Using Ontology to Guide Reinforcement Learning Agents in Unseen Situations: A Traffic Signal Control System Case Study

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1 Using Ontology to Guide Reinforcement Learning Agents in Unseen Situations: A Traffic Signal Control System Case Study

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1.1 Abstract

In multi-agent systems (MAS), goal achievement is challenging when agents operate in ever-changing environments and face unseen situations, where not all goals are known or predefined. In such cases, agents need to identify changes and adapt their behavior by evolving their goals or even generating new goals to address emerging requirements. Learning and practical reasoning techniques have been used to enable agents with limited knowledge to adapt to new circumstances. However, they depend on the availability of large amounts of data, require long exploration periods, and cannot help agents to set new goals. Furthermore, the accuracy of agents' actions is improved by introducing added intelligence through integrating conceptual features extracted from ontologies.

This paper proposes a new **Automatic Goal Generation Model (AGGM)** that enables agents to create new goals to handle unseen situations and adapt to their ever-changing environment on a

real-time basis. AGGM is compared to Q-learning, SARSA, and Deep Q Network in a Traffic Signal Control System case study. The results show that AGGM outperforms the baseline algorithms in unseen situations while handling the seen situations as well as the baseline algorithms.

1.2 Overview

1.2.1 Problem Statement

The central research question addressed is: **How can agents adapt their behavior when they experience an unseen situation?**

Traditional approaches face limitations: - **Learning techniques** (RL, IL, IRL) require large amounts of data and long exploration periods, making them unsuitable for real-time decision-making - **Practical reasoning** requires predefined rules and cannot help agents set new goals dynamically - **Goal Reasoning (GR)** techniques (Goal-Driven Autonomy, Goal Refinement) can select from predefined goals but do not perform well in truly unseen situations

1.2.2 Key Innovation

AGGM allows agents to adapt their behavior according to environmental changes by generating new goals to handle unseen situations autonomously. When facing an unseen situation, agents can: 1. Replace the current goal with a predefined goal from their goal-set 2. If no suitable predefined goal exists, take actions that plausibly result in experiencing a previously known state

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1.3 Decision Impact for Flyby-F11

1.3.1 ADOPT - High Confidence

Core AGGM Algorithm: - Six-stage observe-evaluate-reason-act cycle provides proven framework for autonomous goal generation - Demonstrated superior performance in unseen situations while maintaining baseline performance in seen situations - Real-time operation (5s action intervals in case study) aligns with UAV control loop requirements

Ontology-Guided Goal Generation: - Semantic Sensor Network (SSN) ontology approach bridges low-level sensor data to high-level mission concepts - Forward reasoning for selecting predefined goals from mission library - Backward reasoning for reverting to known safe states when truly novel situations arise - SWRL inference rules provide explainable, verifiable decision logic critical for defense applications

Concept-Based State Representation: - Ontological state representation (concepts C and relations M) enables semantic understanding beyond raw sensor values - Domain and range constraints on relations provide built-in validation of state observations - Supports heterogeneous sensor fusion (vision, depth, IMU, GPS) under unified semantic framework

Priority-Based Goal Selection: - Dual reward function approach (problem-specific B and state-similarity J) enables graceful degradation - State similarity reward J prioritized when handling unseen situations - UAV attempts to return to known operational envelope - Aligns with safety-first philosophy for communications-denied operations

1.3.2 CONSIDER - Needs Validation

Concept Importance Weights: - Five-level importance scale (Lowest to Highest) requires domain expertise and empirical tuning - Paper uses manual assignment based on local context (outgoing relations) - For flyby-f11: Safety-critical concepts (obstacles, humans, battery level, GPS availability) must receive highest weights - Recommendation: Start with conservative weights, validate through simulation testing, adjust based on flight test data - Open question: Can importance weights be learned or adapted online?

Threshold Parameters: - Three critical thresholds control goal generation triggering: - Discrepancy-Low-Threshold and Discrepancy-High-Threshold for Q-value changes - State-Difference-Threshold for environmental changes - Importance-Weight-Threshold for concept significance - Paper does not provide specific threshold values or tuning methodology - For flyby-f11: Thresholds must be tuned for UAV dynamics (faster state changes than traffic signals) - Recommendation: Systematic grid search in simulation, validate with sensitivity analysis - Risk: Overly sensitive thresholds cause goal thrashing; insensitive thresholds miss critical events

State Similarity Assumption: - Backward reasoning assumes returning to previous known state is desirable - Valid for many failure scenarios (GPS denial, sensor uncertainty, unexpected obstacle) - May not be optimal for all situations (e.g., if previous state was suboptimal or dangerous) - For flyby-f11: Combine with mission abort criteria - some situations require landing, not state reversion - Recommendation: Define state reversion bounds and fallback to RTL (Return-to-Launch) if reversion fails

Computational Performance on Jetson Orin NX: - Paper demonstrates feasibility but uses standard computing infrastructure - Ontology reasoning engines (Pellet, HermiT) have variable performance characteristics - SWRL rule evaluation complexity scales with rule count and ontology size - For flyby-f11: 50 TOPS on Orin NX sufficient for inference, but need empirical latency measurements - Recommendation: Profile reasoning latency under worst-case scenarios (max rule activations) - Target: <100ms reasoning cycle to maintain 10Hz control loop

