Fast Detection of Deflagrations Using Image Processing

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Abstract

Most of the common fire detection algorithms are able to detect different kinds of fires in a sufficient time. However, in the special case of detecting deflagrations, current algorithms fail. Furthermore, today's deflagration detection systems based on optical sensors do not have the capability to provide information concerning dimension or location of the deflagration.

In this paper a novel algorithm for detecting deflagrations is proposed, which aims at providing more reliable and more detailed information compared to today's deflagration sensor systems. The proposed algorithm consists of two main parts; identification of the pixels indicating a potential deflagration and analysis of the expansion of the identified region. The pixels are identified by a rule-based thresholding of the red, blue and intensity channel of the image. Additionally rise time of the intensity is considered by applying a high-pass filtering.

Using a high-speed camera (operating at 210 fps) the whole detection process is completed within 15 ms or less, which is sufficiently fast to allow the suppression of a deflagration in its initial stage. Closing experimental results show the performance and advantages of the developed algorithm.

Keywords: Deflagration Detection; Image Processing; Fire Detection

Introduction

Today's systems used for deflagration detection within closed compartments, e.g. armored vehicles, are based on infrared sensors. These sensors are sensitive to the light emission of hydrocarbon-based combustion products. In combination with an efficient control unit, these sensors basically enable a fast detection of a deflagration. A short detection time is necessary to suppress a deflagration already in its initial stage.

Thus conventional systems are just focused on hydrocarbon-based combustions. Furthermore they do not yield any information on the dimension and location of the deflagration to feed the extinguishing devices with. Precisely this sort of information could be important for developing future deflagration suppression systems which might use water mist instead of the current chemical extinguishing agents.

Image processing applied to high-speed camera monitoring is a novel approach for detecting deflagrations. The use of image processing for low-speed fire detection is an already well-established method. The majority of the approaches are based on color and motion analysis [1].

Most of the approaches use the RGB color space, sometimes in combination with HSI/HSV saturation [2]. For identification of fire-colored pixels the mainly rule-based approaches use Gaussian-smoothed color histograms [3] and statistically generated color models [4].

Another technique for detecting fire is given by the moving-object method. An analysis of moving regions is used to determine whether the motion is due to fire or a fire-like moving object. The most commonly used basis algorithm is background subtraction [5] [6].

However, none of the up-to-date fire detection algorithms is capable for a reliable detection of a sudden explosion in form of a deflagration [7]. In addition, the special environment of the application (crew compartments of armored vehicles) and the required short reaction time represent challenges for current detection algorithms.

Deflagration Features

A deflagration is defined as an exothermic reaction in an explosive mixture. Its ignition is due to heat conduction in the subsonic range. Thus a deflagration generates considerable light and heat emissions in a very short time [8]. As shown in **figure 1**, the color of a deflagration usually appears white in the core and reddish at the edges. The white core results from saturation of the image sensor, the red corona corresponds with its flame temperature. This reveals that a deflagration emits light of high intensity in combination with a high red level. Furthermore intensity depends on the exposure time of the camera and the backlight in the observation area.

Fig. 1. Sequence of an exemplary deflagration, number indicates frame (210 fps)

