Fire Frontline Monitoring by Enabling UAV-Based Virtual Reality with Adaptive Imaging Rate

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***Abstract*—Recently, using drones for forest fire management has gained a lot of attention from the research community due to their advantages such as low operation and deployment cost, flexible mobility, and high-quality imaging. It also minimizes human intervention, especially in hard-to-reach areas where the use of ground-based infrastructure is troublesome. Drones can provide virtual reality to firefighters by collecting on-demand high-resolution images with adjustable zoom, focus, and perspective to improve fire control and eliminate human hazards. In this paper, we propose a novel model for fire expansion as well as a distributed algorithm for drones to relocate themselves towards the front-line of an expanding fire field. The proposed algorithm comprises a light-weight image processing for fire edge detection that is highly desirable over computational expensive deep learning methods for resource-constrained drones. The positioning algorithm includes motions tangential and normal to fire frontline to follow the fire expansion while keeping minimum pairwise distances for collision avoidance and non-overlapping imaging. We proposed an action-reward mechanism to adjust the drones' speed and processing rate based on the fire expansion rate and the available onboard processing power. Simulations results are provided to support the efficacy of the proposed algorithm.**

***Index Terms*—UAV networks, fire monitoring, virtual reality, autonomous control, image-based edge detection.**

I. Introduction

Wildfires are one of the costliest and deadliest natural disasters in the US, especially in the West, resulting in damage to millions of hectares of forest resources, evacuation of thousands of people, burning of homes and damage to infrastructure, and most importantly, threatening the lives of people and animals [1]. Moreover, wild-land fires directly impact forestry operations, which produce wood fiber and biomass fuels, and other forms of agriculture, by spreading into farms and damaging ecosystems with negative consequences on water quality and other ecosystem services [2], [3]. NIST estimates that the annualized costs of wildfires range from \$7.6 billion to \$62.8 billion, while the annualized losses due to the wildfires are an order of magnitude higher, ranging from \$63.5 billion to \$285.0 billion [1]. Wildfire suppression costs exceeded \$2 billion in 2017, breaking the all-time record [4]. The rapidly increasing risk of fire, due to recent widespread extreme drought conditions and climate change, calls for new national strategies to prevent and manage wildfires.

This work considers using a fleet of autonomous unmanned aerial vehicles (UAVs), known as drones to enable virtual reality (VR) for enhanced forest fire monitoring by providing on-demand high-resolution closed-up images from fire front line. Unmanned aerial vehicles (UAVs) known as drones offer flexible, low-cost, and scalable solutions for many applications due to their inherent advantages such as free-mobility, low operation cost, and limited human interventions especially after recent advances in enhancing their flight stability, autonomous control and computational capacity [6]–[8]. Several research teams are working to solve technical issues related to the use of autonomous drones by introducing spectrum management methods [9], [10], networking [11], predictive routing protocols [12], [13], optimal compression policies [14], autonomous path planning [15]–[17], and 5G communication [18].

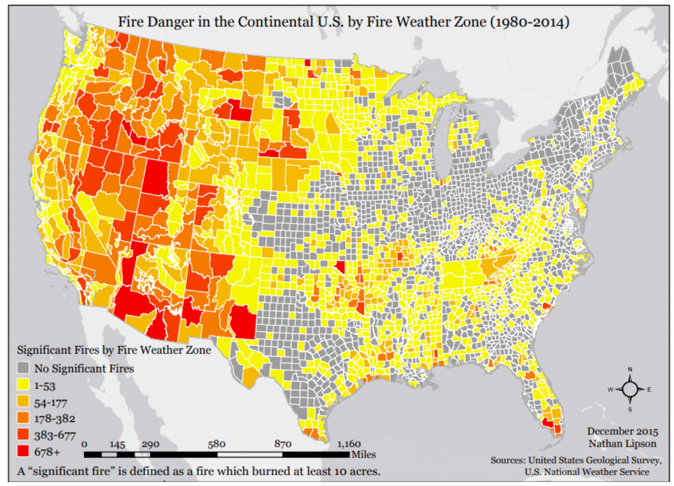


Fig. 1: Fire danger map in the continental U.S. by fire weather zone (2980-2014) [5]

