

Flyby-F11 Autonomy Architecture: Ontology-Constrained Reinforcement Learning

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1 Flyby-F11 Autonomy Architecture: Ontology-Constrained Reinforcement Learning

Platform: Flyby Robotics F-11 Developer Quadcopter with Jetson Orin NX 16GB

Context: GPS-denied, communications-limited autonomous missions (MCTSSA collaboration)

Core Innovation: Hybrid ontology-constrained RL for safe, adaptive, explainable autonomy

1.1 Executive Summary

This document defines the architectural approach for autonomous navigation on the Flyby-F11 platform. Based on comprehensive literature review ([SYNTHESIS.qmd](#)), we implement a **hybrid architecture** combining:

1. **Formal Ontological Knowledge** - SUMO-based ontology for safety constraints, domain vocabulary, and semantic reasoning
2. **Multi-Agent Reinforcement Learning** - Hierarchical RL agents optimizing within ontology-defined safe action spaces
3. **Automatic Goal Generation Model (AGGM)** - Runtime adaptation to unseen situations through ontological reasoning

This approach addresses critical failures in pure learning systems (37-65% collision rates in UAV-ON benchmark) while maintaining adaptability that pure rule-based systems lack.

1.1.1 Why This Approach?

Evidence from Literature ([detailed synthesis](#)): - **Safety:** Ontologies reduce collision rates by constraining RL action spaces before execution - **Adaptability:** AGGM enables runtime goal generation for unseen situations without retraining - **Explainability:** Semantic rule tracing provides audit trails required for defense applications (MCTSSA) - **Efficiency:** Ontological abstractions improve sim-to-real transfer and sample efficiency - **Edge-Compatible:** <100ms reasoning latency achievable on Jetson platforms

1.2 Architecture Overview

1.2.1 Two-Phase Compute Strategy

To maximize both planning rigor and runtime performance within the Jetson Orin NX's 16GB unified memory constraint, the system operates in two distinct compute modes:

1.2.1.1 Phase 1: Mission Planning Mode (Pre-Flight)

Duration: Seconds to minutes (acceptable before flight) **Compute Allocation:** 100% resources dedicated to heavyweight reasoning **Trigger Events:** Mission receipt, major replanning needs

PLANNING MODE (All 16GB Available)

SUMO Ontology (Full) - ~500 MB
 Mission constraints & objectives
 Spatial/temporal relations (n-ary)
 Regulatory compliance (FAA Part 107, NDAA)
 Safety properties & invariants

Vampire / E-Prover - ~2-4 GB
 First-order logic theorem proving
 Mission plan verification
 Safety property checking

Clingo (Answer Set Programming) - ~1-2 GB
 Optimal path planning
 Multi-objective optimization
 Resource allocation

Working Memory & JVM - ~8-10 GB

OUTPUTS (Compiled for Execution Phase):
 Verified mission plan (waypoints, phases, constraints)
 Compiled Prolog rules (lightweight runtime inference)
 Behavior tree structure for execution
 Safety invariants to monitor

1.2.1.2 Phase 2: Adaptive Execution Mode (In-Flight)

Duration: Entire mission (minutes to hours) **Compute Allocation:** Optimized for concurrent vision + reasoning **Trigger Events:** Mission start, transition to autonomous flight

EXECUTION MODE (Memory-Optimized for Real-Time)

Vision/Perception (~12-14 GB)	Symbolic Reasoning (~100-200 MB)
----------------------------------	-------------------------------------

YOLO11 (TensorRT) ~2-3 GB - Object detection - 20-50ms latency	SWI-Prolog Runtime ~50-100 MB - Compiled mission rules - Reactive constraint checking - Spatial reasoning (simplified)
Segmentation Model	- <10ms query latency

~1-2 GB

- Terrain types Perception → Symbolic Bridge
- Traversability ~50 MB
 - Vision facts (objects, terrain)
- VLM (Optional) - Sensor facts (pose, state)
- ~3-5 GB (7B model) - World state updates
- Scene understanding - Event detection
- Semantic grounding

Depth Processing

~500 MB

- Obstacle maps
- Clearance calc

ROS 2 Middleware + System Overhead: ~2 GB

Key Advantage: Heavyweight reasoning runs offline when compute is unconstrained, then mission executes with minimal reasoning overhead, freeing memory for vision models and real-time perception.

