A Review on Image-Based Wildfire Detection Systems

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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 number 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 the recent application of machine learning methods such as YOLO (You Only Look Once) and 3DFCN (Fully Convolutional Network) showed promising results. We analyze these recent works and perform our preliminary tests on a machine learning method.

IMAGE PROCESSING-BASED SYSTEMS

a) Image Processing: 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.

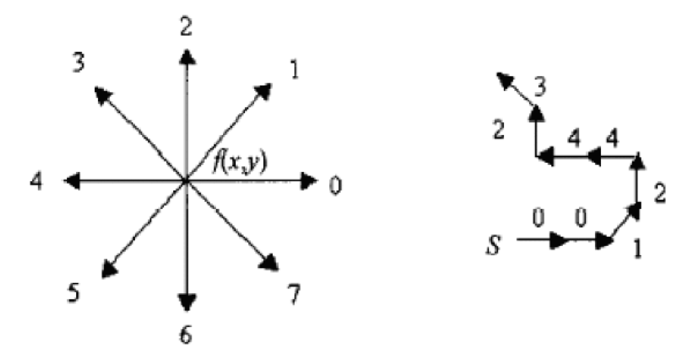

Fig. 2. Potential Gradients Adjacent to a Pixel (LEFT). Edge Tracing Using Sharpest Gradients (Right) [1]

b) Fire Detection: Once an image is transformed, Premal's work [2] utilizes multiple rules to check pixels and determine if a fire is presented. 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 smooths 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.

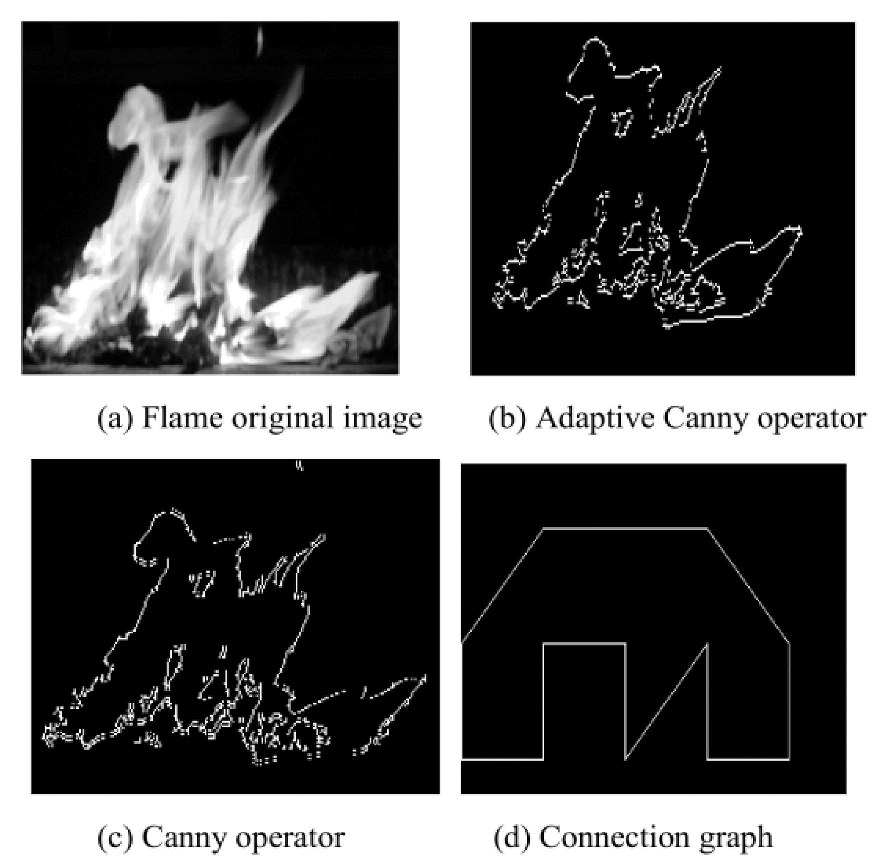

Fig. 3. Steps of Canny Edge Detection [1]

MACHINE LEARNING-BASED SYSTEMS

Machine learning allows computers to self-learn from a training dataset by making connections without human intervention. 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 illustrates 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 are pre-trained on the ImageNet classification task at half the resolution and then double the resolution for detection [3].

