CS6380 Project: Large-scale UAS Traffic Management

Tom Henderson et al.







Acknowledgment

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(DDDAS-based Geospatial Intelligence)





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Futuristic Vision

(Slide from Jared Esselman; UDOT)





Commercial Use Cases

- 3D Mapping, Video Collection
- Delivery (Amazon, etc.)
- Inspections
- Data (Re)Transmission
- Air Taxis

→Investment 2017: \$506M
→1000's of flights per day





Drone HW Investment (\$B)

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Concerned Communities

- FAA/NASA
- Local & State Governments
- Service Vendors
- Users
- Public





FAA/NASA Architecture





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Local & State Governments

- Regulation of Flight
- Infrastructure for flight management
 - Radar
 - 5G
 - RTK GPS
 - Emergency Service
 - Data Acquisition & Analysis





Service Vendors

- Low cost
- Efficiency
- E.g.: Airmap







Users (Flying UAS's)

- Low Cost
- Privacy
- Reliability





General Public

Positive Aspects:

- Lower cost of goods
- Lower cost of delivery
- Improve delivery time
- Negative Aspects:
 - Noise
 - Pollution
 - Privacy





What's Wrong Currently

Service Suppliers must share flight plans

- Safety levels & prediction difficult
- Arbitrary paths NP-space hard





Our Proposal

- Lane-based airways
 - UAS configuration space becomes 1D
 - Allows strategic deconfliction
- Airway roundabouts for intersections
 - No crossing; just merging or diverging

Computationally tractable





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Utah Urban Air Mobility Idea

(Slide from Jared Esselman; UDOT)







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UDOT UAM (cont'd) (Slide from Jared Esselman; UDOT)



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Proposal:

Airways above roadways.

UDOT UAM (cont'd)





Creating Airways









UAM: Need to Plan Flights





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Which Path To Take? → Use lanes What about Wind? What about Rain? → Use lanes Reinforcement Learning For Optimal Policies







Dynamic UAV Flight Path Planning in Urban Environments

DDDAS-GEOINT: Geospatial Intelligence System Knowledge 8 **Argumentation Logic** Databases **Internet Data Acquisition** Presentation & Query **Active Data Acquisition** Interface Wargaming Models **Uncertainty Quantification** (Maps, **Imagery Orthorectification** Assertions **Physics Models** Processing UQ) HUMINT SW Systems







Resource Allocation Agent Coordination Sensor Placement Feature Selection Uncertainty Reduction





BRECCIA







- Resource Allocation
- Agent Coordination
- Sensor Placement
- Feature Selection
- Uncertainty Reduction





BRECCIA





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Applications Models

e.g., Wind/Obscurant Simulations





Advanced Algorithms

e.g., Probabilistic Logic





Application Methods

e.g., Path Planning





Software Infrastructure

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e.g., BRECCIA Multi-agent Server



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BRECCIA: Summary

- Provides middleware for:
 - real-time coupling of computation and knowledge
 - across heterogeneous platforms





BRECCIA: Summary

Provides uncertainty analysis for

- mission planning
- involving combination of:
 - human statements
 - simulation results
 - sensor measurements





BRECCIA: Summary

- Agents driven by uncertainty reduction:
 - identification of major uncertainty sources
 - uncertainty quantification
 - propose measures for uncertainty reduction

 Next Version: URBAN (urban UAS flight planning)





URBAN: <u>Uncertainty Reduction</u> <u>Based Agent Network</u>

- A mult-agent system specifically designed for geospatialtemporal analysis across massive distributed datasets.
- Leverages the GeoWave project developed at the National Geospatial-Intelligence Agency (NGA) (<u>http://locationtech.github.io/geowave/</u>) and the open source frameworks Apache Hadoop (for distributed processing) and Accumulo (for key/value database storage).
- Conceptually, a layer atop GeoWave that provides probabilistic logical reasoning over space and time.





URBAN (cont'd)

- Dissemination of knowledge in the form of probabilistic sentences and maps published to GeoServer (<u>http://geoserver.org/</u>)
- Addresses tasking, processing, exploitation, and dissemination of data (TPED) with an *agile sensor network* and the unifying concept of *uncertainty reduction*.





URBAN Implementation

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- The BRECCIA Agent represents the • core abstraction for all agents in the system.
- Agents are **distributed** across • specialized machines such as UAVs, mobile laptops, or high performance computers.
- The inherited components of each • **BRECCIA** agent enable an overall system that is dynamic and datadriven.



Example Instantiations of the BRECCIA Agent



Hadoop

Accumulo

GeoServer

DB



URBAN Implementation



- The Belief-Desire-Intention (BDI) engine serves a dual purpose
 - As a software architecture it facilitates the discussion and design of agents
 - As a software cognitive model it enables goal-driven behavior
- Jason (<u>http://Jason.sourceforge.net/wp/</u>) provides the language interpreter and BDI engine to BRECCIA agents.