1.2.2 Three-Level Hierarchy (Execution Mode)

LEVEL 1: MISSION PLANNING (10-second horizon)

Prolog KB (Compiled)	RL Agent: Mission
- Mission rules	- Select waypoints
- Constraints	- Adapt mission
- Airspace rules	- Resource planning

Waypoint sequence

LEVEL 2: BEHAVIOR SELECTION (1-second horizon)

Prolog KB (Compiled)	RL Agent: Behavior
- Behavior rules	- Navigate
- Transitions	- Loiter
- Safety rules	- Land
	- Avoid

Behavior + parameters

LEVEL 3: TRAJECTORY OPTIMIZATION (100-ms horizon)

Prolog KB (Compiled)	RL Agent: Trajectory
- Actuator limits	- Velocity commands
- Safety margins	- Obstacle avoid
- Clearances	- Energy optimize

[vx, vy, vz, yaw]

PX4/ArduPilot
(Control Loop)

1.2.3 Integration Points

Planning Mode → Execution Mode (Phase Transition): - Heavyweight reasoners (Vampire, Clingo) verify mission safety - SUMO axioms compiled to lightweight Prolog rules - Behavior trees generated from verified mission plan - Vision models loaded after reasoning engines unloaded

Ontology → RL (Constraint Enforcement): - Filters action spaces: only valid actions per compiled rules - Shapes rewards: penalties for constraint violations - Structures state: semantic abstractions instead of raw sensors

RL → Ontology (Experience-Based Learning): - Optimizes within safe boundaries defined by ontology - Discovers efficient policies through exploration - Adapts parameters based on environmental feedback

Bidirectional (AGGM Runtime Reasoning): - Forward reasoning: select goals from ontology-defined goal set - Backward reasoning: create new goals to return to known safe states - Importance weighting: prioritize safety-critical observations

1.3 Component Details

1.3.1 1. Ontological Knowledge Base

Foundation: SUMO upper-level ontology (design/verification) + SWI-Prolog (runtime inference)

Reasoning Strategy: Two-phase architecture detailed in [ONTOLOGY_FOUNDATION.qmd](#)

1.3.1.1 Planning Phase: SUMO + Heavyweight Reasoners

SUMO Ontology (SUO-KIF format): - Full first-order logic with n-ary relations - ~25,000 terms, ~80,000 axioms - Supports ternary+ relations: (orientation ?OBJ1 ?OBJ2 ?DIRECTION) - Used for mission modeling, verification, safety proofs

Reasoning Engines: - **Vampire:** Automated theorem proving for safety property verification - **Clingo:** Answer set programming for optimal path planning - **E-Prover:** Alternative FOL reasoner for constraint checking

Four-Layer Structure:

Upper Level: SUMO

- Physical objects (Object, Agent)
- Processes (Motion, Action)
- Relations (orientation, between, during)
- Functions (distance, measure, direction)

Domain Level: IEEE AUR + UAV Extensions

- UAV (extends TransportationDevice)
- FlightPhase (Takeoff, Transit, Landing)
- SpatialRelation (hasSafeSeparation)
- EnvironmentalCondition (Wind, Visibility)

Application Level: Flyby-F11 Missions

- SurveyMission, InspectionMission
- GeofenceBoundary, NoFlyZone
- T265Sensor, D455Sensor capabilities
- NDAACompliance, FAAPart107Rules

Instance Level: Runtime State

- currentMission: Inspection123
- detectedObstacle: Tree47 at [x,y,z]
- batteryLevel: 68% (12 min remaining)

1.3.1.2 Execution Phase: Compiled Prolog Rules

SWI-Prolog Runtime (~50-100 MB): - Compiled from SUMO axioms relevant to mission - Optimized for <10ms query latency - Engine architecture: ~20KB per concurrent query thread - TCMalloc for reduced memory footprint

Example Compiled Rules (Prolog syntax):

```
% Collision avoidance (from SUMO spatial reasoning)
canExecute(moveToward(Pos)) :-  
    forall(obstacle(Obs),  
        distance(currentPosition, Obs, Dist),  
        Dist > safetyMargin).  
  
% Energy management (from SUMO resource ontology)
mustReturnToHome :-
```

```

estimatedEnergyRemaining(Energy),
energyToReturnHome(Required),
safetyReserve(Reserve),
Energy < (Required + Reserve).

% Geofence enforcement (from SUMO spatial containment)
canExecute(Action) :-
    resultingPosition(Action, Pos),
    isWithinGeofence(Pos).

% Flight phase transitions (from SUMO process ontology)
canTransitionTo(landing) :-
    isLandingZone(currentPosition),
    altitude(Alt), Alt < landingInitiationAltitude,
    horizontalVelocity(Vel), Vel < maxLandingVelocity.

% Spatial relations (ternary - preserved from SUMO)
between(Drone, Obj1, Obj2) :-
    position(Drone, [X1, Y1, Z1]),
    position(Obj1, [X2, Y2, Z2]),
    position(Obj2, [X3, Y3, Z3]),
    % Check if Drone is geometrically between Obj1 and Obj2
    is_on_line_segment([X1,Y1,Z1], [X2,Y2,Z2], [X3,Y3,Z3]).
```