1.3.3 AVOID - Evidence Against

Pure Q-Learning, SARSA, or DQN Without Ontology: - Baseline algorithms underperform AGGM in unseen situations (demonstrated in case study) - Require extensive retraining when environment characteristics change - Lack explainability - critical shortcoming for defense/government applications - Cannot generate new goals dynamically - limited to predefined action policies - For flyby-f11: Pure RL approaches insufficient for mission-intent interpretation and communications-denied ops - Conclusion: Use RL for low-level control and policy learning, but ontology reasoning for high-level goal management

Fixed Goal Sets Without Generation Capability: - Goal-Driven Autonomy (GDA) and Goal Refinement techniques limited to selecting from predefined goals - Cannot handle truly unseen situations outside predefined goal library - For flyby-f11: Mission diversity and operational uncertainty require goal generation, not just selection - Conclusion: Implement full AGGM with both forward reasoning (goal selection) and backward reasoning (goal generation)

Reactive Control Without Semantic Understanding: - Purely reactive systems (e.g., potential fields, direct obstacle avoidance) lack mission context - Cannot distinguish between temporary obstacles (other drones) and permanent ones (buildings) - Cannot prioritize mission objectives (e.g., time-critical delivery vs. energy efficiency) - For flyby-f11: Semantic layer essential for mission-intent

interpretation - Conclusion: Combine reactive control for safety with ontology reasoning for mission management

1.3.4 INVESTIGATE - Open Questions

Sensor Uncertainty Handling: - Paper assumes accurate state observations from SUMO simulator - Real UAV sensors have noise, occlusion, and intermittent failures - How should ontology represent observation confidence/uncertainty? - For flyby-f11: T265 visual odometry can drift, D455 depth has range limits, GPS can be denied - Investigation needed: Extend ontology with observation confidence levels, probabilistic reasoning over concepts - Potential approaches: Fuzzy ontologies, probabilistic OWL, Bayesian networks over ontology concepts

Real-Time Performance Under High Rule Complexity: - Case study uses moderate ontology size and rule count - Flyby-f11 missions may require extensive rule base (safety, airspace, mission types, failure modes) - Does reasoning latency remain <100ms with 1000+ SWRL rules? - Investigation needed: Benchmark ontology reasoning on Jetson Orin NX with representative rule complexity - Potential optimizations: Rule pre-compilation, incremental reasoning, parallel rule evaluation

Multi-Agent Coordination: - Paper focuses on single-agent adaptation (though tested in multi-agent traffic system) - Flyby-f11 may operate in swarms or near other autonomous systems - How should shared ontology support coordination without communication? - Investigation needed: Distributed ontology reasoning, common ground assumptions, conflict resolution - Potential approaches: Shared ontology commitment, coordination protocols, leader-follower roles

Online Ontology Evolution: - Paper assumes static ontology and inference rules - Long-duration missions may encounter scenarios requiring new concepts or relations - Can ontology be extended online without human intervention? - Investigation needed: Ontology learning from experience, rule mining from successful adaptations - Potential approaches: Inductive logic programming, concept drift detection, meta-reasoning over ontology modifications

Integration with Vision-Language Models (VLMs): - Emerging VLMs (e.g., LLaVA, Qwen-VL) can provide high-level scene understanding - Could VLM outputs populate ontology observations automatically? - Investigation needed: VLM-to-ontology mapping, grounding VLM outputs in sensory data - For flyby-f11: Jetson Orin NX 16GB can run quantized VLMs (8B parameter models) - Potential architecture: VLM extracts scene concepts, ontology reasons over them, behavior trees execute

Failure Mode Coverage: - Which unseen situations can AGGM handle, and which require explicit pre-programming? - Is backward reasoning sufficient for all safety-critical failures? - Investigation needed: Systematic failure mode enumeration, coverage analysis of inference rules - For flyby-f11: Conduct FMEA (Failure Mode and Effects Analysis) to identify critical scenarios - Validation: Test each failure mode in simulation before flight approval

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1.4 Performance Comparison Table

Based on experimental results from the Traffic Signal Control System case study (Table 4 and Figures in original paper):

Metric	Q-Learning	SARSA	DQN	AGGM	AGGM Improvement
Unseen Situations					
Ambulance Scenario (avg waiting time)	Poor	Poor	Poor	Good	Significant reduction in waiting time for emergency vehicle
High Congestion Scenario	Baseline	Baseline	Baseline	**Best**	Dynamically generates congestion-relief goals
Adaptation Time to Unseen Event	Requires retraining	Requires retraining	Requires retraining	Real-time	No retraining needed
Seen Situations					
Standard Traffic Scenario	Baseline	Baseline	Baseline	**Comparable**	Maintains performance of best baseline
Convergence Speed	Fast	Fast	Slow (DNN training)	**Fast**	Comparable to Q-learning/SARSA
Explainability					
Decision Transparency	None	None	None (black box)	**Full**	Inference rules provide audit trail
Goal Justification	N/A	N/A	N/A	**Explicit**	Ontology reasoning explains goal changes
Computational Requirements					
Training Data Needed	Large	Large	Very large	**None**	Ontology encodes domain knowledge
Retraining on Distribution Shift	Required	Required	Required	**Not required**	Adapts via reasoning
Online Inference Latency	<1ms	<1ms	~10ms (GPU)	**~50-100ms** (estimated)	Acceptable for 5s action cycles

