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A Modern Approach for Early Wildfire Detection

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Abstract

Wildfire is a constant threat to wildlife, vegetation, and society in history. Thus, detecting such fires in an early stage is of high relevance, raising the need for automatic approaches building on visual object detection, namely to detect smoke. To this end, typically feature-based approaches have proven to work well in the past. However, the goal of this work was to evaluate whether or not modern approaches building on neural networks would be beneficial in this context. To this end, we generated a new dataset, allowing us to train and evaluate neural-network-based smoke detectors. In addition, we demonstrate that each of the approaches has benefits and shortcomings, however, also that a carefully designed fusion strategy can improve the detection results in practice.

1. Introduction and Problem Statement

As also recent events in Australia, the USA, Russia, Germany, and even Austria show, wildfires have massive consequences for nature, wildlife, and the human population. Due to climate change, socio-economic changes, and general population development, the wildfire situation is likely to become worse [6]. Besides prevention, the best way to minimize damage to nature and wildlife is to early detect wildfires. However, the flames are often not directly visible in an early stage, requiring to apply indirect approaches to detect smoke. The most common approach is human inspection. Indeed, fire watchers are sitting on fire watchtowers and looking out for smoke plumes in the distance.

However, the detection by humans is very time-consuming, monotonously and thus tiring, and very expensive. An alternative to traditional smoke detection methods is given by terrestrial visual detection systems such as *IQ FireWatch*[1], building on three different camera sensors: a monochrome sensor for the detection in daylight, an RGB sensor, which provides a better view for the human eye, and a sensor working in the near-infrared (NIR) spectrum for night vision. One sensor system can reliably cover a radius of 15 kilometers in a 360 degrees view, which is illustrated in Figure 1.

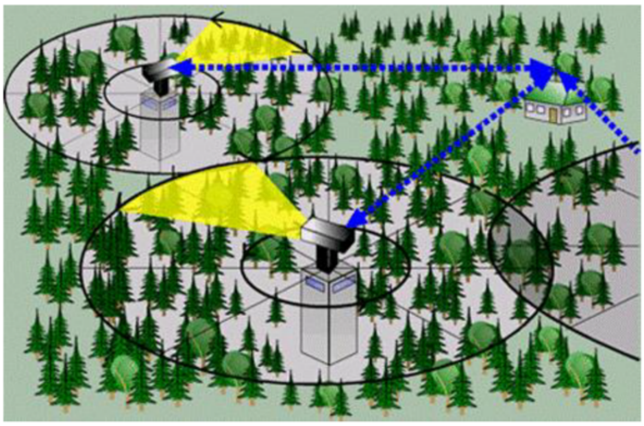

Figure 1. IQ FireWatch sensor system in practical use.

Even though data from different sensors is available, in this work we focus on high-resolution monochrome images, which are characterized by higher light sensitivity, which is beneficial when detecting smoke [2]. To this end, we compare the *F-Shell detector* [1] building on handcrafted features, to Faster R-CNN [3] using learned features. For that purpose, we created a new benchmark dataset for smoke detection. In addition, we evaluated how these approaches can be combined effectively for real-world scenarios

2. Smoke Detection

To detect the smoke, in this work we considered three approaches: the feature-based F-Shell detector [1], the neural-network-based Faster R-CNN [3], and a combination of both.

F-Shell follows a three-stage process: defining candidate regions, feature extraction, and classification, where three queues are run in parallel on a sequence of images. Using a sophisticated background subtraction to identify the regions of interest, these are described by (a) region properties such as shape or size, (b) by correlation to distinguish between

[1] https://www.iq-firewatch.com/.

moving objects and smoke clusters, and (c) by texture properties. Finally, an alarm is raised if at least one of the three queues yields a response.

Similarly, R-CNN builds on two stages: First, the region proposal network predicts regions of interest class-agnostically. Second, these proposals are cropped and finally classified. Yielding the best trade-off of speed and accuracy, we finally decided to build our system on an InceptionV2 backbone [5]. We pre-trained it using the COCO dataset and finetuned it with our newly generated dataset.

The finally obtained results for the individual detectors are summarized in Table 1 (*F-Shell* and *FRC*). Showing a similar accuracy (acc.), we see differences in other practically relevant metrics such as true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), false negative rate (FNR), and thus in precision (prec.).

Detector	**Acc.**	**TPR**	**FPR**	**TNR**	**FNR**	**Prec.**
F-Shell	0.80	0.68	0.07	0.92	0.31	0.90
FRC	0.81	0.83	0.19	0.80	0.16	0.81
COMB	0.82	0.80	0.14	0.85	0.19	0.84

Table 1. Detection results of individual detectors.

Thus, the idea was to combine both approaches to get the best tradeoff for all of these parameters. In particular, we applied the *The COMBINATOR* (*COMB*) [4] to combine the individual results, which additionally takes into account the confidence and the complementarity coefficients of each detector. As can be seen from Table 1 (*COMB*), in this way, a higher number of detections can be provided while still maintaining a decrease in false alarms.

3. Discussion and Conclusion

In this paper, we tackled the problem of wildfire detection in the context of the *IQ FireWatch* system. In particular, we investigated smoke detection using high-resolution monochrome images using two different approaches: *F-Shell* and *Faster R-CNN*. Since both approaches have pros and cons, we finally proposed a combination of both, i.e., using *The COMBINATOR*, providing a reasonable trade-off in practice. For more details, we would like to refer to [7].

Future work will include establishing a larger dataset allowing for both training and evaluation and further combinations of the different approaches.

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