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Reinforcement-Learning-Guided Particle Swarm Optimization for Robust Quadcopter PID Controller Tuning

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INTRODUCTION & AIM

Cascaded PID control is widely used in quadcopter systems because it is simple, interpretable, and easy to implement.
However, tuning the coupled attitude and altitude loops is challenging under model uncertainty, actuator limitations, sensor perturbations, and external disturbances.
This work investigates a reinforcement-learning-guided particle swarm optimization method for tuning the PID gains of a quadcopter controller.
The objective is to improve disturbance rejection while preserving the original cascaded PID control structure.
Aim:
To compare an initial PID controller, standard PSO-tuned PID, and RL-PSO-tuned PID under feedback-path and plant-side disturbances using Monte Carlo robustness evaluation.

METHOD

Three PID tuning strategies were evaluated:

Initial PID:
A baseline cascaded PID controller obtained from classical tuning and manual refinement.

PSO-tuned PID:
Particle swarm optimization directly searches the PID gain vector.

RL-PSO-tuned PID:
A reinforcement learning agent guides the PSO search by adapting the PSO hyperparameters online. The agent selects between exploration, balanced, and exploitation modes, which modify the inertia weight and acceleration coefficients according to swarm progress and diversity.

The optimized gain vector contains 12 PID parameters corresponding to proportional, integral, and derivative gains for roll, pitch, yaw, and altitude loops.
Controller performance was evaluated in MATLAB/Simulink on a spiral tracking task. Two disturbance scenarios were considered:

Feedback-path disturbance:
Measurement-path perturbations with bias and sinusoidal components.

Plant-side disturbance:
Gust-like force disturbances applied directly to the plant.

A Monte Carlo benchmark with 30 randomized disturbance realizations was used. For fairness, each randomized disturbance profile was applied identically to all three controllers.