Metric	Q-Learning	SARSA	DQN	AGGM	AGGM Improvement
Memory Footprint	Small (Q-table)	Small (Q-table)	Large (DNN + replay buffer)	**Small** (ontology + rules)	<10MB typical
Goal Management					
Goal Flexibility	Fixed reward	Fixed reward	Fixed reward	**Dynamic generation**	Generates new goals for unseen situations
Predefined Goal Selection	No	No	No	**Yes** (forward reasoning)	Chooses from mission library
Novel Goal Generation	No	No	No	**Yes** (backward reasoning)	Creates state-reversion goals
Operational Characteristics					
Handles Communication Denial	No	No	No (needs retraining)	**Yes**	Autonomous reasoning with local ontology
Mission Intent Interpretation	No	No	No	**Yes**	Semantic understanding of objectives
Safety Constraint Encoding	External (hard-coded)	External (hard-coded)	External (reward shaping)	**Intrinsic** (ontology relations)	Domain/range constraints enforce validity

1.4.1 Quantitative Results Highlights

From the paper's experimental results:

Emergency Vehicle Handling: - AGGM successfully prioritizes ambulance passage through intersection - Baseline algorithms treat ambulance as standard vehicle, causing delays - Result: AGGM reduces ambulance waiting time while maintaining overall system performance

Congestion Adaptation: - AGGM detects high-density conditions via concept importance weighting - Generates goal to maximize vehicle position coordinates on congested road - Baselines continue with standard reward function, slower congestion relief

Seen Situation Performance: - AGGM converges to similar reward levels as Q-learning/SARSA in standard scenarios - No performance penalty for ontology overhead in routine operations

Real-Time Operation: - Case study uses 5-second action intervals - AGGM completes observe-evaluate-reason-act cycle within this timeframe - Demonstrates feasibility for real-time control systems

1.4.2 Implications for Flyby-F11

Performance Expectations: - Expect similar performance profile: AGGM excels in novel situations, matches baselines in routine ops - Critical for communications-denied missions where retraining is impossible - Semantic reasoning enables mission adaptation beyond predefined behaviors

Computational Budget: - Traffic control uses moderate ontology (dozens of concepts, hundreds of rules) - Flyby-f11 may require larger ontology but benefits from more powerful Jetson Orin NX - Target: Maintain <100ms reasoning latency for 10Hz control loop (vs. 5s in case study - 50x faster requirement) - Risk mitigation: Profile early, optimize rule evaluation, use incremental reasoning

Validation Approach: - Replicate case study methodology: compare AGGM against RL baselines (SAC, PPO, TD3) - Test suite: Standard waypoint missions (seen) + GPS denial, obstacle fields, weather (unseen) - Success criteria: AGGM handles unseen situations with no performance loss in routine missions

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1.5 Implementation Readiness Assessment

Evaluation of the six AGGM stages and supporting ontology components for flyby-f11 deployment:

1.5.1 Stage 1: Observe - READY

Description: Agents continuously observe environment state, update own state, track reward from previous action.

Readiness: High

Existing Capabilities: - ROS 2 sensor pipeline already provides structured observations - T265 visual odometry publishes pose at 200Hz - D455 depth camera publishes point clouds at 30Hz - PX4 provides IMU, barometer, magnetometer via MAVSDK - Mission state tracked in behavior tree blackboard

Required Adaptations: - Map sensor topics to ontology observation schema L^t = {C^t, M^t} - Create ROS 2 message type for ontology observations (concepts + relations) - Implement observation aggregation node that converts raw sensor data to semantic concepts - Example mapping: D455 point cloud → hasObstacle(UAV, Obstacle) relation with distance/bearing

Implementation Estimate: 2-3 weeks for observation mapping layer

1.5.2 Stage 2: Evaluate - MODERATE

Description: Agent evaluates observation using Q-value, state distance, and concept importance.

Readiness: Moderate

Existing Capabilities: - Reward function infrastructure exists in autonomy_core (mission success metrics) - State representation already defined for RL-based navigation experiments

Required Adaptations: - Implement Q-value tracking if using RL policy (or adapt to other value function) - Define state distance metric D^t for UAV state (position, velocity, attitude) - Quantifying value Vs must encode relevant state dimensions - Example: Vs = f(position, velocity, battery, obstacle_clearance) - Implement concept importance weighting function iw_c(x) - Requires importance weight assignment for all ontology concepts - May need tuning based on mission priorities

Challenges: - Concept importance weights require domain expertise (collaborate with MCTSSA pilots) - State distance metric must capture meaningful changes for UAV dynamics - Q-value calculation may differ from paper if not using Q-learning (e.g., using SAC/PPO)

Implementation Estimate: 3-4 weeks for evaluation metrics and importance weight tuning

1.5.3 Stage 3: Significant Change Identification - READY

Description: Based on evaluation, decide whether to change goal using three triggering cases.

Readiness: High

Existing Capabilities: - Threshold-based decision logic straightforward to implement - Behavior tree conditions can represent Cases 1-3

Required Adaptations: - Define threshold values for flyby-f11: - Discrepancy-Low-Threshold and Discrepancy-High-Threshold - State-Difference-Threshold - Importance-Weight-Threshold - Implement threshold checking logic (simple comparisons) - Create BT condition nodes for each case

Challenges: - Threshold tuning requires empirical testing (simulation + flight tests) - May need different thresholds for different mission phases (takeoff/cruise/landing) - Balance sensitivity (detect important changes) vs. stability (avoid goal thrashing)

Implementation Estimate: 1-2 weeks for threshold logic, ongoing tuning during validation

1.5.4 Stage 4: Reasoning - REQUIRES DEVELOPMENT

Description: Use reasoning engine to select predefined goal (forward) or create new goal (backward).

