Decision-making by a Combination of Feature-based and AI-based Algorithms for Early Wildfire Detection

Kurt, Winter
IQ wireless GmbH, Berlin, Germany

Abstract

Wildfire is a constant threat for wildlife, vegetation and society in history, and the recent years show that fires are likely to become worse and more frequent in summer. Traditional approaches for detecting fires are outdated and more and more replaced by new approaches like terrestrial systems for visual object detection. Feature-based approaches such as the F-Shell detector have shown good results over the years. However, recently, modern approaches building on AI-based methods, for example neural networks, have shown to deliver good results for a variety of tasks. In this paper, we show different methods to combine the partial results of different smoke detection algorithms for a successful decision-making process in the field of smoke detection.

For that, the feature-based F-Shell detector and the newly trained neural network Faster R-CNN InceptionV2 are used for combination. Four ways of combining the partial results are presented: AND, OR, ANDplusTH and The COMBINATOR. The results show that two combination methods, ANDplusTH and The COMBINATOR, outperform the single detectors by increasing the number of detection while reducing the false alarms. This paper is proving that a combination of partial results of different types of smoke detectors is a quick way of improving smoke detection systems.

Keywords: Early wildfire detection, object detection, combination, neural networks, feature-based

Introduction

Wildfire always has been a devastating event with massive consequences for nature, wildlife and human population. Due to the climate change, socio-economic changes and general population development, the wildfire situation is likely to become worse and more important [20]. Recent fires with enormous destruction in Australia, the USA, Russia, and Germany show that it is a worldwide problem to face.

The prevention of wildfires is the best way of coping with the problem. As this is not always possible, an early detection of wildfires is needed to minimize the damage. Since the flames of wildfires are often not directly visible in an early stage, a transition to the detection of smoke plumes is needed. However, smoke, being non-rigid and translucent, is a very difficult object to detect.

An alternative to traditional smoke detection methods, which is very time consuming, monotonously and tiring, on top of being very expensive, is given by terrestrial visual detection systems. Such a system is developed by IQ wireless, named IQ FireWatch. IQ FireWatch provides several algorithms for the sensors of different wavelength, which currently work totally separate of each other.

For our work we choose the algorithm working on the monochrome images, called F-Shell detector [1], due to the higher light-sensitivity and slightly higher resolution of monochrome images [3], which both are critical points in the detection of smoke. Feature-based algorithms delivered good results in the field of smoke detection in the past. However, new methods of object detection with neural networks provide good results in several applications.

Therefore, we want to develop a novel decision-making method for the smoke detection task, based on a combination of the partial results of existing feature-based and new AI-based algorithms. Fig. 1. provides an exemplary flow chart of the combination process.

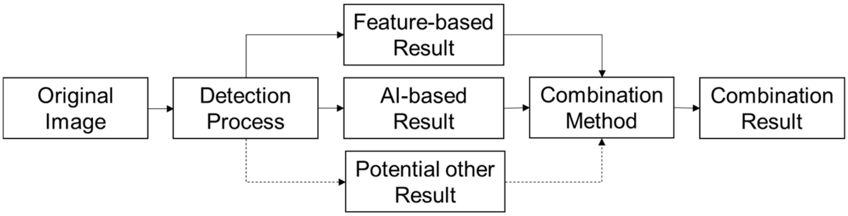

Fig. 1. Combination of the partial results of the different algorithms.

Related Work

Nearly all feature-based methods are working in a three-step way of defining candidate regions, feature extraction and classification [10]. For identifying candidate regions, several ways are used in smoke detection, including motion detection done by background subtraction by frame differencing or calculating the optical flow. Various features within images are extracted for smoke detection like energy, texture, colour or shape. These features are then often combined for better results. The common third step in feature-based approaches of smoke detection is the classification.

Approaches like threshold-based and rule-based classification, Fuzzy logic, Hidden Markov models, Clustering, machine-learning approaches, like support vector machines (SVM), AdaBoost, Bayesian classifiers are used [2], [10].

Deep convolutional neural networks need large amounts of data for training and testing, especially real-life data, for achieving state-of-the-art accuracy. This is often not possible due to the lack of data. However, some work on which popular network layout is suitable for smoke detection is already done. Filonenko et al. [7] did a comparison on modern convolutional neural networks for smoke detection, resulting in Xception [4] and Inception V3 [18] working best. Wu and Zhang [21] compared Faster R-CNN [16], YOLO [15] and SSD [14].

Several new convolutional neural networks are introduced, like Frizzi et al. [8] for identifying fire and smoke combined in videos, or Tao et al. [19]. Newer work includes Yin and Wei [23], who propose a convolutional neural network and cascading classification combination. Zhang et al. [24] introduce an attention mechanism into their shallow detection network by focusing on regions with obvious discrimination. Gu et al. [9] propose a new dual-channel neural network for the task of smoke detection.

