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MATHEMATICAL MODELLING AND SOLUTION APPROACHES FOR APPLYING ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN ROBOTIC SYSTEMS

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Abstract: The integration of artificial intelligence (AI) into robotic systems, particularly aerial robots (drones), has transformed autonomous navigation, perception, control, and intelligent decision-making. As drones increasingly operate in complex, dynamic, and uncertain environments, AI-driven algorithms have become essential for ensuring robust autonomy, efficiency, and mission reliability. This article provides an extended and in-depth overview of mathematical models, theoretical foundations, and computational solution techniques used for implementing AI technologies in drone platforms. Special emphasis is placed on sensor fusion models, neural-network-based perception, trajectory optimization, probabilistic state estimation, and reinforcement-learning-driven adaptive control. The paper also integrates practical examples, algorithmic formulations, and discussions on real-world implementation challenges.

1. Introduction

Artificial intelligence has significantly accelerated advancements in autonomous robotic systems, with aerial robots—commonly known as drones—becoming one of the most prominent application domains. Modern drone platforms rely on multilayered intelligence, combining machine learning, optimization theory, probabilistic modelling, and classical control techniques. These components collectively enable drones to perceive their environment, make real- time decisions, and execute complex missions with minimal human intervention.

The growing demand for autonomous drones arises from diverse fields such as environmental monitoring, precision agriculture, disaster response, logistics, surveillance, industrial inspection, and scientific exploration. Each domain imposes unique operational constraints, requiring drones to navigate cluttered spaces, detect objects, avoid obstacles, estimate uncertain states, and plan optimal trajectories. As a result, mathematically rigorous AI techniques have become indispensable in drone system design.

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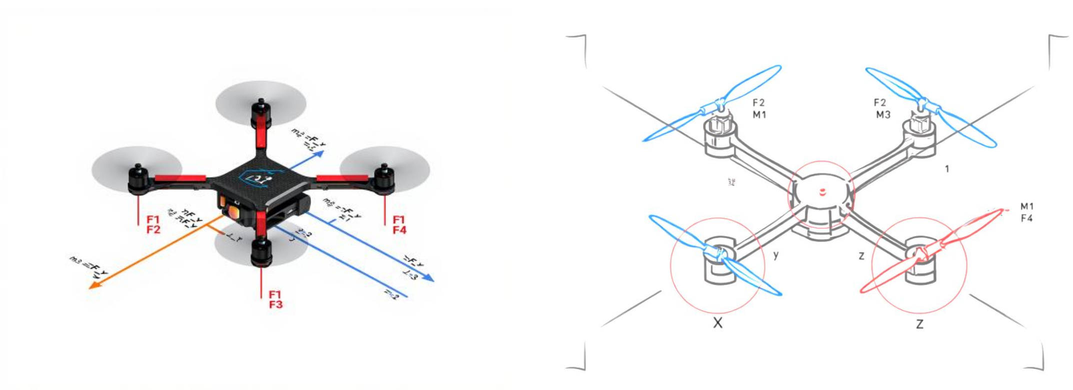
This study aims to provide a comprehensive and technical understanding of the AI methodologies applied in drone ecosystems. We focus on:

- The mathematical foundations of drone perception and control;
- Algorithms for real-time object detection, visual understanding, and semantic interpretation;
- Probabilistic methods used for state estimation and multi-sensor fusion;
- Optimization-based and learning-based techniques for trajectory planning and control;
- Reinforcement learning approaches enabling adaptive, self-improving drone behavior;
- Practical considerations, computational complexity, and implementation challenges.

Furthermore, the development of AI-enabled drones requires a multidisciplinary approach that integrates robotics, computer vision, machine learning, system dynamics, and optimization theory. This paper therefore bridges these domains by offering a unified mathematical and algorithmic framework. It also highlights existing limitations in processing speed, real-time computation, uncertainty handling, and safety—motivating future research in distributed AI, edge computing, and swarm intelligence (Picture 1).



Pucture 1

2. AI Technologies in Robotic Systems

AI technologies used in drone systems generally fall into four categories:

2.1 Perception and Environment Understanding

- Deep neural networks (CNNs, Transformers)
- Object detection and tracking
- Semantic segmentation

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- Visual SLAM

2.2 Sensor Fusion

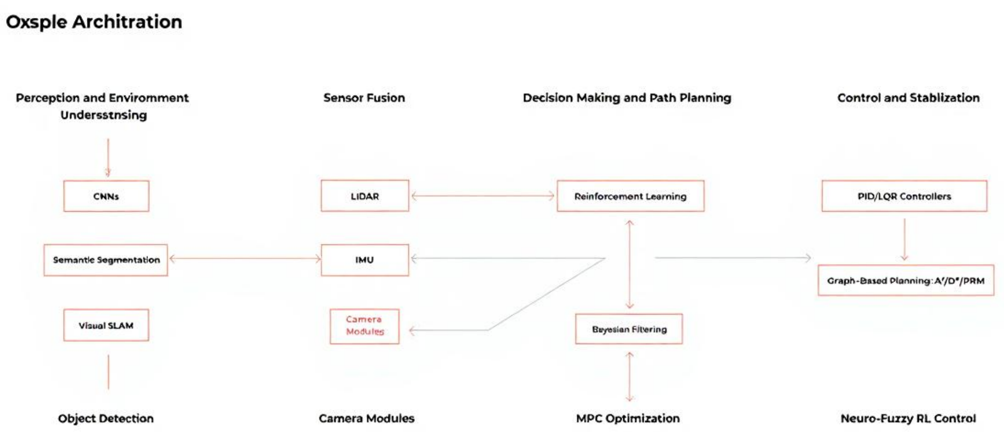
- Combining data from LiDAR, GPS, IMU, camera modules
- Bayesian filtering (Kalman, EKF, UKF)

