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NÂNG CAO HIỆU NĂNG BÁM QUỸ ĐẠO CỦA USV DƯỚI TÁC ĐỘNG CỦA NHIỄU MÔI TRƯỜNG: NGHIÊN CỨU SO SÁNH CÁC BỘ ĐIỀU KHIỂN FUZZY-LQI VÀ PSO-LQI

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Tóm tắt: Điều khiển bám quỹ đạo chính xác cho Tàu mặt nước không người lái (USV) đặt ra một thách thức lớn do đặc tính thủy động lực học phi tuyến cao và các nhiễu động môi trường khó lường như gió và sóng. Các phương pháp truyền thống như Điều khiển tối ưu toàn phương tuyến tính (LQR) thường gặp phải sai số xác lập dưới tác động của nhiễu hằng số, trong khi các phương pháp tiếp cận thích nghi dựa trên Logic mờ (Fuzzy Logic) lại phụ thuộc nhiều vào kinh nghiệm chuyên gia và có xu hướng tiêu tốn năng lượng điều khiển. Bài báo này đề xuất một chiến lược tinh chỉnh tham số tối ưu cho bộ điều khiển Tích phân Tuyến tính (LQI) sử dụng thuật toán Tối ưu hóa Bầy đàn (PSO) nhằm giải quyết bài toán đánh đổi giữa độ chính xác bám quỹ đạo và mức tiêu thụ năng lượng. Thuật toán PSO được áp dụng để tìm kiếm toàn cục các ma trận trọng số tối ưu (Q, R), từ đó triệt tiêu sai số bám đồng thời giảm thiểu hiện tượng bão hòa cơ cấu chấp hành. Kết quả mô phỏng so sánh dưới các điều kiện nhiễu gió khắc nghiệt chứng minh rằng phương pháp PSO-LQI đề xuất có hiệu năng vượt trội đáng kể so với LQR tham số cố định và bộ điều khiển Fuzzy-LQI thích nghi. Cụ thể, chiến lược PSO-LQI giảm Sai số toàn phương trung bình (RMSE) xuống chỉ còn 0.663 mét (đạt mức cải thiện 92% so với LQR và 42.2% so với Fuzzy-LQI), đồng thời tiết kiệm 21.2% năng lượng điều khiển so với giải pháp Fuzzy. Những kết quả này khẳng định PSO-LQI là một phương pháp tiếp cận bền vững, hiệu quả về năng lượng và mang tính khả thi cao để thay thế cho các quy trình tinh chỉnh thủ công phức tạp.

Từ khóa: *Tàu mặt nước không người lái (USV); bám quỹ đạo; LQI; tối ưu hóa bầ[1]y đàn (PSO); logic mờ.*

PERFORMANCE ENHANCEMENT OF USV PATH FOLLOWING UNDER ENVIRONMENTAL DISTURBANCES: A COMPARATIVE STUDY OF FUZZY-LQI AND PSO-LQI CONTROLLERS

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Abstract: Precise trajectory tracking control for Unmanned Surface Vehicles (USVs) presents a significant challenge due to highly nonlinear hydrodynamics and unpredictable environmental disturbances such as wind and waves. Conventional methods like Linear Quadratic Regulator (LQR) often suffer from steady-state errors under constant disturbances, while adaptive approaches based on Fuzzy Logic rely heavily on expert heuristics and tend to consume excessive control energy. This paper proposes an optimal tuning strategy for a Linear Quadratic Integral (LQI) controller using the Particle Swarm Optimization (PSO) algorithm to address the trade-off between tracking accuracy and energy consumption. The PSO algorithm is employed to globally search for the optimal weighting matrices (Q, R) to eliminate tracking errors while minimizing actuator saturation. Comparative simulation results under severe wind disturbance conditions demonstrate that the proposed PSO-LQI approach significantly outperforms both the fixed-parameter LQR and the adaptive Fuzzy-LQI controller. Specifically, the PSO-LQI reduces the Root Mean Square Error (RMSE) to 0.663 m (an improvement of 92% compared to LQR and 42.2% compared to Fuzzy-LQI), while simultaneously saving 21.2% of control energy compared to the Fuzzy method. These results validate that PSO-LQI is a robust, energy-efficient, and practical alternative to complex manual tuning procedures.

Keywords: *USV; trajectory tracking; LQI, particle swarm optimization (PSO), fuzzy logic.*

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1. Introduction

1.1. Background and research necessity

In recent years, advancements in autonomous maritime technology have significantly accelerated the research and deployment of Unmanned Surface Vehicles (USVs). Capable of operating autonomously in harsh environments, USVs have emerged as a pivotal solution for various critical missions, including maritime border security surveillance, hydrographic surveying, and oceanographic data acquisition (Liu, et al., 2016; Manley, 2008). A fundamental technical prerequisite for the successful execution of these operations is the capability of the USV to accurately and reliably follow a predefined reference path (trajectory tracking).

Nevertheless, trajectory tracking control for USVs remains a formidable challenge due to the inherently complex dynamic characteristics of marine vessels. USVs represent highly nonlinear and underactuated systems characterized by fewer available control inputs than degrees of freedom that are continuously subjected to unknown environmental disturbances. Exogenous factors such as wind, waves, and ocean currents not only induce positional errors but also generate stochastic yaw moments, thereby compromising the vessel's heading stability (Fossen, 2011). Consequently, the design of a robust control strategy capable of simultaneously rejecting environmental disturbances and ensuring optimal energy consumption is an imperative requirement in practical operations.

