Flame and Ember Localization Using Color and IR Cameras

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Abstract

The approval of fire extinguishers requires the conduction of tests to prove the extinguishing capacity of a fire extinguisher model. In order for this test to be independent of the abilities of human firefighters, the performance is to be automated. To this end, the state of the art in research is being examined for algorithms that can localize flames and embers with the help of a color and an infrared camera, respectively. This information is to be used to carry out the extinguishing attempt effectively and efficiently. For this purpose, six algorithms for the localization of flames in color images and three algorithms for the localization of embers in infrared images are compared. The comparison is carried out on the basis of the criteria sensitivity, false positive rate, intersection over union and average execution time. Based on these comparison results, one algorithm each is selected for the automated extinguishing of the standard fire test.

Keywords: Flame Localization, Image Processing, Ember Localization, Infrared Thermography

Introduction

Fire is a significant threat to human life and a lot of effort has been put into the development of early warning systems to decrease the number of casualties. An increased danger is emanating from fires in confined spaces with no possibility of escape, like in aircraft, spacecraft, ground vehicles or submarines. A second aspect increasing the threat in these kinds of scenarios is: Counteractions in form of suppression are only possible to a limited extent because the amount of available suppression agent is restricted due to space or weight restrictions. The attempt of suppression is, howver, essential when saving the life of crews in such circumstances. Hence the application of limited supply of suppression agent has to quench as many flames as possible.

Fire extinguishers are an essential tool for fire safety in many structures. Due to their safety-critical role standards have been introduced to ensure a reliable quality. The European norm EN 3-7 [1] for example describes characteristics and performance of fire extinguishers. This includes their construction and also their ability to quench fires. For the validation of the fire suppression capability of an extinguisher, the norm prescribes a test involving the suppression of a wood crib fire. It shall be conducted by a human firefighter without any further guideline of the procedure. Consequently, the test suffers from a lack of comparability and reproducibility. The automation of this test would on the one hand be a suitable simplification of the general scenario of automated fire suppression. On the other hand, its automation would help to increase the quality of the certification due to the rise in reproducibility and transparency of the conducted suppression.

Nonetheless, the methods employed by human firefighters in the certification experiments are forged by extensive experience to be very efficient. Accordingly, such a procedure carried out by a seasoned firefighter is chosen to be the reference for the conduction of automatic fire suppression with the constraint of limited supply of suppressant. This suppression procedure, conducted by an experienced human firefighter, has been analyzed revealing a procedure consisting of two phases: In the first phase the firefighter seeks to suppress the flames from every side of the wood crib. This phase continues until there are no flames left on the wood crib. In the second phase the firefighter continues by cooling down remaining embers with precise pulses of suppression agent to prevent them from reigniting. Hence, the key information needed to conduct this suppression procedure are the locations of the flames and embers. They also need to be distinguished in order to apply the correct means of suppression.

The contribution presented by this work is the comparison of a selection of different methods for flame and ember localization. Each comparison is conducted with a unified dataset. The comparative evaluation is carried out with regard to the suitability for the automation of the manual fire suppression process during the standard fire suppression experiment.

This work first presents the state of the art for camera-based flame localization methods and for ember localization methods. Subsequently, the evaluation metrics for the comparative evaluation are explained and the test data is presented. This is followed by the results of the comparison, a discussion of the results and a conclusion.

State of the Art in Flame Localization

The localization of flames in images has been developed because it enables the surveillance of wide areas and open spaces. Image-based flame detection can trigger as soon as flames are visible to the cameras without a transport delay. Additionally, it enables the extraction of additional information.[2]

The localization of flames in images usually relies on a combination of characteristic features. The most frequently used is the flame color which is for example used in the methods [3–5] to localize fire. Those approaches usually rely on selecting a certain region in a color space (e.g. RGB, HSI, etc.). A slightly extended approach is used in [4]. Here the colors described in various color spaces that most likely belong to a fire are learned on suitable training data. Because color as the single feature would lead to a high number of false positive detections, most algorithms (including [3–5]) use additional features. For example in [3] the texture is described by linear binary patterns (LBP) which are computed on a superpixel-level. In [4] the texture is classified as fire based on the entropy. Another feature that has regularly been employed in algorithms for the localization of flames is their motion. This can for example be used to find the moving flames in front of a comparably static background [5].

Fire detection algorithms increasingly use deep learning-based methods to find flames in images. Most of those approaches are employing transfer learning to adapt a convolutional neural network (CNN) that is pretrained with a vast dataset of everyday objects to a special application such as fire localization. Such methods are for example presented in [6–8]. In [6] a pretrained CNN with the SqueezeNet architecture is used. This architecture only produces a binary classification of the whole image. Activations of the hidden layers are used for the localizations. The YOLO CNN used in [7] has a bounding box around the detected flames as its output and in [8] the output is a pixelwise classification.