The naive combination approaches are following the simple AND or OR combination rules. De Beugher et al. [5] use the OR combination rule for combining a pedestrian detector and a face detector for better results of overall detection. De Smedt et al. [17] propose a different approach of combining the results of different detectors for pedestrians, which they called The COMBINATOR. Their approach is based on a confidence measure and complementarity measure for each detector, which they use for weighting all detections. A similar approach is used by Xu et al. [22] for again combining pedestrian detectors. They use belief function and combination rules for weighting the detection scores after the clustering of bounding boxes. Lee et al. [12], [13] introduce an approach, which is based on the ambiguity in the detections and propose the Dynamic Belief Fusion (DBF) to combine the detections of feature-based object detectors and CNNs by dynamically assigning probabilities to hypotheses. Karaoglu et al. [11] combine different object detectors with the help of learning to rank. They base the award of a detection on the correlation of the single detectors.

Database

For training and testing, the database of IQ FireWatch was used. The database mostly consists of high-resolution, monochrome and colour images with a depth of 16 bit, which are recorded simultaneously of the same situation. The emphasis of the images lies on Brandenburg, Germany, but also includes images of other parts of the world. Over 20 % of the database is labelled manually following the standardized PASCAL VOC format [6].

Further, the images include some very smoke specific metadata and relevant information, like smoke colour, smoke transparency, smoke distance, but also overall interesting information for object detection, especially for understanding possible false positives, like weather, cloud appearance, light reflections or wind turbines.

Combination

For combining the partial results of the different smoke detectors, we decided for the feature-based F-Shell detector, which is working in the mentioned three-step way of identifying candidate regions, extract features, and a threshold-based classification [1]. Secondly, the neural network Faster R-CNN InceptionV2 is chosen, because this model delivers good results in terms of speed and accuracy.

Several ways of combining the partial results of the single detectors are used. First, the naive combination approaches, AND and OR, are implemented. Although, they are widely-used in several applications, their limitations are evident. The AND combination rule lowers the number of false alarms, but also the number of detections, which increases the chance of missing a fire. In contrast, the OR combination method increases the number of detections resulting in a higher chance of detecting the fire, but also in an increase of false alarms. Thus, we introduced a new mix of both approaches, called ANDplusTH. This is done by applying the naive AND combination and adding all detection of the neural network over a certain threshold. In this way, a higher number of detections can be provided while still maintaining a decrease of false alarms. Lastly, the approach of De Smedt et al. [17], The COMBINATOR, is applied. We want to test if their approach works as good in the environment of non-rigid and translucent objects, like smoke.

Results

The AND and OR combination methods delivered the results we have been expecting. AND decreases the amount of false alarms significantly, but also the number of correct detections slightly. OR increases the number of detections, as well as the amount of false alarms. However, ANDplusTH and The COMBINATOR manage to increase the number of correct detections and still are able to keep the number of false alarms at a moderate level respectively decrease it.

Fig. 2 shows the results of the two single detectors and the outcome of the four different combination methods on the same image of the test set, which contains a difficult example of a smoke source, which is located in the top right corner of the image.

The neural network manages to detect the smoke plume, but the F-Shell detector fails to detect it. One of the two single detectors is not detecting the smoke, so the AND combination fails as well.

In contrast, the OR combination correctly shows the bounding box. In this example the weak point of the combination mix can be seen, which is similar to the one of the AND combination. If only one detector detects the smoke correctly and the neural networks' detection score is not high enough, no resulting bounding box will be shown. However, The COMBINATOR approach is able to show the detection correctly, since it weights the single results, but considers all of them.

a) F-Shell.

b) Faster R-CNN InceptionV2.

c) AND.

d) OR.

e) ANDplusTH.

f) The COMBINATOR.

Fig. 2. Results of the combination methods of an image with smoke in it.

In Fig. 3, the results of the two single detectors and the outcome of the four different combination methods on the same image of the test set is shown. The situation contains a difficult example of a light ray shining through the clouds, but no smoke plume. The neural network incorrectly results in a detection, the F-Shell detector does not.

In this example, the limits of the OR combination can be seen, since it is the only combination method which is still maintaining the smoke detection. The other three methods are managing to discard the detection correctly, since there is no overlap between both detectors and the score of the detection of the neural network is very low.


g) F-Shell. h) Faster R-CNN InceptionV2.


i) AND. j) OR.


k) ANDplusTH. l) The COMBINATOR.

Fig. 3. Results of the combination methods of an image without smoke in it.

Conclusion

In this paper, a decision-making method was searched for the task of smoke detection, based on a combination of the partial results of existing feature-based and new AI-based algorithms. For the combination, two smoke detectors were used. First, the existing feature-based smoke detector F-Shell, and the newly trained neural network Faster R-CNN InceptionV2. We managed to introduce four different combination possibilities into our system: AND, OR, ANDplusTH, and The COMBINATOR.

