Mechanical and Aerospace Engineering

THE LABORATORY FOR AUTONOMY IN DATA-DRIVEN AND COMPLEX SYSTEMS

ARC

Some New Challenges in Chance-Constrained Path Planning for UAS in Unstructured Uncertainty: Part 1 (Fusion)

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THE OHIO STATE UNIVERSITY

LADDCS TEAM

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LADDCS (Lab) TEAM


Alex Soderlund (May, 2020)


Rachit Aggarwal (May, 2021)


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Indranil Nayak


Andrew VanFossen


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Alexandra Mangel


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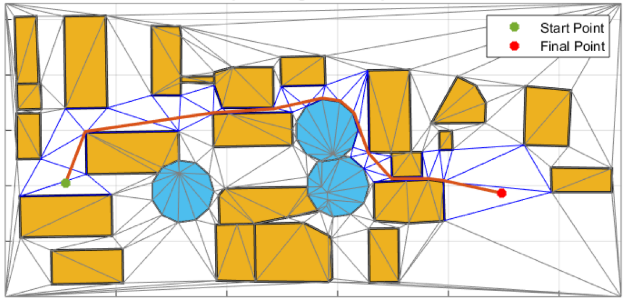
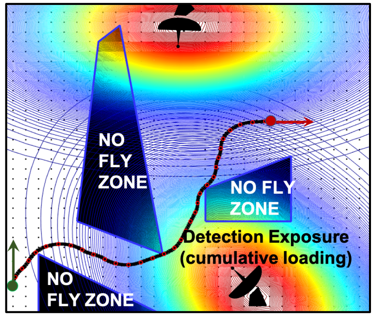
LADDCS PROFILE





forecasting

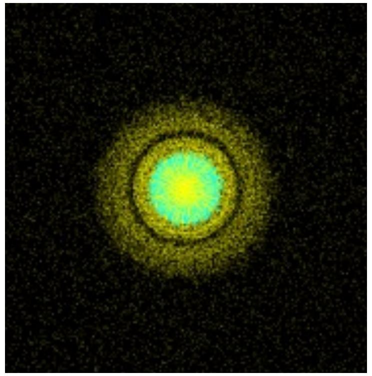
- closed-loop MC
- probability of failure
- threat assessment
- asset sustainment
- black-box models

missions in adversity

- chance-constrained path planning
- integral constraints
- evidential sensor fusion
- platform dev
- wildfire missions

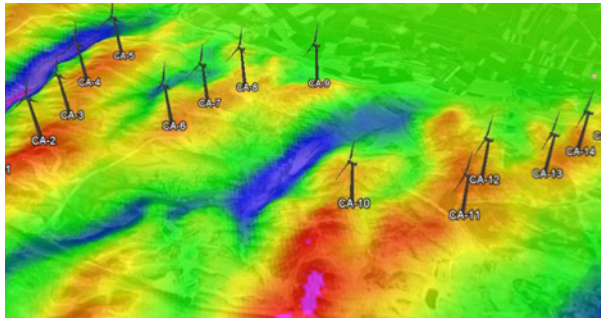
data-driven systems

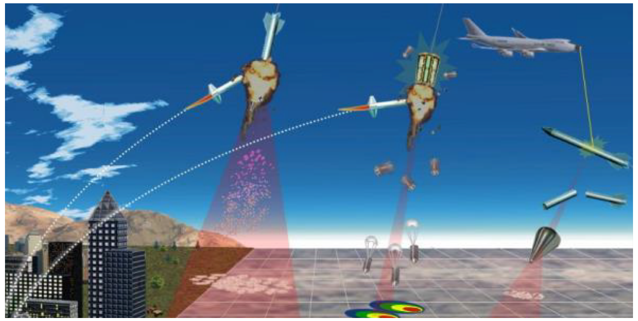
- DMD + Koopman theory
- learning dynamics
- situational awareness
- space explosions/ plasma mechanics

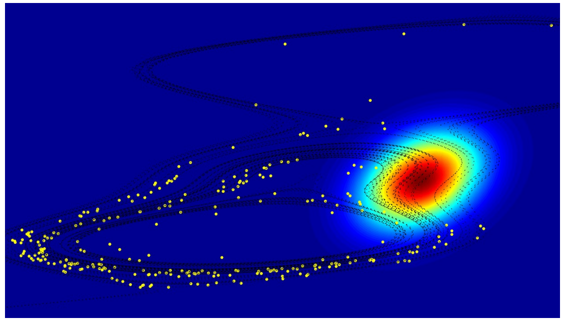


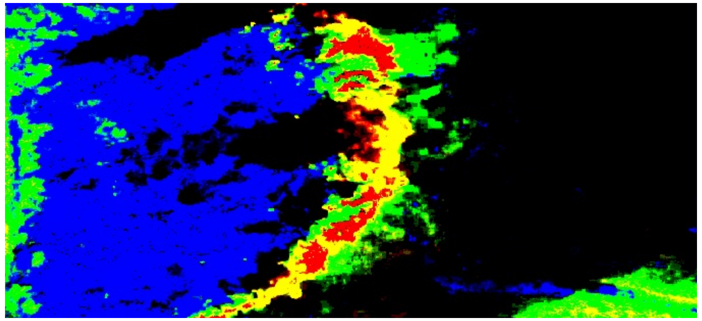
NSF Ohio Third Frontier Innovation Creating Opportunity

- autonomy
- space









TALK OVERVIEW

1. UAS Missions in Unstructured Uncertainty
    - A couple scenarios

2. Obstacle Characterization: Evidential Sensor Fusion
    - Traditional Bayes' formalism
    - The Dempster-Shafer alternative
    - Sensor belief modeling – temperature & vision sensors (examples)
    - Application to real fire: case study
    - Summary

3. UAS Path-Planning
    - Chance-constraints
    - Path-dependent resource/loading constraints
    - Graph Search – Hybrid A*
    - Backtracking
    - Numerical studies
    - Summary

