Abstract: A Review on Image-Based Wildfire Detection Systems

***Abstract*— With the constant threat of wildfires, humanitarian organizations and local communities call for an effective localized detection and warning system of wildfire. Wildfire detection personnel from agencies such as FIRESafe Marin and CalFire currently observe many cameras at once to find potential wildfires, leading to fatigue and requiring massive amounts of manpower. Implementing automated wildfire detection through image processing and machine learning can lead to 24-hour camera monitoring over large areas of interest using less personnel. This review compares image-based wildfire detection methods to find suitable candidates for automatic wildfire detection systems.**

Keywords—wildfire, detection, image processing, machine learning

I. Introduction

Wildfires have burned through 3.7 million acres this year in California and pose a constant threat to millions of people. Humanitarian organizations and local communities call for an effective localized detection and warning system of wildfire which requires reliable and accurate fire detection. Currently, fire detection personnel observe many monitoring cameras day and night to find potential fires, which requires a large amount of employees and leads to fatigue. Many of these cameras are unable to find fires without a person manning them, allowing some fires to go undetected and grow rapidly. Implementing automation allows for 24-hour monitoring without intensive human intervention and the ability to increase the monitored areas of interest just by installing additional automatic devices. There are a number of research works on wildfire detection. Some of them use image processing such as YCbCr and Canny edge detection, and recent application of machine learning methods such as YOLO (You Only Look Once) and 3D-3DFCN showed promising results. We analyze these recent work and perform our preliminary tests on a machine learning method.

II. Image Processing-Based Systems

A. Image Processing and Fire Detection

These methods require image transformation algorithms and classifiers. An algorithm is given an image (in RGB color, infrared, etc.) and transforms it through changing pixel values, analyzing the movement of objects, or other methods. YCbCr method converts the red, green, and blue values of an RGB image to luminance (Y) and chrominance (Cb and Cr) values of the new image, creating the distinction between fire and landscape as shown in Fig. 1.

Fig. 1. RGB Image (left), YCbCr Processed Image (Right)

The Canny edge detection method applies a first derivative operator to all pixels that calculates the gradient and magnitude direction of each. Then, the edges are tracked by following the sharpest gradient differences between nearby pixels which creates a connect-the-dots pattern in Fig. 2.

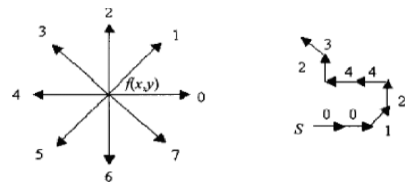

Fig. 2. Potential Gradients Adjacent to a Pixel (LEFT). Edge Tracing Using Sharpest Gradients (Right) [1]

B. Classifiers

Once an image is transformed, a classifier can be implemented to check pixels and determine if a fire or an object of interest is presented. A classifier introduced in Premal's work [2] utilizes multiple rules. For instance, one rule checks if the average luminance value (Y) is greater than the chrominance values (Cb and Cr) to ensure there is a high luminance value somewhere in the image. A classifier used in Qin's work [1] extracts the edges after following the sharpest gradients, then smoothes the boundaries to make clearer edges. The two classifier equations are a 2D Gaussian filtering template to remove flickering and a derivative classifier that uses two directional derivatives to finalize the edges. The results of the algorithm and classifiers are in Fig. 3.

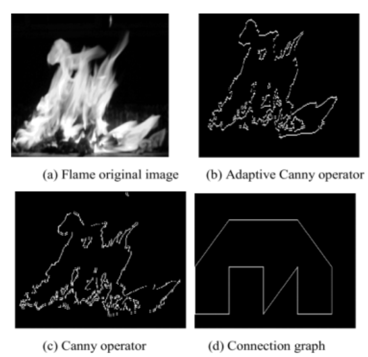

Fig. 3. Steps of Canny Edge Detection [1]

III. Machine Learning-Based Systems

YOLO is an object detection method that uses the entire image to train and gain a global context for many objects, as compared to other detection methods that train using separate image regions. Fig. 4 illustrate its architecture: the detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1 x 1 convolutional layers reduce the features space from preceding layers. Convolutional layers

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are pretrained on the ImageNet classification task at half the resolution and then double the resolution for detection [3].