Figure 2 shows the run of an exemplary deflagration. For further discussion of the algorithms one single pixel located in the middle of the frame is picked out. It can be seen that with increasing expansion of the deflagration the intensity and red values increase up to a saturation level. Both intensity and red reach their maximum within two frames (equates to 10 ms).
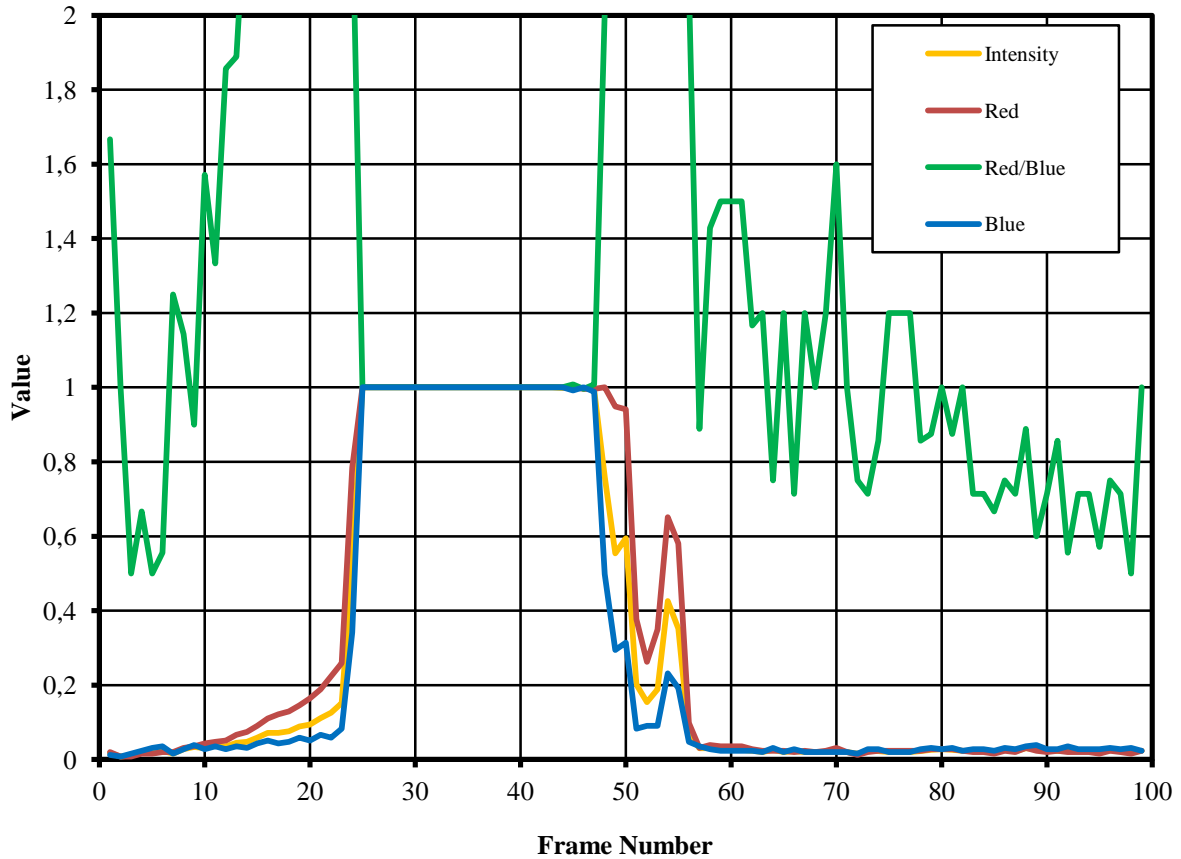
Fig. 2. Characteristic values of a center pixel of the deflagration shown in figure 1 (resolution 646 × 486 pixel, 210 fps)

For a first selection of probable deflagration pixels the ratio of the red and the blue color channel proves to be the best procedure. As can be seen in figure 2, the blue value is always smaller than or equal to red. Thus a ratio of red and blue equal to or greater than one may represents a fire or deflagration pixel.

In addition, the pixel intensity is an important indicator for detection of deflagrations. By defining a threshold for the intensity, deflagration-like pixels can be identified. The threshold depends on the exposure time of the camera and must be defined according to the operation conditions.