4. Wrap up and lookahead

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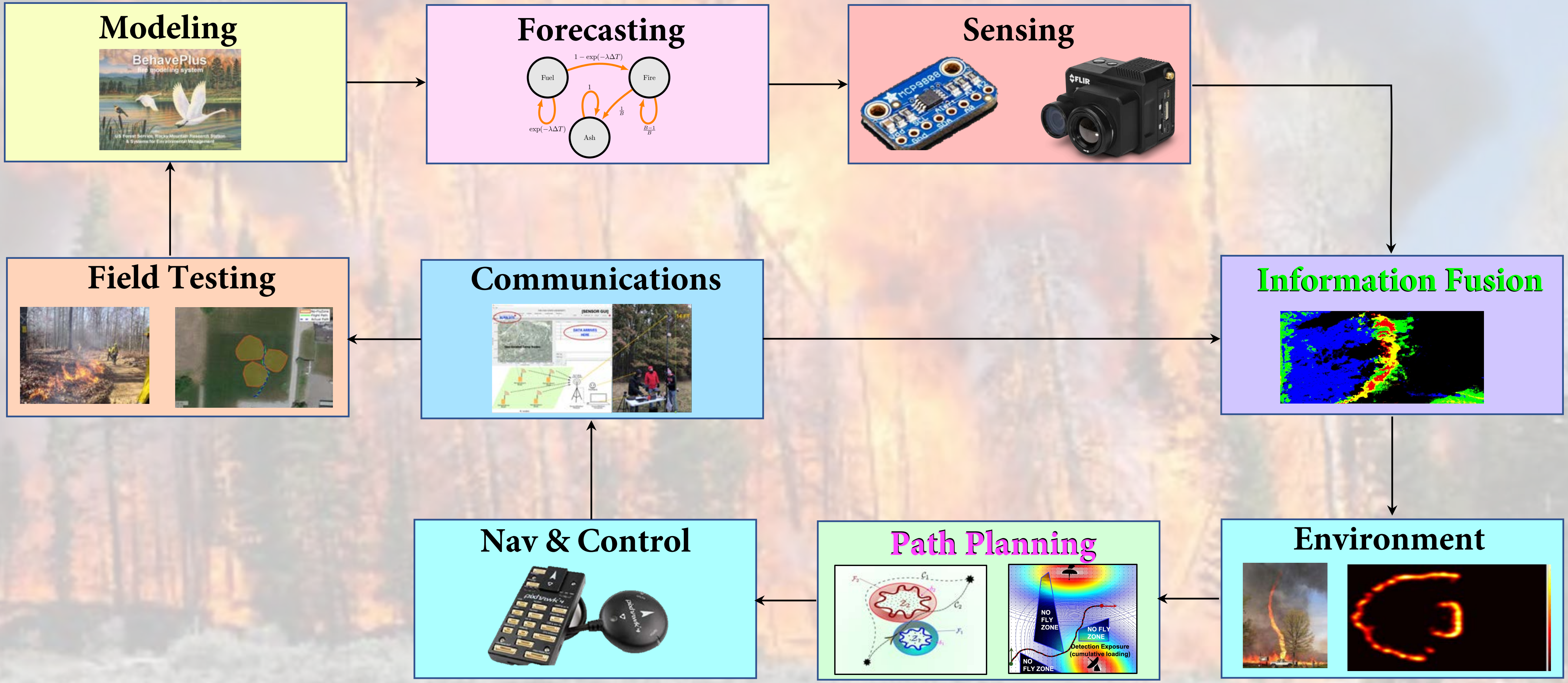
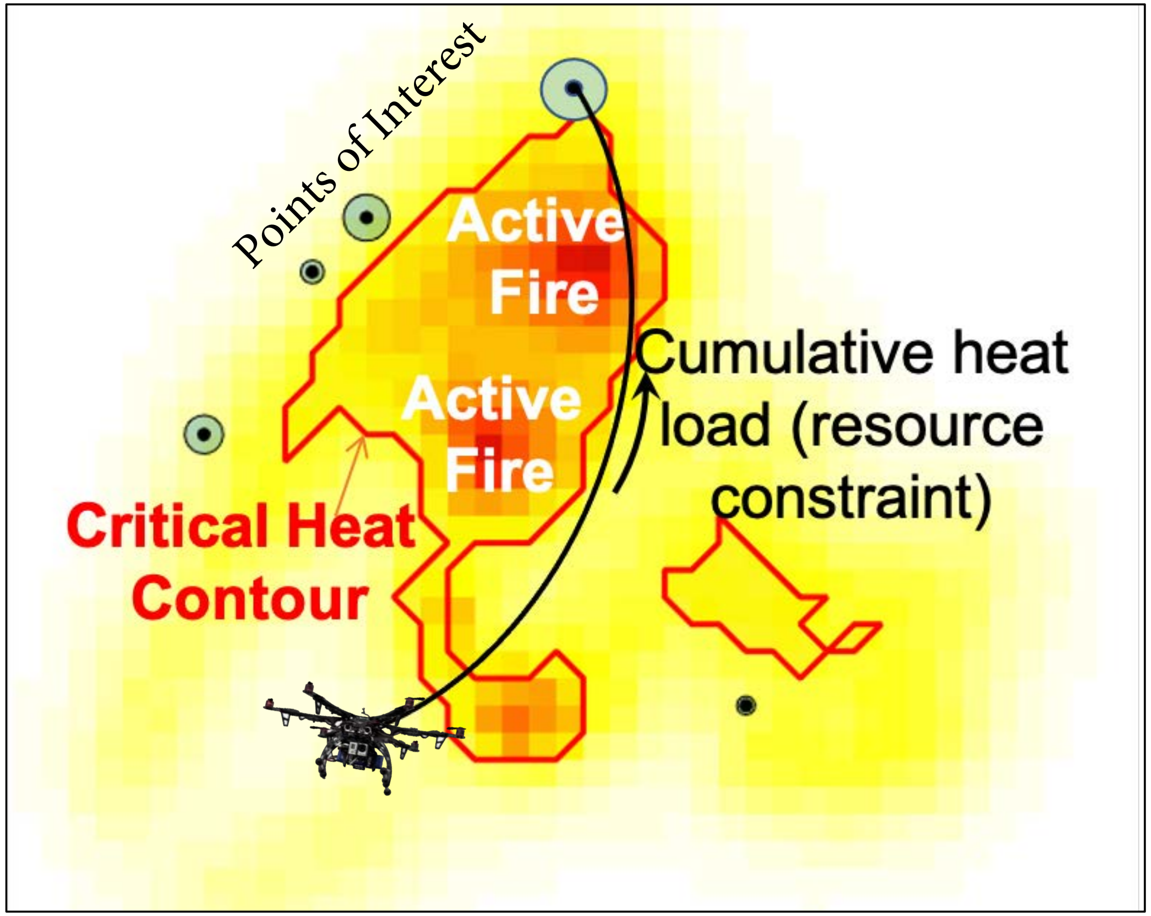
UAS MISSION PLANNING

- Missions in *unstructured uncertainty:* ● *poor models* ● *sensing conflict and anomalies* ● *"broken", dynamic environment*