A newly introduced application is forest fire control, where a network of UAVs can offer virtual reality to firefighters through on-demand high-resolution video streaming, which minimizes human intervention and hazard risks [19]. It has a clear advantage over satellite imaging as well as observation towers in terms of controllability, flexible perspective and focus, higher update rate, and lower cost [20]. Recently, the idea of using drones to ignite managed fires to burn out the vegetation fuel of surrounding regions to control fire expansion

Note that there are alternative approaches for fire detection and monitoring, e.g., using ground sensors, remotely piloted vehicles (RPV), or satellite imaging [21]. However, their drawbacks are (i) delayed fire detection due to missing small fire at early stages, (ii) time lag for satellites to overpass the field, and (iii) infeasibility of using a wide range of sensors with limited sensing distance range (e.g., chemical-based smoke detectors). Current forest fire suppression and management involve ground-based personnel and equipment, and manned aircraft, which puts flight personnel at risk and is costly to operate.

Most of the projects that utilize drones for fire monitoring and management use remote controlling to guide drones for monitoring and control operations, that can be troublesome in vast forest fires in hard-to-reach areas when human intervention is costly and risky. This paper offers a fully automated and distributed navigation algorithm for UAV networks to optimally cover the front-line of an expanding fire field.

II. System Model

Suppose that a set of N drones denoted by $n_1, n_2, \ldots, n_N$ are utilized to monitor an expanding fire field with the goal of following fire front-line while maintaining maximal pairwise distances to ensure maximal coverage. The expanding fire field is modeled as a continuous time-varying closed region $D = (x, y)$ as elaborated in section II-A.

In [15], a navigation method is proposed based on Q-learning to guide drones from their randomly initialized positions towards the fire front-line while avoiding collision to stationary obstacles. Using this approach, in this work we assume that the drones are located on the fire boarder line with positions denoted by $\mathbf{p}_1(0), \mathbf{p}_2(0), \ldots, \mathbf{p}_N(0)$, where $\mathbf{p}_i(t) = (x_i(t), y_i(t))$ is the position of drone n_i at time t. The drones maintain a minimum pairwise distance d_{min} for collision avoidance.

Each drone is assumed to be equipped with a thermal camera with a limited field of view and a distance tracking system. Drones are not allowed to convene with one another nor with a ground station and take their decisions based on on-board processing of their captured images, to enable a robust and scalable system.

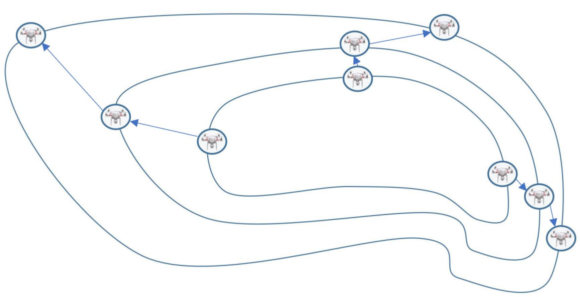


Fig. 2: Autonomous relocation of drones with respect to the evolving fire.

