Cooperative Multi-UAV Active SLAM for Traversing Partially Mapped Terrain

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Introduction: Localisation, Mapping and Control

- **SLAM Context**: External navigation aids (GPS) or prior terrain map unavailable or unreliable

- **Vehicle control actions** now have a significant effect on Localisation and Mapping

- **The research** is concerned with Localisation, Mapping and Control for UAVs and the coupling between these elements
- Coupling control actions into the estimation process: **Active SLAM**

- Understand the connection between localisation, mapping and control

- Design intelligent control strategies for maximising localisation and mapping performance
• Multiple Cooperating Platforms: Multi-Vehicle Active SLAM

• Understand the interaction and coupling between coordinated motions and shared information

• Design cooperative control strategies to maximise shared localisation and mapping information
Overview

- Introduction

- Airborne Simultaneous Localisation And Mapping (SLAM)

- Paper: Cooperative SLAM for Traversing Partially Mapped Terrain

- Future Work: dealing with computational complexity
Single Vehicle Inertial-SLAM

**INS**
- Accel.
- Rotation Rates

**Co-ordinate Transform**

**Velocity**
- Position
- Attitude
- Feature Position
- Feature Observations

**EKF SLAM**
- Correct/Update IMU Biases
- Correct/Update PVA
- Feature Map

**Feature Map**

**Terrain Feature Sensor**

Mitch Bryson
Airborne Simultaneous Localisation And Mapping (SLAM)

- Start at unknown location with no a priori map information.
- Predict motion through INS.
- Make relative observations to local features and build a map through these observations.
- Predict and re-observe features which are in the map and begin to correlate
- Correlation assists in constraining drift in inertial solution
- Update the vehicle and feature estimates at each observation
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All Correlated to Vehicle also

Correlations Between Features
Multi-UAV SLAM

- Multiple UAVs perform SLAM over a common area
- UAVs share map information with one another over a wireless communication link
- Map information from other UAVs fused such that each has a common picture of the whole environment
- UAV localisation performance is now coupled to other vehicles; UAV can use features mapped by other UAVs to assist in localisation

Each UAV Builds Own Local Map
Multi-UAV SLAM

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Builds Correlations over Whole Map
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Cooperative SLAM for Traversing Partially Mapped Terrain

- Aim: to explore cooperative airborne SLAM strategies for traversal across semi-mapped terrain in GPS-denied environments
  - Some terrain information is available (i.e. from past mapping missions or from satellite imagery)
  - Vehicles use navigation estimates for control and/or tracking other objects: want to constrain errors in navigation state estimates
Cooperative SLAM Scenario

- Objective: Navigate across the terrain to the objective in a time-efficient manner, while maintaining localisation accuracy above a given threshold.

Prior Map Information

Objective Destination

Team of UAVs

Prior Map Information
Cooperative SLAM Scenario

Objective Destination
Cooperative SLAM Scenario

Prior Map Information

Objective Destination

Prior Map Information
Cooperative SLAM Scenario

Objective Destination

Prior Map Information

Localisation Uncertainty

New Features

Prior Map Information
Cooperative SLAM Scenario

Prior Map Information

Localisation Uncertainty Grows

Objective Destination

Prior Map Information
Cooperative SLAM Scenario

Move to Make Observations of Prior Map Features

Prior Map Information

Move to Make Observations of Prior Map Features

Prior Map Information

Objective Destination
Cooperative SLAM Scenario

- How do we balance between exploring new terrain and moving to prior features?

Objective Destination

Prior Map Information

Close the loop on Mapped Features

Prior Map Information
Approach

- Produce Paths to destination

- Predict Localisation performance along path
  - Using a Ricatti equation, approximate the localisation and mapping information along the path
  - Problem: How do we predict localisation performance over unknown terrain?