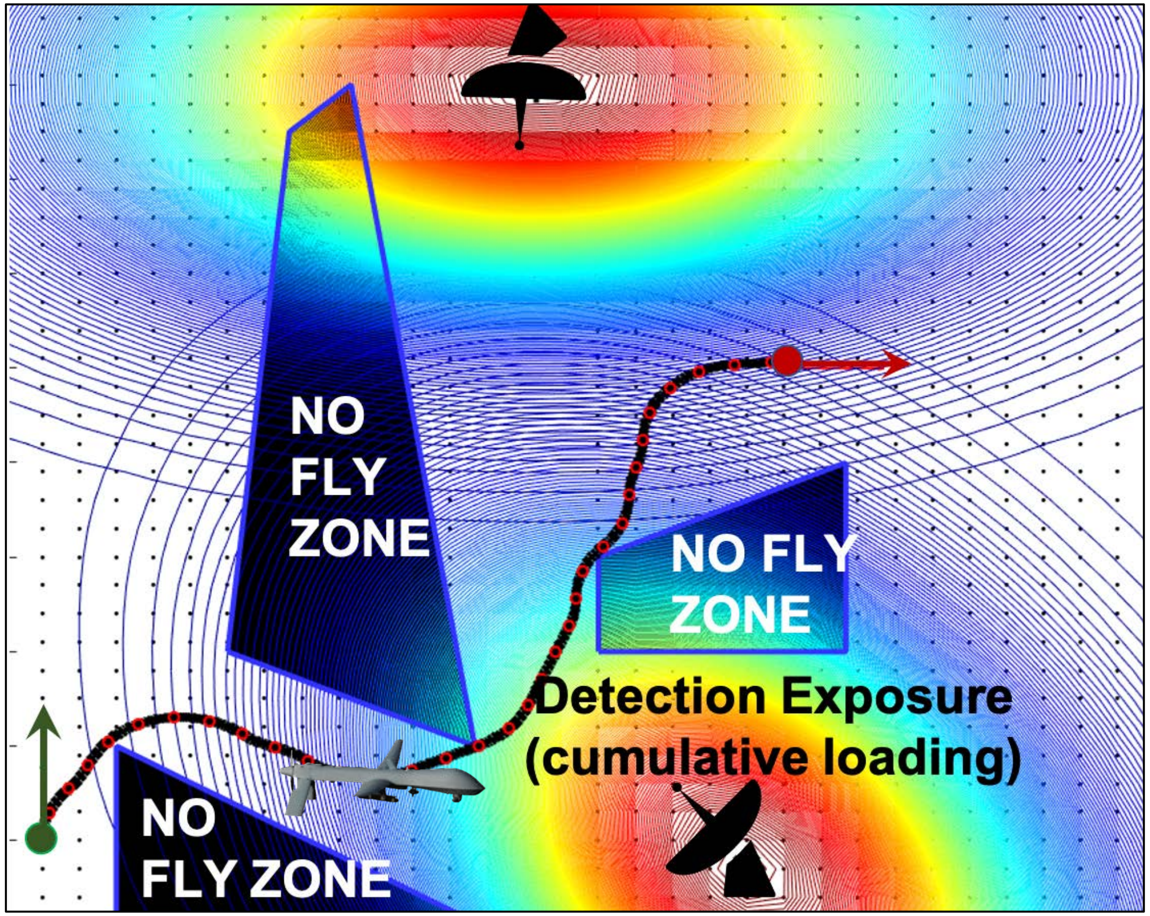
UAS MISSION PLANNING: Intangible Obstacle Scenarios

Scenario 1.



Flight above active fire: UAS safety constraints

Scenario 2.



Flight through enemy territory: constraint on radar detection, tracking and eventual attack

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Evidential Information Fusion: Obstacle Characterization

CONTEXT Timely and precise characterization of an **evolving wildfire** is critical to the success of its suppression and its propensity to threaten communities.

1. Current wildland fire containment efforts require improvement in two areas: i.) Early detection of fire presence and, ii.) Preventing the spread of the wildfire to highly volatile fuel, such as dry grassland

2. Decision-making regarding wildfire containment can be aided with knowledge of the probabilistic belief states of the fire's presence as it spreads

Challenges

- An adverse environment is typified by high incidence of poor priors (in the Bayesian sense),

- Trust in sensor data is an issue,

- Sensor conflict is common.

❑ **HOW TO CONDUCT OBSTACLE CHARACTERIZATION?**

Traditional Bayes' Information Fusion

- "*Traditional*" estimation proceeds via the **Bayes' rule:**

$$\underset{\textit{posterior}}{\mathbb{P}(A|B)} = \frac{\overset{\textit{likelihood}}{\mathbb{P}(B|A)}\,\overset{\textit{prior}}{\mathbb{P}(A)}}{\sum_{i=1}^{n} \mathbb{P}(B|A_i)\mathbb{P}(A_i)}$$

- **Criticisms** of the Bayesian framework, especially pertinent in *unstructured uncertainty:*

  - Bayesian view does not allow belief to be withheld from one proposition without according that belief to its complement:

$$\mathbb{P}(A) + \mathbb{P}(\bar{A}) = 1$$

  - The prior probability $\mathbb{P}(A)$ may not be adequately known.

  - The certainty of event B is required.

The Dempster-Shafer Alternative 1/3

- The Dempster-Shafer theory of probable reasoning (DST) is an alternative belief framework to conventional probability theory.
- Key Aspects:

did it not not snow?

did it snow?

  1. Beliefs in events are represented as intervals, as opposed to point probabilities.
  2. Beliefs can be assigned to sets of mutually-exclusive events.
  3. Beliefs are assigned based on the available supporting evidence.
- Consider a question with multiple finite possible hypotheses:

$$\Theta = \{\theta_1, \theta_2, \ldots, \theta_i, \ldots, \theta_n\}$$

- A proposition A is a set of mutually-exclusive hypotheses.
- The numerical "amount" of belief for any proposition $A \subseteq \Theta$ supplied by an expert E is quantified through the mass number $m_E(A)$.
- The mass numbers that are assigned over the entire frame of discernment Θ is the mass number array $\mathbf{m}_E$ defined as:

$$\mathbf{m}_E = (m_E(A_1), \ldots, m_E(A_i), \ldots, m_E(A_{|2^\Theta|}))$$

where $\sum_{A_i \in 2^\Theta} m_E(A_i) = 1$ and $m_E(\emptyset) = 0$

- The mass assigned to a proposition composed of multiple hypotheses is not, in general, divisible into the masses of its constituent parts - e.g. $m(\Theta) \neq m(\{\theta_1\}) + m(\{\theta_2\}) + \cdots + m(\{\theta_n\})$
- Ignorance is defined as $m(\Theta)$

The Dempster-Shafer Alternative 2/3

- The belief in A from expert E, $\mathrm{Bel}_E(A)$, is interpreted as the sum of evidence directly implying A:

$$\mathrm{Bel}_E(A) = \sum_{B \subseteq A} m_E(B)$$

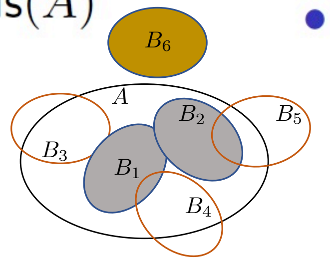
- The plausibility in A from expert E, $\mathrm{Bel}_E(A)$, is interpreted as the sum of evidence that does not contradict A:

$$\mathrm{Plaus}_E(A) = \sum_{B \cap A \neq \emptyset} m(B)$$

- The inequality $\mathrm{Bel}(A) \leq \mathrm{Plaus}(A)$ always holds.