A. Fire Propagation Model

OF), and (ii) burned-out (BO). Also, each cell, within a continuous region with an arbitrary shape, is associated with a randomly initialized fuel value $f(i, j)$ to mimic the effect of vegetation fuel across the forest. The fire ignition is started with K randomly selected seed points and probabilistically spreads out to the neighbouring cells considering the fuel and wind factors. In particular, if vector $\vec{w}$ represents the wind direction, and $\vec{v}_{n,m}$ is the vector connecting adjacent cells $n(i, j)$ to $m(i \pm 1, j \pm 1)$, then the state of node m changes to OF if the following conditions are satisfied: (i) $p(n) = OF$, (ii) $p(m) = NF$, and (iii) $f(m) \geq 0$. The state change occurs with probability $p_{n,m} = p_0 + p_1 \langle \vec{u}_{n,m}, \vec{w} \rangle$, where p_0 is the baseline fire spread probability, and p_1 captures the wind effect. On-fire

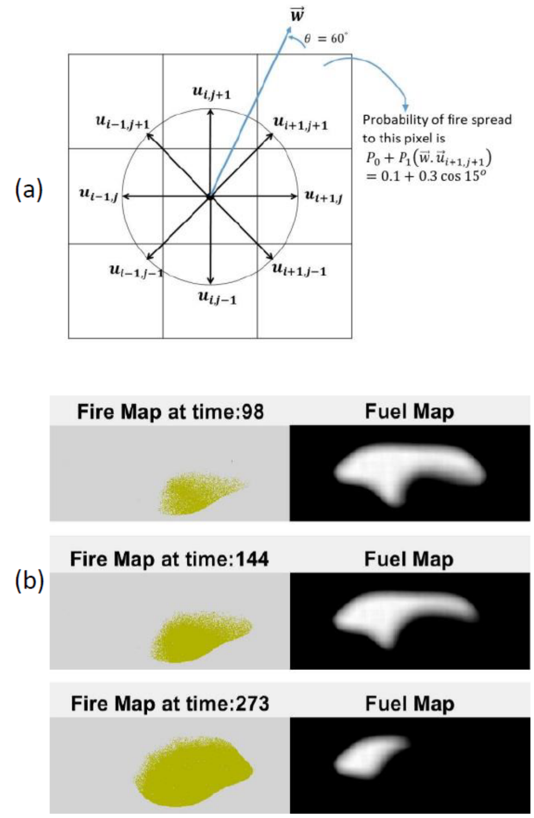


Fig. 3: Fire propagation model. **top:** fire spread model that represents probability of fire spread to adjacent cell for nominal values of baseline propagation probability $p_0 = 0.1$, the wind-dependent propagation probability $p_1 = 0.3$, and wind vector $\vec{w} = 1e^{j30^\circ}$. bottom: shows a typical fire spread model for three time points $t = 98$, $t = 144$ and $t = 273$. Left column shows the fire spread, and the right column represent the fuel burnout.

cells change to BO after their fuel burns out with a predefined rate. Note that this gives discrete states for cells; however, we apply a 2D Median filter to smooth out the discrete values into a continuous field, which translates the density of on-fire cells into higher fire intensity as a reasonable model for thermal camera. Fig.3 illustrates the proposed fire expansion model.

III. Autonomous Navigation

The navigation algorithm operates based on determining the fire front-line orientation, as follows.

A. Fire Edge Detection

Each drone has a limited field of view (FoV), represented by a $(w \times w)$ square, based on the utilized thermal camera sensitivity and the hovering altitude. Here, we used the following multi-step procedure to find a line tangential to fire map (See Fig. 6). The first stage is **denoising**, where we use median filtering (2D median filter) to smooth out the image. The next step is **segmentation**, where each input heatmap is clustered into two segments based on the fire intensity using the unsupervised k-means clustering algorithm. This segmentation provides binary labels for each pixel, which is used by

Fig. 4: Field of View (FOV) of a drone.

the subsequent **classification** stage to find the optimal linear line that separates the region into two segments using a support vector machine (SVM). The coefficients of support vectors in SVM are used to obtain the tangential line passing through the border between the two regions. The third state is **validation** to avoid calling a false fire frontline, especially when the covering heatmap essentially includes only one dominant region (OF or NF). In these circumstances, the obtained frontline is shaky and can significantly change from one-time point to the next. We use this fact and reject the results if the difference between the orientation of current and previously obtained frontline exceeds a predetermined threshold (i.e., $|\theta_t - \theta_{t-1}| \geq \theta_{\max}$). The proposed three-step algorithm provides a reliable edge detection mechanism with a complexity far below the popular convolutional neural networks [22]; therefore, it is appropriate for drones with limited computation powers. A summary of the proposed method is presented in Algorithm 1.