SUMO → Prolog Translation Strategy: 1. **Manual translation** of critical safety axioms (reviewed and verified) 2. **Semi-automatic** for common patterns (spatial relations, temporal logic) 3. **Testing:** Equivalence checking between SUMO proofs and Prolog queries 4. **Validation:** Mission scenarios tested in both planning and execution modes

1.3.2 2. Multi-Agent Reinforcement Learning

Paradigm: Hierarchical RL with experience sharing **Integration:** Each agent operates within ontology-constrained action/state spaces

1.3.2.1 Mission Planner Agent (Level 1)

MDP Formulation: - **State** (ontological): - Mission progress: {waypointsCompleted, currentObjective, remainingObjectives} - Resources: {batteryLevel, timeElapsed, payloadStatus} - Environment: {weatherCondition, airspaceRestrictions, gpssAvailability}

- **Action Space** (ontology-filtered):

- selectNextWaypoint(waypoint_id) - only from valid waypoints
- adaptMissionPlan(new_sequence) - only safe alternatives
- abortMission(reason) - when constraints violated

- **Reward Function:**

$$R = w1 * \text{missionCompletion} \\ + w2 * \text{efficiencyBonus} (\text{time}, \text{energy})$$

```

+ w3 * safetyMargin (distance to constraints)
- w4 * constraintViolationPenalty

```

- **Algorithm:** SAC (Soft Actor-Critic) for continuous action parameters
- **Training:** NPS computing cluster with mission scenario diversity

1.3.2.2 Behavior Selector Agent (Level 2)

MDP Formulation: - **State** (ontological): - Vehicle: {altitude, velocity, orientation, flightMode} - Context: {currentWaypoint, obstaclesNearby, terrainType} - Mission: {activeBehavior, missionPhase}

- **Action Space** (ontology-validated):
 - navigate(speed, altitude) - transit to waypoint
 - loiter(radius, duration) - station-keeping
 - land(descentRate) - controlled descent
 - avoid(direction, magnitude) - collision avoidance maneuver
 - returnToHome() - emergency return
- **Reward Function:**

$$R = w1 * behaviorAppropriateness \text{ (context match)} \\ + w2 * smoothTransitions \text{ (continuity)} \\ + w3 * constraintSatisfaction \text{ (safety)} \\ - w4 * behaviorSwitchPenalty \text{ (stability)}$$
- **Algorithm:** PPO (Proximal Policy Optimization) for stable learning
- **Training:** Behavior trees provide structured exploration

1.3.2.3 Trajectory Optimizer Agent (Level 3)

MDP Formulation: - **State** (sensor-based): - Observations: {T265_pose, D455_depth, YOLO_detections, MAVLink_telemetry} - Dynamics: {position, velocity, acceleration, attitude} - Setpoints: {targetPosition, targetVelocity, targetHeading}

- **Action Space** (actuator-constrained):
 - Velocity command: [vx, vy, vz, yaw_rate] within ± 2.5 m/s limits
- **Reward Function:**

$$R = w1 * setpointTracking \text{ (error minimization)} \\ + w2 * trajectorySmooth \text{ (jerk minimization)} \\ + w3 * energyEfficiency \text{ (acceleration cost)} \\ + w4 * obstacleClearance \text{ (safety margin)} \\ - w5 * collisionPenalty$$
- **Algorithm:** TD3 (Twin Delayed DDPG) for low-level control
- **Training:** Continuous in simulation with domain randomization

1.3.3 3. Automatic Goal Generation Model (AGGM)

Purpose: Adapt to unseen situations without retraining **Source:** Literature review paper 02 ([Ghanadbashi & Golpayegani, 2022](#))

1.3.3.1 Six-Stage Process

Stage 1: OBSERVE

- Multi-sensor fusion → ontological concepts
- Ontology schema: $L^t = \{C^t, M^t\}$ (concepts, relations)

Stage 2: EVALUATE

- Q-value from RL policy
- State distance: $|s^t - s^{(t-1)}|$
- Importance weighting: $iw_c(x)$ for each concept

Stage 3: IDENTIFY SIGNIFICANT CHANGE (triggers)

