Hybrid Estimation for Unmanned Aircraft Systems Detect and Avoid

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Motivation

- Airspace integration for Unmanned Aircraft Systems (UAS) flights beyond vision line of sight
- Replace pilot vision functionality through appropriate sensors
- The need for Detect and Avoid (DAA): UAS must be able to identify the non-cooperative intruder aircraft for integration into National Airspace System (NAS)
  - Certifiable DAA sensors
Motivation

- **RTCA MOPS (Radio Technical Commission for Aeronautics - Minimum Operational Performance Standards) – Phase II**[1]
  - Extended requirements for UAS operation, much larger scope through different airspace classes
  - Sensors and architectures to enable DAA equipment to be installed on a wider range of UAS (Phase 1 focused on large high-performance UAS)

- **Analyze operations and encounters of smaller UAS at low altitude**
  - Allow the use of airborne non-cooperative sensors (no ADS-B) and with less performance than the Phase 1 Air-to-Air Radar (new MOPS for Electro-Optical sensors)

Contributions/Objectives

- Develop new methods to apply safety standards in Detect and Avoid (DAA) functions with a maneuvering intruder
  - Advance previous work that have used linear predefined trajectories
  - Generate random trajectories using an established Encounter Model
  - Target Tracking
    - Multiple Model Adaptive Estimation (MMAE)
    - Interactive Multiple Model (IMM)
  - Hazard States Error Analysis using the IMM
  - New method for Closest Point of Approach (CPA) estimation based on the IMM prediction
Self-Separation

- Self-separation: visual requirement to remain well clear\textsuperscript{[2]}
  - Well clear threshold (WCT) definition (RTCA SC-228)\textsuperscript{[3]}:
    - Time to horizontal closest point of approach (CPA): $\tau = 35\text{s}$
    - Horizontal miss distance of 4000ft and vertical miss distance of 450ft

\textsuperscript{[2]} 14 CFR 91.113
\textsuperscript{[3]} RTCA SC-228, Draft DAA MOPS, V3.3, Apr 2016
• Our own aircraft has to detect and estimate the intruder aircraft trajectory
• Uncertainty in the measurement due to estimation error
  – As the DAA sensors gets more measurements, our estimated trajectory error decreases
• Tracking maneuvering targets

• Two main difficulties:
  – Measurement uncertainty (sensor noise)
  – Unknown intruder aircraft intent

• A potential solution is a Kalman filter (KF)
  – Limited in performance for such problems
  – Single motion model
  – Response to dynamics changes as the target maneuvers
Multiple Model Approach

- Another alternative is the Multiple Model Adaptive Estimation (MMAE) for state estimation
  - Account for different target behavior
  - It is assumed that the system obeys one of a finite number of dynamic models
  - Multiple filters (running in parallel) estimate the states of targets with changing dynamics

- These systems are called hybrid
  - Continuous dynamics
  - Discrete mode changes (multiple model)
**IMM Algorithm**

- Optimal MMAE estimation: must account for any potential estimation history
  - Would require $r^k$ filters (estimation histories) for $r$ modes and $k$ epochs

- The Interactive Multiple Model (IMM) algorithm
  - State estimate is computed under each possible current model using $r$ filters
  - Each filter uses a different combination of the previous estimates
    - Mixed initial conditions
  - Target dynamics modeled with simple kinematics (corresponding to an individual mode)

- Typically, IMM is a good compromise between complexity and performance, [⁴] to be evaluated in our specific problem

IMM Algorithm

1 - Calculation of Mixing Probability
2 - Mixed initial states and covariances
3 - Kalman filter: different modes/filters run in parallel
5 - Outputs of IMM only, not part of the algorithm recursions

Prior state estimates:
- $x_1(k-1|k-1), P_1(k-1|k-1)$
- $x_2(k-1|k-1), P_2(k-1|k-1)$

Mixing:
- $x_{1m}(k-1|k-1), P_{1m}(k-1|k-1)$
- $x_{2m}(k-1|k-1), P_{2m}(k-1|k-1)$
- Likelihood functions $\Lambda_1(k)$, $\Lambda_2(k)$

4 - Mode probability update
- Mode Probability $\mu(k-1|k-1)$
- Mode Probability $\mu(k|k)$
- $\mu(k)$

State estimate and covariance combination:
- $x(k|k), P(k|k)$
How do we define intruder trajectories for the IMM analysis

Another tool that we are using is an encounter model

- Simulations that can represent realistic trajectories
- They are generated with the same likelihood as found in real aircraft trajectories

MIT Lincoln Lab Encounter Model: based on US radar data[5]

- Trajectory construction is not provided with the encounter model
- The initial conditions do not specify position or direction of velocity
- It gives as output initial conditions and control variables for each time step

• At the encounter cylinder, start position and angle:
  - The encounter cylinder is assumed to have ± 3000ft height [10]/ 5.5 NM radius
  - Intruder aircraft starts at a random position at the encounter cylinder surface, at a random heading angle

IMM - Modes

- Based in an ATC scenario\cite{7,8,9}, the motions of an aircraft can be summarized as ascent/descent, straight level flight, turning, and change of speed
  - Mode 1 - Constant Velocity
  - Mode 2 - Constant Velocity 3D (non-zero \( \hat{h} \))
  - Mode 3 - Coordinated Turn
  - Mode 4 - Coordinated Turn 3D (non-zero \( \hat{h} \))
  - Mode 5 - Constant Linear Acceleration
  - Mode 6 - Constant Linear Acceleration 3D (non-zero \( \hat{h} \))