URBAN Implementation

The Jason Reasoning Cycle. From Programming Multi-Agent Systems in AgentSpeak SCHOOL OF Using Jason (pg. 68), by Rafael H. Bordini et al., 2007, England: John Wiley and Sons Ltd. BRECCIA Agent BDI Engine Uncertainty Reduct. Goal P.L. Logic Module GeoWave Connector Specialized Functions







URBAN Implementation

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BRECCIA Agent BDI Engine Uncertainty Reduct. Goal P.L. Logic Module GeoWave Connector Specialized Functions

- How does Jason enable data-driven behavior?
 - Plans are executed due to events which may be achievement requests or a change in belief.
 - Example: Consider the case where a UAV is executing a path and periodically querying the geospatial database for path obstruction. To cause the agent to re-plan in the event of an obstruction, the code is as follows:

+path_obstructed(PathName) -> !replan(PathName)

React to the belief that path is obstructed...

...by replanning

• The language defined by Jason is inherently data-driven.


URBAN Implementation

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GeoWave Connector

- GeoWave enables agents to simultaneously access a distributed geospatial-temporal database.
- Agents publish geospatial knowledge, written to the database, via GeoServer. This enables remote sharing of this type of knowledge.
- In Jason, internal actions coded into the GeoWave connector provide direct access to the databases.
- Example from weather agent:

+!share_storm_info(Location, Agent) ->

geowaveConnector::get_wms_url(Location, WmsUrl);

.send(Agent, tell, storm_info(WmsUrl).

 Data-driven response from UAV agent: +storm_info(WmsUrl) -> !check_path_obstruction(WmsUrl)



URBAN Implementation

BDI Engine Uncertainty Reduct. Goal P.L. Logic Module GeoWave Connector Specialized Functions

BRECCIA Agent

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• Distributed approach enables web-based user access:

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BRECCIA Chat Room ×	Devid
$\leftarrow \rightarrow \mathbb{C}$ (i) localhost:9001	🖈 🔶 🙆 🔛 :
Apps	
	9 H B CHI S TO B S COMMENDER AND
	mission_planner(raven_air_control_ok[p(0.9)]),
	weather_monitor(wind_under_17[p(0.9]]),
	mission_planner(cnf(collection_done,[raven_infra_red,target_loiter_ok])),
Туре Неге	Send

Prototype BRECCIA Client interface and Chat Window Featuring Map of Salt Lake City from Local GeoServer Instance



URBAN Implementation

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- Specialized Functions
 - Current implementations of specialized functions include
 - Connecting to MATLAB instances (Agents who know how to use MATLAB)
 - RRT* path planner (Agents who know how to plan over space with vehicle constraints)
 - Wind Simulator (Agent that runs a wind vortex simulator)
 - Ongoing work of specialized functions
 - GDELT database query (Agents that can query the massive GDELT global event database (<u>http://www.gdeltproject.org/</u>)
 - OpenWeather API Agent (Agents that can query distributed weather information)
 - UAV simulator (Agents that can run real-time UAV simulators)
 - UAV controller (Agents that can control quadcopters in real-time)





Back to Airways

UUTM UW/Demo







(a) Airspace Volumes

(b) Action Directions





Problem: Strategic Deconfliction

Planning collision free flight paths
Typically PSPACE-hard

Reduce configuration space to 1D
 tractable
 allows capacity analysis





Related Problems

- (Commercial) Air Traffic Flow management
- Job scheduling problem (schedule sections)
- Multi-robot motion planning
- Traffic Assignment Problem
- Optimization Problems





Air Corridors: 1D Problem





UAS₁ Enters at t=2; exits At t=7





Roundabouts



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Issues of Interest

• Relationship between:

- Airspace structure and capacity
- Demand and reliability

Experiments (simulation)





Simulation Experiments

- Given network graph
- Demand: uniform distribution of vertex pairs
- Ground speed: 5 m/s
- Space Headway: 25m
- Yields 500 time slots to schedule
- Can't violate headway requirement





Air Traffic Network











Reliability: variability in scheduled release versus desired

 Lateness: amount of time after desired release time

 Earliness: amount of time before desired release time



Simulation Example









Demand vs Successful Flights

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Critical point



Utilization vs Requests







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Mean Lateness vs Earliness



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Measures of Effectiveness

The results in previous slides used:

- To set flight parameters
- To design lanes (fast vs slow, to reduce congestion, etc.)
- To assure low variance in lateness
- etc.





