



# **Coordinated Control of UAVs for Human-Centered Active Sensing of Wildfires**

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- American Control Conference 2020 (ACC'20) Best Student Paper Award Finalist
- Links:
  - Link to IEEE Xplore: [to be added]
  - Link to arXiv: <u>https://arxiv.org/pdf/2006.07969.pdf</u>
  - Link to Robot Experiment Video: <u>https://www.youtube.com/watch?v=j3YdIO5u\_fE</u>

Abstract - Fighting wildfires is a precarious task, imperiling the lives of engaging firefighters and those who reside in the fire's path. Firefighters need online and dynamic observation of the firefront to anticipate a wildfire's unknown characteristics, such as size, scale, and propagation velocity, and to plan accordingly. In this paper, we propose a distributed control framework to coordinate a team of unmanned aerial vehicles (UAVs) for a human-centered active sensing of wildfires. We develop a dual-criterion objective function based on Kalman uncertainty residual propagation and weighted multi-agent consensus protocol, which enables the UAVs to actively infer the wildfire dynamics and parameters, track and monitor the fire transition, and safely manage human firefighters on the ground using acquired information. We evaluate our approach relative to prior work, showing significant improvements by reducing the environment's cumulative uncertainty residual in firefront coverage performance to support human-robot teaming for firefighting. We also demonstrate our method on physical robots in a mock firefighting exercise.





- According to I.I.I and USFA (U.S., 2016-2019):
  - More than 245,634 wildfires
  - More than 30.9 million acres burned
  - More than 30,000 structures destroyed, and hundreds of people killed
  - More than \$53 billion in damage



- I.I.I. Insurance Information Institute
- USFA United States Fire Administration

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# **Motivation – UAVs for Wildfire Monitoring**

#### • UAVs for Wildfire Monitoring:

- Firefighters need frequent, high-quality images to monitor the fire propagation and plan accordingly
- Due to their agility and hovering capability, UAVs are good candidates to provide firefighters with realtime fire monitoring information









### **Motivation – Human-Centered Active Sensing**







#### **Motivation – Human-Centered Active Sensing**





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# **Preliminaries – Wildfire Propagation Model**





















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### **Method – Uncertainty Control Component**





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- Criteria 1 Uncertainty-based Controller:
  - Firefront Uncertainty Map:





















- Uncertainty Controller Component:
  - Total Uncertainty Map:

$$\mathcal{U}_t^{tot} = \mathcal{U}_t^f + \mathcal{U}_t^h$$

- Uncertainty Controller Input  $(u_d^{ucc})$ :

$$\underbrace{u_{d,t}^{ucc}}_{d,t} = -\kappa_1 \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d} = -\left[\kappa_{x1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^x}, \kappa_{y1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^y}, \kappa_{z1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^z}\right]$$

- Formation Controller Component:
  - Formation Controller Input  $\left(u_d^{fcc}\right)$ :  $u_d^{fcc} = -\kappa_2 \frac{\partial \mathcal{E}_t}{\partial p_d} = -\left[\kappa_{x2} \frac{\partial \mathcal{E}_t}{\partial p_d^x}, \kappa_{y2} \frac{\partial \mathcal{E}_t}{\partial p_d^y}, \kappa_{z2} \frac{\partial \mathcal{E}_t}{\partial p_d^z}\right]$
- Combining the Two Forces:  $p_{t+\delta t}^{v} = p_{t}^{v} - (u_{d}^{ucc}) - (u_{d}^{fcc}) \delta t$
- Path Planning Controller:

$$u_{d,t} = \sum_{i} \left( u_{d,t}^{att} + u_{d,t}^{rep} \right)$$
 ,  $\forall i \in \{\mathcal{F}_t\}$ 



• Final UAV Position Update:  $p^d_{t+\delta t} = p^d_t + u_{d,t} \delta t$ 





### **Empirical Evaluation – Simulation**



World size	# initial firespots	location range	(e.g., $R_t$ , $U_t$ , $\theta_t$ )	# drones	Initial UAV location range	UAV's initial altitude	UAV's allowable altitude range	UAV's camera half-angles	$\delta$ and $\Delta$
$500 \times 500$	20	[50, 100]	According to Pham et al. (2017)	5	[50, 300]	0	[15, 45]	$\left[\frac{\pi}{4}, \frac{\pi}{6}\right]$	50 and 500





# **Empirical Evaluation – Coverage Performance**

#### • Benchmarks:

- 1. Model-based Distributed Controller (Pham et al. 2017)
  - Incorporates the FARSITE model and a model for heat-intensity
  - Artificial Potential Field Based Distributed Controller

#### 2. Deep Reinforcement Learning (RL) Baseline

- Policy network with 4 convolutional layers and 3 fully-connected layers
- Image of fire-area as an input and direction for UAVs as output
- Reward is the negative sum of all uncertainty residuals across entire map



World size	# initial firespots	Initial firespots location range	FARSITE Model Parameters (e.g., $R_t$ , $U_t$ , $\theta_t$ )	# drones	Initial UAV location range	UAV's initial altitude	UAV's allowable altitude range	UAV's camera half-angles	$\delta$ and $\Delta$
$500 \times 500$	20	[50, 100]	According to Pham et al. (2017)	5	[50, 300]	0	[15, 45]	$\left[\frac{\pi}{4}, \frac{\pi}{6}\right]$	50 and 500





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- Image of fire-area as an input and direction for UAVs as output
- Reward is the negative sum of all uncertainty residuals across entire map
- 3. Deep RL Wildfire Coverage Benchmark (Haksar et al. 2018) (not included in this paper)



World size	# initial firespots	Initial firespots location range	FARSITE Model Parameters (e.g., $R_t$ , $U_t$ , $\theta_t$ )	# drones	Initial UAV location range	UAV's initial altitude	UAV's allowable altitude range	UAV's camera half-angles	$\delta$ and $\Delta$
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### **Empirical Evaluation – Safety Index**