1.2. Literature review

To address the motion control problem for marine vessels, a wide array of algorithms has been proposed in the literature. Historically, classical controllers such as the Proportional-Integral-Derivative (PID) and the Linear Quadratic Regulator (LQR) have been widely adopted due to their structural simplicity and ease of practical implementation (Naeem, et al., 2003). Although the LQR provides an optimal control law for linearized systems, its primary drawback is the emergence of steady-state errors when the system is subjected to persistent, unidirectional disturbances (e.g., constant crosswinds). To mitigate this issue, the Linear Quadratic Integral (LQI) approach was developed by augmenting the state vector with an integral term, which effectively eliminates steady-state errors (Anderson and Moore, 2007). However, the performance of the LQI controller is highly contingent upon the selection of the weighting matrices, Q and R. The determination of these parameters predominantly relies on time-consuming trial-and-error methods, which do not guarantee the identification of a globally optimal operating point.

To enhance adaptive capabilities, recent studies have integrated Fuzzy Logic into the LQI framework (Lê, 2005; Precup and Hellendoorn, 2011). These hybrid Fuzzy-LQI controllers can automatically tune the gain parameters based on the instantaneous tracking error, enabling the system to react more flexibly to environmental fluctuations. Despite significantly improving tracking accuracy compared to the fixed-gain LQR, this approach inherently suffers from two primary limitations:

Subjective Dependency: The design of the fuzzy rule base and membership functions relies heavily on heuristic expert knowledge, making it subjective and difficult to standardize across different operating conditions.

Energy Consumption: If the inference rules are not rigorously optimized, the controller tends to exhibit aggressive responses. This behavior frequently leads to actuator saturation and unnecessary energy expenditure (Kennedy and Eberhart, 1995).

To overcome the reliance on human expertise and to achieve multi-objective optimization specifically balancing tracking precision and energy efficiency meta-heuristic algorithms such as Particle Swarm Optimization (PSO) have been successfully applied in the field of automatic control (del Valle, et al., 2008). For highly nonlinear systems like USVs, PSO demonstrates superior efficacy due to its rapid global search capabilities, algorithmic simplicity, and derivative-free nature regarding the objective function (Song, et al., 2017).

1.3. Research objectives and contributions

Building upon the aforementioned analysis, this study focuses on resolving the fundamental trade-off between path-tracking accuracy and energy efficiency for Unmanned Surface Vehicles (USVs) operating under severe environmental disturbances. The primary objective is to propose an automated parameter-tuning strategy for the LQI controller utilizing the Particle Swarm Optimization algorithm (hereafter referred to as PSO-LQI). This approach is explicitly designed to replace conventional manual tuning methods and subjective fuzzy-logic-based heuristics.

The primary contributions of this paper are summarized as follows:

Mathematical modeling: A comprehensive 3-Degree-of-Freedom (3-DOF) dynamic model of the Cybership II USV is established, explicitly incorporating the coupled effects of wind and wave-induced stochastic disturbances.

Optimal control strategy (PSO-LQI): A PSO-based algorithm is developed to systematically search for the globally optimal weighting matrices (Q and R) for the LQI controller. A bespoke objective function (fitness function) is formulated to prioritize the minimization of tracking errors while strictly maintaining control energy constraints.

Rigorous comparative evaluation: A comprehensive simulation framework is executed to benchmark three distinct control architectures: Fixed-LQR, Fuzzy-LQI, and the proposed PSO-LQI. Quantitative results demonstrate that the PSO-LQI solution not only minimizes the Root Mean Square Error (RMSE) to the lowest level among the tested methods but also achieves substantial energy savings compared to the Fuzzy-LQI approach, thereby validating the efficacy and practical viability of the proposed algorithm.

2. Problem formulation and error dynamics

2.1. USV model and assumptions

This study employs the 3-degree-of-freedom (3-DOF) Cybership II model. Details regarding the nonlinear dynamic equations and hydrodynamic parameters are adopted from (Lê, 2005). To design the LQI controller in this paper, the following operational assumptions are made:

1) The vessel operates at a constant surge velocity ($u = Uspd$).

2) Higher-order nonlinear components and Coriolis forces are treated as disturbances or linearized about the nominal operating point.

2.2. Linearized error dynamics for path following

The control objective is to minimize the cross-track error (y_e) and the heading error (ψ_e) with respect to the reference trajectory. Based on the Serret–Frenet frame geometry, the error kinematics under the small-angle approximation ($\sin\psi_e \approx \psi_e$) can be expressed as follows:

$$\begin{cases} \dot{y}_e \approx \dot{U}_{spd}\psi_e + v \\ \dot{\psi_e} = r \end{cases} \quad (1)$$

By combining this with the linearized vessel dynamics, the state-space representation is formulated as follows:

$$\dot{x}_{sys} = A_{sys}\dot{x}_{sys} + B_{sys}\tau_r \quad (2)$$

where the basic state vector $x_{sys} = [v, r, \psi_e, y_e]^T$, and the system matrices A_{sys} and B_{sys} are given by:

$$A_{sys} = \begin{bmatrix} -Y_v/m & -U_{spd} & 0 & 0 \\ -N_r/I_z & -N_r/I_z & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & U_{spd} & 0 \end{bmatrix} \qquad B_{sys} = \begin{bmatrix} 1/m \\ 1/I_z \\ 0 \\ 0 \end{bmatrix} \quad (2)$$

2.3. Augmented state-space for LQI design

To eliminate the steady-state error induced by constant disturbances, the integral term of the cross-track error ($x_I = \int y_e dt$) is augmented to the state vector. The resulting augmented system is expressed as follows:

$$\dot{x} = \boldsymbol{A}x + \boldsymbol{B}\tau_r \quad (3)$$

Here, the new state vector is denoted by$x = [v, r, \psi_e, y_e]^T$, (comprising 5 state variables). The augmented system matrix $\boldsymbol{A} \in R^{5x5}$ $\boldsymbol{B} \in R^{5x1}$ are restructured as follows:

$$\boldsymbol{A} = \begin{bmatrix} A_{sys} & 0_{4x1} \\ C_{err} & 0 \end{bmatrix}, \qquad \boldsymbol{B} = \begin{bmatrix} B_{sys} \\ 0 \end{bmatrix} \quad (4)$$

where $\boldsymbol{C}_{err} = [0, 0,0,1]$ is a row vector used to extract the cross-track error y_e for integration.