RESULTS & DISCUSSION

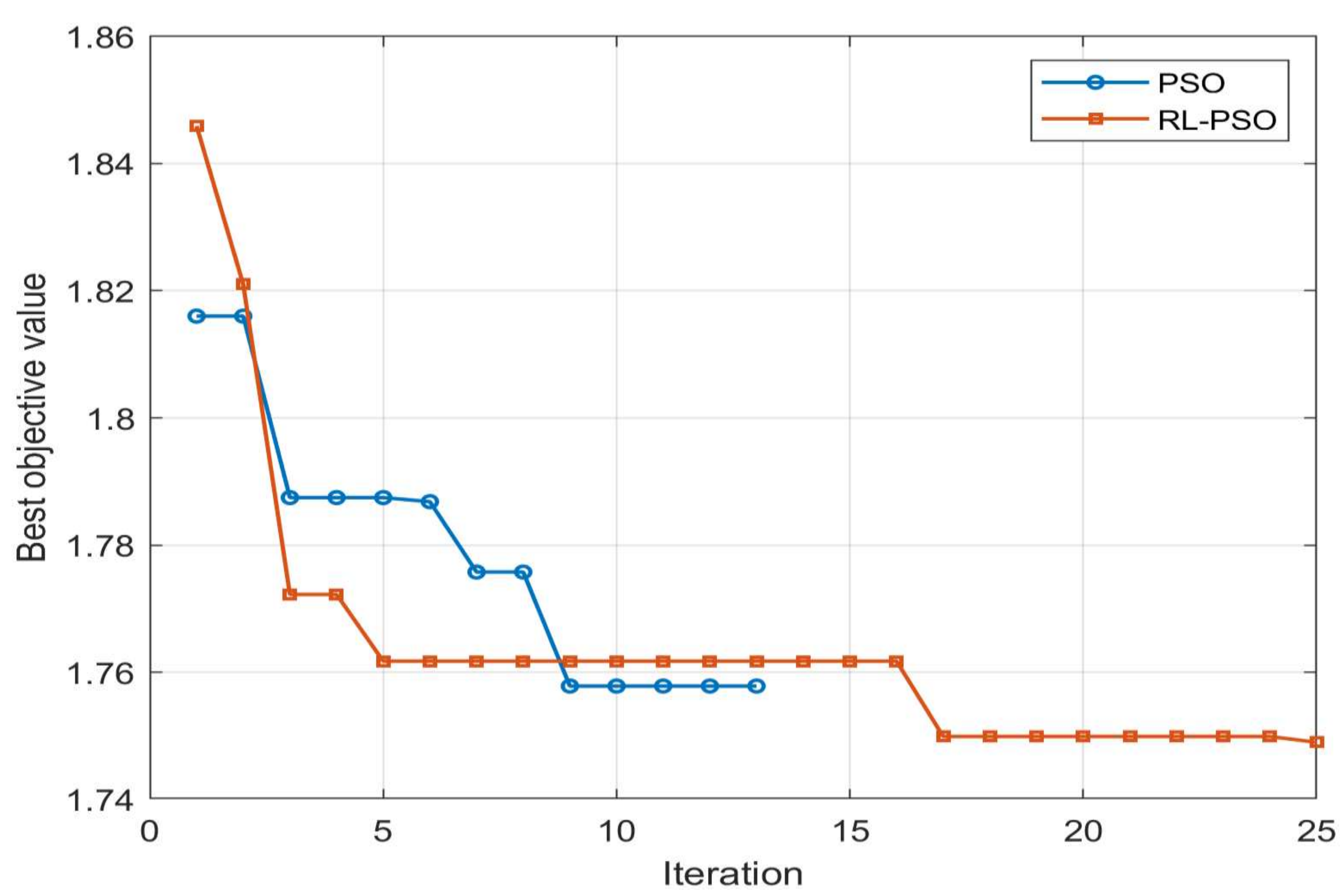

Figure 1. PID tuning convergence.

The convergence curve shows that RL-PSO continued improving the objective value after standard PSO reached a plateau, achieving the lowest final objective value after 25 iterations.

CONCLUSIONS

RL-PSO provides a practical simulation-based approach for robust PID tuning of a quadcopter without changing the underlying cascaded control architecture.

Compared with the initial PID and standard PSO, RL-PSO achieved lower overall 3D tracking error, lower peak-error statistics, shorter violation duration, and faster recovery in the tested disturbance scenarios.

The results suggest that reinforcement learning can improve PSO-based tuning by adapting the search behavior according to swarm progress and diversity.