The AND and OR combination methods did not deliver an optimal outcome, since AND decreases the number of detections, as well as the false alarms, and OR vice versa. However, ANDplusTH and The COMBINATOR manage to increase the number of correct detections and still are managing to keep the number of false alarms at a moderate level respectively even lower it. This paper proves, that a combination of the partial results outperforms the single detectors and is a efficient way to improve a terrestrial visual smoke detection system.

References

[1] Th. Behnke et al. "*Verfahren und Vorrichtung zur automatischen Waldbranderkennung.*" European pat. (EU). Deutsches Zentrum für Luft- und Raumfahrt e.V. Feb. 22, 2006.

[2] A. E. Çetin et al. "*Video fire detection – Review.*" Digital Signal Processing 23 (2013), pp. 1827-1843.

[3] A. Chakrabarti, W. T. Freeman, and T. Zickler. "*Rethinking color cameras.*" In: Proc. IEEE Int'l Conf. on Computational Photography. 2014.

[4] F. Chollet. "*Xception: Deep Learning with Depthwise Separable Convolutions.*" In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition. 2017.

[5] S. De Beugher, G. Brône, and T. Goedemé. "*Automatic analysis of in-the-wild mobile eye-tracking experiments using object, face and person detection.*" In: Proc. Int'l Joint Conf. on Computer Vision, Imaging and Computer Graphics Theory and Applications. 2014.

[6] M. Everingham et al. "*The Pascal Visual Object Classes (VOC) Challenge.*" Int'l Journal of Computer Vision 88.2 (2010), pp. 303–338.

[7] A. Filonenko, L. Kurnianggoro, and K.-H. Jo. "*Comparative study of modern convolutional neural networks for smoke detection on image data.*" In: Proc. Int'l Conf. on Human System Interactions. 2017.

[8] S. Frizzi et al. "*Convolutional neural network for video fire and smoke detection.*" In: Proc. Annual Conf. of the IEEE Industrial Electronics Society. 2016.

[9] K. Gu et al. "*Deep Dual-Channel Neural Network for Image-Based Smoke Detection.*" IEEE Transactions on Multimedia 22.2 (2020), pp. 311–323.

[10] R. Kaabi et al. "*Video smoke detection review: State of the art of smoke detection in visible and IR range.*" In: Proc. Int'l Conf. on Smart, Monitored and Controlled Cities. 2017.

[11] S. Karaoglu, Y. Liu, and T. Gevers. "*Detect2Rank: Combining Object Detectors Using Learning to Rank.*" IEEE Trans. on Image Processing 25.1 (2016), pp. 233–248.

[12] H. Lee and H. Kwon. "*DBF: Dynamic Belief Fusion for Combining Multiple Object Detectors.*" IEEE Trans. on Pattern Analysis and Machine Intelligence (2019), pp. 1–1.

[13] H. Lee et al. "*Dynamic belief fusion for object detection.*" In: Proc. IEEE Winter Conference on Applications of Computer Vision. 2016.

[14] W. Liu et al. "*SSD: Single Shot MultiBox Detector.*" In: Proc. European Conf. on Computer Vision. 2016.

[15] J. Redmon and A. Farhadi. "*YOLO9000: Better, Faster, Stronger.*" In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition. 2017.

[16] S. Ren et al. "*Faster R-CNN: Towards Real-time Object Detection with Region Proposal Networks.*" In: Advances in Neural Information Processing Systems. 2015.

[17] F. De Smedt et al. "*The COMBINATOR: Optimal Combination of Multiple Pedestrian Detectors.*" In: Proc. Int'l Conf. on Pattern Recognition. 2014.

[18] C. Szegedy et al. "*Rethinking the Inception Architecture for Computer Vision.*" In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition. 2016.

[19] C. Tao, J. Zhang, and P. Wang. "*Smoke Detection Based on Deep Convolutional Neural Networks.*" In: Proc. Int'l Conf. on Industrial Informatics - Computing Technology, Intelligent Technology, Industrial Information Integration. 2016.

[20] R. S. Vachula, J. M. Russell, and Y. Huang. "*Climate exceeded human management as the dominant control of fire at the regional scale in California's Sierra Nevada.*" Environmental Research Letters 14.10 (2019), p. 104011.

[21] S. Wu and L. Zhang. "*Using Popular Object Detection Methods for Real Time Forest Fire Detection.*" In: Proc. Int'l Symposium on Computational Intelligence and Design. 2018.

[22] P. Xu, F. Davoine, and T. Denoeux. "*Evidential Combination of Pedestrian Detectors.*" In: Proc. British Machine Vision Conf. 2014.

[23] H. Yin and Y. Wei. "*An Improved Algorithm Based on Convolutional Neural Network for Smoke Detection.*" In: Proc. IEEE Int'l Conf. on Ubiquitous Computing Communications and Data Science and Computational Intelligence and Smart Computing, Networking and Services. 2019.

[24] D. Zhang et al. "*An Attention Convolutional Neural Network for Forest Fire Smoke Recognition.*" In: Proc. Int'l Conf. on Systems and Informatics. 2019.