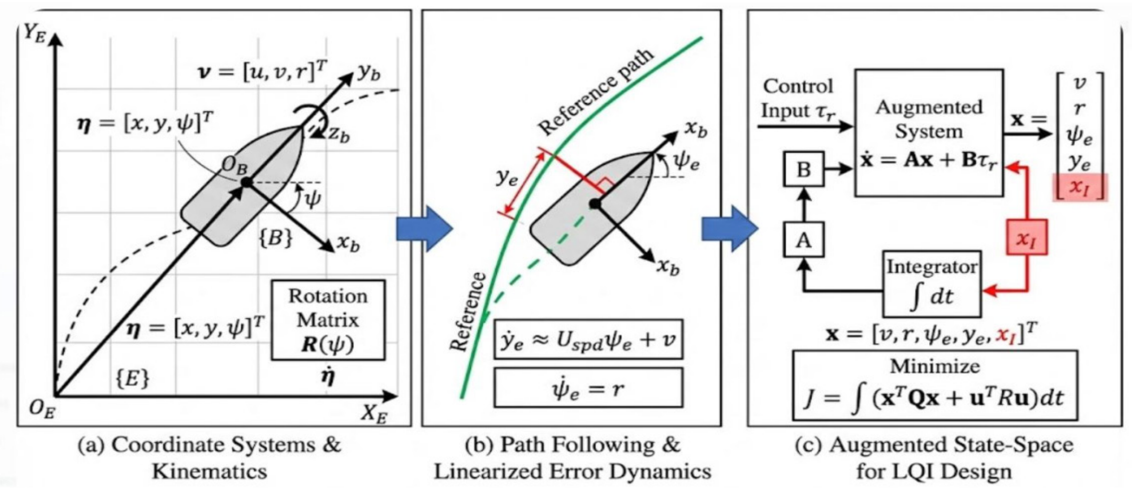
The optimal control problem then becomes determining the control law u = - $\boldsymbol{K}x$ that minimizes the scalar cost function:

$$J = \int_0^\infty (x^T Q_x + u^T R u) dt \quad (5)$$

Herein, the primary challenge lies in determining the elements of the weighting matrices Q (specifically the penalty weights qy and qint) and R o achieve an optimal balance between tracking accuracy and control effort. This constitutes an optimization problem that will be addressed by the PSO algorithm in the subsequent section.

To provide an intuitive overview of the established theoretical framework, Figure 1 summarizes the system modeling process from the physical kinematics to the control structure. The diagram illustrates the close relationship among the reference coordinate frames (Figure 1a), the linearized tracking error determination mechanism (Figure 1b), and, most importantly, the augmented state-space structure (Figure 1c). Notably, the integral state variable (xI) is highlighted to emphasize its central role in handling the steady-state error, thereby laying the foundation for the optimal controller design in the following section.

Figure 1. USV Modeling, Error Kinematics, and Augmented LQI State Space



Source: A visual synthesis of the theoretical framework used in the authors' study.

3. Proposed PSO-LQI control strategy

To address the trade-off between tracking accuracy and energy consumption, this section presents an optimal controller design approach. The proposed strategy comprises two steps: formulating the LQI state-feedback control law, and applying the PSO algorithm to determine the globally optimal weighting parameters.

3.1. LQI control law formulation

In the motion control architecture of marine vessels, the control problem is frequently decoupled into surge control and steering control due to their significantly different response times (Fossen, 2011). This study focuses on the steering control problem subject to disturbances, wherein the surge velocity is maintained constant by an independent cruise controller.

Based on the augmented state-space model (Equation 3) established in Section 2.3, the optimal state-feedback control law is given by:

$$\tau_r(t) = -Kx(t) = -\left[K_{fb}\ k_I\right]\begin{bmatrix} v \\ r \\ \psi_e \\ y_e \\ x_I \end{bmatrix} \quad (6)$$

Where $K \in R^{1x5}$ is the control gain vector to be determined. The objective is to minimize the following quadratic cost function:

$$J = \int_0^{\infty}(x^T Q_x + r\tau_r^2)dt \quad (7)$$

Under the assumption of a constant surge velocity u the system is treated as Linear Time-Invariant (LTI), which allows for the computation of a unique feedback gain matrix K by solving the Continuous-time Algebraic Riccati Equation (CARE). However, the control performance of K depends heavily on the selected weighting pair (Q, r). Rather than determining these weights through a conventional trial-and-error approach, this study employs Particle Swarm Optimization (PSO) to search for the globally optimal solution.

3.2. Particle swarm optimization algorithm for LQI tuning

PSO is a population-based stochastic search algorithm inspired by the social behavior of bird flocking or fish schooling. Within a multidimensional search space, the individuals (referred to as particles) update their positions based on both their personal experience and the collective experience of the swarm, thereby converging toward the global optimum [9] (del Valle, et al., 2008).

3.2.1. Particle definition and search space

In this study, the LQI controller optimization problem is formulated as a search for a parameter vector X within a 3-dimensional space (D=3). Each i-th particle in the swarm represents a candidate configuration of the controller weights:

$$X_i = \left[q_y^{(i)}, q_{int}^{(i)}, r^{(i)}\right]^T \quad (8)$$

Where:

$q_y^{(i)}$: Penalty weight for the cross-track error.