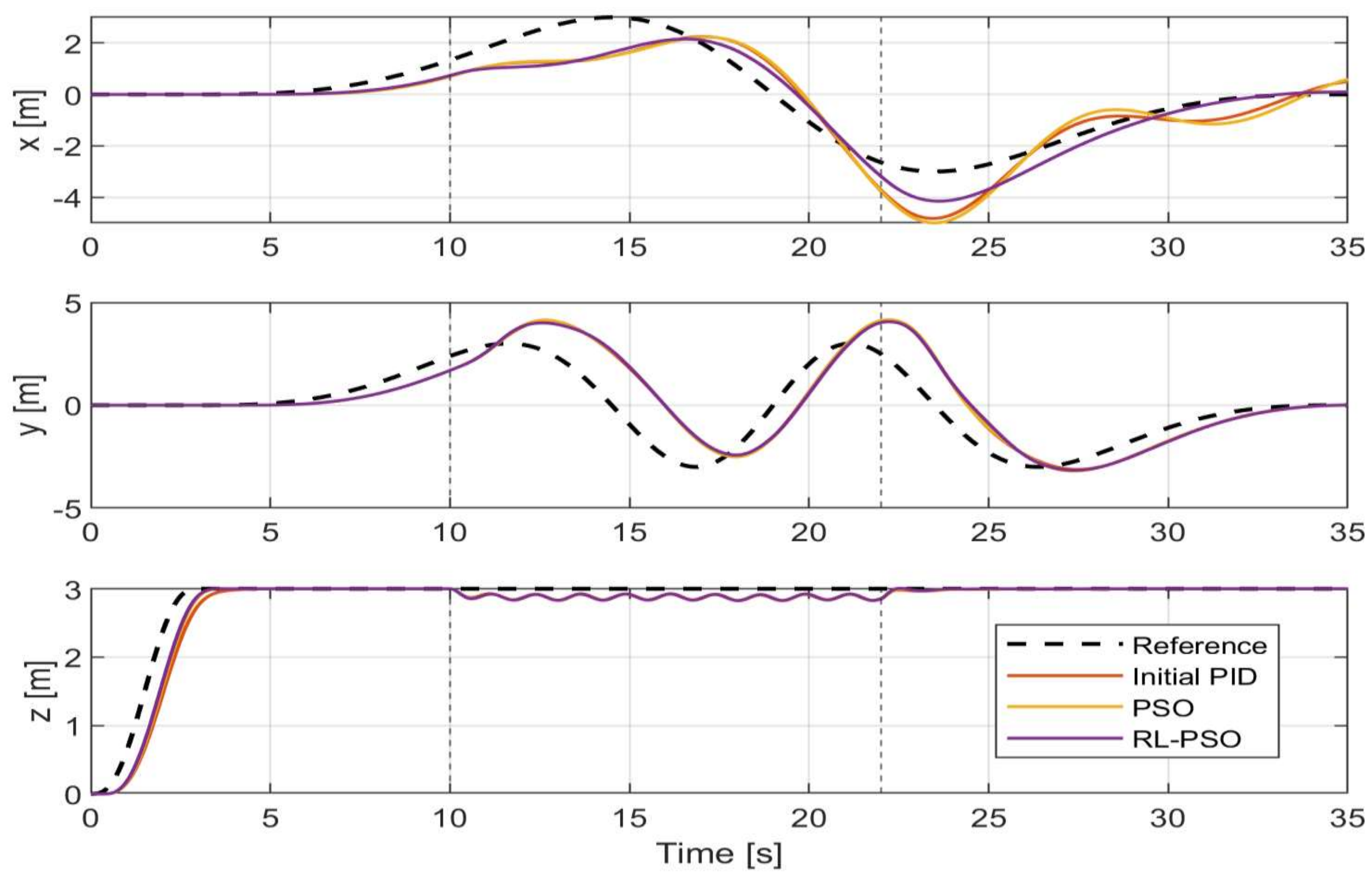

Figure 2. Feedback-path disturbance response.
Spiral tracking response under measurement-path perturbations. The dashed vertical lines indicate the disturbance interval.

