In contrast, the success rate of the main-passive fusion tracing method remains largely unchanged, still exceeding 80%, with no significant variation in the average iteration count, which remains around 80. This indicates that variations in pollutant discharge intensity and river flow velocity have little impact on the success rate and iteration count of the main-passive fusion tracing method. In comparison to the BAS algorithm and its improved version, it demonstrates greater robustness.

4. Design and implementation of water pollution traceability platform

4.1. Design and implementation of the mobile traceability platform

This study introduces a mobile tracing platform based on an unmanned boat. The hardware relationships of the mobile tracing platform are depicted in Fig.6.

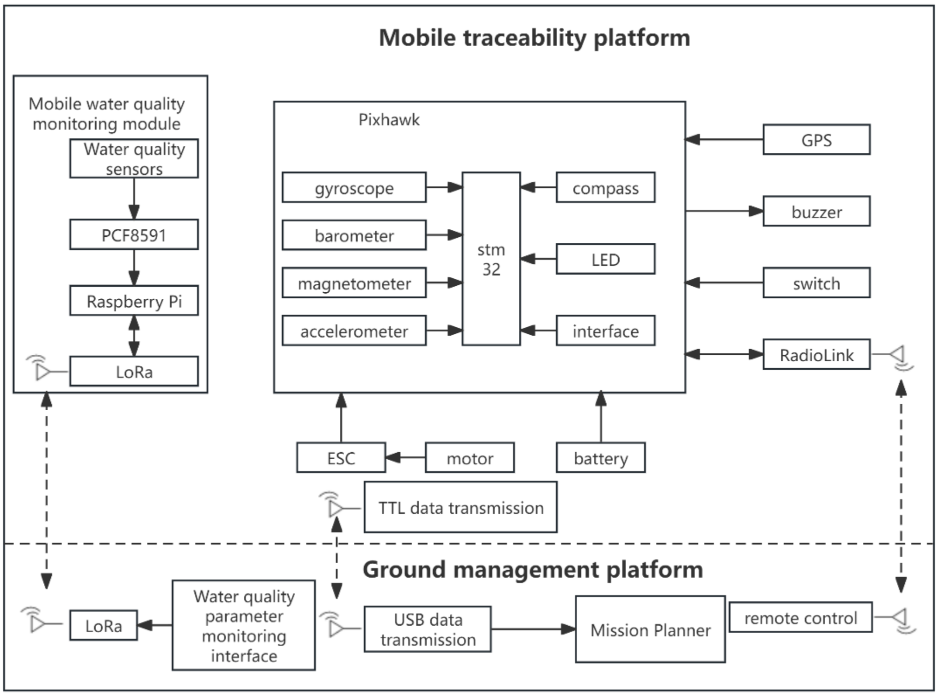
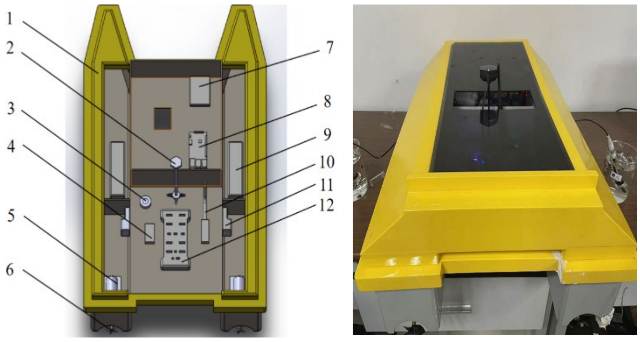


Fig.6. Relationship diagram of various modules on the mobile traceability platform

Raspberry Pi serves as the onboard computer of the mobile traceability platform. It uses the PCF8591 module to convert analog data obtained from water quality sensors into digital for data retrieval. The data is transmitted to the water quality parameter monitoring platform via the LoRa module. Simultaneously, Raspberry Pi invokes the tracing program to issue motion commands to the

Pixhawk controller based on water quality data obtained from both the fixed monitoring platform and onboard water quality sensors, thereby achieving pollution source tracing. The Pixhawk controller, through a data transmission module, sends navigation trajectories and data to the Mission Planner ground station. This ground station enables the Pixhawk controller to receive instructions for tasks such as fixed-point cruising and return voyages.

Additionally, manual control of the Pixhawk controller is facilitated through a handheld remote controller, allowing for alterations in the mobile tracing platform's direction and speed. The core components of the mobile traceability platform are illustrated in Fig. 7(a): 1. Hull; 2. GPS; 3. Buzzer; 4. Receiver; 5. Motor; 6. Propeller; 7. Power bank; 8. Raspberry Pi; 9. Battery; 10. Data transmission module; 11. ESC (Electronic Speed Controller); 12. Pixhawk. The appearance picture of the mobile tracing platform is presented in Fig. 7(b).



(a) 3D model （b）appearance picture

Fig.7. Installation layout diagram of various modules on the mobile traceability platform

4.2. Ground management platform design and implementation

4.2.1 Design of water quality parameter monitoring platform based on Qt

The upper computer software needs to record data such as water quality parameters and time from the mobile traceability platform. In this study, MySQL is chosen for data storage. QPushButton (button) controls are used to send corresponding instructions, which are parsed and executed upon reception. These instructions include opening the serial port, starting, viewing, saving, and clearing the water quality monitoring data from the mobile traceability platform. The stored water quality parameters are processed in the background and plotted as line graphs, allowing for more intuitive observation of water quality changes.