State of the Art in Localization of Embers

The standalone detection of embers, in contrast, has not attracted the same interest in the research community. However, several areas of application exist. One of those is remote sensing where [9] presents a method for detecting smoldering peat fires from a satellite in earth orbit within the infrared (IR) spectrum. This method selects areas from the IR images that fall in a certain temperature range. The respective threshold temperatures lie well above the ambient temperature but also below the temperature of a flaming combustion.

In some methods the localization of embers is included in the detection and localization of fire as for example in [10]. Here the temperature threshold is set to a value so low that it also detects non-flaming combustion. The method employs a stereo pair of longwave IR cameras. An approach that has been developed in [11] for the localization of hotspots in photovoltaics can be transferred to the localization of embers after suppression of the flames. This approach clusters the pixels in every image to find a cluster with a temperature above the ambient.

Evaluation Metrics for the Comparison

The suppression of the wood crib test fire with a limited amount of suppression agent demands targeted application. Accordingly, the algorithms will be evaluated on their ability to localize flames. This is done by first evaluating their sensitivity s to flames which is calculated with equation (Eq. 1). Here TP are the true positive detections and FN are the false negative detections.

$$s = \frac{TP}{FN + TP} \qquad \text{(Eq. 1)}$$

Additionally, the intersection over union (IoU) in equation (Eq. 2) is used to determine the accuracy of the location and size of the flames found by the algorithms. The localization performance will be evaluated only by bounding boxes. Thereby all algorithms get assessed on the same basis. Here A_s is the intersection of detected bounding box and ground truth data and A_v is the union of those two.

$$IoU = \frac{A_s}{A_v} \qquad \text{(Eq. 2)}$$

Because it is vital for the success of the suppression attempt to use the suppression agent effectively, it is also evaluated how likely the algorithms detected non-fire objects in the images as fire. This is evaluated using the false positive rate (FPR), given in equation (Eq. 3). Here FP denotes the number of false positive and TN the number of true negative detections.

$$FPR = \frac{FP}{FP + TN} \qquad \text{(Eq. 3)}$$

As a final measure the average processing time T is introduced. It is determined as the average time needed by the tested algorithm to process a single image of the test data. For the purposes of the automated suppression this value should be small in order to control the suppression in real-time.

Test Data for the Comparative Evaluation

For the comparative evaluation separate datasets for the flame and for the ember localization algorithms have been employed. The machine learning-based methods have been trained using data suitable for the respective method: the training of [3] and has been conducted with the training data provided by [3]. The Methods [6–8] have each been trained with single images from [12] and from our test fire. The ground truth has been added manually as a binary mask for [6] and [8] and as a bounding box for [7]. Images used for training are not part of the videos in the test dataset. The test data for the flame localization has been collected from two different sources. One part is from our own test fires and the other part originates from the fire dataset provided in [12].

In both cases the ground truth bounding boxes needed for the evaluation, as seen in Fig. 1(a), have been added manually. All tested algorithms are given the complete test dataset and are compared based on the respective results in order to select the best suitable algorithms for the application in automated fire suppression. The test dataset consists of 65 videos with a total of 4394 single images. Example images from this dataset are given in Fig. 1.

Fig. 1. Examples from the flame localization dataset; (a) contains a single flame marked with a yellow ground truth bounding box. (b) does not contain flames and thus does not have bounding boxes.

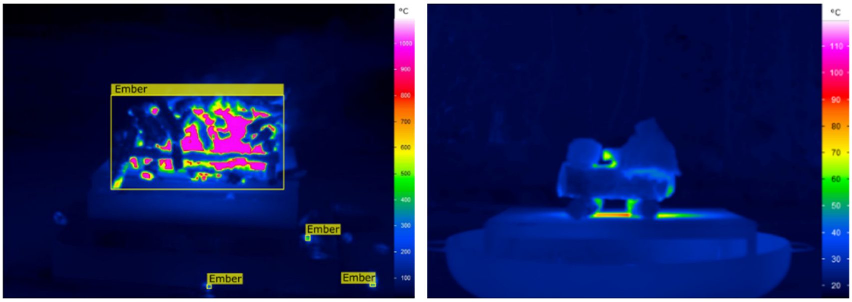

Fig. 2. Examples for ember localization dataset. (a) contains embers marked with yellow ground truth bounding boxes. (b) does not contain embers and thus does not have bounding boxes.

For the comparative evaluation separate datasets for the flame and for the ember localization algorithms have been employed. The test data for the ember detection algorithms are collected only from the test fires mentioned above. The dataset consists of 86 IR images from which one half contains glowing embers and the other half does not (see Fig. 2). As the algorithms do not rely on machine learning, separate training data is not necessary. The evaluation has been run in Matlab on a laptop computer with a i7-8565U processor with 1,6 GHz base tact and 16 GB RAM.