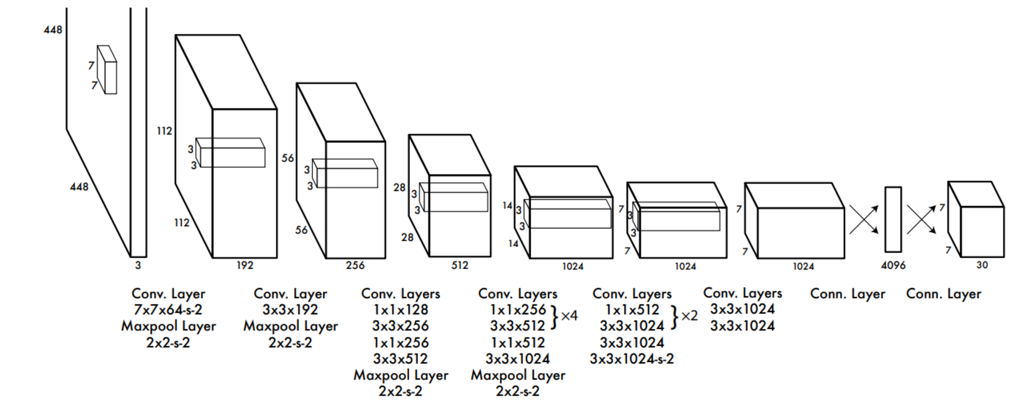

Fig. 4. YOLO v3 Architecture [3]

3DFCN uses deep learning to segment 3D objects into their labeled parts. Fig .5 shows its structure, where the density of the grid represents the pixel level. The solid line in Fig. 5 upsamples back to the original amount of pixels using a 2D deconvolution layer. The dash-dotted line combines prediction from both the final layer and the 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.

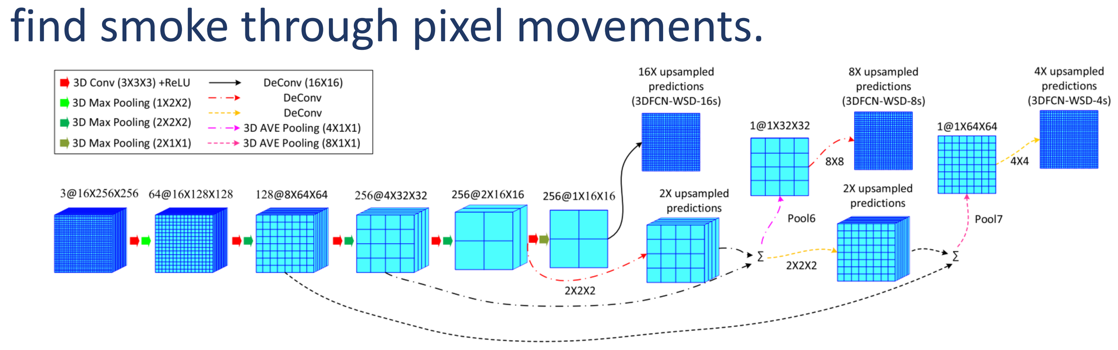

Fig. 5. Structure of 3DFCN [4]

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

COMPARISON BETWEEN WILDFIRE DETECTION SYSTEMS

Image-based fire detection requires image processing and rules or a classifier to determine the object of interest. The reviewed YCbCr method and rule-based decision performs pixel-wise segmentation and has the ability to locate the position of the fire in an image. However, the author only uses binary detection (fire or no fire) to get a higher detection rating. 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.

TABLE I. COMPARISON OF DETECTION SYSTEMS

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

In our preliminary tests, we trained a YOLO v5 network for 150 epochs on a dataset of 190 images varying in distances and illumination, and 50% of them are with wildfires and 50% without wildfires. Our validation results in Fig. 7 show great potential for automatic fire detection using machine learning. The mAP (mean average precision) value using this detector's own training set for validation was upwards of 0.97, proving YOLO's ability to train using wildfire-based datasets.

Fig. 7. Test Results Using YOLO v5.

CONCLUSION AND FUTURE WORK

Wildfires are a devastating problem that requires effective monitoring to mitigate. Limited capability of the current camera systems and low level of automation calls 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 on our preliminary test, we confirm that machine learning has great potential for future automatic wildfire detection systems. We will continue to explore the methods to build a prototype automatic wildfire detection system and conduct real-world experimentations.

References

[1] Q. Jiang and Q. Wang, "Large Space Fire Image Processing of Improving Canny Edge Detector Based on Adaptive Smoothing," 2010 International Conference on Innovative Computing and Communication and 2010 Asia-Pacific Conference on Information Technology and Ocean Engineering, Macao, 2010.

[2] C. E. Premal and S. S. Vinsley, "Image processing based forest fire detection using YCbCr colour model," 2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014], Nagercoil, 2014.

[3] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016.

[4] X. Li, Z. Chen, Q. M. J. Wu and C. Liu, "3D Parallel Fully Convolutional Networks for Real-Time Video Wildfire Smoke Detection," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 1.

[5] D. Shen, X. Chen, M. Nguyen and W. Q. Yan, "Flame detection using deep learning," 2018 4th International Conference on Control, Automation and Robotics (ICCAR), Auckland, 2018.