4.2.2 Debugging of navigation interface based on Mission Planner

Mission Planner is an open-source ground station software used for configuring, controlling, and monitoring Ardupilot unmanned aerial vehicle flight control systems on the Windows platform. It provides an intuitive interface that allows navigation commands to be issued to the unmanned boat thought the ground station, while real-time navigation data and trajectories can be obtained.

4. Conclusions

This paper proposes a fused passive and active tracing method and designs a water pollution traceability platform based on a mobile traceability unit and a ground management platform, utilizing the advantages of unmanned boats such as efficiency, flexibility, and speed to enhance the success rate of pollution source tracing by personnel. The main research achievements of this paper include:

(1) To address the inefficiency of single-tracing algorithms in water pollution tracing, a fused passive and active tracing method for basin pollution is proposed. The active tracing algorithm serves as the pollution source tracing strategy, combined with passive tracing to adjust the search step, avoiding failures due to limited diffusion model accuracy and issues like getting trapped in local solutions or deviating from pollution belts. A two-dimensional curved river concentration field is simulated using Python, validating the feasibility of this method.

(2) Multiple concentration simulation scenarios are generated by altering river flow velocity and emission intensity to conduct tracing simulation experiments with different algorithms. Success rate and average iteration count are used as evaluation metrics to comprehensively compare the performance of three algorithms, Improved the BAS algorithm, and fused passive and active tracing method. The results indicate that the improved the BAS algorithm outperforms the BAS algorithm in algorithm performance but is susceptible to factors such as flow velocity and emission intensity. On the other hand, the fused passive and active tracing method not only exhibits excellent tracing capability but also shows less sensitivity to factors such as river flow velocity and emission intensity, demonstrating good robustness.

(3) A water pollution mobile tracing platform is designed and developed. When combined with corresponding tracing algorithms, this platform enables water quality monitoring and pollution source tracing. Additionally, a ground management platform is developed, enabling real-time monitoring of both water quality data and navigation data from the mobile tracing platform.

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REFERENCES

[1]. Zhang X N, Guo Q P, Shen X X, et al. Water quality, agriculture, and food safety in China: Current situation, trends, interdependencies, and management[J]. Journal of Integrative Agriculture, 2015, 14(11): 2365-2379.
[2]. Lu X, Mei K. Emergency treatment of sudden water pollution accident[J]. China Water & Wastewater, 2007, 23(8): 14-18.
[3]. Yang J, Luo X. A study on water pollution source localization in sensor networks[J]. Journal of Sensors, 2016, 2016: 1-11.
[4]. Sidauruk P, Cheng A D, Ouazar D. Groundwater contaminant source and transport parameter identification by correlation coefficient optimization[J]. Groundwater, 1998, 36(2): 208-214.
[5]. Kachiashvili K, D Gordeziani, R Lazarov,et al. Modeling and simulation of pollutants transport in rivers[J]. Applied mathematical modelling, 2007, 31(7): 1371-1396.
[6]. Akcelik V, Biros G, Ghattas O, et al. A Variational Finite Element Method for Source Inversion for Convective-Diffusive Transport[J]. Finite Elements in Analysis & Design, 2003, 39(8):683-705.
[7]. Poggio T, Torre V, Koch C. Computational vision and regularization theory[J]. Readings in Computer Vision, 1987: 638-643.
[8]. Zhang S P, Xin X K. Pollutant source identification model for water pollution incidents in small straight rivers based on genetic algorithm[J/OL]. Applied Water Science, 2017, 7(4): 1955-1963.
[9]. Prakash O, Datta B. Sequential optimal monitoring network design and iterative spatial estimation of pollutant concentration for identification of unknown groundwater pollution source locations[J]. Environmental Monitoring & Assessment, 2013, 185(7): 5611-5626.
[10]. Jiang J, Han F, Zheng Y, et al. Inverse uncertainty characteristics of pollution source identification for river chemical spill incidents by stochastic analysis[J]. Frontiers of Environmental Science & Engineering, 2018, 12(5): 1-16.
[11]. Zou K. The dynamic detection of water quality monitoring and pollution prevention and control[C]. Journal of Physics: Conference Series, 2022, 2152(1): 12-17.
[12]. Farrell J A. Chemical plume tracing via an autonomous underwater vehicle[J]. IEEE Journal of Oceanic Engineering, 2005, 30(2). 428-442.
[13]. Hwang J, Bose N, Fan S. AUV adaptive sampling methods: A review[J]. Applied Sciences, 2019, 9(15): 3145.
[14]. Vergassola M, Villermaux E, Shraiman B I. 'Infotaxis' as a strategy for searching without gradients[J]. Nature, 2007, 445(7126): 406-409.
[15]. Russell R A. Chemical source location and the robomole project[J]. Proceedings Australian Conference on Robotics and Automation, 2003: 1-6.
[16]. Passino K M. Biomimicry of bacterial foraging for distributed optimization and control[J]. IEEE Control Systems Magazine, 2002, 22(3): 52-67.
[17]. Mohamed A A, Mohamed Y S, El-Gaafary A A, et al. Optimal power flow using moth swarm algorithm[J]. Electric Power Systems Research, 2017, 142: 190-206.
[18]. Xue J, Shen B. Dung beetle optimizer: A new meta-heuristic algorithm for global optimization[J]. The Journal of Supercomputing, 2023, 79(7): 7305-7336.
[19]. Jiang X, Li S. BAS: Beetle antennae search algorithm for optimization problems[J]. International Journal of Robotics and Control, 2017, 4(1): 1-3.