plausibility

belief



- The mass numbers of two independent experts $E1$ and $E2$ can be combined into a new mass number array through Dempster's Rule of Combination:

$$m_{\mathbb{C}}(A) = K \sum_{A_i \cap B_j = A} m_{E1}(A_i) m_{E2}(B_j)$$

- The normalization constant $K = \frac{1}{1-\kappa}$, is computed from the *degree of conflict* $\kappa \in [0, 1]$ between the masses of the two experts $E1$ and $E2$:

$$\kappa = \sum_{A_i \cap B_j = \emptyset} m_{E1}(A_i) m_{E2}(B_j)$$

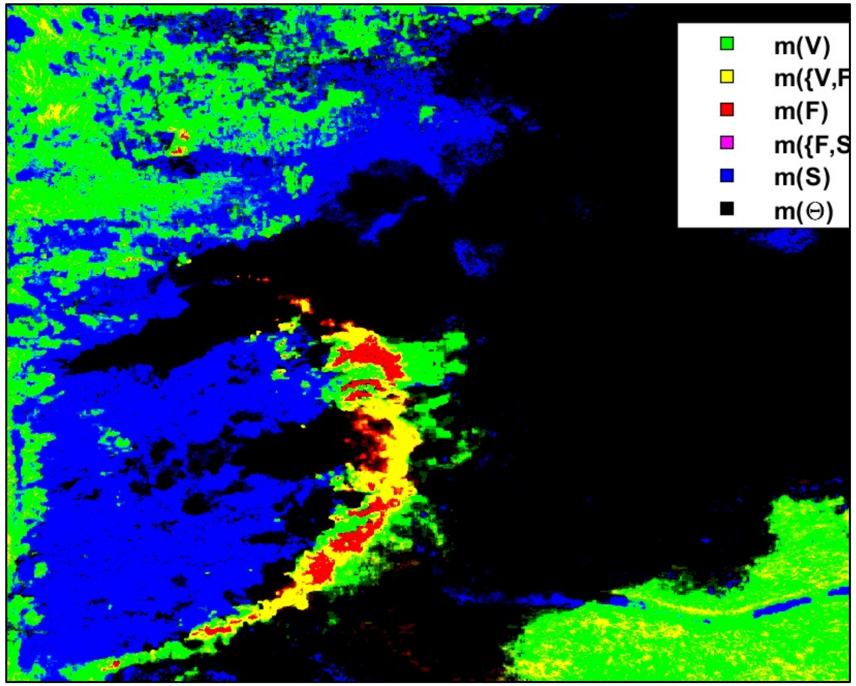
- The combination of two belief functions is valid where two experts do not completely contradict, i.e. $\kappa < 1$.

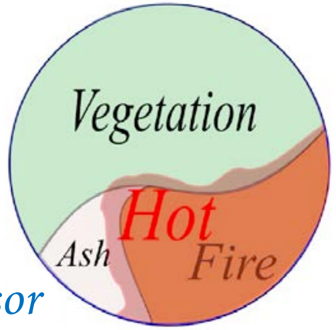
The Dempster-Shafer Alternative 3/3

The Process

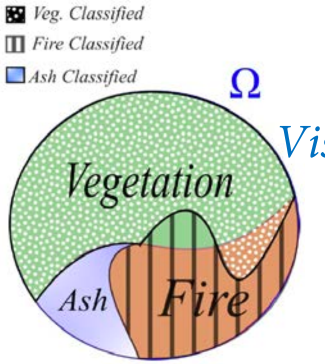
The Experts/Witnesses

The Evidential Estimate





Temp Sensor



Vision Sensor: more complex!

Propositions for Evidential Fusion: Wildfire

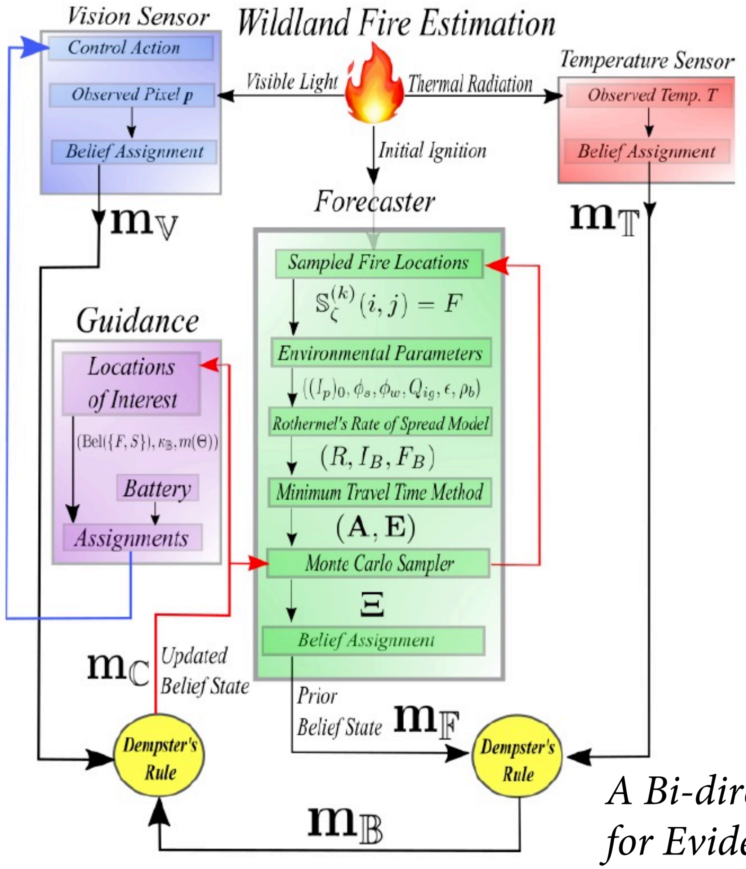
Wildfire frame of discernment: $\Theta = \{\ \text{Vegetation}(V),\ \text{Fire}(F),\ \text{Nonburnable}(S)\}$

Finite power set of propositions: $2^{\Theta} = \{\emptyset,\ V, \{V,F\},\ F, \{F,S\},\ S,\ \{V,S\},\ \Theta\}$

Feasible set of propositions: $\mathcal{F} = \{V, \{V,F\},\ F, \{F,S\},\ S,\ \Theta\}$

Sources of information (will expand):

1. Computational Forecaster: based on Monte Carlo sims
2. Thermal sensors: indirect fire detection through increase in ambient temperature readings
3. Airborne vision sensors: pattern recognition to classify feasible propositions



A Bi-directional Feedback Architecture for Evidential Wildfire Estimation

Belief Construction: Temperature Sensor 1/2

- A series of temperature readings over an activation period of τ timesteps $\mathbf{T}_h = [T_h^1, \ldots, T_h^{(k)}, \ldots, T_h^{\tau}]$ can be generated for *each* headfire spread rate within a given range $R_h \in [R_{min}, R_{max}]$.
- By cataloging the actual environmental states of the sensor's location $\mathbb{S}^{(k)}(i,j)$ for each spread rate R_h and activated time $T_h^{(k)}$, a frequentist chance value of proposition A at each time can be obtained as

$$q_A^{(k)} = \frac{\sum_{i \in m} \sum_{j \in n} \{1 \mid \mathbb{S}^{(k)}(i,j) \subseteq A\}}{\sum_{i \in m} \sum_{j \in n} \{\mathbb{T}^{(k)}(i,j)\}}$$