\cite{7} Kochenderfer, M., et al., Uncorrelated Encounter Model of the NAS. Project Report ATC-345, MIT Lincoln Lab, 2008
\cite{9} Bar-Shalom, Y., Kirubarajan, T., & Li, X. (2007). Estimation with applications to tracking and navigation:. New York, NY: Wiley
IMM - Transition Matrix

- Transition Matrix of the Markov Chain ($M_{ij}$) – used on the mode probability update - is based on Encounter Model runs ($10^6$), with 1 second timesteps
  - Homogeneous Markov Chain: time-invariant

$$
M_{ij} = \begin{bmatrix}
0.98038 & 0.00692 & 0.00562 & 0.00093 & 0.00508 & 0.00108 \\
0.02536 & 0.96022 & 0.00246 & 0.00509 & 0.00200 & 0.00487 \\
0.03263 & 0.00280 & 0.95063 & 0.00646 & 0.00624 & 0.00123 \\
0.01280 & 0.01891 & 0.01456 & 0.94566 & 0.00172 & 0.00636 \\
0.02551 & 0.00250 & 0.01098 & 0.00077 & 0.95314 & 0.00710 \\
0.00926 & 0.01860 & 0.00204 & 0.01147 & 0.01049 & 0.94814
\end{bmatrix}
$$

- The mode probability initial values:

$$
\mu_{ip} = \begin{bmatrix}
0.55117 & 0.15393 & 0.10708 & 0.04781 & 0.09292 & 0.04709
\end{bmatrix}
$$
Hazard States

- At the definition of the Hazard States in the **DAA MOPS**
  
  - Calculation of the CPA is time based

  \[
  CPA = \sqrt{(d_x + v_{rx} t_{CPA})^2 + (d_y + v_{ry} t_{CPA})^2}
  \]

  \[
  t_{CPA} = \max(0, -\frac{d_x v_{rx} + d_y v_{ry}}{v_{rx}^2 + v_{ry}^2})
  \]

  where: \( v_{rx} = \dot{x}_2 - \dot{x}_1 \) is the relative horizontal velocity in the x dimension

  \( v_{ry} = \dot{y}_2 - \dot{y}_1 \) is the relative horizontal velocity in the y dimension

  \( d_x = x_2 - x_1 \) is the current horizontal separation in the x dimension

  \( d_y = y_2 - y_1 \) is the current horizontal separation in the y dimension

- Vertical separation for alerting performance requirements are based on actual altitudes

  - We assume constant vertical velocity to account for the lookahead time alert criteria
In order to minimize prediction errors on the Hazard States, we introduce a new method instead of using the MOPS calculations (which are based on a linear trajectory propagation)

- Use Kalman prediction step as estimation for CPA (IMM Prediction)

There will be four main different CPA definitions:

- **MOPS:** using the formula as defined by the MOPS

- **IMM-MOPS:** using the formula as defined by the MOPS and the best trajectory estimation by the IMM

- **IMM-Predicted:** estimated closest point of approach calculated at each timestep, using the IMM prediction (new method)

- **True:** only known after the simulation has ended (influenced by future mode switches)
IMM Prediction

- Under maneuvers, the Hazard States estimation will be changing at each timestep
IMM Prediction

- We don’t know future aircraft intent (maneuver changes)
  - Using the knowledge of the current maneuver can improve our estimation
  - Our estimation will get better as the IMM recognizes the maneuver
Simulation

- Own aircraft: linear trajectory, constant velocity of 200kt
- Intruder aircraft: randomly generated by the encounter model
- Simulation time: 50s / sample rate: 1Hz
- Zero sensor noise
IMM Prediction - Results

- Trajectory graph showing a circular path.
- Control Variables graph showing various acceleration and velocity trends over time.
- CPA Prediction error graph comparing different prediction methods (Pred, IMM-MOPS, MOPS) over time.
• The estimation get better after the IMM recognizes the maneuver and adapts to the new predictions

• The overall prediction error when compared to the True CPA is considerably reduced using the new method

• Use the Encounter Model together with these tools for a safety evaluation
  – Based on the NMAC/LoWC probability associated with the encounter rate

\[
P(\text{LoWC}) = \lim_{N_s \to \infty} \sum_{j=1}^{N_s} P(\text{LoWC}|E_j)
\]

\[
\lambda_{\text{enc}} = \rho \bar{V}
\]

\[
\lambda_{\text{LoWC}} = P(\text{LoWC})\lambda_{\text{enc}}
\]
Summary

- Developing new tools for evaluate a DAA system performance with a maneuvering intruder
  - Define system requirements

- In this work, we investigated an intruder dynamics estimation method using an Interactive Multiple Multiple Model approach
  - Using an established encounter model to generate trajectories which include maneuvering intruders in proportion of their likelihood of occurrence

- Developed a new method for Hazard States estimation based on the IMM prediction
Future Work

- Future research:
  - Further analysis on the error sources (mode transition adaptation; mode transition prediction; modeling error; sensor noise)
  - Considerations with respect to Field of Regard from the MOPS\textsuperscript{[11]}
    - $\pm 110$ with respect to the longitudinal axis
    - $\pm 15$ vertically referenced to the flight path
  - Safety evaluation based on the NMAC/LoWC probability associated with the encounter rate

\textsuperscript{[11]} RTCA MOPS for Air-to-Air Radar for Traffic Surveillance
Thank you!

Questions?

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