Algorithm 1 Algorithm for Fire Spread Monitoring

Initialization: Initialize model parameters (assign fuel value to each cell; locate natural obstacles; set the wind speed, and wind-based propagation model parameters) Set the locations for the drones

while *Fire in-progress* **do**
  for *UAV i=1 to N* **do**
    Take picture of pixel size $w_i \times h_i$
    Use median filtering to smooth out the image
    Use K-means to classify pixels between fire vs background
    Use SVM classifier to draw the boundary between the fire and non-fire region
    Validate the new boundary by comparing against its history; reject if substantial changes are observed
    Move UAV to the new position according to the method in section III-B
    Move to the optimal position
  end
end

B. Optimal Positioning

The goal of this step (positioning) is to relocate drones according to the expanding fire frontline. In order to perform the positions, following our previous work [15], we use an action-reward mechanism.

To calculate the reward for each action, each drone considers the following three factors: (i) distance between its position and the estimated mid-point location of the fire line, (ii) its alignment with respect to the fire line's midpoint (whether the drone is within a region adjacent to the mid-point or not) and (iii) the location of other drones within a circular area surrounding the drone. It is expected for the drones to keep a minimal distance $d^c_{\min}$ from one another to avoid collision and also overlapping FOV. Likewise, they shall keep the minimum distance $d^f_{\min}$ from the fire frontline to avoid the hazardous effect of the fire. Drones encounter two different cases when fining the optimal locations.

Case-I, where the Euclidean distance between two nearby drones is $d^c_{\min}$ or more. In that scenario, drones do not need to consider the location of nearby drones for determining the optimal location. In that case, the optimal location lies on the perpendicular line to the fire front tile passing through the midpoint, where the gradient of the change is maximum (vertical motion). The distance from the midpoint d_v, however, depends on the fire expansion rate as well as the minimum allowable distance to the fire front line (i.e. $d_v > d^f_{\min}$) to ensure the safety of drones.

Case-II, where the Euclidean distance between two nearby drones is below $d^c_{\min}$. To avoid overlapped scanning, two drones should increase their pair-wise distances by moving alongside the fire frontline in the opposite directions until they achieve the minimal pairwise distances $d^c_{\min}$ (tangential motion). These two scenarios are demonstrated in Fig. 5.

In order to reduce the onboard processing burden, we define a parameter called processing rate (p_r). Initially, the parameter is assigned to a default value based on the prior information. During the mission, this parameter is adjusted based on the fire expansion rate as well as the available

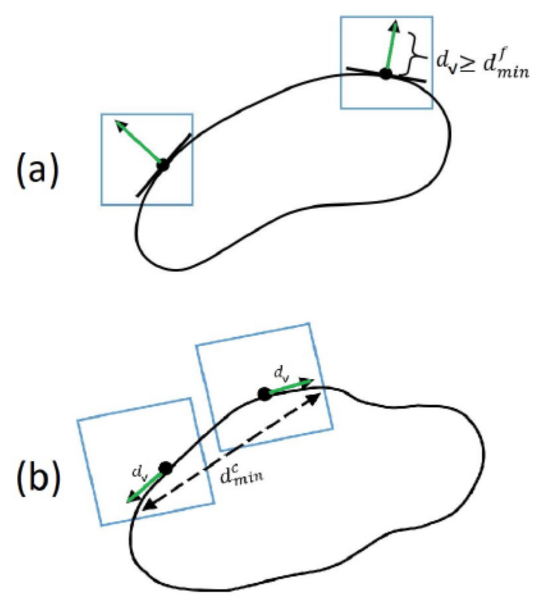


Fig. 5: Drone re-positioning. (a) vertical motion in case I to follow fire front line; (b) tangential motion in case II to avoid collision.

computational resources. In order to make the algorithm robust and responding to the change in fire direction/speed, we developed a simple optimization function that optimizes the motion steps by minimizing the lag from the fire frontline location, while keeping the frequency of measurements within the constraint defined by the onboard processing power of drones.