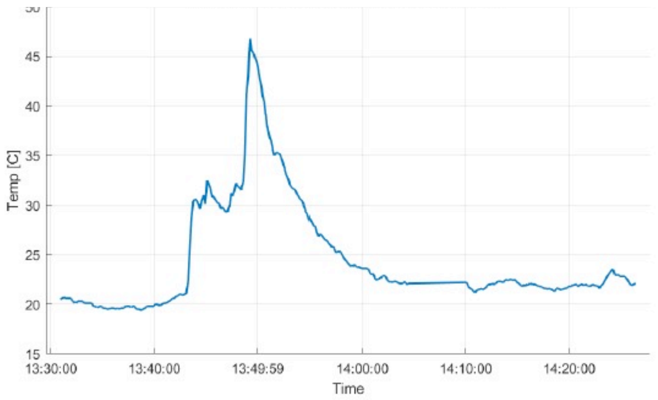
MCP9808 Sensor posted shortly before a prescribed burn in Marion, Ohio.

- The array of mass numbers for each temperature sub-expert at each time can be constructed as

$$m_{\mathbb{T}-B}^{(k)}(A) = \begin{cases} q_B^{(k)}, & \text{if } A = B \\ 1 - q_B^{(k)}, & \text{if } A = \Theta \\ 0, & \text{otherwise} \end{cases}$$

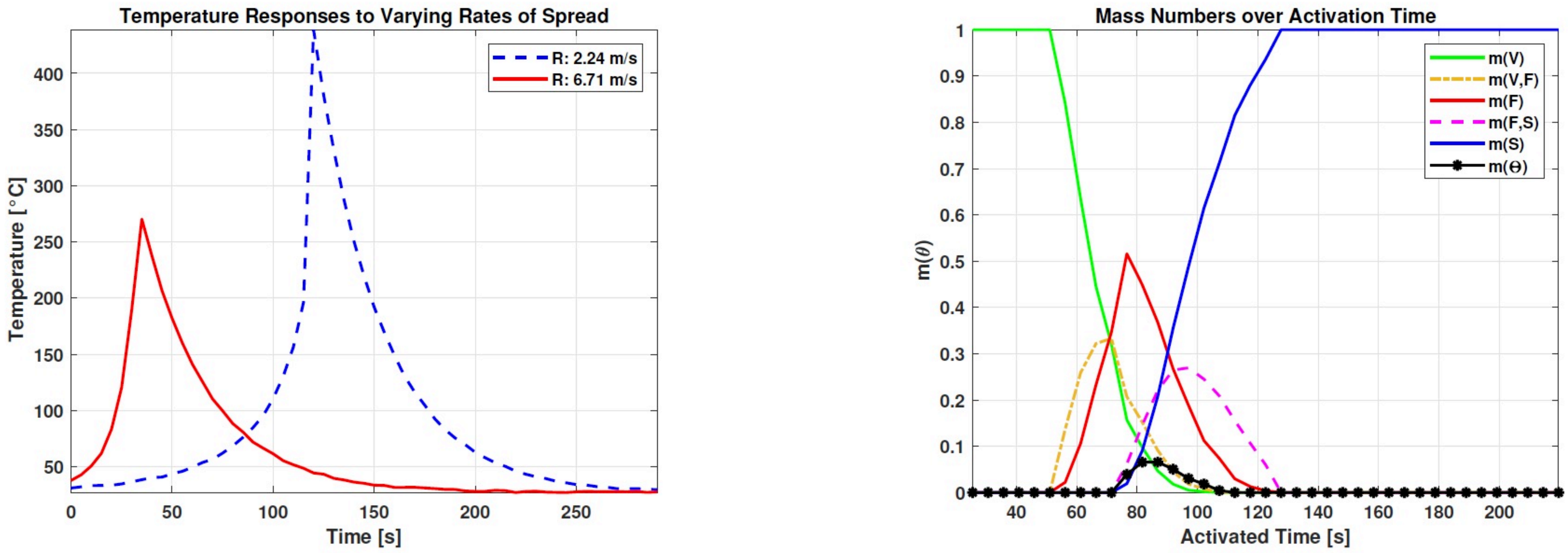
- The internally-combined set of beliefs for the temperature agent $\mathbf{Bel}_{\mathbb{T}}^{(k)}$ are computed as:

$$\mathbf{Bel}_{\mathbb{T}}^{(k)} = \mathbf{Bel}_{\mathbb{T}-V}^{(k)} \oplus \mathbf{Bel}_{\mathbb{T}-\{V,F\}}^{(k)} \oplus \mathbf{Bel}_{\mathbb{T}-F}^{(k)} \oplus \mathbf{Bel}_{\mathbb{T}-\{F,S\}}^{(k)} \oplus \mathbf{Bel}_{\mathbb{T}-S}^{(k)}$$



Temperature reading of a sensor during the passing of a fire front.

Belief Construction: Temperature Sensor 2/2

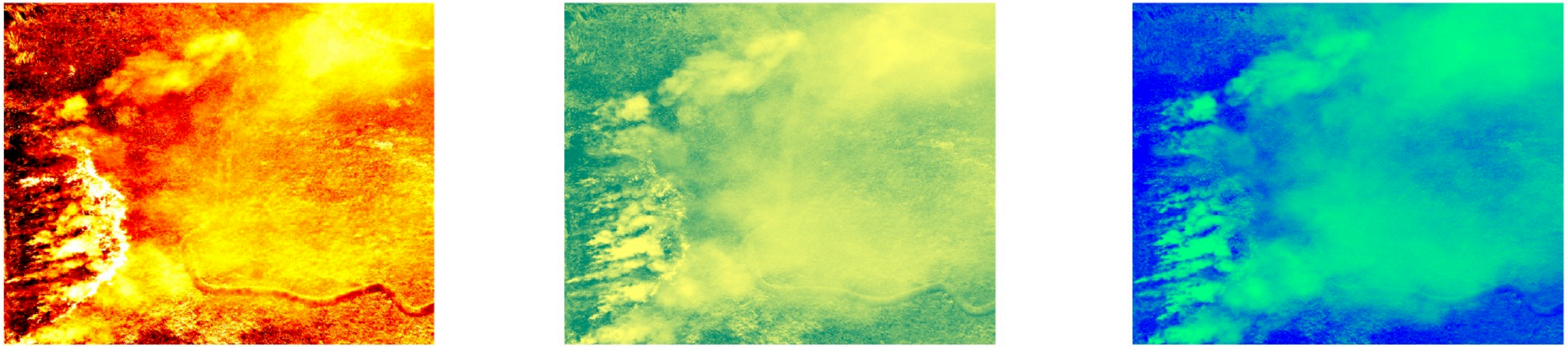


(a) (b)

(a) The temperature response when encountering a flame front with the highest and lowest spread rates.
(b) The mass numbers for each proposition over the temperature agent's activation time.