$q_{int}^{(i)}$: Penalty weight for the integral error (which dictates the capability to eliminate the steady-state error).

$r^{(i)}$: Penalty weight for the control effort (which dictates the energy consumption).

To guarantee system stability and prevent impractical solutions, the search space is constrained by the lower bounds$\boldsymbol{X}_{\min}$ and the upper bounds $\boldsymbol{X}_{\max}$.

To guarantee system stability and prevent impractical solutions, the search space is constrained by the lower boundsXmin and the upper bounds Xmax.

3.2.2. Velocity and position update rules

At each iteration k, each particle i updates its velocity Vi and position Xi according to the two fundamental equations of PSO:

At each iteration k, each particle i updates its velocity $\mathbf{V}_i$ and position $\mathbf{X}_i$ according to the two fundamental equations of PSO:

$$V_i^{k+1} = \omega . V_i^k + c_1 r_1 \left(P_{best,i}^k - X_i^k\right) + c_2 r_2 \left(G_{best}^k - X_i^k\right) \quad (9)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (10)$$

Where:

ω: Inertia weight, which balances the exploration (global search) and exploitation (local search) capabilities.

c_1; c_2: Acceleration coefficients, representing the cognitive (personal experience) and social (swarm experience) components, respectively.

r_1; r_2: Random numbers uniformly distributed within the interval [0, 1], introducing stochasticity to the algorithm.

$P_{best,i}$: The personal best position achieved by the i-th particle so far.

V_{best}: The global best position found by the entire swarm up to the current iteration.

3.2.3. Fitness function formulation

The fitness function plays the most critical role in guiding the swarm toward the optimal solution. To address the multi-objective problem (balancing tracking accuracy and energy consumption), this study proposes the fitness function Jfitness as a weighted sum of two performance indices:

Tracking Accuracy: Quantified by the Root Mean Square Error (RMSE) of the cross-tra error over the entire simulation time T:

$$RMSE(y_e) = \sqrt{\frac{1}{T}\int_0^T \left[y(t) - y_{ref}(t)\right]^2 dt}$$

<u>Control Effort</u>: Calculated by the integral of the squared control signal (yaw moment):

$$E_{total} = \int_0^T \tau_r(t)^2 dt$$

Weighting coefficients (α, β): α, β are positive coefficients utilized for normalization a prioritization. Given that the USV is subjected to strong wind disturbances, the tracking err remains the top priority. Consequently, α is selected to be significantly larger than β ($\alpha \gg$ to compel the controller to eliminate the steady-state error, while maintaining a soft constrai to prevent actuator saturation.

3.2.4. Optimization procedure

The execution procedure of the PSO-LQI algorithm is summarized in the following steps:

Step 1 - Initialization: Initialize a swarm of N particles with random positions and velocities within the valid search space.

Step 2 - Evaluation: For each particle Xi:

Solve the Continuous-time Algebraic Riccati Equation (CARE) to determine the feedback gain matrix Ki

Simulate the closed-loop USV system with the controller Ki over the simulation time T

Calculate the fitness function value Jfitness based on the feedback data from the simulation.

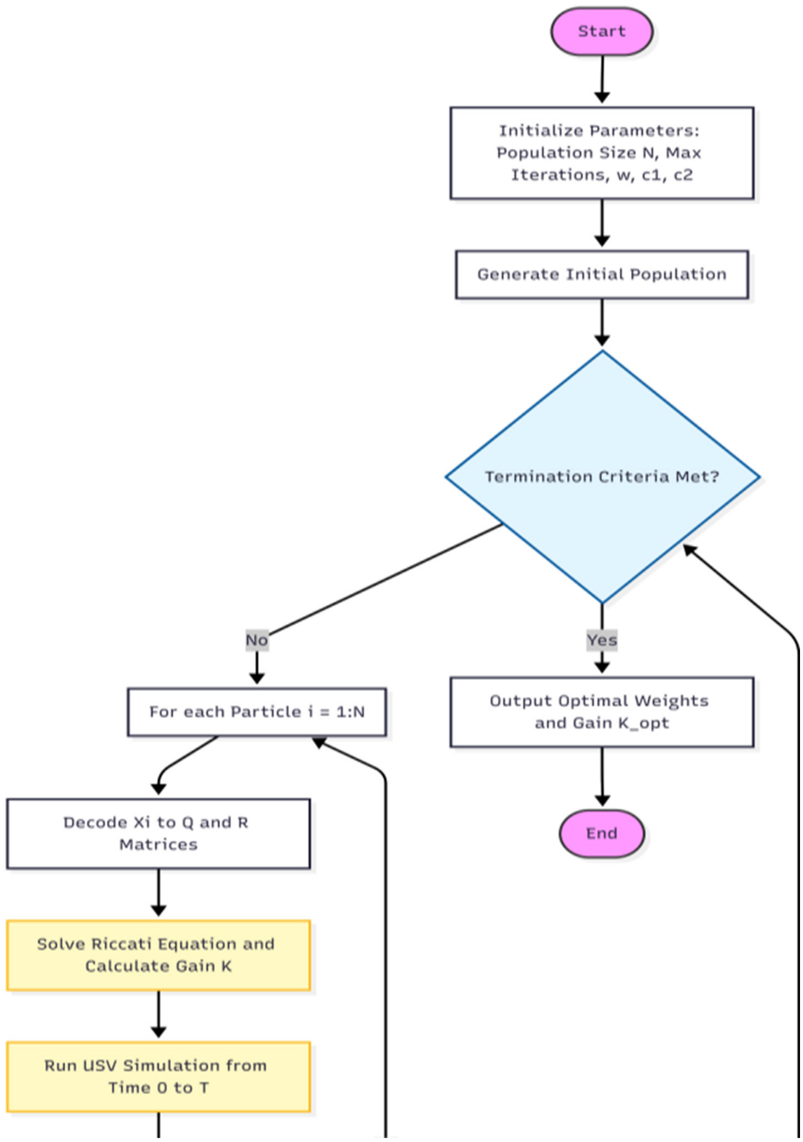
Step 3 - Pbest/Gbest update: Compare the current Jfitness with the historical best values to update Pbest,i and Gbest.