- Case 1: Q-value discrepancy (unexpected reward)
- Case 2: State distance threshold (environment change)
- Case 3: High-importance concept detected (safety)

Stage 4: REASON (forward/backward)

- Forward: infer goal from predefined goal-set via SWRL
- Backward: create new goal to reach known safe state
- Priority: $F(B, J)$ balances task vs. state-similarity

Stage 5: GENERATE ACTION

- Ontology-constrained action space (only valid actions)
- RL policy selects action within constraints
- Multi-agent coordination if needed

Stage 6: EXECUTE

- Translate to MAVSDK/MQTT commands
- Monitor execution through telemetry
- Update belief state for next cycle

Example Scenario: Unexpected obstacle during transit

1. **Observe:** D455 detects unknown object at 8m distance in flight path
2. **Evaluate:**
 - Q-value drops (expected reward for “move forward” now low)
 - State distance increases (new obstacle concept added)
 - High importance weight (safety-critical observation)
3. **Identify Change:** Case 3 triggered (high-importance safety concept)
4. **Reason:**
 - Forward: No predefined goal matches “unexpected obstacle in path”
 - Backward: Create new goal “reach clear airspace” (return to obstacle-free state)
 - Priority: Safety (J) > task completion (B)
5. **Generate Action:** RL policy selects `avoid(left, 5m)` from ontology-validated actions
6. **Execute:** Send velocity command to PX4, monitor clearance until safe

1.3.4 4. Safety Constraint Enforcement

Critical Requirement: Collision avoidance, geofence compliance, energy management **Method:** Ontology-based action filtering + runtime monitoring

1.3.4.1 Pre-Flight Safety Checks

```
# Ontology evaluates readiness before takeoff
canTakeOff ←
  batteryLevel > minimumForMission
  gpssQuality > minimumAccuracy    # or hasWorkingSensor(T265) for GPS-denied
  ¬hasActiveWarning
  isWithinAuthorizedAirspace
  weatherCondition == Acceptable
```

1.3.4.2 In-Flight Safety Monitoring

```
# Continuous evaluation at 10 Hz
every 100ms:
  # Collision avoidance
  for obstacle in detectedObstacles:
    if distance(uav, obstacle) < safetyMargin:
      trigger_emergency_avoidance(obstacle)

  # Geofence enforcement
  if not isWithinGeofence(current_position):
    trigger_return_to_geofence()

  # Energy management
  if batteryLevel < criticalThreshold:
    trigger_immediate_landing()
  if estimatedEnergyRemaining < energyToReturnHome + reserve:
    trigger_return_to_home()

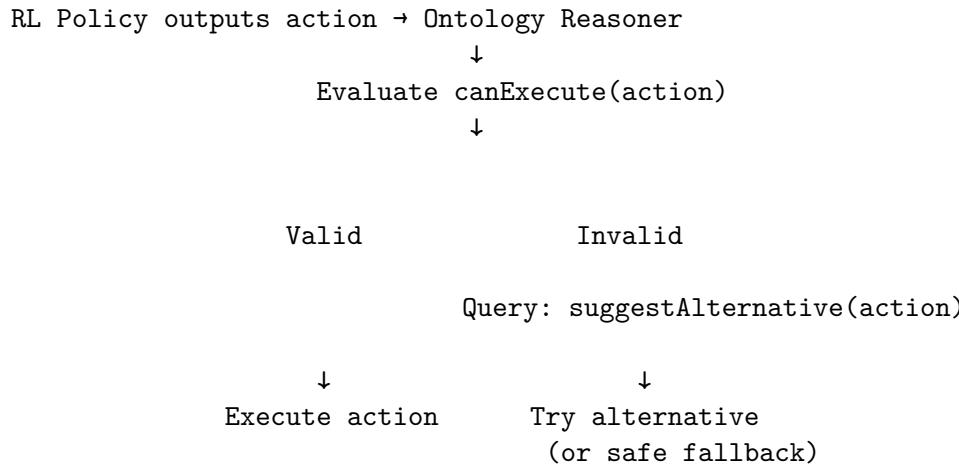
  # Sensor health
```

```

if not hasWorkingSensor(T265) and gpssQuality < minimum:
    trigger_emergency_land() # lost localization