Comparison of Algorithms for Flame Localization

The comparative evaluation of the algorithms has been conducted by implementing the algorithms following the respective publications wherever possible. Table 1 gives an overview of the tested algorithms, the features used for the localization and the algorithms' output, respectively. For the methods producing a binary mask as an output the corresponding bounding boxes have been calculated for the evaluation. The application of the test data to the implemented algorithms leads to the results shown in Table 2. Regarding the sensitivity, the results show that F2, F3 and F4 have the highest values in the comparison. F1 and F5 yield a slightly reduced sensitivity and F6 exhibits the lowest sensitivity of all tested algorithms. Also, many of the algorithm expose a quite high FPR. Only F2 and F5 deviate from this finding with a comparably low FPR. The method F4 has the best IoU of the tested algorithms, followed by F2 and F1 whereas F6 yields the lowest IoU. The method F3 has the lowest processing time, which originates from a specialization on fast execution. Interestingly, the CNN-based algorithm F4 also can be executed with a comparably high speed.

Table 1. Overview of the tested algorithms for flame localization.

Identifier	**Algorithm**	**Extracted Features**	**Output**
F1	[3]	Color, LBP	Binary mask
F2	[4]	Color, entropy	Binary mask
F3	[5]	Color, motion, brightness	Binary mask
F4	[6]	CNN (SqueezeNet)	Binary mask
F5	[7]	CNN (YOLO)	Bounding box
F6	[8]	CNN (DeepLab)	Binary mask

Table 2. Results of the flame localization algorithms on the test data.

Identifier	**Sensitivity**	**FPR**	**IoU**	**T**
F1	72.53 %	69.73 %	51.46 %	20.71 ms
F2	83.59 %	18.63 %	53.12 %	72.75 ms
F3	82.12 %	93.04 %	26.13 %	8.24 ms
F4	81.95 %	68.27 %	60.08 %	30.46 ms
F5	74.85 %	1.86 %	45.22 %	81.87 ms
F6	43.81 %	92.02 %	14.78 %	583.6 ms

Taking all the results into account F2 and F5 yield the best results. F2 has a better sensitivity and IoU but F5 has the best FPR in this comparison and is only slightly inferior in the other evaluation metrics. Nonetheless, F2 presents the best overall performance and has consequently been selected for the use in automated suppression of the wood crib test fire and its increased FPR is tolerated.

Comparison of Methods for Ember Localization

For the comparative evaluation of ember localization methods Table 3 displays the implemented algorithms. The algorithms are applied to the test data. The results yielded by the algorithms on the test data are shown in Table 4. They show that all tested methods detect the embers in the test images very reliably. All identify the same amount of the embers in the ground truth data correctly. Also, all presented algorithms can be executed faster than the flame localization algorithms. This is due to the much-reduced complexity of the algorithms.

Table 3. Overview of the tested algorithms for ember detection.

Identifier	Algorithm	Classifier	Output
E1	[10]	Lower and upper threshold	Binary mask
E2	[9]	K-Means Clustering	Binary mask
E3	[11]	Lower threshold	Binary mask

Additionally, the IR images have a smaller resolution and only an intensity channel compared to three color channels of the color images. Especially E3, however, does not reject non-ember hotspots reliably and thus produces a high number of false positives. It lacks a reference to an absolute temperature and accordingly always puts all available pixels into two temperature clusters. As E1 exhibits the overall best performance it will be used for localizing embers in the context of the automated suppression of the wood crib test fire.

Table 4. Results of the ember localization algorithms on the test data.

Identifier	Sensitivity	FPR	IoU	T
E1	99.15%	6.52%	81.04%	0.1ms
E2	99.15%	41.89%	71.62%	0.1ms
E3	99.15%	91.76%	64.58%	8.35ms

Discussion

The evaluation results on the test data show that, on the one hand, it is possible to localize flame and embers with the proposed setup of a color and an infrared camera. Nevertheless, it also shows, that these methods are fallible. The application in automated fire suppression, however, does not require sensitivities as for example required by early warning systems for wildfires and the localization results will not be considered isolated from the context: the experimental setup as well as the detection history can be considered. The aspect of the processing time needs to be considered together with the general dynamics of the system. The fire suppression agent travels approximately 100 ms from the nozzle to the fire introducing a lag into the system.

Conclusion and Future Work

This work presents the results of a comparative analysis of several flame and ember localization methods using a unified dataset, respectively. The evaluation metrics have been selected with respect to the task of localizing the respective phenomena in order to automatically suppress a wood crib test fire. The evaluation results yield that F2 has the overall best performance for flame localization based on the test data used. For ember localization the single lower temperature thresholds turned out as the most useful method. Those two algorithms will be used as the basis for future research work on the automation of the wood crib test fire. The algorithms will be used separately to determine the most suitable targets for the fire suppression agent and also control the succession of the suppression procedure. Consequently, future work will focus on the implementation of those algorithms in a physical suppression system.

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