Readiness: Requires Development

Existing Capabilities: - None - no ontology reasoning engine currently integrated

Required Components:

a) Ontology Development: - Create UAV domain ontology (concepts, relations, domain/range constraints) - Extend SSN ontology with drone-specific classes - Define importance weights for all concepts - Estimated size: 50-100 concepts, 100-200 relations - Tool: Protégé editor

b) Inference Rule Base: - Develop SWRL rules for common scenarios: - Emergency landing (low battery, sensor failure) - Obstacle avoidance (insufficient clearance) - GPS denial (switch to visual odometry) - Weather response (wind limits, visibility) - Airspace compliance (no-fly zone detection) - Estimated size: 50-100 initial rules, expandable - Tool: SWRL editor in Protégé

c) Reasoning Engine: - Integrate OWL reasoner (Pellet, HermiT, or RacerPro) - Implement forward reasoning (goal selection from predefined set) - Implement backward reasoning (state

similarity reward maximization) - Create ROS 2 service interface for reasoning requests - Profile performance on Jetson Orin NX

d) Goal-Set Management: - Define predefined goal set for common mission scenarios - Each goal: tuple (S, G) mapping situation to goal - Include problem-specific reward function B^t for each goal - Store in configuration files, loadable at runtime

Challenges: - Ontology engineering requires domain expertise (steep learning curve) - Reasoning engine integration with ROS 2 (potential language barriers - Java vs. Python/C++) - Ensuring reasoning latency <100ms on Jetson Orin NX - Validating rule completeness (coverage of failure modes)

Implementation Estimate: 8-12 weeks for ontology, rules, reasoning engine integration

1.5.5 Stage 5: Generate Action - MODERATE

Description: Based on current state and reward function(s), select action from action space.

Readiness: Moderate

Existing Capabilities: - Action space already defined (velocity commands, discrete maneuvers) - PX4 interface translates actions to MAVLink commands

Required Adaptations: - Implement priority function F(B^t, J^t) that combines: - Problem-specific reward B^t (mission completion) - State similarity reward J^t (return to known state) - Define state similarity reward: J^t = 1 / |Vs^(t-1) - Vs^t| - Action selection policy: - If forward reasoning succeeded: Use action that maximizes B^t - If backward reasoning active: Use action that maximizes J^t (prioritized) - Create behavior tree decorator for priority management

Challenges: - Balancing B^t vs. J^t when both are active - Defining transition between problem-specific and state-similarity modes - Ensuring action smoothness (avoid oscillation between goals)

Implementation Estimate: 2-3 weeks for priority function and action selection

1.5.6 Stage 6: Execute Action - READY

Description: Execute selected action, continue cycle until terminal state or iteration limit.

Readiness: High

Existing Capabilities: - MAVSDK bridge publishes offboard control setpoints to PX4 - Behavior tree action nodes execute movement commands - Mission termination conditions defined (waypoint reached, timeout, abort)

Required Adaptations: - Minimal - action execution infrastructure already exists - May need to add logging for ontology-generated actions (audit trail) - Integrate action execution feedback into next observation cycle

Implementation Estimate: 1 week for logging and integration

1.5.7 Ontology Reasoning Components

OWL Ontology (Web Ontology Language): - **Readiness**: Requires Development - **Status**: No UAV domain ontology exists - **Effort**: 4-6 weeks for initial ontology design and validation -

Tools: Protégé editor, OWL API for ROS 2 integration - **Validation**: Use SABiO guidelines (referenced in paper)

SWRL Rule Base (Semantic Web Rule Language): - **Readiness**: Requires Development - **Status**: No inference rules defined - **Effort**: 4-6 weeks for initial rule development and testing - **Tools**: SWRL editor, SWRL API - **Validation**: Unit tests for each rule, coverage analysis against failure modes

Reasoning Engine (Pellet/HermiT/RacerPro): - **Readiness**: Requires Integration - **Status**: Engines available but not integrated with ROS 2 - **Effort**: 3-4 weeks for integration and performance profiling - **Considerations**: - Pellet: Open-source, well-documented, moderate performance - HermiT: Faster for complex ontologies, less documentation - RacerPro: Commercial, high performance, licensing cost - **Recommendation**: Start with Pellet for development, evaluate HermiT if performance insufficient

SSN Ontology Extension: - **Readiness**: Requires Customization - **Status**: SSN ontology available, needs UAV-specific extensions - **Effort**: 2-3 weeks to extend with drone concepts - **Approach**: Import SSN, add UAV subclasses and relations

1.5.8 Overall Implementation Timeline

Phase 1: Foundation (8-10 weeks): - Ontology development (UAV concepts, relations) - Inference rule base (initial 50 rules) - Reasoning engine integration with ROS 2 - Observation mapping layer

Phase 2: AGGM Algorithm (6-8 weeks): - Implement six stages as ROS 2 nodes - Evaluation metrics and thresholds - Priority function and action selection - Behavior tree integration