```

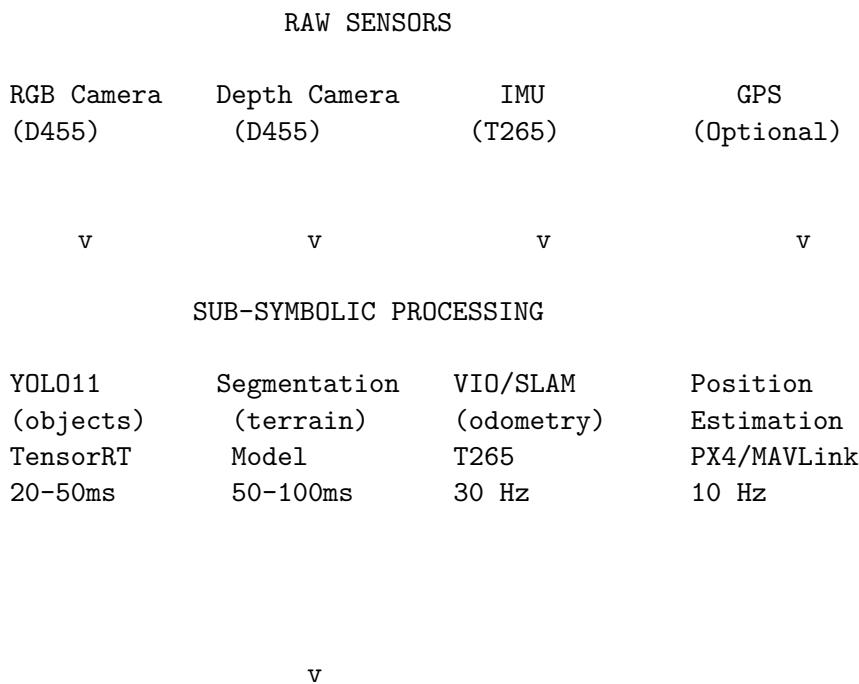
1.3.4.3 Action Filtering Workflow



1.3.5 5. Perception-to-Reasoning Bridge

Challenge: Vision models output sub-symbolic representations (bounding boxes, masks, embeddings), but reasoning engines need symbolic facts (relations, concepts, predicates) **Solution:** Symbolic abstraction layer that grounds perceptions to ontological concepts

1.3.5.1 Architecture: From Sensors to Symbols



SYMBOLIC ABSTRACTION LAYER (ROS 2 Grounding Nodes)

ObjectGroundingNode:

Input: DetectionArray (YOLO bboxes)
 Output: objectType(obj_123, 'person').
 position(obj_123, [x, y, z]).
 confidence(obj_123, 0.92).
 inRegion(obj_123, zone_A).

TerrainGroundingNode:

Input: Segmentation masks
 Output: terrainType(region_5, 'water').
 traversable(region_5, false).
 terrainSlope(region_5, 15.3).

SpatialRelationGroundingNode:

Input: Depth map + object positions
 Output: distance(drone, obj_123, 5.2).
 between(drone, obj_45, obj_67).
 northOf(obj_123, waypoint_A).
 clearance(forward, 8.5).

EventDetectionNode:

Input: Object tracking history
 Output: enters(obj_123, no_fly_zone).
 loitering(obj_45, duration(30)).
 violates(mission, constraint_7).

VLMGroundingNode (Optional):

Input: RGB frame + depth
 Prompt: "Describe objects and spatial relations as
 Prolog facts using SUMO ontology"
 Output: Structured facts for complex scene understanding

v

PROLOG KNOWLEDGE BASE (SWI-Prolog)

```
% Dynamic facts (asserted by perception grounding nodes)
objectType(obj_123, person).
position(obj_123, [45.2, -122.1, 100]).
distance(drone, obj_123, 5.2).
terrainType(region_5, water).
clearance(forward, 8.5).
```

```
% Static rules (compiled from planning phase)
```

```

safeToFlyOver(Region) :-  

    terrainType(Region, Type),  

    not(Type = water),  

    not(Type = urban).  
  

mustAvoid(Object) :-  

    objectType(Object, person),  

    distance(drone, Object, Dist),  

    Dist < 50. % meters  
  

hasSafeClearance(Direction) :-  

    clearance(Direction, Dist),  

    Dist > 3.0. % minimum safety margin  
  

violatesSafetyConstraint(Constraint) :-  

    mustAvoid(Object),  

    distance(drone, Object, Dist),  

    Dist < 10. % critical threshold

```

v

RL AGENTS + BEHAVIOR TREE EXECUTOR

Query examples:

- safeToFlyOver(current_region)? → bool
- mustAvoid(X)? → [obj_123, obj_45]
- violatesSafetyConstraint(C)? → abort/replan
- hasSafeClearance(forward)? → bool