Another important feature of deflagrations is their fast variation in time. As shown in figure 1, the fireball expands and contracts within 40 frames or about 190 ms. This fast expansion distinguishes a deflagration from a static fire. Considering the dynamic feature for detection, first the pixel intensity $I(x, y)$ is low-pass filtered

$$I_{LP}^{(n)}(x, y) = I_{LP}^{(n-1)}(x, y) \cdot \alpha + I^{(n)}(x, y) \cdot (1 - \alpha), \tag{1}$$

where the top indices indicate the frame number and the tuples (x, y) the pixel location. The factor α and the frame time Δt define the time constant of this first order delay element

$$T_{\mathrm{LP}} = \frac{\alpha}{\alpha - 1} \cdot \Delta t \,. \tag{2}$$

The variation in time is represented by the difference between the current pixel intensity and its low-pass filter mean value

$$\Delta I(x, y) = I(x, y) - I_{\mathrm{LP}}(x, y), \tag{3}$$

which represents the smoothed intensity slope. The curve of the intensity slope for the chosen exemplary deflagration is displayed in figure 3.
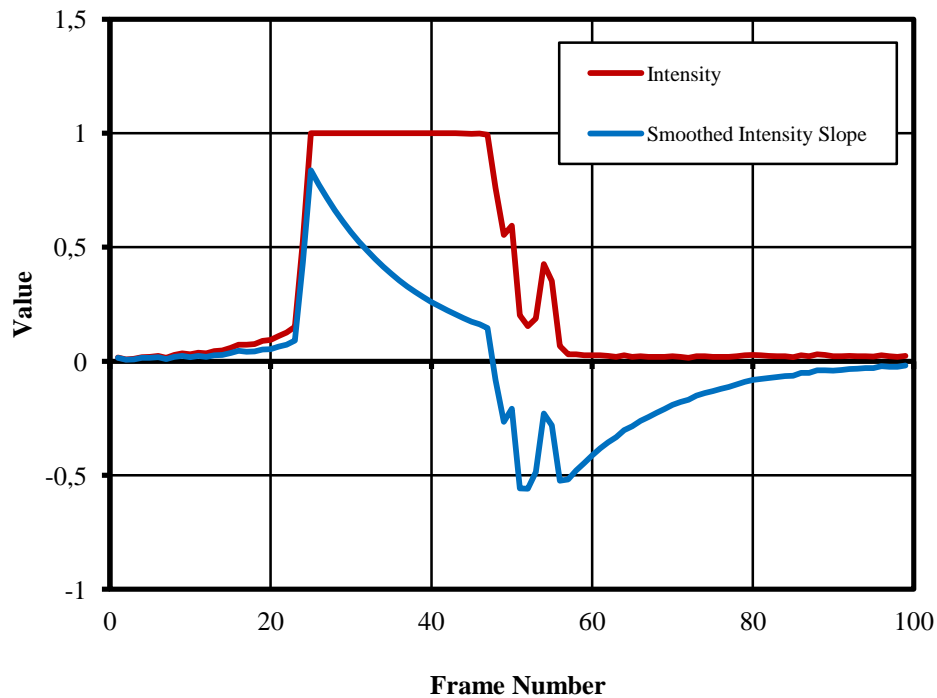

Fig. 3. Smoothed intensity slope in comparison to the intensity of a center pixel of the deflagration shown in figure 1

A steep slope of the pixel intensity due to the fast deflagration causes a high peak at frames number 23 to 25. As the deflagration progresses, the curve decreases at a higher or lower rate according to the weighting factor α, here 0.925 is chosen. In combination with a threshold, it is possible to select pixels indicating the formation of a deflagration. Moreover, a decaying deflagration is also detectable as it causes a negative intensity slope. Consequently under challenging conditions the camera has to be adjusted in a way to allow for the intensity increase to be detected.
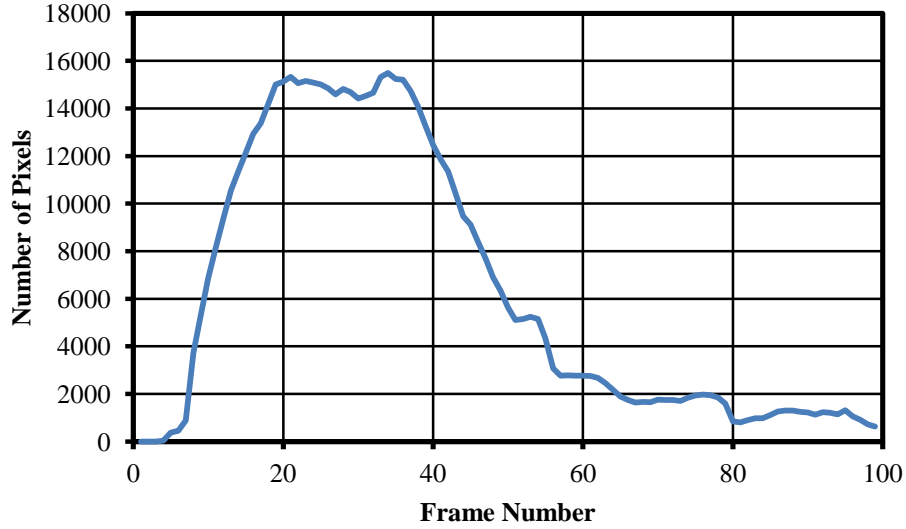
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Fig. 4. Number of identified deflagration-like pixels for the exemplary deflagrations shown in figure 1