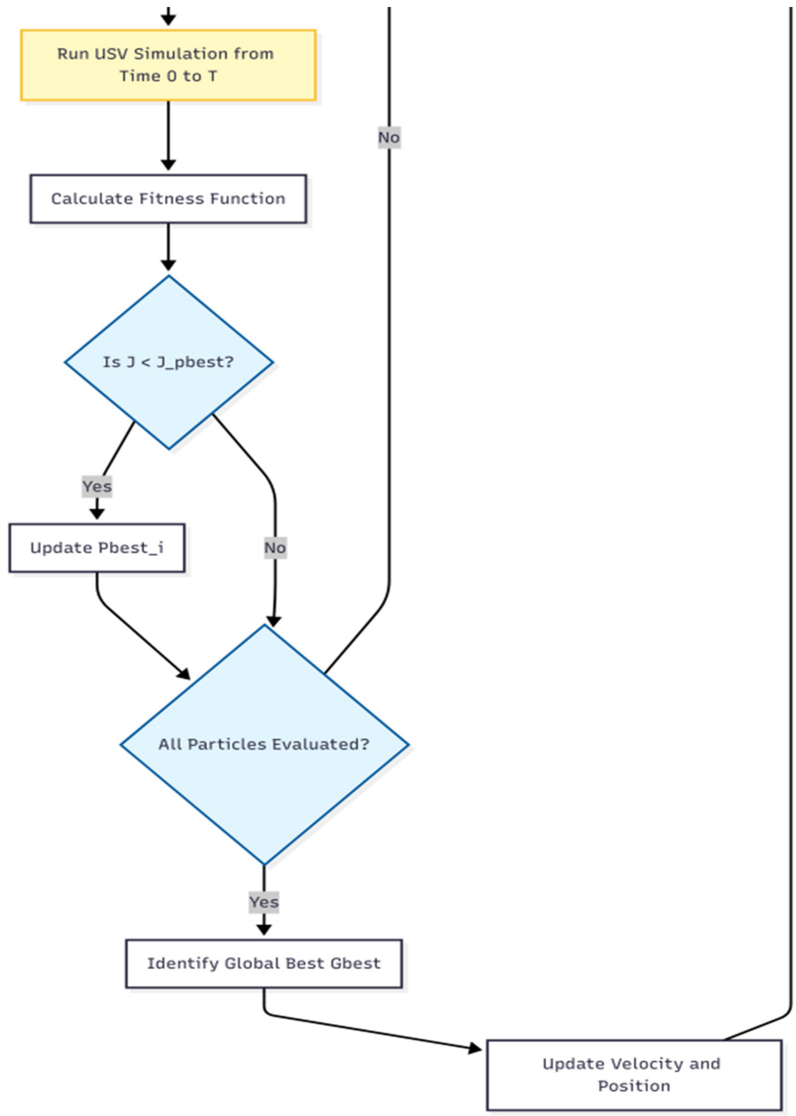
Step 4 - Velocity and position update: Update the velocity and position of the particles according to the aforementioned equations.

Step 5 - Termination check: If the maximum number of iterations is reached or Jfitness converges below a predefined error threshold, the algorithm terminates and outputs the optimal parameter set Xopt = Gbest. Otherwise, return to Step 2.

To explicitly illustrate the interaction between the optimization algorithm and the plant model, the execution sequence of the proposed control strategy is summarized in Figure 2. This flowchart details the closed-loop process: starting from the initialization of a random particle swarm, solving the algebraic Riccati equation to determine the control law, running simulations to evaluate the fitness function Jfitness based on the vessel's feedback, and repeating the update process until the algorithm converges to the globally optimal parameter set Gbest.

Figure 2. Flowchart of the proposed PSO-based LQI tuning strategy





4. Simulation results and discussion

To validate the effectiveness of the proposed PSO-LQI control strategy, numerical simulations are conducted on the Cybership II vessel model using Python. The simulation scenario is specifically designed to evaluate the system's course-keeping capability and disturbance rejection performance under harsh marine environmental conditions.

4.1. Simulation setup

The configuration parameters for the PSO algorithm and the initial states of the vessel are detailed in Table 1. To ensure a fair comparison, three controllers are evaluated under identical operating conditions:

Fixed-LQR: The conventional LQR controller without the integral component ($xI = 0$), serving as the baseline.

Fuzzy-LQI: An adaptive controller employing Fuzzy Logic for parameter tuning (referenced from a previous study (Lê, 2005).

Proposed PSO-LQI: The optimized controller proposed in this study. The simulated environmental disturbances encompass a constant crosswind Fbias = 4.0 N and a random wave disturbance with an amplitude of Awave = 1.5 N, these induce a substantial drift force, severely challenging the path-following capability of the underactuated vessel lacking a lateral actuator.