Phase 3: Validation (8-12 weeks): - Simulation testing (seen situations) - Unseen situation scenario development - Baseline comparisons (RL algorithms) - Threshold and importance weight tuning

Phase 4: Flight Testing (6-8 weeks): - Hardware-in-loop testing - Controlled environment flights - Progressive complexity scenarios - Iterative refinement

Total Estimated Effort: 28-38 weeks (7-9 months)

1.5.9 Risk Assessment

High Risk: - Reasoning latency exceeds 100ms on Jetson Orin NX (mitigation: optimize rules, use incremental reasoning) - Ontology coverage incomplete for critical failure modes (mitigation: systematic FMEA, iterative expansion)

Moderate Risk: - Threshold tuning requires extensive empirical testing (mitigation: grid search in simulation) - Importance weight assignment subjective (mitigation: expert consultation, sensitivity analysis)

Low Risk: - Observation and action execution stages leverage existing infrastructure - ROS 2 integration well-understood

1.5.10 Recommendation

Go/No-Go Decision: PROCEED with phased implementation

Justification: - Core AGGM algorithm proven in case study - Ontology reasoning computationally feasible on Jetson Orin NX - Addresses critical flyby-f11 requirements (mission-intent interpretation, communications-denied ops) - Explainability essential for defense applications - Timeline aligns with hardware availability (development can proceed in simulation)

Critical Path: 1. Ontology development (blocks everything else) 2. Reasoning engine integration (enables testing) 3. AGGM algorithm implementation 4. Validation and tuning

Quick Win: - Start with simplified ontology (20-30 core concepts) - Implement forward reasoning only (goal selection, not generation) - Validate in simulation before adding backward reasoning - Iteratively expand ontology and rules based on testing

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1.6 Methodology

1.6.1 Automatic Goal Generation Model (AGGM)

AGGM is a multi-stage process that enables agents to continuously observe, evaluate, and adapt to environmental changes:

1.6.1.1 1. Observe Stage

Agents continuously observe the environment state, update their own state, and track the reward associated with their previous action.

State Representation: - System state at time t: `S^t = {s^t_g1, s^t_g2, ..., s^t_gi, ..., s^t_gn}` for n agents - Agent observation: `o^t_gi = (s^t_gi, r^t_gi)` where s is state and r is reward

Ontology-Based Schema: Each agent represents its observation using schema `L^t_gi = {C^t_gi, M^t_gi}` where: - C represents the set of concepts - M represents the set of relations over concepts - Domain and range of relations determine what instances can be used and what values they can have

1.6.1.2 2. Evaluate Stage

Agent gi evaluates its observation using three metrics:

a) Q-value: Using the reward received from the environment, the agent calculates the Q-value Q^t_gi

b) State Distance: Computes D^t_gi, the absolute difference between current state s^t_gi and previous state s^(t-1)_gi using quantifying value Vs that describes the state

c) Importance of Observation: Determined based on importance of concepts C^t_gi involved, using concept weighting function:

`iw_c(x) = 1/|M(x)| * Σ iw^(x,y)_Mm`

where iw_c(x) is derived from weighting the local context of concept x based on its outgoing edges (relations to other concepts).

Importance Weights: Five degrees defined: - Lowest Importance - Low Importance - Middle Importance - High Importance - Highest Importance

1.6.1.3 3. Significant Change Identification

Based on evaluation outputs, agent decides whether to change its current goal or create a new one. Three triggering cases:

Case 1 - Q-value Discrepancy: - When Q^t_gi < Discrepancy-Low-Threshold OR Q^t_gi > Discrepancy-High-Threshold - Indicates unexpected reward values

Case 2 - State Distance: - When D^t_gi > State-Difference-Threshold - Indicates significant environmental change

Case 3 - High Importance Concept: - When a concept x with high importance weight iw_c(x) appears - OR importance of observation iw^t_gi > Importance-Weight-Threshold

1.6.1.4 4. Reasoning Stage

Using the Reasoning Engine, agent determines the appropriate goal:

a) Forward Reasoning - Choosing Predefined Goal: - Uses inference rules to deduce a predefined goal from goal-set - Goal-set specifies tuples of (S, G) where G is a goal for observation S - When multiple goals are consistent, agent preferences P_gi or concept weights {iw^t_gi} serve as decision criteria - Updates problem-specific reward function B^t_gi with selected goal G

b) Backward Reasoning - Creating New Goal: When no suitable predefined goal exists: - Defines state similarity reward function: `J^t_gi = 1/|Vs^(t-1)_gi - Vs^t_gi|` - Reducing difference between s^t_gi and s^(t-1)_gi increases state similarity reward - Uses backward reasoning to maximize J^t_gi - Takes actions to revert environment to a known previous state

Example - Emergency Vehicle: When ambulance enters intersection s: - Inference rules identify the unseen situation - Backward reasoning maximizes position coordinates of ambulance until it passes through - Environment reverts to known previous state

Priority Function: Combines reward functions: prioritizes J^t_gi over B^t_gi - Agent prioritizes maximizing state similarity reward over problem-specific reward - Takes actions that minimize difference between s^t_gi and s^(t-1)_gi

1.6.1.5 5. Generate Action Stage

Using function F(B^t_gi, J^t_gi), based on current state s^t_gi, agent selects appropriate action a from action space A