IV. Results

In this section, we illustrate some numerical results based on the simulated fire expansion (using the model provided in section II-A) as well as one exemplary real-world fire image.

Fig. 6 illustrates the accuracy of the proposed method to estimate the fire frontline (shown by the red line) through processing the acquired heatmap after proper validation (section III-A).

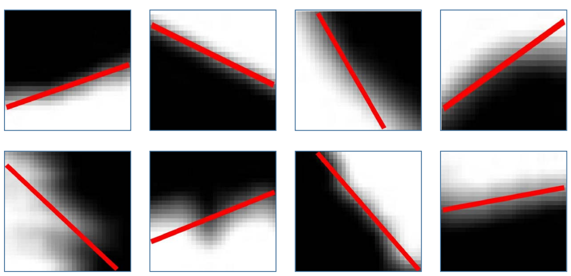


Fig. 6: Fire frontline detection using the three-step algorithm.

Fig. 7 shows that the developed action-reward mechanism performs well in adjusting the average motion rate with the fire expansion rate under a constant step motion size d_v. It shows that the rate of motion almost linearly increases for faster-expanding fires. Part of the non-linearly is due to fire edge detection errors as well as tangential re-positioning for collision avoidance. Also, for larger motion step sizes, the rate is lower as expected.

Likewise, Fig. 8 presents the relationship between the FoV processing rate and the fire expansion rate at different step sizes. The algorithm achieves lower processing rates for slow-growing fire regions that show the efficacy of the proposed rate-adaption mechanism to control the processing rate of drones (by adjusting p_r) in order to save in the costly onboard processing units that can prolong the mission time. Also, it is seen that the required processing rate is higher when the relocation step size is lower. This observation highlights the need for further investigation to balance between the agility and optimality of the proposed imaging-based navigation algorithm.

In order to show the utility of the proposed algorithm in real-world scenarios, we also apply the fire frontline detection to an exemplary fire image in Fig. 9 after some proper modifications to the algorithm. This figure presents a wildfire captured by the satellite (top) as well as the identified fire filed (bottom). Initially, we detect the fire area by implementing image segmentation based on color characteristics detection. Our method is to identify pixels that represent fire based on a set of rules that processes color characteristics of an image

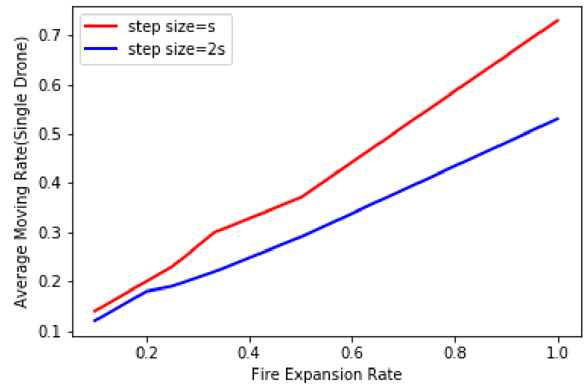


Fig. 7: Performance of Drones in responding the change in fire expansion rate.