Table 1. Simulation setup parameters and PSO configuration

Category	Parameter	Value
Initial conditions	Initial position *(x0, y0)*	(0, 0) m
	Surge velocity U_{spd}	0.5 m/s
	Initial heading $\psi 0$	0 rad
PSO configuration	Number of particles *N*	30
	Maximum number of iterations	50
	Inertia weight ω	0.9 to 0.4 (decreasing)
	Acceleration coefficients c1, c2	2.0
	Weighting coefficients α, β	α =10, β =0.001

4.2. Optimization convergence analysis

The search performance of the PSO algorithm is illustrated through the reduction of the cost function. Experimental data indicates that the algorithm exhibits remarkably rapid convergence. The objective function value decreases from an initial value of 9.5197 to an optimal level of 8.8 after only 5 iterations, and strictly maintains a stable value of 8.8066 up to the 20th iteration (Figure 3). This demonstrates the algorithm's robustness in avoiding entrapment in local optima.

Figure 3. Simulation results

```
>>> RUNNING PSO (Finding Optimal Trade-off Parameters)...
PSO Iter 0: Cost = 9.9511
PSO Iter 5: Cost = 8.8146
PSO Iter 10: Cost = 8.8066
PSO Iter 15: Cost = 8.8066
PSO Iter 20: Cost = 8.8066
DONE! Optimal Params: q_y=1.00, q_int=50.00, r=1.00

>>> STARTING COMPARATIVE SIMULATION...
--------------------------------------------------------------------------------
Method            | RMSE (m)    | Energy (J) | Remarks
--------------------------------------------------------------------------------
Fixed LQR         | 8.411       | 913.8       | High drift (Wind effect)
Fuzzy-LQI         | 1.147       | 2768.4       | Good tracking, High energy
PSO-LQI           | 0.663       | 2180.2       | Optimal (Best Trade-off)
--------------------------------------------------------------------------------
```

At the final iteration, the global optimal parameter set $\mathbf{G_{best}}$ is determined as:

$$X_{opt} = [q_y, q_{int}, r] = [1.00, 50.00, 1.00]$$

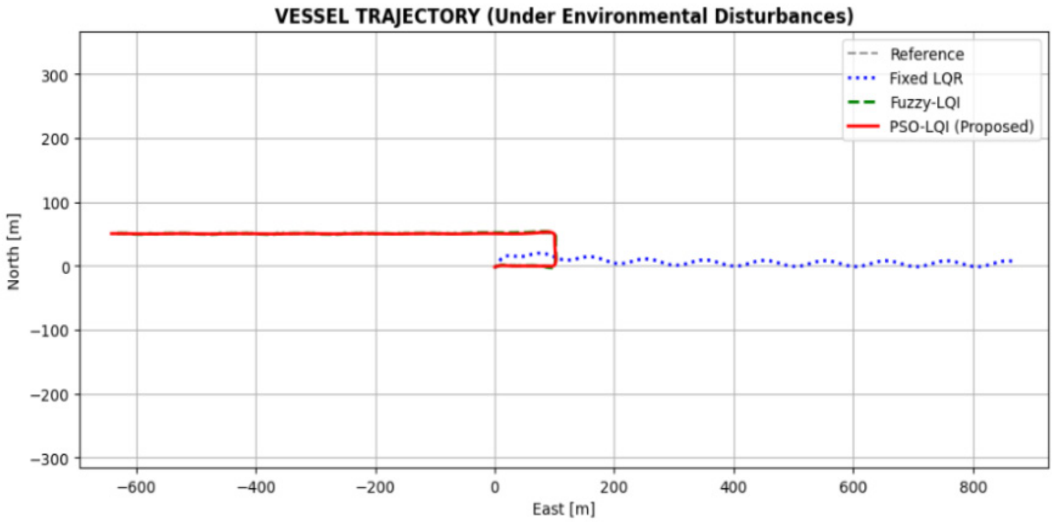
The aforementioned result highlights the predominant value of the integral weight ($q_{int} = 50.00$) compared to the cross-track error weight ($q_y = 1.00$). This accurately reflects the physical nature of the simulation scenario: Subjected to a constant crosswind bias, the instantaneous error (y_e is less critical than the accumulated error. Consequently, the controller necessitates a robust integral action to generate a stable crabbing angle, thereby completely eliminating the steady-state error ($\lim_{t\to\infty} y_e(t) = 0$).

4.3. Comparative performance analysis

To comprehensively evaluate the effectiveness of the proposed control strategy, comparative simulations are conducted among three controllers: Fixed-LQR (baseline), Fuzzy-LQI (adaptive fuzzy), and PSO-LQI (proposed) under identical environmental disturbance conditions (wind and waves).

Evaluation of trajectory tracking performance: The disturbance rejection effectiveness is visually demonstrated in Figure 4. Subjected to a crosswind (bias force) and ocean waves, the Fixed-LQR controller (blue dotted line) exhibits severe performance degradation; the vessel completely drifts away from the reference trajectory due to the absence of an integral component to compensate for the steady-state error. Conversely, both the Fuzzy-LQI and PSO-LQI successfully maintain the vessel's course. However, upon closer inspection at the waypoints, the trajectory generated by the PSO-LQI (solid red line) exhibits greater smoothness and adheres more strictly to the reference path compared to the Fuzzy-LQI, particularly regarding its rapid stabilization capability after turning maneuvers.