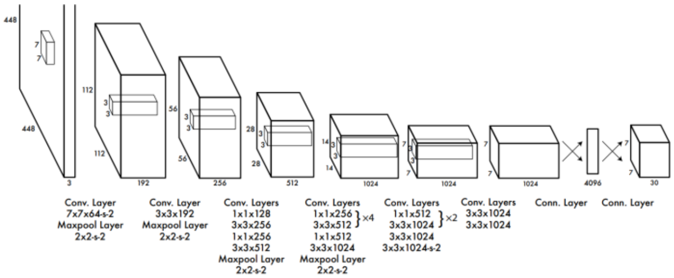

Fig. 4. YOLO v3 Architecture [3]

3DFCN uses deep learning to segment 3D objects into their labelled parts. Fig .5 shows its structure, where the density of the grid represents the pixel level. The denser the grid, the higher the pixels. Solid line upsamples back to pixels using one 2D deconvolution layer. Dash-dotted line combines prediction from both the final layer and Pool3 layer using 3D deconvolution. Dotted line adds prediction with Pool2 [4]. For wildfire detection, Li, et. al.'s work aimed to detect smoke trails and determine their location through video clips of movement as illustrated in Fig. 6. The neural network observes smoke movement during training videos to find smoke through pixel movements.

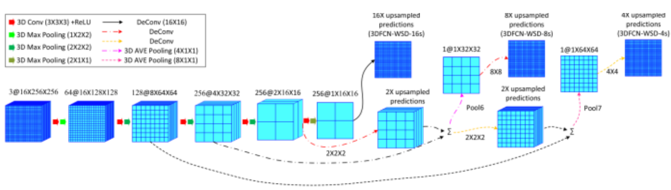

Fig. 5. Structure of 3DFCN [4]

Fig. 6. Original Image (Left), 3DFCN Isolation of the Smoke After Detection (Middle), Smoke Outlined Based on the Isolated Image (Right). [4]

IV. Comparison Between Wildfire Detection Systems

Image based fire detection requires image processing and a classifier to determine the object of interest. Both require considerable amounts of computational complexity, as shown in the reviewed paper, but can lead to promising results in wildfire and edge detection with room for improvement. The reviewed YCbCr method had a 99.4% detection rate but 12% false alarm rate. In comparison, Shen et al's YOLO training model [5] reached detection accuracies of up to 76% after extensive training. Li's 3DFCN neural network method [4] reached up to 90% accuracy in detecting smoke trails. Table I gives a comparison of the discussed detection systems. The ability for YOLO and 3DFCN to discover the most miniscule patterns in objects we are looking for is exceptional, especially in our preliminary experiment results.

TABLE I. COMPARISON OF DETECTION SYSTEMS

	YCbCr	Canny edge	YOLO v3	3DFCN
Cost	Low	Low	Medium	Medium
Faulty alarms repetition	High	Medium	Low	Low
Fire detection accuracy	Medium	Medium	High	High
Detection delay	Low	Low	Low	Low
Adaptively for other object detection	Low	Low	High	High

In our preliminary tests, we trained a YOLO v3 network with a relatively small database of 30 pictures of wildfires varying in distances and illumination. Although it is recommended to have about 400 images to create a detection system, our test results in Fig. 7 shows great potential for automatic fire detection using machine learning.

Fig. 7. Preliminary Test Results Using YOLO v3.

V. Conclusion and Future Work

Wildfires are a devastating problem that require effective monitoring to mitigate. Limited capability of the current camera systems and low level of automation call for implantation of automated detection. Our review shows some image processing methods can be very robust for different illumination scenarios or locations, and machine learning can be trained and adapted to various deployment scenarios. Based our preliminary test, we confirm that machine learning has a great potential for future automatic wildfire detection systems. We will continue explore the methods to build a prototype automatic wildfire detection system and conduct real world experimentations.

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