• Individualized Temporal Human Safety-Index:





### **Empirical Evaluation – Safety Index**

• Individualized Human Safety-Index:



Ratio is the direction unit vector

















#### • References:

- 1. Pickem, Daniel, et al. "The Robotarium: A remotely accessible swarm robotics research testbed." 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017.
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- 4. Pham, Huy X., et al. "A distributed control framework for a team of unmanned aerial vehicles for dynamic wildfire tracking." 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017.
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# **Appendix – Wildfire Propagation Model**



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• Criteria 1 – Uncertainty-based Controller: – Firefront Uncertainty Map: $\hat{q}_t = argmax \rho(q_{t-1}, p_{t-1}, \mathcal{M}_t, \mathcal{O}_t, q_t)$ $q_t$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $
Transition Jacobian Matrix: $ \frac{\partial f}{\partial \Theta_i}\Big _{\hat{\Phi}_{t'}} = \frac{q_t^x}{p_t^{(3)}} \left  \begin{array}{ccc} q_t^x & q_t^y & p_{t'}^{(3)} & R_{t'} & U_{t'} & \theta_{t'} \\ 1 & 0 & 0^{(3)} & \frac{\partial q_t^x}{\partial R_{t'}} & \frac{\partial q_t^x}{\partial U_{t'}} & \frac{\partial q_t^y}{\partial \theta_{t'}} \\ 0 & 1 & 0^{(3)} & \frac{\partial q_t^y}{\partial R_{t'}} & \frac{\partial q_t^y}{\partial U_{t'}} & \frac{\partial q_t^y}{\partial \theta_{t'}} \\ 0 & 0 & 0^{(3)} & 0 & 0 & 0 \\ 0 & 0 & 0^{(3)} & 1 & 0 & 0 \\ 0 & 0 & 0^{(3)} & 0 & 1 & 0 \end{array} \right  $	$\min \mathcal{H} = \operatorname*{argmax}_{q_t^i, p_t^d} \left( \int_{i \in Q} \mathcal{U}_t^{tot} \left( q_t^i \right) dq - \int_{d \in N} \mathcal{E}_{dj} \left( \left\  p_t^d - p_t^{j/d} \right\  \right) dp \right)$
$\frac{\partial q_t}{\partial R_{t-1}} = \left(1 - \frac{LB(U_{t-1})}{LB(U_{t-1}) + \sqrt{GB(U_{t-1})}}\right) D(\theta) \delta t \qquad \qquad$	
$\frac{\partial q_t}{\partial \theta_{t-1}} = R_{t-1} \left( \frac{1 - LB(U_{t-1})}{LB(U_{t-1}) + \sqrt{GB(U_{t-1})}} \right) \frac{\partial D(\theta)}{\partial \theta} \delta t$	
$\frac{\partial q_t}{\partial U_{t-1}} = \frac{R_{t-1} \left( LB(U_{t-1}) \frac{\partial GB(U_{t-1})}{\partial U_{t-1}} - GB(U_{t-1}) \frac{\partial LB(U_{t-1})}{\partial U_{t-1}} \right)}{\left( LB(U_{t-1}) + \sqrt{GB(U_{t-1})} \right)^2} D(\theta) \delta t$	







- Uncertainty Controller Component:
  - Total Uncertainty Map:

$$\mathcal{U}_t^{tot} = \mathcal{U}_t^f + \mathcal{U}_t^h$$

- Uncertainty Controller Input  $(u_d^{ucc})$ :

$$u_{d,t}^{ucc} = -\kappa_1 \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d} = -\left[\kappa_{x1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^x}, \kappa_{y1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^y}, \kappa_{z1} \frac{\partial \mathcal{U}_t^{tot}}{\partial p_d^z}\right]$$

- Formation Controller Component:
  - Formation Controller Input  $\left(u_d^{fcc}\right)$ :  $u_d^{fcc} = -\kappa_2 \frac{\partial \mathcal{E}_t}{\partial p_d} = -\left[\kappa_{x2} \frac{\partial \mathcal{E}_t}{\partial p_d^x}, \kappa_{y2} \frac{\partial \mathcal{E}_t}{\partial p_d^y}, \kappa_{z2} \frac{\partial \mathcal{E}_t}{\partial p_d^z}\right]$
- Combining the Two Forces:

$$p_{t+\delta t}^{v} = p_{t}^{v} - \left(u_{d}^{ucc} - u_{d}^{fcc}\right)\delta t$$

• Path Planning Controller:

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$$u_{d,t} = \sum_{i} \left( u_{d,t}^{att} + u_{d,t}^{rep} \right) \text{ , } \forall i \in \{\mathcal{F}_t\}$$



Final UAV Position Update:  

$$p_{t+\delta t}^{d} = p_{t}^{d} + u_{d,t}\delta t$$

 $\mathcal{D}_{d}^{rep} = \begin{cases} \frac{1}{2} \kappa_{g} \left( \frac{1}{\|p_{g}^{d} - p_{t}^{d}\|} - \frac{1}{\gamma} \right)^{2} & if \quad \left\| p_{g}^{d} - p_{t}^{d} \right\| < \gamma \\ 0 & \text{otherwise.} \end{cases}$  $u_{d}^{rep} = -\zeta \nabla \mathcal{D}_{d}^{rep}$  $= -\zeta \kappa_{g} \left( \frac{1}{\|p_{g}^{d} - p_{t}^{d}\|} - \frac{1}{\gamma} \right) \frac{1}{\|p_{g}^{d} - p_{t}^{d}\|^{3}} \left( p_{g}^{d} - p_{t}^{d} \right)$