



Anis Koubaa<sup>1</sup>   Khaled Gabr<sup>2</sup>

<sup>1</sup>AlfaisalX Center of Excellence, Alfaisal University, Saudi Arabia

<sup>2</sup>RIOTU Lab, Prince Sultan University, Saudi Arabia

[akoubaa@alfaisal.edu](mailto:akoubaa@alfaisal.edu)

January 14–16, 2025 — Tunis, Tunisia

# AlfaisalX: Center of Excellence

- ▶ **Institution:** Alfaisal University, Riyadh, KSA
- ▶ **Focus Areas:**
  - ▷ Cognitive Robotics & Autonomous Agents
  - ▷ UAV/Drone Technologies
  - ▷ AI & Large Language Models
- ▶ **Collaboration:** RIOTU Lab, Prince Sultan University
- ▶ **Mission:** Advancing intelligent aerial systems for defense, disaster response, and logistics



# Problem Statement

## The Challenge

UAVs are increasingly deployed in **defense, surveillance, and disaster response**, yet most remain limited to **SAE Level 2–3 autonomy**.

- ▶ **Reliance on rule-based control** restricts adaptability
- ▶ **Narrow AI** limits response in dynamic environments
- ▶ **No context-aware reasoning** for complex missions
- ▶ **No ecosystem integration** with external services

## Research Question

*How can we design a UAV architecture that fuses LLM-driven reasoning with real-time perception and ecosystem integration for general-purpose autonomy?*

# Gap Analysis: Current UAV Limitations

**Existing approaches fall short:**

Approach	Strength	Limitation
Classical Control (A*, RRT*)	Efficient, deterministic	Fails under uncertainty
Reinforcement Learning	Adaptive policies	Low-dimensional only
Swarm Intelligence	Distributed coordination	No cognitive reasoning
LLM Integration (REAL, UAV-VLN)	Semantic parsing	Isolated planner only

## Critical Gap

**No UAV system leverages LLM agents with tool-calling for:**

- ▶ Real-time knowledge access and API interaction
- ▶ Ecosystem-level integration (databases, alerts)
- ▶ Peer-to-peer reasoning in multi-agent swarms

# Key Contributions

## ① Architectural Novelty

- ▶ First **five-layer architecture** fusing LLM reasoning with continuous perception and flight control

## ② Ecosystem Integration

- ▶ Novel Integration Layer enabling tool-calling, API interaction, and multi-agent protocols (MCP, ACP, A2A)

## ③ Collaborative Swarm Cognition

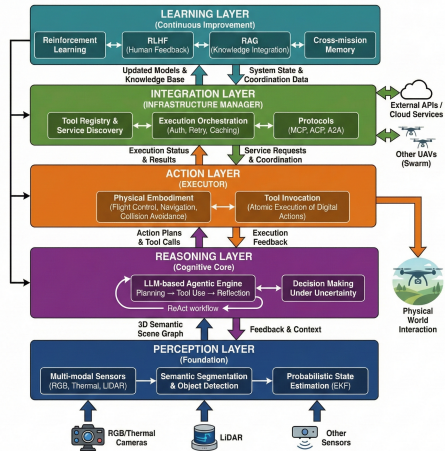
- ▶ First demonstration of distributed LLM-based reasoning for task negotiation among UAV swarms

### Novelty

Transforms UAVs from **isolated planners** to **networked cognitive agents**

# Methodology: Five-Layer Architecture

Figure 1: Five-Layer UAV System Architecture



# Reasoning Layer: LLM-Driven Cognition

## ReAct Workflow

The LLM operates as a stateful agentic engine via LangGraph:

- ▶ **Planning:** Decomposes high-level goals into action sequences
- ▶ **Tool Use:** Invokes APIs, databases, weather services
- ▶ **Reflection:** Monitors outcomes, triggers replanning on failure