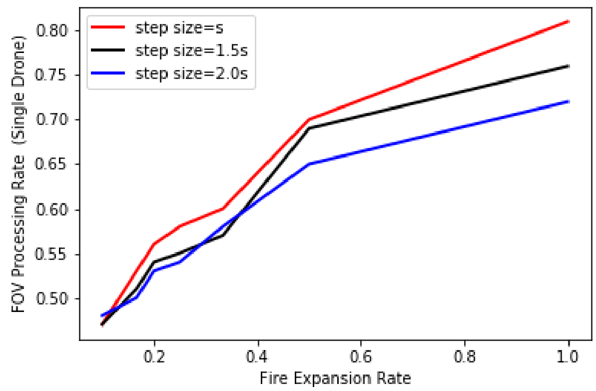
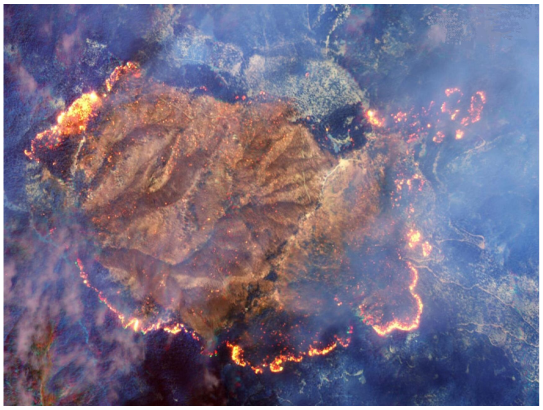


Fig. 8: FOV processing rate vs fire expansion rate.

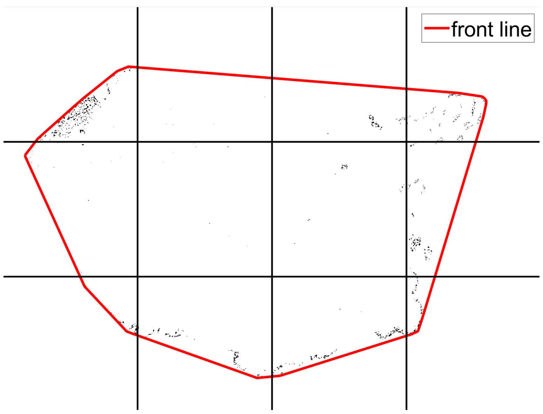
in RGB format as well as the hue/saturation/intensity (HSI) proprieties, proposed in [24]. Then, we identify a closed loop that encompasses all the fire pixels within one curved convex shape.

The study in [24] provides 4 rules for the fire area segments based on comparing the color components (intensity of pixels in any of the R, G, and B planes) and the image saturation (S) and overall intensity (I) against predefined thresholds. For instance, R_T is the threshold of the Red component that should be set between 55 and 56 by experiment. Likewise, S_T is the threshold of the pixel situation which is set to 125 through intensive test [24]. To increase the segmentation accuracy, we add pixel intensity (I) to the fire segmentation rules, which should be greater than $I_T = 83$.

Essentially, the process of fire frontline detection of real-world fire images includes the following steps. Firstly, we traverse all of the pixels to identify pixels that comply with the color characteristics rules. Then, we associate binary labels to the pixels that represent fire vs non-fire pixels. Finally, we find out the optimal linear borderline of the fire area. Fire area segmentation based on the color detection rules provides a high accuracy through a simple and low-complexity algorithm compared to more computationally-expensive deep-learning methods; therefore highly desirable for resource-constrained UAVs. We can also improve the accuracy of segmentation by adding more constraint rules.



(a)



(b)

Fig. 9: (a) A fire image in Klamath National Forest taken by the SWIR sensor on Digital Globe's new WorldView-3 satellite [23]. (b): detected fire frontline.

V. Conclusions

This paper implements a novel navigation algorithm for a fleet of autonomous drones to optimally monitor a spreading fire frontline through localized fire edge detection. The positioning algorithm comprises two tangential and vertical motions with respect to the fire edge, where the first is to maintain a minimum distance between adjacent drones and the latter is to ensure drones follow the fire frontline. This approach minimizes human intervention through the remote control of drones in hazardous situations. The trade-off between the agility and optimality of the algorithm is addressed by adjusting the relocation step size and the image processing rate based on an action-reward mechanism, which needs further investigation. Simulation results verify the performance of the proposed algorithm.

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