Figure 4. Comparison of vessel trajectories among controllers under environmental disturbances

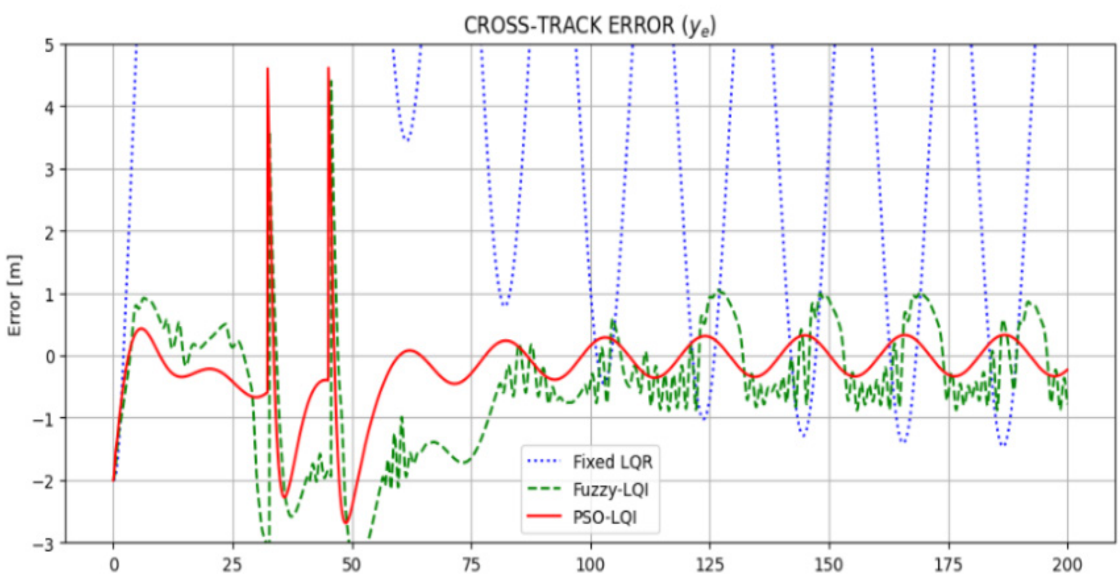


Evaluation of tracking accuracy: The superior accuracy is explicitly demonstrated through the transient profile of the cross-track error (ye) in Figure 5 and the aggregated data in Table 2.

Fuzzy-LQI: Although it successfully reduces the error to 1.147 m, the plot in Figure 5 reveals that the error oscillation amplitude remains considerable, failing to completely counteract the wind effects.

PSO-LQI: Achieves the highest precision with an RMSE of merely 0.663 m. This corresponds to a tracking performance improvement of 42.2% compared to the Fuzzy-LQI and 92.1% compared to the Fixed-LQR.

Figure 5. Time history comparison of cross-track error (ye) among control strategies

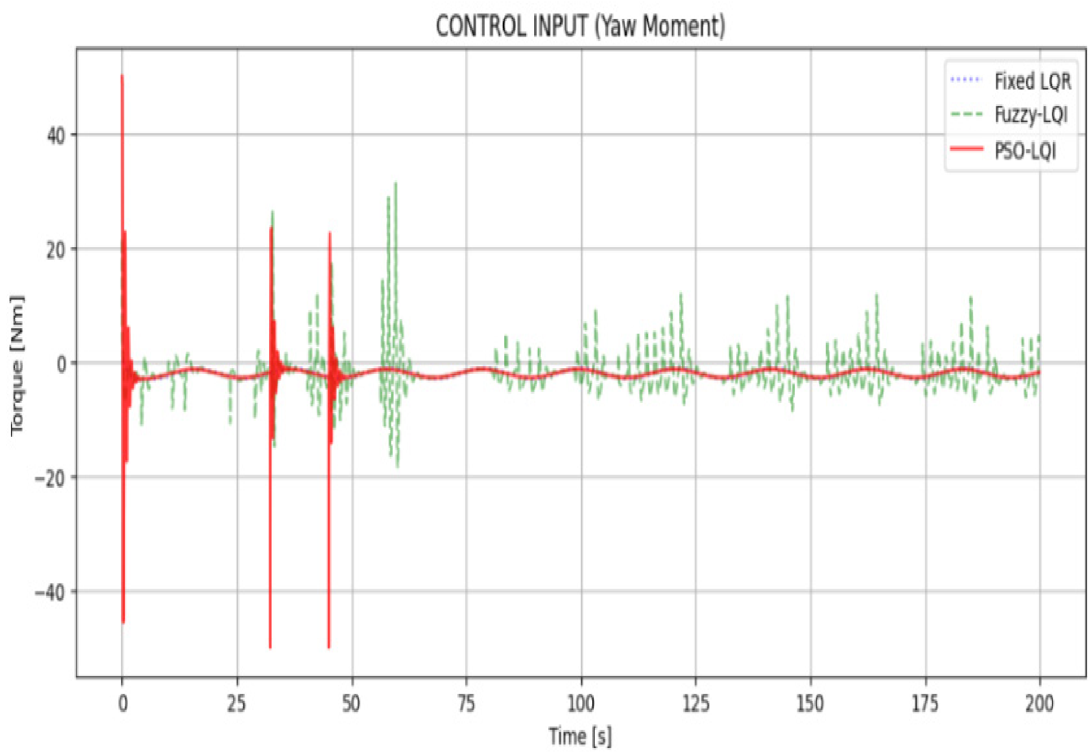


Evaluation of energy consumption and control effort: One of the most significant findings of this study lies in the analysis of energy consumption, as illustrated in Figure 6 and the 'Energy' column of Table 2.