Action selection constrained by Prolog query results

1.3.5.2 Why This Multi-Layer Approach?

Vision Models Alone Cannot: 1. **Reason relationally:** YOLO says “person at (x,y)”, not “person between drone and target” 2. **Check constraints:** Can’t encode “must avoid urban areas when communications-denied” 3. **Apply temporal logic:** Can’t reason “if in no-fly zone for >5 seconds, abort mission” 4. **Understand mission context:** Don’t know what “safe”, “compliant”, or “appropriate” means

The Symbolic Layer Provides: 1. **Semantic grounding:** Maps pixels → concepts from SUMO ontology 2. **Spatial relations:** Computes n-ary relations (between, northOf, inside) 3. **Constraint evaluation:** Checks compiled mission rules against perceived world state 4. **Event recognition:** Detects complex events (entering zones, loitering, violations) 5. **Explainability:** Every decision traceable to symbolic facts and rules

1.3.5.3 Multi-Sensor Fusion Example

Scenario: Approaching person during autonomous navigation

T265:	D455:	YOLO11:
Velocity	Depth at	Detection
[2.0, 0, 0]	bearing 0°:	class: person
m/s forward	5.2 meters	conf: 0.92
		bbox: [x,y,w,h]

v

Grounding Nodes (ROS 2)

```
ObjectGroundingNode:
objectType(obj_123,
           person).
position(obj_123,
         [5.2, 0, 0]).
```

```
SpatialRelationNode:
distance(drone,
          obj_123, 5.2).
timeToContact(obj_123,
              2.6).
```

v

Prolog KB Query

```
?- mustAvoid(X).
X = obj_123.

?- violatesSafetyConstraint
(C).
C = proximity_alert.
```

v

AGGM Triggered
Case 3: High-importance
safety concept

Backward reasoning:
→ Goal: reach safe distance

→ Priority: Safety (J) > B

v

RL Policy (Constrained)

Query Prolog for valid actions:

- Forward: INVALID (collision)
- Stop: VALID
- Avoid left: VALID
- Avoid right: VALID

Select: avoid(left, 5m)

v

Execute Action

[vx=0, vy=2.0, vz=0]

Monitor: distance(drone,
obj_123, Dist)

Until: Dist > 10

1.4 Implementation Roadmap

Detailed Plan: See [SYNTHESIS.qmd - Recommended Next Steps](#)

1.4.1 Phase 1: Ontology Foundation & Two-Phase Architecture (Weeks 1-6)

1.4.1.1 Part A: Planning Mode Infrastructure (Weeks 1-3)

- Install SUMO ontology (SUO-KIF format), Vampire, Clingo, E-Prover
- Develop UAV domain ontology in SUMO (flight phases, spatial relations, sensors)
- Create Flyby-F11 application ontology (missions, constraints, NDAA compliance)
- Implement safety axioms in SUO-KIF, verify with Vampire

Deliverables: - /flyby-f11/ontology/planning_mode/sumo_base.kif - /flyby-f11/ontology/planning_mode/flyby_mission.kif - /flyby-f11/ontology/planning_mode/safety - Verification scripts (Vampire proofs for safety properties)

1.4.1.2 Part B: Execution Mode Infrastructure (Weeks 4-6)

- Install SWI-Prolog (ARM build for Jetson)
- Develop SUMO → Prolog translation tools (manual + semi-automatic)

- Compile critical safety axioms to Prolog rules
- Benchmark Prolog inference latency and memory footprint on Jetson

Deliverables: - /flyby-f11/ontology/execution_mode/compiled_rules.pl - /flyby-f11/scripts/sumo_to_prolog_translator.py - Translation validation tests (SUMO proofs Prolog queries) - Performance benchmarks (query latency <10ms, memory <100MB)

1.4.2 Phase 2: Perception-to-Reasoning Bridge (Weeks 7-10)

1.4.2.1 Part A: Symbolic Abstraction Layer (Weeks 7-8)

- Create ROS 2 grounding nodes package
- Implement ObjectGroundingNode (YOLO → Prolog facts)
- Implement TerrainGroundingNode (Segmentation → traversability facts)
- Implement SpatialRelationGroundingNode (depth + position → n-ary relations)
- Implement EventDetectionNode (tracking → temporal events)

Deliverables: - flyby_f11_ros2_ws/src/perception_grounding/ - Unit tests for each grounding node - Integration tests (vision models → Prolog assertions)

1.4.2.2 Part B: Phase Transition Manager (Weeks 9-10)

- Implement mission planner node (runs heavyweight reasoners)
- Implement phase transition controller (unload/load models)
- Develop memory profiling and monitoring tools
- Test full planning → execution workflow