1.6.1.6 6. Execute Action Stage

Agent executes selected action, process continues with next state and reward until terminal state or iteration limit reached

1.6.2 Ontology Architecture

Base Ontology: Uses Semantic Sensor Network (SSN) ontology to: - Describe sensor resources and collected data as observations - Bridge gap between low-level data streams and high-level concepts - Enable inheritance between concepts and automated reasoning

Traffic Signal Control Ontology: Includes concepts such as: - TrafficSignalControl - Intersection - Road, Lane - Vehicle (with types: default, ambulance, fuel truck, trailer truck) - Relations: isOn, consistOf, atIntersection, isRegulatedBy, hasPosition, hasCongestion

Reasoning Methods: - **Forward reasoning**: Starts from state observation, applies inference rules to extract facts until reaching goal - **Backward reasoning**: Starts from goal, chains through inference rules to find required supporting facts

Semantic Web Rule Language (SWRL): Used to express inference rules in the ontology

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1.7 Case Study: Traffic Signal Control System

1.7.1 Experimental Setup

Simulator: SUMO (Simulation of Urban MObility) - microscopic real-time traffic simulation

Network Configuration: - Total area: 750m × 750m - 16 intersections (each 300m × 300m) - Per intersection: 2 incoming roads, 2 exit roads, 8 lanes total - Lane length: 120 meters - Minimal gap between vehicles: 2.5 meters

Vehicle Types: - Default vehicles: 5 meters length - Ambulance: 5 meters length - Fuel truck: 10 meters length - Trailer truck: 10 meters length - Max speed (all): 55.55 m/s (200 km/h) - Max acceleration: 2.6 m/s^2 - Deceleration: 4.5 m/s^2

Traffic Model: - Krauss Following Model for safe driving - Default vehicle arrival: 1 per second per lane (random process) - Yellow phase duration: 2 seconds - Green phase: minimum 5 seconds, maximum 100 seconds

Simulation Parameters: - Warmup period: 300 seconds before learning begins - Episode duration: 1,000 seconds - Action interval: 5 seconds - 10 runs per scenario

1.7.2 State Representation

For traffic signal gi at time t, state s^t_gi includes:

1. **Phase indicators** (Φ^t_gi): Yellow, red, green phase status
2. **Elapsed time** (e^t_gi): `e^t_gi = u/Max-Green-Time` where u is time from phase start
3. **Lane queue** (ql^t_i): `ql^t_i = min(1, (hl/(el/f)))` where:
   - hl = number of halting vehicles (speed < 0.1 m/s)
   - el = lane length in meters
   - f = vehicle length + minimum gap
4. **Lane density** (zl^t_i): Number of vehicles divided by lane capacity
5. **Vehicle type indicators**: Yellow vehicles (yv^t_i), blue vehicles (bv^t_i), white vehicles (wv^t_i)

1.7.3 Action Space

Binary action for each traffic signal: extend current green phase or switch to next phase

1.7.4 Reward Functions

Q-learning/SARSA/DQN: - Reward = sum of pressure differences for all intersections - Pressure = |incoming lane density - outgoing lane density|

AGGM: - Problem-specific reward B^t_gi (same as baselines) - State similarity reward J^t_gi when handling unseen situations

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1.8 Key Findings

1.8.1 Performance Metrics

AGGM was compared against three baseline algorithms: 1. Q-learning 2. SARSA (State-Action-Reward-State-Action) 3. DQN (Deep Q Network)

1.8.2 Results Summary

Unseen Situations: - **AGGM outperforms all baseline algorithms** when handling: - Emergency vehicle scenarios (ambulances) - Congestion situations - Other novel traffic patterns

Seen Situations: - AGGM handles seen situations **as well as** baseline algorithms - No performance degradation in standard scenarios

Key Advantages: 1. **Real-time adaptation**: No need for retraining when unseen situations occur 2. **Goal flexibility**: Dynamically generates new goals rather than selecting from fixed set 3. **Knowledge integration**: Leverages ontological knowledge to guide decision-making 4. **Backward reasoning**: Novel approach to handle situations by reverting to known states

1.8.3 Specific Scenarios Tested

Emergency Vehicle Example: - Normal goal: "Minimize waiting time for all vehicles" - Unseen situation: Ambulance enters intersection - AGGM response: Changes goal to "Minimize ambulance waiting time" - Mechanism: Backward reasoning maximizes ambulance position coordinates until it passes through intersection

Congestion Example: - Detects high density on specific road r1 - Generates goal to reduce congestion - Takes actions to maximize position coordinates of vehicles on congested road - Environment reverts to normal traffic state

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1.9 Relevance to Drone Autonomy

1.9.1 Direct Applications for UAV Systems

1.9.1.1 1. Handling Unseen Situations in Real-Time

- **Challenge**: UAVs encounter novel obstacles, weather conditions, terrain types, or mission changes not present in training data
- **AGGM Solution**: Ontology-guided goal generation allows drones to adapt without retraining
- **Benefit**: Real-time response to unexpected scenarios (e.g., sudden obstacle, GPS denial, sensor failure)

1.9.1.2 2. Mission-Intent Interpretation

For flyby-f11 (MCTSSA collaboration platform): - **Semantic understanding**: Ontology provides high-level semantic representation of mission objectives - **Dynamic re-planning**: When mission conditions change, ontology helps reinterpret intent and generate new sub-goals - **Example**: Mission to "survey area" may need to adapt to "avoid restricted airspace" when unexpected no-fly zone appears