Table 2. Quantitative performance comparison (empirical data)

Method	Cross-track RMSE (m)	Energy consumption (J)	RMSE improvement (%)	Energy savings (%)
Fixed-LQR	8.411	913.8	-	-
Fuzzy-LQI	1.147	2768.4	86.3% (vs LQR)	-
PSO-LQI	0.663	2180.2	92.1% (vs LQR)	21.2% (vs Fuzzy)

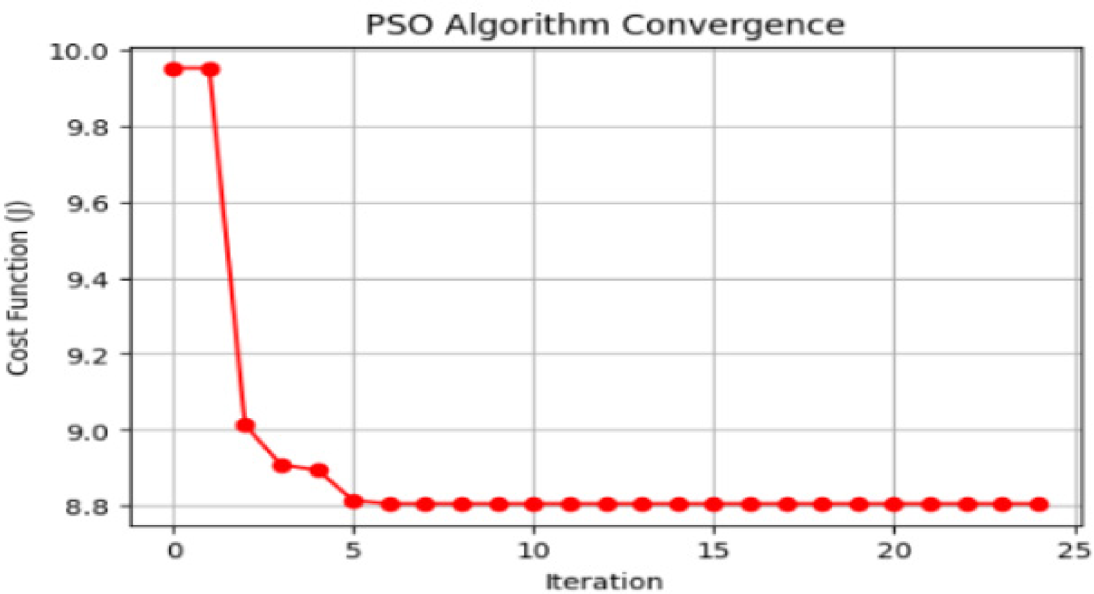
Figure 6. Time history comparison of control input (Yaw moment) signals



Observing Figure 6, the control signal of the Fuzzy-LQI (dashed line) exhibits high-frequency oscillations (chattering). This phenomenon is the primary cause for the surge in energy consumption to 2768.4 J. Conversely, the control signal from the PSO-LQI (solid line) is considerably smoother, exhibiting vigorous responses only when necessary (during turning maneuvers) and maintaining low-amplitude harmonic oscillations for wave rejection. By virtue of the global optimization mechanism, the PSO-LQI achieves a "Pareto optimal" state: simultaneously enhancing tracking accuracy and reducing energy consumption by 21.2% compared to the Fuzzy approach.

Convergence analysis: The rationale behind attaining this optimal parameter set is elucidated in Figure 7. The optimization process employing the PSO algorithm exhibits remarkably rapid convergence, decreasing the cost function J from its initial value to the minimum level within merely 5 iterations. This demonstrates that the algorithm not only identifies the optimal trade-off between tracking error and energy consumption but also ensures practical implementation feasibility due to its low computational cost.

Figure 7. Convergence profile of the cost function in the PSO algorithm



Conclusion: By identifying the "sweet spot" parameter set [1.00, 50.00, 1.00], the PSO-LQI has successfully resolved the trade-off problem, yielding a smoother tracking trajectory and enhanced energy efficiency.

The superiority of the PSO-LQI over the Fuzzy-LQI can be elucidated through their respective optimization mechanisms. Fuzzy Logic tunes parameters based on local rules and empirical design expertise, which frequently results in the system operating at a sub-optimal state. In contrast, PSO searches across the entire parameter space and evaluates performance based on a fitness objective function Jfitness that integrates both tracking error and energy consumption throughout the entire voyage. Consequently, PSO derives a more forward-looking control strategy, averting redundant control actions that lead to energy waste.

5. Conclusion

This paper has successfully developed and verified an optimal trajectory tracking control strategy for surface vessels using a Particle Swarm Optimization-based Linear Quadratic Integral (PSO-LQI) framework. The proposed controller has demonstrated superior robustness in handling constant environmental disturbances compared to traditional methods. Specifically, comparative simulation results confirm that the PSO-LQI strategy achieves the highest tracking accuracy with a Root Mean Square Error (RMSE) of merely 0.663 meters. Furthermore, by thoroughly eliminating the high-frequency chattering phenomenon in the control signal, the proposed method reduces energy consumption by 21.2% compared to the adaptive Fuzzy-LQI approach. The optimization algorithm also exhibits high computational efficiency, rapidly converging to the globally optimal parameters within a mere five iterations, thereby affirming its feasibility for real-time system applications.

Despite achieving promising results, this study possesses certain limitations that must be acknowledged. The current validation is restricted to numerical simulations, implying that practical factors such as sensor noise, actuator dynamics, and complex hydrodynamic effects have not been fully integrated. Additionally, the controller design relies on the assumption of a constant surge velocity. In actual maritime operations, velocity variations can significantly alter the vessel's dynamics, thereby potentially affecting the stability of the control system. Finally, the current framework focuses solely on trajectory tracking and has not yet incorporated dynamic collision avoidance capabilities.

Addressing these limitations will constitute the primary focus of future research endeavors. Subsequent work will involve conducting empirical tests on a scaled physical ship model to verify the real-time performance and robustness of the proposed algorithm in real-world environments. Moreover, the control strategy will be extended to handle time-varying velocity conditions via a speed-heading coupled control mechanism. Lastly, the integration of local path planning algorithms, such as Artificial Potential Fields or the Dynamic Window Approach (DWA), will be investigated to enable autonomous, COLREGs-compliant collision avoidance in dynamic maritime scenarios.

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