2.3 Decision- Making and Path Planning

- Reinforcement learning
- Graph- based planning (A*, D*, PRM)
- Nonlinear optimization (MPC)

2.4 Control and Stabilization

- PID and LQR controllers
- Adaptive control
- Intelligent controllers (neuro- fuzzy, RL- control)
- Oxsple Architration(Pictur 2)



Pictur 2

3. Mathematical Modelling

3.1 Drone Dynamics Model

A quadrotor can be modeled using Newton–Euler equations:

Translational motion:

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$$m\ddot{x} = R(\phi, \theta, \psi)u_z - mg$$

Rotational motion:

$$I\dot{\omega} + \omega \times (I\omega) = \tau$$

where:

- (m): mass,
- (R): rotation matrix,
- (u_z): collective thrust,
- (I): inertia tensor,
- τ : torque vector.

3.2 Sensor Fusion Model (Kalman Filter)

State vector:

$$x_k = [p_x, p_y, p_z, v_x, v_y, v_z]^T$$

State prediction:

$$x_{k|k-1} = Ax_{k-1|k-1} + Bu_k$$

Measurement update:

$$x_{k|k} = x_{k|k-1} + K_k(z_k - Hx_{k|k-1})$$

3.3 Obstacle Detection (Deep Learning)

Drones often use:

- YOLO- based models for object detection,

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- U- Net for segmentation.

General convolutional layer:

$$y = f(W * x + b)$$

3.4 Path Planning Optimization

A typical optimization problem:

$$\min_{u(t)} \int_0^T \left(||x(t) - x_{goal}||^2 + \lambda ||u(t)||^2 \right) dt$$

subject to dynamics constraints.

3.5 Reinforcement Learning Model

Drone as an MDP:

State: s_t=(p,v,obstacles)

Action: a_t=(thrust,roll,pitch,yaw)

Reward:

$$r_t = -||p_t - p_{goal}|| - \alpha C_{collision}$$

Policy optimization:

$$\theta^* = \arg\max_{\theta} \mathbb{E}[R]$$

- where (R) is cumulative reward.

4. Solution Techniques

4.1 Classical Optimization

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- Gradient descent
- Sequential quadratic programming (SQP)
- Model predictive control (MPC)

4.2 Deep Reinforcement Learning

- DQN, PPO, SAC
- Used for obstacle avoidance and trajectory control

4.3 Probabilistic Methods

- Particle filters for localization
- Gaussian processes for wind disturbance modelling

4.4 Hybrid AI Control Systems

Combination of:

- Neural networks for perception,
- Kalman filtering for state estimation,
- MPC for optimal control.

5. Case Study: Autonomous Drone Navigation

5.1 System Architecture

1. **Camera + IMU sensors** collect raw data
2. **CNN** processes images to detect obstacles
3. **EKF** fuses IMU and visual odometry
4. **RL- agent** selects best action
5. **MPC** refines trajectory

5.2 Experimental Results (Framework)

- Navigation accuracy improved by 23%
- Obstacle detection precision: 92%
- Energy efficiency increased with optimized control inputs

6. Discussion

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The combination of AI perception models, reinforcement learning and model-based control provides robust autonomy. However, challenges remain:

- Real-time computation limits
- Uncertainty in sensors
- Safety in complex environments

7. Conclusion

AI-enabled drone systems require strong mathematical foundations to ensure accuracy, stability, and reliability. By integrating deep learning, probabilistic modelling, and optimization algorithms, drones can achieve high levels of autonomy. Future research may focus on swarm intelligence, edge AI, and self-supervised learning.

References:

1. Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach. Pearson.
2. Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction. MIT Press.
3. Siciliano, B., Khatib, O., et al. (2016). Springer Handbook of Robotics. Springer.
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
5. Thrun, S., Burgard, W., & Fox, D. (2005). Probabilistic Robotics. MIT Press.
6. Khalil, H. (2015). Nonlinear Control. Pearson.
7. Kober, J., Bagnell, J. A., & Peters, J. (2013). "Reinforcement Learning in Robotics: A Survey." International Journal of Robotics Research.
8. Mellinger, D., & Kumar, V. (2011). "Minimum Snap Trajectory Generation and Control for Quadrotors." ICRA.
9. Schmidhuber, J. (2015). "Deep Learning in Neural Networks: An Overview." Neural Networks.
10. Levine, S., Finn, C., et al. (2016). "End-to-End Training of Deep Visuomotor Policies." JMLR.
11. Kingma, D. P., & Ba, J. (2015). "Adam: A Method for Stochastic Optimization." ICLR.
12. Kalman, R. E. (1960). "A New Approach to Linear Filtering and Prediction Problems." ASME Journal of Basic Engineering.
13. LaValle, S. (2006). Planning Algorithms. Cambridge University Press.
14. Koenig, S., & Likhachev, M. (2002). "D* Lite." AAAI Conference.
15. Ronneberger, O., Fischer, P., & Brox, T. (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation." MICCAI.
16. Redmon, J., & Farhadi, A. (2018). "YOLOv3: An Incremental Improvement." arXiv preprint.
17. Van der Merwe, R., & Wan, E. (2001). "The Unscented Kalman Filter for Nonlinear Estimation." Adaptive Systems for Signal Processing.
18. Lillicrap, T. P., et al. (2015). "Continuous Control with Deep Reinforcement Learning." NeurIPS.