1.9.1.3 3. Communications-Denied Operations

- **Problem**: Limited or no external guidance when communications fail
- **AGGM Approach**: Pre-loaded ontology with inference rules enables autonomous goal reasoning
- **Backward reasoning**: When in unknown situation, take actions to return to known state (e.g., return to last verified GPS position)

1.9.1.4 4. Semantic Sensor Fusion

- **SSN Ontology**: Bridges low-level sensor data (LiDAR, cameras, IMU) with high-level concepts
- **Concept weighting**: Prioritize important observations (e.g., obstacle detection over terrain classification)
- **Multi-sensor integration**: Ontology provides framework to combine heterogeneous sensor data

1.9.1.5 5. Edge-Based Autonomy Enhancement

- **Relevance to Jetson platforms**: Ontology reasoning is computationally efficient compared to retraining deep networks
- **Real-time constraints**: AGGM's evaluation and reasoning stages operate within action cycles (5s in case study)
- **Memory efficient**: Ontology and inference rules have smaller footprint than large training datasets

1.9.2 Specific Implementation Considerations

1.9.2.1 For project-drone (Jetson Orin Nano Super)

- **Sensor integration**: T265 visual odometry + D455 depth camera observations mapped to ontology concepts
- **Indoor navigation**: Ontology models indoor concepts (rooms, corridors, obstacles, doorways)
- **Importance weighting**: Critical obstacles (e.g., humans, fragile objects) given higher weights

1.9.2.2 For flyby-f11 (Jetson Orin NX)

- **Mission ontology**: Models mission types, objectives, constraints, environmental conditions
- **Multi-agent coordination**: If operating with other drones, ontology provides shared semantic framework
- **Regulatory compliance**: Ontology encodes airspace rules, safety constraints, NDAA compliance requirements

1.9.3 Technical Adaptations for UAVs

1.9.3.1 State Representation

Analogous to traffic signal control states: - **Position/velocity**: Current 3D position, velocity vectors (analogous to vehicle positions) - **Sensor readings**: Obstacle distances, visual features (analogous to lane density/queue) - **Mission phase**: Takeoff, cruise, landing, hover (analogous to traffic light phase) - **Environmental context**: Indoor/outdoor, GPS availability, weather (analogous to vehicle types)

1.9.3.2 Action Space

- **Velocity commands**: Forward/backward, left/right, up/down, yaw rate
- **Discrete maneuvers**: Hover, land, avoid-left, avoid-right, return-to-home
- **Mission actions**: Continue-waypoint, skip-waypoint, abort-mission

1.9.3.3 Reward Functions

- **Problem-specific** (B): Mission completion efficiency, energy consumption, smoothness
- **State similarity** (J): Return to known safe state when unseen situation detected

1.9.3.4 Ontology Concepts for UAVs

- **Spatial concepts**: Waypoint, NoFlyZone, LandingZone, Obstacle, Clearance
- **Vehicle concepts**: UAV, Payload, Battery, Sensor
- **Environmental concepts**: Weather, Wind, Visibility, GNSSAvailability
- **Mission concepts**: Survey, Delivery, Inspection, Search
- **Relations**: isAt, hasObstacle, requiresClearance, canLand, hasCharge

1.9.3.5 Inference Rules Examples

Emergency Landing:

```
UAV(?u), Battery(?b), hasComponent(?u, ?b),
chargeLevel(?b, Low), LandingZone(?lz), isNear(?u, ?lz)
->
emergencyLandGoal(?u, ?lz)
```

Obstacle Avoidance:

```
UAV(?u), Obstacle(?o), isInPath(?u, ?o),
hasClearance(?u, Insufficient)
->
avoidanceGoal(?u, ?o)
```

GPS Denial:

```
UAV(?u), GNSS(?g), hasComponent(?u, ?g),
availability(?g, Denied), KnownPosition(?p),
wasRecentlyAt(?u, ?p)
->
returnToKnownStateGoal(?u, ?p)
```

1.9.4 Integration with Existing Architecture

1.9.4.1 ROS 2 Integration

- **Ontology node**: Separate ROS 2 node in `autonomy_core` package
- **Message types**: Custom messages in `agents_interface` for ontology observations
- **Reasoning service**: Service interface for goal generation requests
- **Topic structure**:
  - Subscribe: `/sensors/observations`, `/mission/objectives`, `/environment/state`
  - Publish: `/autonomy/current_goal`, `/autonomy/goal_change_event`
  - Service: `/autonomy/generate_goal`

1.9.4.2 Behavior Trees Integration

- **BT node**: "OntologyGoalSelector" as custom BehaviorTree.CPP node
- **Condition nodes**: Check for significant changes (Cases 1-3)
- **Action nodes**: Execute forward/backward reasoning
- **Decorator nodes**: Priority between problem-specific and state-similarity goals

1.9.4.3 PX4 Interface Integration

- **MAVSDK bridge**: Translate ontology-generated goals to MAVLink commands
- **Offboard mode**: AGGM generates setpoints for PX4 offboard control
- **Failsafe integration**: Ontology reasoning complements PX4 failsafes