Reinforcement Learning for Optimal Policies

Bellman Equations:

$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum P(s' \mid s, a) U(s')$

Optimal Policy:

$$\pi^*(s) = \operatorname{argmax}_{a \in A(s)} \sum_{s'} P(s' \mid s, a) U(s')$$





Reinforcement Learning

- States
- Rewards
- Actions
- Transition Probabilities



Learning Optimal Action Policy

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4x4 Grid







Bellman Equations

$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum P(s'|s, a) U(s')$

where: U(s) is the utility of state s a is an action A(s) is the set of actions in state s R(s) is the reward for state s γ is a horizon coefficient





State Representation

state space: S = Z³xR³xR⁺xR
* 3 integer grid coordinates
* 3 wind vector values (x,y,z)
* 1 precipitation value
* 1 temperature value





State Representation: Reduced

state space: $S = G^3 \times W \times P \times T$ * G = {1,2,3,4}: grid indexes * W = {0,1}: no wind; wind * P = {0,1}: no rain; rain * T = {0,1,2}: cold, normal, hot (temp)





Actions

$A = \{X, -X, Y, -Y, Z, -Z\}$

* move in one of the coordinate directions







Probabilistic State Transition

Action	X	-X	Y	-Y	Z	-Z
1	0.60	0.00	0.10	0.10	0.05	0.15
2	0.00	0.60	0.10	0.10	0.05	0.15
3	0.10	0.10	0.60	0.00	0.05	0.15
4	0.10	0.10	0.00	0.60	0.05	0.15
5	0.15	0.15	0.15	0.15	0.40	0.00
6	0.05	0.05	0.05	0.05	0.40	0.80

Table 2. Probabilities Used for Transitions for Actions given Normal Temperature, No Wind and No Precipitation.





Reward Function

$$R(s) = \begin{cases} -0.04 & s \neq \text{goal,excluded state} \\ -1 & \text{excluded state} \\ +1 & \text{goal state} \end{cases}$$





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Value Iteration Algorithm

function VALUE-ITERATION(mdp, ϵ) returns a utility function inputs: mdp, an MDP with states S, actions A(s), transition model P(s' | s, a), rewards R(s), discount γ ϵ , the maximum error allowed in the utility of any state local variables: U, U', vectors of utilities for states in S, initially zero δ , the maximum change in the utility of any state in an iteration repeat $U \leftarrow U'; \delta \leftarrow 0$ for each state s in S do

 $U'[s] \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s' \mid s, a) \ U[s']$ if $|U'[s] - U[s]| > \delta$ then $\delta \leftarrow |U'[s] - U[s]|$ until $\delta < \epsilon(1 - \gamma)/\gamma$ return U From: Russell & Norvig

Figure 17.4 The value iteration algorithm for calculating utilities of states. The termination condition is from Equation (17.8).





Experiments

- Start Location: 1,1,1 (index 1)
- Goal Location: 4,4,4 (index 64)
- Blocked Cell: 4,4,3 (index 60)

→ Can't exit 4x4x4
→ Preference for horizontal motion



State Utilities and Path





(b) Flight Path Trace

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Convergence for Utilities









Optimal Policies



Table 3. Optimal Policies for the states.

X: RIGHT



Optimal Policies



(a) Action Numbers



(b) Directions



3

5

5

5



Cell Travel Density





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Policies with Wind in Y



G No action Х in Y axis!

(b) Directions Strong Wind in Y Direction


Current Work: Get Data!

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Transitions: UDOT UTM: Real-time Data Acquisition







Current Work: Testing! Deseret UAS







Conclusions

 Developed effective and efficient optimal policy method

- Converted core BRECCIA system to work for UAS Traffic Management
 - allows communicating, autonomous agents
 - Cloud computing





Future Work

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Contingency Handling



Colleague: Ella Atkins, Univ of Michigan



Contingency Handling



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5G Communications



Colleague: Tadilo Bogale, NC A&T



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If we knew about trains, maybe we could do drones

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Eurobalise

RBC

TO

Radar

Corridor

Occupancy

Movement

Authority

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Verification of the American Air Traffic Management System In Real-Time Maude?

- Guarantee safety?
- Measure reliability & performance?
- Measure and improve capacity?

Qualitatively analyze safety using timed model checking?

Quantitatively analyze capacity & energy?





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Need to Read & Understand:

Verification of the European Rail Traffic Management System in Real-Time Maude

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Abstract

The European Rail Traffic Management System (ERTMS) is a state-of-the-art train control system designed as a standard for railways across Europe. It generalises traditional discrete interlocking systems to a world in which trains hold on-board equipment for signalling, and trains and interlockings communicate via radio block processors. The ERTMS aims at improving performance and capacity of rail traffic systems without compromising their safety.





Large-scale Simulation

• <u>http://www.cs.utah.edu/~cem/uav/</u>









Questions?







Creating Airways

F





UTAH UAV Fleet

















Require: $r_d, r_e, r_l, path, v_q$ $r_d \leftarrow$ desired release time $r_e \leftarrow$ earliest release time $r_l \leftarrow$ latest release time $path \leftarrow$ requested segment ids $v_q \leftarrow \text{speed}$ $seats \leftarrow$ available time slots $l_s \leftarrow 0$ {The segment length} for each segment in path do seats_{segment} \leftarrow seats on segment at $t \in [r_e, r_l] + \frac{t_s}{v_e}$ $seats \leftarrow seats_{segment} \mid seats \{ Binary OR \}$ $l_s \leftarrow$ segment length end for $r_t \leftarrow \text{open seat closest to } r_d$ return r_t