### Example Output:

```
{"goal": "Inspect anomaly", "steps": [{"action": "call_tool", "tool": "weather.get_forecast"}, {"action": "fly_to", "target": "Anomaly-01"}]}
```

## Key Innovation

LLM decides *what* to do; Action Layer executes; Integration Layer manages *how*

# Integration Layer: Ecosystem Connectivity

## Transforms UAVs into networked digital actors:

- ▶ **Tool Registry:** Dynamic catalog of APIs, databases, services
- ▶ **Execution Orchestration:** Authentication, retry logic, caching
- ▶ **Protocol-Governed Communication:**
  - ▷ *MCP*: Model Context Protocol for secure LLM tool use
  - ▷ *ACP*: Agent Communication Protocol for UAV-to-cloud
  - ▷ *A2A*: Agent-to-Agent for peer negotiation
- ▶ **Security:** mTLS, JWT tokens, prompt injection detection

## Multi-Agent Coordination

Task allocation, spatial deconfliction, shared situational awareness



# Experimental Validation: Setup

## Simulation Environment:

- ▶ **Platform:** Gazebo Harmonic + PX4 SITL v1.14.3
- ▶ **Middleware:** ROS 2 Humble
- ▶ **Perception:** YOLOv11 @ 30 Hz (Intel RealSense D455)
- ▶ **Reasoning:** GPT-4 API + Local Gemma-3 (4B parameters)
- ▶ **Hardware:** Intel i7-13900K, 32GB RAM, RTX 4070

## Scenario: Hajj Pilgrimage Search & Rescue

- ▶ **Scenario 1:** Normal activity monitoring (crowd surveillance)
- ▶ **Scenario 2:** Emergency medical intervention (collapsed person)

**Dataset:**  $n = 44$  samples per system,  $N = 132$  total detections


# SAR Scenario Demonstrations

## Scenario 1: Normal Monitoring

### Detection Report

Generated on 2025-05-26 18:23:04

Frame: 3  
Object ID: 13



Person HIGH

Match Found	Yes
Location	Open sandy area
Details	Person standing upright on both feet, wearing a white garment
Surroundings	Sandy terrain with no visible crowd
Actions	No deployment action required

[Back to All Reports](#) [View Raw JSON](#)

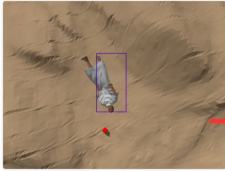
- ▶ Normal pilgrim activity detected
- ▶ Contextual understanding provided
- ▶ No intervention required

## Scenario 2: Emergency Response

### Detection Report

Generated on 2025-05-26 18:26:13

Frame: 221  
Object ID: 26



Person HIGH

Match Found	Yes
Location	Sandy terrain with a person inside a purple box
Details	The person is lying on the ground, wearing a white garment.
Surroundings	Sandy environment, no visible crowd
Actions	LAND_AND_DEPLOY_RESCUE_KIT, ALERT_MEDICAL_UNIT

[Back to All Reports](#) [View Raw JSON](#)

- ▶ Collapsed person detected (conf: 0.89)
- ▶ Emergency classified in  $\leq$  3 sec
- ▶ Alert + rescue kit deployed

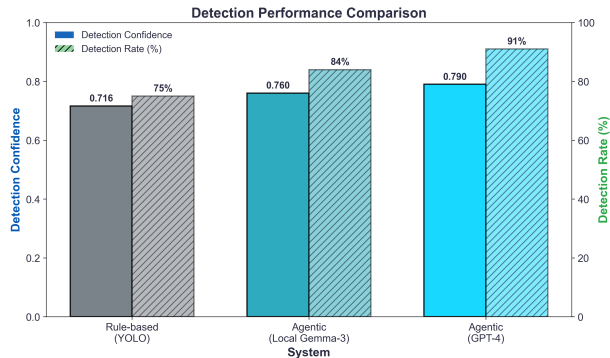
# Results: Detection Performance

Metric	YOLO	Local	GPT-4
Confidence	0.716	0.760	<b>0.790</b>
Detection	75%	84%	<b>91%</b>