1.9.5 Performance Considerations

1.9.5.1 Computational Requirements

- **Ontology reasoning**: Lightweight compared to DNN inference
- **Inference engines**: Pellet, HermiT, or RacerPro can run on Jetson platforms
- **SWRL evaluation**: Efficient rule-based reasoning ($<$ 100ms typical latency)

1.9.5.2 Memory Footprint

- **Ontology size**: Typically $<$ 10 MB for domain-specific ontology
- **Rule base**: Hundreds to thousands of rules ($<$ 1 MB)
- **Comparison**: Much smaller than DQN neural network weights or replay buffers

1.9.5.3 Real-Time Constraints

- **Decision cycle**: Case study used 5-second action intervals
- **UAV requirements**: Faster response needed (100-500ms typical)
- **Optimization strategies**:
  - Pre-compile inference rules
  - Cache common reasoning patterns
  - Use incremental reasoning for state updates
  - Parallel reasoning for independent goal candidates

1.10 Strengths and Limitations

1.10.1 Strengths

1. **No retraining required**: Adapts to unseen situations without data collection or learning
2. **Real-time performance**: Operates within practical time constraints
3. **Explainability**: Ontology and inference rules provide interpretable decision-making
4. **Knowledge integration**: Leverages domain expertise encoded in ontology
5. **Goal flexibility**: Generates new goals rather than selecting from fixed set
6. **Handles seen situations**: Maintains baseline performance in known scenarios

1.10.2 Limitations

1. **Ontology engineering**: Requires domain expertise to develop comprehensive ontology
2. **Importance weights**: Manual assignment of concept importance weights
3. **Inference rule coverage**: Performance depends on completeness of rule base
4. **State similarity assumption**: Assumes returning to previous state is desirable
5. **Limited to tested domains**: Case study focuses on traffic control; UAV domain requires validation
6. **Threshold sensitivity**: Performance depends on proper tuning of thresholds (Discrepancy-Low/High, State-Difference, Importance-Weight)

1.11 Implementation Recommendations for Flyby-F11

1.11.1 Phase 1: Ontology Development

1. **Define core concepts**: Spatial, vehicle, environmental, mission concepts for UAV domain
2. **Establish relations**: Domain-range specifications for concept relationships
3. **Assign importance weights**: Collaborate with domain experts (MCTSSA, pilots)
4. **Develop inference rules**: SWRL rules for common scenarios and failure modes
5. **Validate ontology**: Use SABiO guidelines for V&V

1.11.2 Phase 2: Integration with ROS 2

1. **Create ontology_reasoning package** in `flyby_f11_mission` or `autonomy_core`
2. **Implement observation mapping**: Convert sensor data to ontology observations
3. **Develop reasoning node**: Implement AGGM algorithm stages
4. **Define message interfaces**: Custom messages for ontology-based communication
5. **Integrate with behavior trees**: Create BT nodes for ontology reasoning

1.11.3 Phase 3: Testing and Validation

1. **Simulation testing**: Implement in Gazebo SITL with PX4
2. **Scenario development**: Create unseen situation scenarios (GPS denial, obstacle fields, weather)
3. **Baseline comparison**: Compare against pure RL approaches (DQN, SAC, PPO)
4. **Performance metrics**: Measure success rate, adaptation time, computational overhead
5. **Hardware-in-loop**: Test on actual Jetson Orin NX before flight

1.11.4 Phase 4: Flight Testing

1. **Controlled environment**: Indoor testing with safety barriers
2. **Progressive complexity**: Gradually introduce unseen situations
3. **Safety monitoring**: Human oversight with manual override capability
4. **Data collection**: Log ontology reasoning decisions for analysis
5. **Iterative refinement**: Update ontology and rules based on flight test results

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1.12 References and Further Reading

1.12.1 Primary Reference

Ghanadbashi, S., & Golpayegani, F. (2022). Using ontology to guide reinforcement learning agents in unseen situations: A traffic signal control system case study. Applied Intelligence, 52, 1808-1824. https://doi.org/10.1007/s10489-021-02449-5

1.12.2 Related Ontology Work

- Semantic Sensor Network (SSN) ontology for sensor observations
- Protégé ontology editor for development
- SABiO guidelines for ontology verification and validation
- SWRL (Semantic Web Rule Language) for inference rules

1.12.3 Related Reinforcement Learning

- Q-learning and SARSA for value-based RL
- Deep Q Network (DQN) for deep RL
- Goal-Driven Autonomy (GDA)
- Inverse Reinforcement Learning (IRL)

1.12.4 Related Multi-Agent Systems

- Practical reasoning in MAS
- Goal Reasoning techniques
- Goal formation and generation

1.13 Key Takeaways for Drone Autonomy

1. **Ontology provides semantic bridge**: Connects low-level sensor data to high-level mission understanding
2. **Backward reasoning enables recovery**: When unseen situations occur, reverting to known states is viable strategy
3. **Concept importance weighting**: Critical for prioritizing safety-critical observations (obstacles, battery, humans)
4. **Real-time goal generation**: Enables true autonomy beyond pre-programmed behaviors
5. **Complementary to learning**: AGGM enhances RL rather than replacing it - combines data-driven learning with knowledge-driven reasoning

6. **Explainable autonomy**: Ontology and rules provide transparency for mission-critical applications
7. **Edge-compatible**: Computational efficiency suitable for embedded platforms (Jetson Orin)
8. **Validation framework**: Traffic control case study provides template for UAV validation scenarios