After the selection of probable deflagration pixels, the number of such pixels has to be evaluated in a final step. Considering again the exemplary deflagration shown in figure 1, the time-dependent number of selected pixels is presented in figure 4. Now the absolute number as well as the slope can be used for final classification of the event.

Algorithm
Using the described chromatic and dynamic features, a rule-based detection algorithm is developed. The structure of the algorithm is constructed as simple as possible to reach the required detection time of less than 15 ms. The algorithm is designed to reduce the number of false alarms in comparison to today's sensors and to supply more precise information about the deflagration.
The algorithm is structured into two stages. First the chromatic features and the dynamic behavior are evaluated to identify deflagration-like pixels. The procedure is described by the following rules:

$$\frac{R(x,y)}{B(x,y)} \geq 1, \tag{4}$$

$$I(x,y) > I_{\mathrm{T}}, \tag{5}$$

$$\Delta I(x,y) > \Delta I_{\mathrm{T}}, \tag{6}$$

where $R(x, y)$ and $B(x, y)$ denote the red and blue value of the single pixel at a spatial location (x, y). The thresholds of intensity I_T and of intensity slope ΔI_T are determined according to the operation conditions. A pixel is classified to be deflagration-like, if all of the three conditions are met.

The second stage considers the spatial formation of the event. Thereby the number of identified pixels in the current frame is compared to the number of pixels in the preceding frame. By relating the difference to the current number of identified pixels, a change becomes more pronounced in case of a small number of identified pixels. Thus it is possible to detect a deflagration in its initial stage. To prevent false alarms caused by an increasing number of a few identified pixels, the ratio is used only if a certain value of identified pixels is exceeded. The decision rules for expansion detection are formulated as:

$$m^{(n)} \geq m_T$$
$$\mu = \frac{m^{(n)} - m^{(n-1)}}{m^{(n)}} \geq \mu_T \tag{7}$$

where $m^{(n)}$ is the number of identified pixels in the current frame and $m^{(n-1)}$ the number of identified pixels in the preceding frame. The thresholds m_T and μ_T define the minimum number pixels and the minimum relative increase caused by a considerable deflagration respectively. If the conditions are met a significant deflagration is assumed.