- Find shortest path where localisation errors are constrained within given bounds
We have prior terrain information
Unexplored Areas: Expect Features to be present
Assumption: Density of features is approximately equal to that seen in the prior terrain features
Expected Feature Locations: Randomly distributed in the unexplored area
We now use these expected locations to predict localisation performance
SLAM Performance over Unknown Terrain

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- Unexplored Areas: Expect Features to be present
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Planning Algorithm

2. Destination Reached?
   - Yes: Finished Planning, Fly Path
   - No: From Current Location, get Local Waypoint Options, Order Options based on Cost of Distance to Destination
3. Exhusted All Local Options?
   - Yes: Go Back to Start of Local Path
   - No: Check Localisation Error and Time Constraints
     - Yes: Meets Constraints?
       - Yes: Goto End of Local Path
       - No: Next Option
     - No: Exhusted All Local Options?
Results – Single UAV

(a) Northing (m) vs. Easting (m)

(b) Northing (m) vs. Easting (m)

(c) Northing (m) vs. Easting (m)
Single UAV: Localisation Accuracy Metrics

Expected Uncertainty Values for Planned Trajectory

- Yaw (deg)
- Roll/Pitch (deg)
- Hor. Pos. (m)
- Vert. Pos. (m)

Time (secs)
Results – Multiple UAVs
Multiple UAVs: Localisation Accuracy Metrics

UAV1

- Yaw (deg)
- Roll/Pitch (deg)
- Hor. Pos. (m)
- Vert. Pos. (m)

Time (secs)

UAV2

- Yaw (deg)
- Roll/Pitch (deg)
- Hor. Pos. (m)
- Vert. Pos. (m)

Time (secs)

UAV3

- Yaw (deg)
- Roll/Pitch (deg)
- Hor. Pos. (m)
- Vert. Pos. (m)

Time (secs)
Results – Different Initial Terrain (Single UAV)
Results – Different Initial Terrain (Multiple UAVs)
Extensions

- **Risk/Stochastic Planning:**
  - Control strategies that account for the risk of not finding any features.

![](image)

**Expected Uncertainty Values for Planned Trajectory**

- Yaw (deg)
- Roll/Pitch (deg)
- Hor. Pos. (m)
- Vert. Pos. (m)

Graph showing uncertainty values over time.
Extensions: Risk Adverse Planning

Variance in Expected Uncertainty Values for Planned Trajectory

- Yaw Prediction Variance
- Roll/Pitch Prediction Variance
- Hor Pos Prediction Variance
- Vert Pos Prediction Variance
Extensioins: Risk Adverse Planning

(a) and (b) show the trajectory of the UAVs from the start point to the finish point.
Online Updating of Plans: control strategies that replan based on newly observed feature information, feature density change
Extensions

Online Updating of Plans: control strategies that replan based on newly observed feature information, feature density change
Conclusions

- **Planning under uncertainty**
  - Simple heuristics for tightening constraints based on uncertainty
  - Rigorous stochastic planning: formulation? computational feasible? Online replanning

- **Global vs. local maxima in utility function**
  - Utility space riddled with local-maxima; better heuristics for planning? (probably)

- **Computational complexity in planning**
  - Computational complexity of evaluating information gains using Ricatti equation: scales poorly with map size/trajectory length
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Airborne SLAM: Computational Complexity in Planning/Utility Evaluation

- So far we have examined filtering strategies for SLAM; computational cost dominated by $O(n^3+M^2)$ evaluation of expected uncertainty through Ricatti equation (state/covariance form)

Dense relationships between all features and vehicle (covariance matrix)
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Exacerbated further in the multi-vehicle case.
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Consider the conditional dependencies formed in SLAM via the information-form (inverse covariance matrix).
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Sparsity in resulting information graph can be exploited for efficient utility evaluation; $\sim O(M+N_p)$ methods exist for fixed/batch graphs; incremental problems more difficult.
Airborne SLAM: Computational Complexity in Planning/Utility Evaluation

- Same idea applied to multi-vehicle problems: some existing efficient methods for distributed solutions
- Computational complexity driven by separator sets
Current/Future Work

- **Efficient, Incremental Utility Evaluation based on Sparse Information-form Representation**
  - Incremental sparse information matrix factorisation
  - Efficient information-measure calculation, covariance recovery algorithms

- **Distributed/Decentralised Multi-UAV Utility Evaluation/Planning Algorithms**
  - Distributed factorisation, junction-tree algorithms
  - How to combine into distributed decision-making?