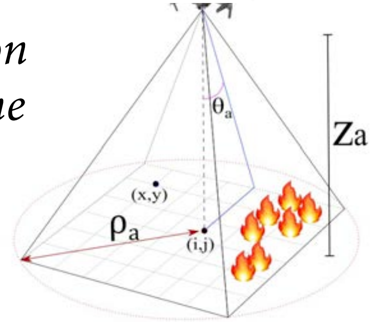
Soderlund, A., Kumar, M. and Yang, C. "*Autonomous Wildfire Monitoring Using Airborne and Temperature Sensors in an Evidential Reasoning Framework*". *In* Sensor Systems and Information Fusion Conference @AIAA SciTech, San Diego, CA, January 7-11, 2019 *(Best Paper Award)*
Soderlund, A. and Kumar, M. "*Estimating the Spread of Wildfires via Evidence-based Information Fusion*". IEEE Transactions on Control Systems Technology, under review

Belief Construction: Vision Sensor 1/3



(a) (b) (c)

The digital camera housed on each drone captures and stores the received visible light information through the additive RGB color model where every pixel at image location and time k contains the array of red, green, and blue intensity values



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Belief Construction: Vision Sensor 2/3

- The pixel observation $\mathbf{p}^{(k)}(x, y)$ can be cast as a "test point" computed to be some distance away from each state proposition distribution $\mathcal{N}_A(\hat{\mathbf{p}}_A, \mathbf{C}_A)$ through the Mahalanobis distance metric:

$$\mathcal{M}_A^{(k)}(x, y) = \sqrt{(\mathbf{p}^{(k)}(x, y) - \hat{\mathbf{p}}_A)^T \mathbf{C}_A^{-1} (\mathbf{p}^{(k)}(x, y) - \hat{\mathbf{p}}_A)}$$

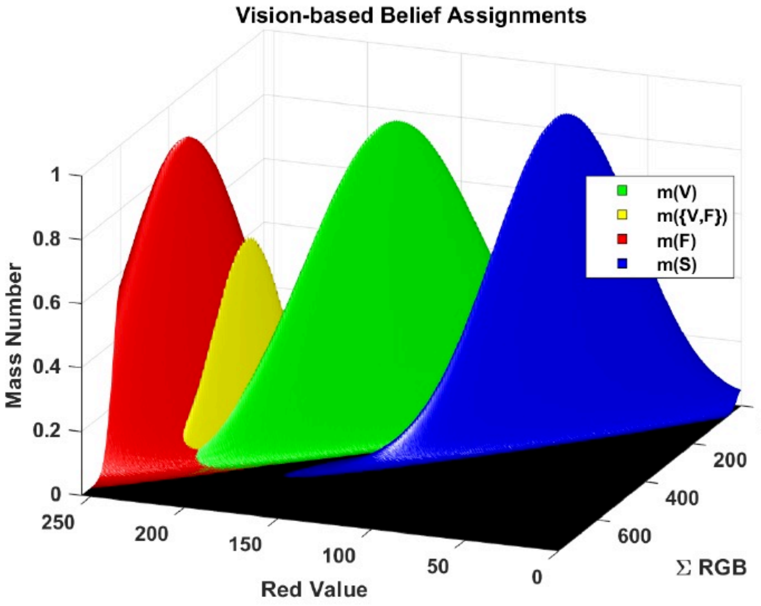
- This can be used to assign the mass number for each proposition A:

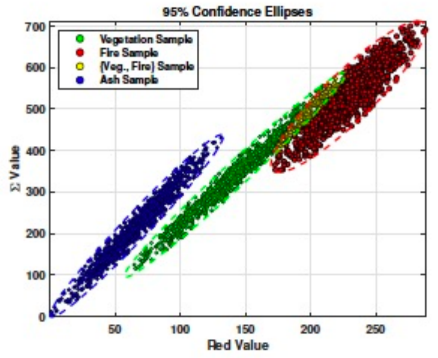
$$m_{\mathbb{V}-B}^{(k)}(A) = \begin{cases} \exp(-C_A \mathcal{M}_A^{(k)}), & \text{if } A = B \\ 1 - \exp(-C_A \mathcal{M}_A^{(k)}), & \text{if } A = \Theta \\ 0, & \text{otherwise} \end{cases}$$

where C_B is some proposition-dependent positive scaling parameter.

- Each mass number set $\mathbf{m}_{\mathbb{V}-A}^{(k)}$ are mapped to the associated belief set $\mathbf{Bel}_{\mathbb{V}-A}^{(k)}$ and combined through Dempster's rule to yield the total belief set:

$$\mathbf{Bel}_{\mathbb{V}}^{(k)} = \mathbf{Bel}_{\mathbb{V}-V}^{(k)} \oplus \mathbf{Bel}_{\mathbb{V}-\{V,F\}}^{(k)} \oplus \mathbf{Bel}_{\mathbb{V}-F}^{(k)} \oplus \mathbf{Bel}_{\mathbb{V}-S}^{(k)}$$