## Key Results

**+16% improvement** in detection rate

ANOVA:  $F(2, 129) \approx 3.96$ ,  $p = 0.021$



# Results: Decision-Making Capability

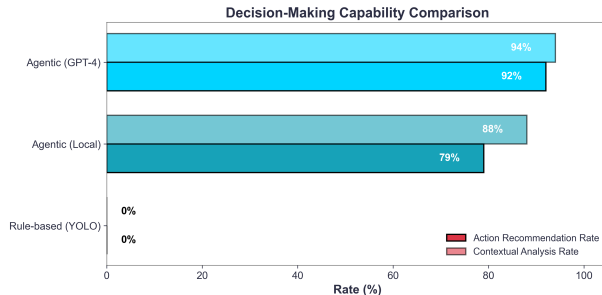
Metric	YOLO	Local	GPT-4
ARR	0%	79%	92%
CAR	0%	88%	94%

## Critical Finding

Rule-based: **0% autonomy**

Agentic: **92% action rate**

$\chi^2 = 82.92, p \ll 0.001$



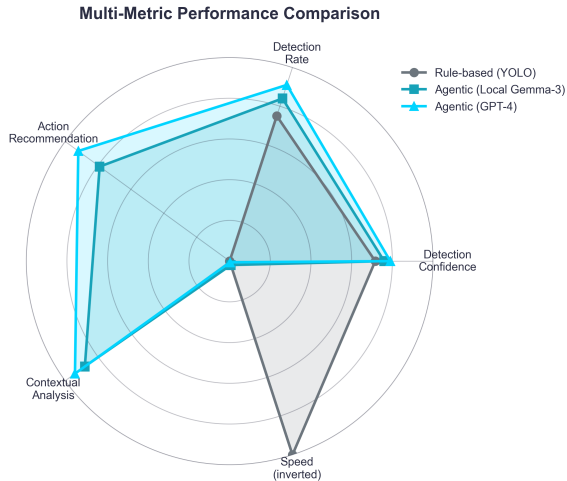
# Results: Multi-Metric Comparison

## Trade-off Analysis:

- ▶ YOLO excels at **speed only**
- ▶ Agentic systems dominate in:
  - ▷ Contextual understanding
  - ▷ Action recommendation
  - ▷ Ecosystem integration
- ▶ Local Gemma-3: **70% faster** than GPT-4 with acceptable quality

## Recommendation

**Hybrid architecture:** YOLO for screening, LLM for critical cases



# Main Findings

## Finding 1: Superior Detection

Agentic UAVs achieve **0.79 confidence** vs 0.72 baseline, **91% detection rate** vs 75%

## Finding 2: Autonomous Decision-Making

**92% action recommendation rate** (rule-based: 0%) – qualitatively new capability

## Finding 3: Computational Trade-off Justified

Modest overhead ( $\sim 5s$ ) enables **contextual reasoning, ecosystem integration, and reduced operator dependence**

**Overall:** Computational cost is an *investment* that elevates UAVs from passive sensors to **intelligent agents**.

## ► **Short-term:**

- ▷ Field trials in controlled outdoor environments
- ▷ Hybrid local-cloud deployment optimization

## ► **Long-term:**

- ▷ Scalable swarm cognition for multi-UAV collaboration
- ▷ Safety assurance for LLM-driven decision-making
- ▷ Regulatory compliance and UTM integration

## ► **Limitations:**

- ▷ Current validation is simulation-based (sim-to-real gap)
- ▷ Real-world factors (wind, GPS degradation) need testing

# Thank You!

## Questions?

**Prof. Anis Koubaa**

AlfaisalX Center of Excellence  
Alfaisal University, Saudi Arabia

akoubaa@alfaisal.edu

aniskoubaa.org

SmartTech 2025

January 14–16, 2025 — Tunis, Tunisia