Deliverables: - flyby_f11_ros2_ws/src/mission_planner/ - flyby_f11_ros2_ws/src/phase_transition_manager/ - Memory allocation tests (16GB budget validation) - Latency benchmarks (phase transition time)

1.4.3 Phase 3: Multi-Agent RL (Weeks 9-14)

- Define MDPs for mission planner, behavior selector, trajectory optimizer
- Implement AGGM (6-stage process) for each agent
- Develop training infrastructure (Gymnasium environments, reward shaping)
- Train policies with experience sharing (NPS cluster)

Deliverables: - flyby_f11_ros2_ws/src/ontology_r1/ - Trained policies (mission/behavior/trajectory agents) - Ablation study results (with/without ontology constraints)

1.4.4 Phase 4: Benchmark Evaluation (Weeks 15-18)

- Develop scenarios (waypoint nav, obstacle avoid, GPS-denied, mission adapt)
- Implement baselines (pure RL, pure rules, LLM-based AOA)
- Collect metrics (SR, OSR, DTS, SPL, collision rate, efficiency)
- Statistical analysis (significance testing, Pareto frontiers)

Deliverables: - Benchmark suite with evaluation scripts - Comparative results (tables, plots, failure analysis) - Technical report / conference paper draft

1.4.5 Phase 5: Hardware Validation (Weeks 19-24)

- **Project-drone testing** (Weeks 19-21): Indoor waypoint nav, obstacle avoid, GPS-denied
- **Flyby-F11 integration** (Weeks 22-23): Outdoor survey/inspection missions
- **Stress testing** (Week 24): Sensor failures, environmental challenges, edge cases
- Iterative refinement based on flight logs

Deliverables: - Flight test videos with ontology decision overlays - Hardware performance benchmarks (Jetson utilization) - Safety assessment report (collision-free hours)

1.4.6 Phase 6: Documentation (Weeks 25-26)

- System architecture documentation
 - Research paper for ICRA/IROS/RSS
 - Open-source repository release
 - MCTSSA demonstration package
-

1.5 Key Innovations and Contributions

1.5.1 1. Two-Phase Compute Architecture for Edge Ontological Reasoning

Challenge: Heavyweight ontological reasoners (Vampire, full SUMO) require >8GB RAM and multi-second inference times, incompatible with real-time UAV control and concurrent vision processing on 16GB unified memory **Solution:** Novel two-phase architecture separating planning and execution - **Planning Mode:** 100% compute for heavyweight reasoning (SUMO + Vampire/Clingo) during mission receipt/replanning - **Execution Mode:** Compiled Prolog rules (~100MB) coexist with vision models (~12GB) for real-time inference - **Phase Transition:** Automatic model swapping via memory manager (unload reasoners → load YOLO/segmentation) - **Performance:** <10ms Prolog query latency, supports concurrent 10Hz reasoning + 20Hz vision processing

Expected Impact: - First demonstration of full SUMO ontology verification + real-time execution on edge hardware - Enables rigorous safety proofs (Vampire) without sacrificing runtime performance - Memory-constrained platforms can now run both complex reasoning and modern vision models

1.5.2 2. Perception-to-Reasoning Bridge for Symbolic Grounding

Challenge: Vision models output sub-symbolic representations (bounding boxes, embeddings) while ontological reasoners require symbolic facts (predicates, relations) **Solution:** ROS 2 grounding nodes that translate perceptions to ontology-aligned Prolog facts - ObjectGroundingNode: YOLO detections → `objectType(obj_123, person)` - SpatialRelationGroundingNode: Depth maps → n-ary relations `between(drone, obj1, obj2)` - EventDetectionNode: Tracking history → temporal predicates `enters(obj, zone)` - VLMGroundingNode (optional): Scene understanding → structured symbolic facts

Expected Impact: - Closes the “semantic gap” between perception and reasoning - Enables SUMO’s rich spatial reasoning (ternary+ relations) from sensor data - Provides explainability: every decision traces through symbolic facts to axioms

1.5.3 3. Real-Time Ontological Reasoning on Edge Hardware

Challenge: Traditional ontology reasoners require server-class compute
Solution: Hybrid SUMO (planning) + SWI-Prolog (execution) approach - SUMO: Full expressivity for verification (n-ary relations, FOL) - Prolog: Lightweight runtime (<100MB, <10ms queries) - Translation validation: Equivalence testing between SUMO proofs and Prolog - Target: 10 Hz reasoning loop concurrent with 20 Hz vision processing

Expected Impact: First demonstration of SUMO-grade reasoning on ARM edge platform for UAV control