Mass number surfaces for the four vision-based propositions

Soderlund, A., Kumar, M. and Yang, C. "*Autonomous Wildfire Monitoring Using Airborne and Temperature Sensors in an Evidential Reasoning Framework*". *In* Sensor Systems and Information Fusion Conference @AIAA SciTech, San Diego, CA, January 7-11, 2019 (Best Paper Award)
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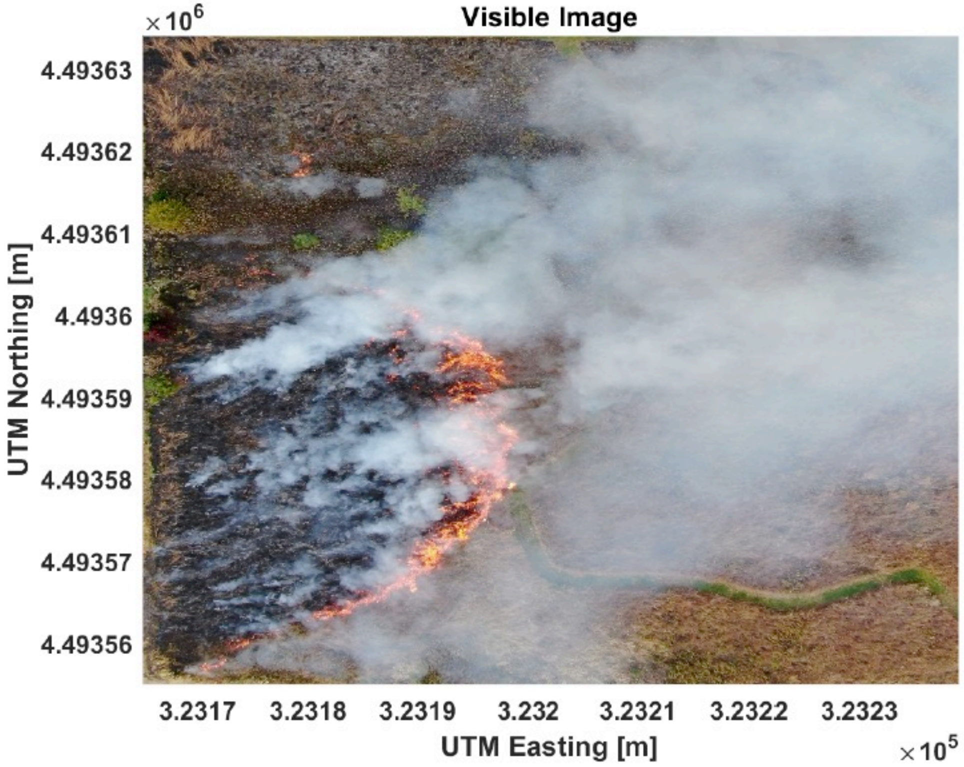
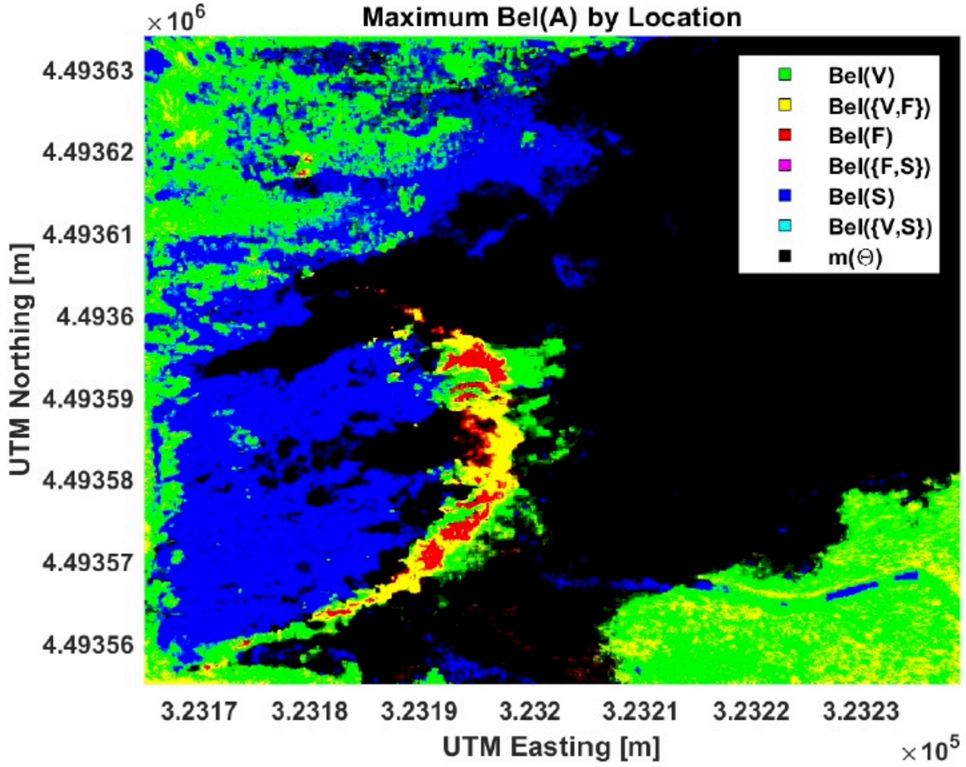
Belief Construction: Vision Sensor 3/3



(a)



(b)

KEYS

- Recognition (ash, fire, grasslands)
- Ambiguity (interfaces)
- Ignorance (smoke)

(a) Visible range image a fire front is captured with a DJI Mavic 2 drone at an altitude of 120 m during a prescribed burn event in Marion, Ohio.

(b) The proposition of highest belief that each pixel contains based on the vision agent's assignments using the color intensity data.