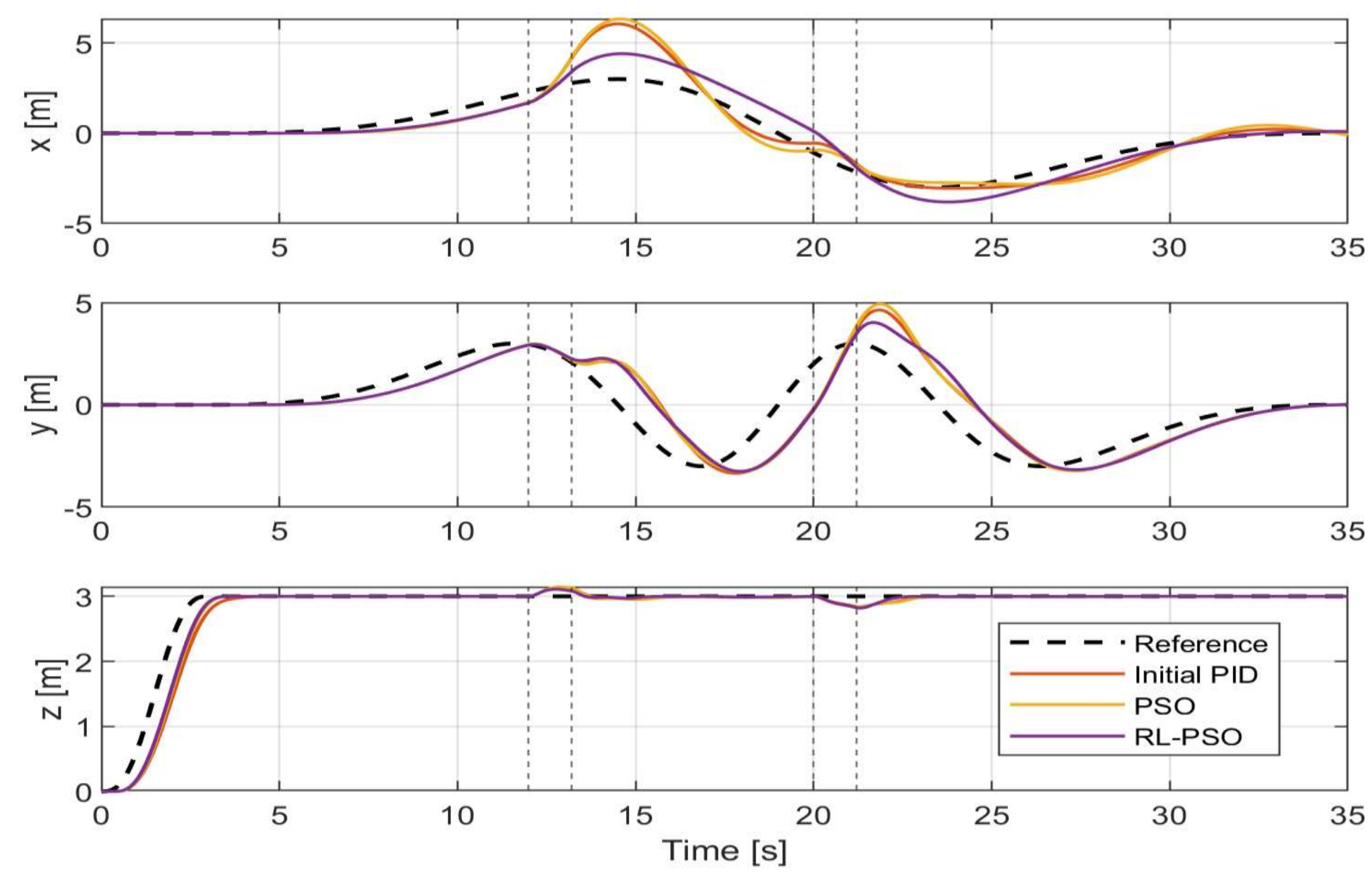

Figure 3. Plant-side disturbance response.
Spiral tracking response under gust-like plant-side disturbance pulses. The dashed vertical lines indicate the disturbance intervals.

The tracking responses show that the initial PID and standard PSO can exhibit large deviations under disturbance, especially in the plant-side case. RL-PSO provides smoother recovery and lower tracking deviation in both disturbance scenarios.

Disturbance case	Controller	RMS 3D error [m]	Peak error P95 [m]	Violation duration [s]	Recovery time [s]
Feedback-path	Initial PID	1.69 ± 0.16	3.87	2.70	Not settled
Feedback-path	PSO	1.32 ± 0.08	3.65	1.41	11.90
Feedback-path	RL-PSO	**1.20 ± 0.06**	**3.44**	**0.73**	**10.39**
Plant-side	Initial PID	7.45 ± 7.81	82.27	12.05	13.62
Plant-side	PSO	1.91 ± 0.79	8.77	4.17	13.40
Plant-side	RL-PSO	**1.18 ± 0.14**	**4.05**	**0.53**	**11.21**

Table 1. Monte Carlo tracking performance under feedback-path and plant-side disturbances.

Values are computed over 30 randomized disturbance realizations. RMS values are reported as mean ± standard deviation. P95 denotes the 95th percentile. A violation is counted when the 3D tracking error exceeds 3 m.
Main observations:
Under feedback-path disturbance, RL-PSO reduced the mean RMS 3D error from 1.69 m with the initial PID and 1.32 m with PSO to 1.20 m. It also reduced the violation duration to 0.73 s and achieved the fastest recovery.
Under plant-side disturbance, RL-PSO achieved the strongest robustness. It reduced the mean RMS 3D error from 7.45 m with the initial PID and 1.91 m with PSO to 1.18 m. It also reduced the 95th-percentile peak error from 82.27 m and 8.77 m to 4.05 m.
Overall, the results indicate that RL-guided hyperparameter adaptation improves the robustness of PSO-based PID tuning, especially by reducing large tracking-error violations and improving recovery after disturbances.

FUTURE WORK/ REFERENCES/ACKNOWLEDGMENT

Future work will extend the evaluation by including actuator saturation, control effort, energy consumption, and model-parameter uncertainty. Additional experiments will investigate larger Monte Carlo sets and real-time implementation on an experimental quadcopter platform.

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