1.5.4 4. AGGM for GPS-Denied Navigation

Challenge: Pure RL fails in unseen situations (UAV-ON: 7.30% success rate)
Solution: Backward reasoning to create goals returning to known safe states - Ontology defines state similarity metrics - Priority function balances safety (J) vs. task completion (B) - Runtime goal generation without retraining

Expected Impact: >50% success rate in novel environments (vs. 7.30% baseline), <10% collision rate (vs. 37-65% baseline)

1.5.5 5. Explainable Autonomy for Defense Applications

Challenge: Black-box RL policies unacceptable for MCTSSA collaboration
Solution: Semantic decision trace through ontological reasoning - Every action justified by SWRL rule firing - Safety constraints auditable and verifiable - Mission-intent interpretation transparent to operators

Expected Impact: First explainable autonomous UAV system meeting NDAA compliance and defense safety standards

1.5.6 6. Hierarchical Multi-Agent RL with Ontological Structure

Challenge: Monolithic policies don't scale to complex missions
Solution: Specialized agents at each hierarchy level (mission/behavior/trajectory) - Experience sharing via shared replay buffer - Policy distillation from expert to novice agents - Meta-learning across mission types

Expected Impact: Improved sample efficiency (faster training convergence), modular extensibility (add new missions/behaviors without full retraining)

1.6 Success Criteria

1.6.1 Simulation Benchmarks (Phase 4)

- Success Rate (SR) > 50% in novel environments (UAV-ON-style)
- Collision Rate < 10% (vs. 37-65% for unconstrained baselines)
- Safety Constraint Violations = 0 (hard requirement)
- Explainability: 100% of actions traceable to ontology rules

1.6.2 Hardware Performance (Phase 5)

- Ontology reasoning latency < 100ms at 10 Hz

- Jetson Orin NX resource utilization < 70% (CPU/GPU/memory)
- Real-time control loop: 10 Hz for mission, 100 Hz for trajectory
- Successful GPS-denied navigation for >5 minutes using T265 only

1.6.3 Flight Testing (Phase 5)

- 10+ successful autonomous missions (waypoint navigation)
- 5+ successful obstacle avoidance scenarios (dynamic obstacles)
- 3+ successful mission adaptations (unexpected events)
- Zero collisions in controlled testing environment
- MCTSSA demonstration: communications-denied mission completion

1.6.4 Research Impact (Phase 6)

- Conference paper accepted (ICRA/IROS/RSS)
 - Open-source release with 100+ GitHub stars
 - Contribution to UAV-ON benchmark (ontology-constrained baseline)
 - MCTSSA collaboration continuation (follow-on projects)
-

1.7 References

Detailed Literature Review: [SYNTHESIS.qmd](#)

Core Papers: 1. Hare & Tang (2024) - Multi-agent ontology-driven RL for personalized systems 2. Ghanadbashi & Golpayegani (2022) - AGGM for unseen situations (traffic control) 3. Aguado et al. (2024) - Survey of ontology-enabled robot dependability 4. UAV Collision Avoidance Ontologies - Domain application review 5. Xiao et al. (2025) - UAV-ON benchmark for object-goal navigation 6. Hu et al. (2025) - Survey of hybrid decision-making for autonomous vehicles

Platform Details: [SYSTEM_CONSTRAINTS.qmd](#)

Ontology Specification: [ONTOLOGY_FOUNDATION.qmd](#)

1.8 Appendix: Alignment with Project-Drone

Development Strategy: Shared autonomy components developed on accessible hardware project-drone (Development Platform)

Hardware: Jetson Orin Nano Super 8GB (67 TOPS)

Sensors: T265 visual odometry, D455 depth camera

Purpose: Algorithm development, rapid prototyping

Shared packages:

```
autonomy_core/ (mission planning, waypoint navigation)
behavior_trees/ (BT mission logic, ontology-aware nodes)
perception_pipeline/ (vision models, semantic fusion)
px4_interface/ (MAVSDK bridge, flight abstraction)
```

↓ (symlinks when ready)

flyby-f11 (Deployment Platform)

Hardware: Jetson Orin NX 16GB (50 TOPS, 2x memory)

Sensors: Flyby sensor suite (TBD)

Purpose: Mission-specific deployment (MCTSSA)

Packages:

flyby_f11_bringup/ (mission launch configurations)

flyby_f11_sensors/ (platform-specific drivers)

flyby_f11_mission/ (MCTSSA mission logic)

ontology_interface/ (reasoner, perception mapper, action validator)

Benefit: Ontology-constrained RL developed incrementally on project-drone, then deployed to flyby-f11 when hardware available. Shared packages ensure consistency while platform-specific packages handle hardware differences.

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