Soderlund, A., Kumar, M. and Yang, C. "*Autonomous Wildfire Monitoring Using Airborne and Temperature Sensors in an Evidential Reasoning Framework*". *In* Sensor Systems and Information Fusion Conference @AIAA SciTech, San Diego, CA, January 7-11, 2019 (Best Paper Award)
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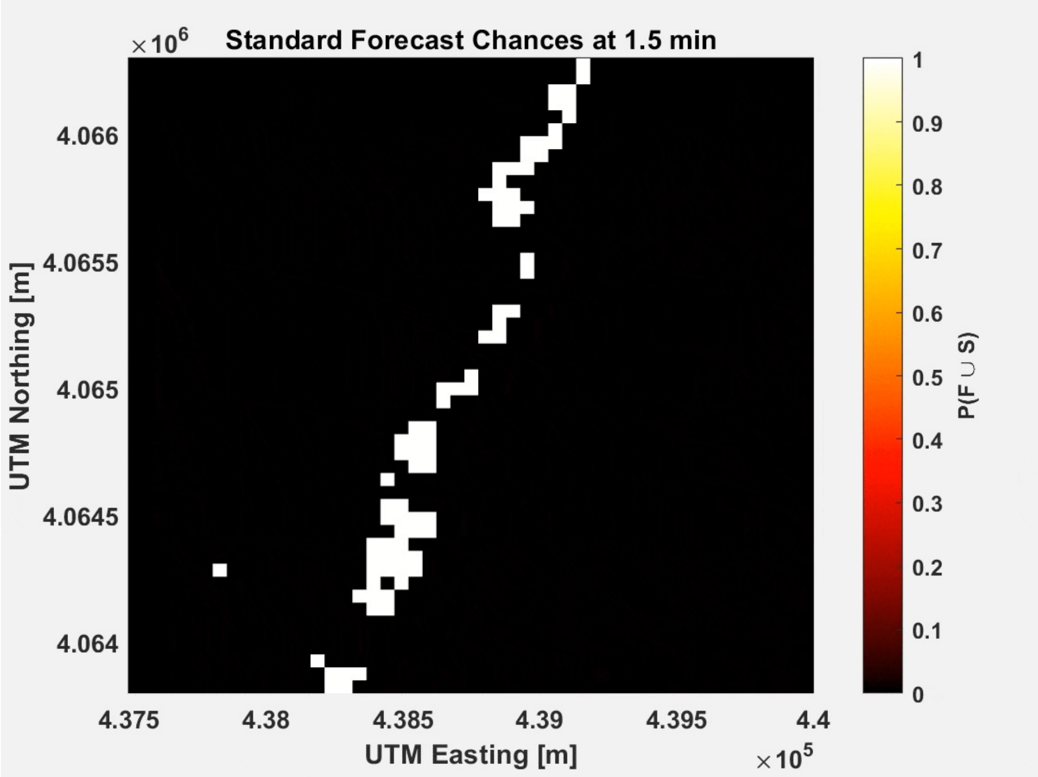
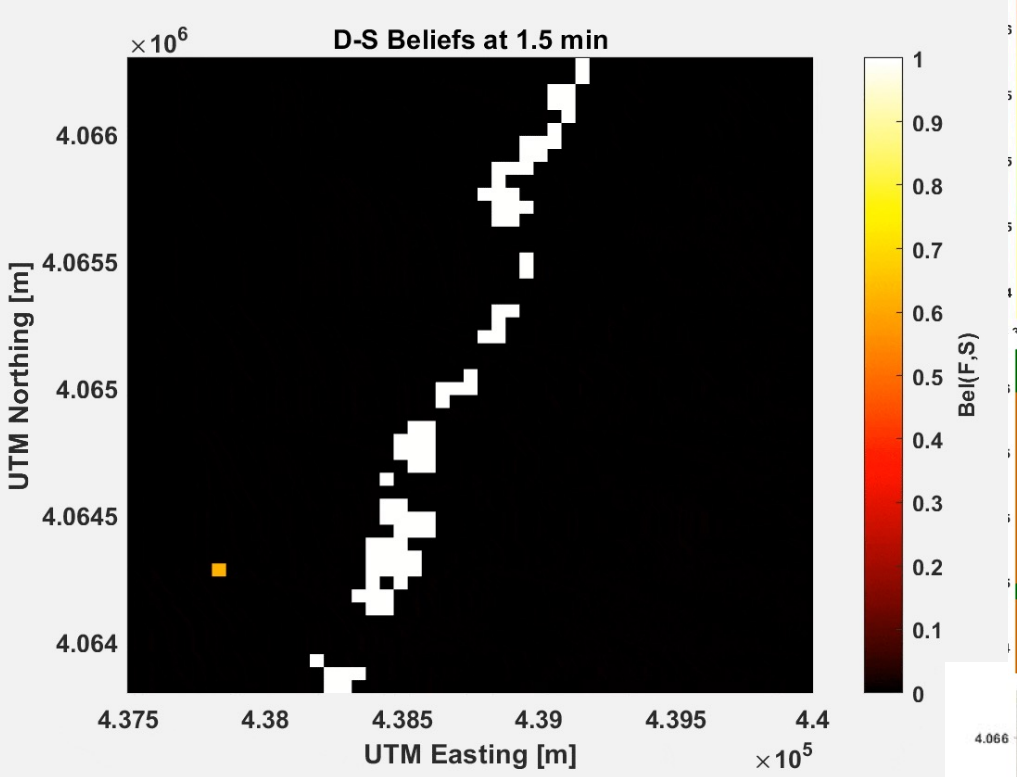
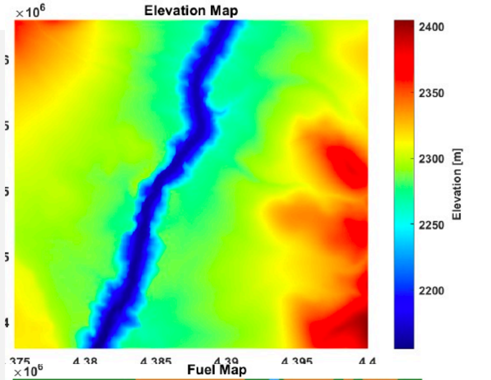
Case Study: Fire in Taos, New Mexico

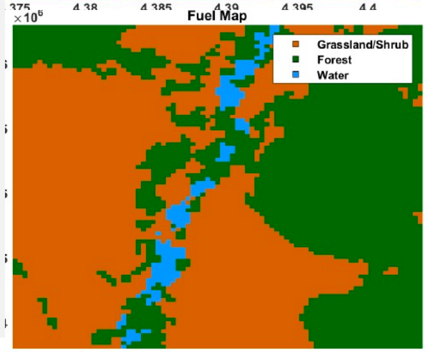


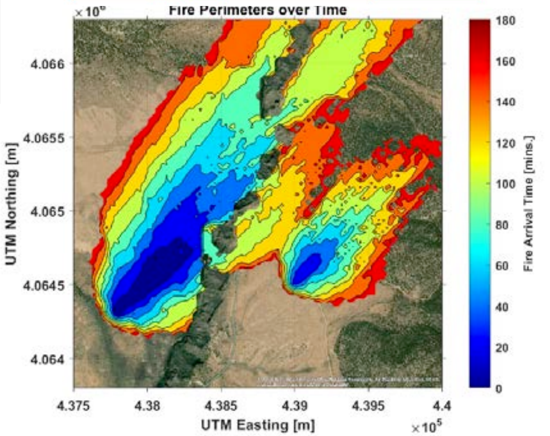
Bayesian Fusion



Evidential Fusion







Soderlund, A., and Kumar, M. "*Autonomous Monitoring of Wildfires with Vision-Equipped UAS and Temperature Sensors via Evidential Reasoning*", F. Darema, E. P. Blasch and and A. J. Aved (Eds.), Springer , 2021

Evidential Fusion: Summary

- An *evidential-expert system* attempts to emulate the decision-making of human beings.

- Decision-making requires a *knowledge base*. When our models of a domain are incomplete, we are forced to represent our uncertainty through epistemic beliefs. DST is one of a myriad of frameworks to do this - the choice is up to the designers.

- The overall approach given here is to i.) form agents' belief models, ii.) combine agents' beliefs and iii.) make decisions regarding those beliefs.

- Why DST was adopted to represent fire belief:
    1. The inputs required for precise forecasts are often not available.
    2. Gathered evidence is ambiguous. This is a limitation of our sensors and the interpretation of their data.
    3. Agent conflict is beneficial to the fire problem. Resolution leads to better forecasts in the future!

- Informed decision-making relies on data and models that may be incomplete. The idea of trust in an autonomous system becomes important here. As an example, trust is quantified through in the DST framework via a "discount factor" prior to evidence combination. More work is needed!

Summary and Lookahead

- Unstructured uncertainty presents special challenges to mission planning and execution

- Use cases in remote, hazardous, “broken” environments present the right context for autonomy

- Learning the environment requires analysis of new modalities of uncertainty, such as ***ignorance*** and ***ambiguity***
  - The evidential framework allows us to perform information fusion despite sensor conflict and bad priors
  - There is need to develop additional mathematical constructs beyond Kolmogorov’s axiomatic framework
  - There is scope to combine evidential reasoning with learning tools to discover new belief functions

- Path planning in a dangerous, unstructured environment presents **path dependent “loading” constraints**, e.g., critical exposure, temperature rise, etc.

- Resource constrained path planning is NP hard. Chance-resource constrained problems have not been considered.

- Graph search offers a suboptimal solution in less time, and allows enforcement of kinematic constraints
  - A new backtracking hybrid A* algorithm has shown excellent results in early tests
  - Current research focuses on stopping criteria and alternate methods for constraint enforcement

- UAS mission planning in unstructured uncertainty (e.g., wildfire) requires many coupled problems to be solved together: much more work is needed on many fronts!

Q&A

Thank You!