The general structure of the detection algorithm is shown in figure 5. As explained before, stage one evaluates the characteristics of the single pixels, stage two the spatial formation of the selected pixels. Further information about the selected pixels, e.g. centroid of the identified area, can be used for additional characterization of the detected event. Finally it has to be decided to alert the extinguishing system accordingly.
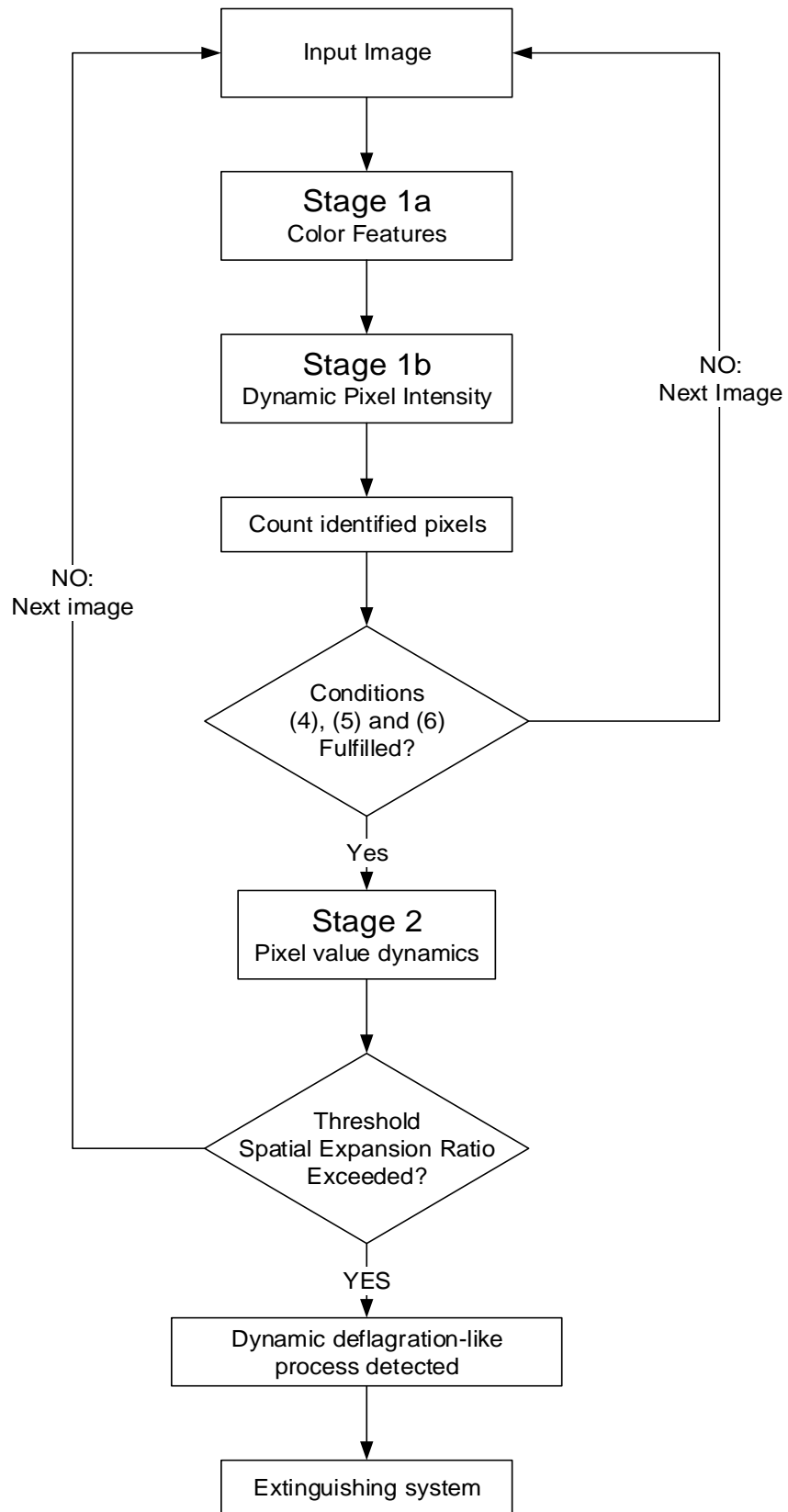
Fig. 5. General structure of the detection algorithm

Experimental results

The algorithm performance is tested by defined deflagration image sequences, which are recorded with a Basler pilot 640-210gc high-speed camera (210 fps). The deflagrations are generated by a self-developed test bench [9]. It consists of a deflagration chamber and further subsystems. All subsystems are integrated into a closed box, which provides defined test conditions.

The first deflagration sequence, displayed in figure 6, simulates a propane-based deflagration at its initial stage. There are some backlight at the top and reflections at the bottom.
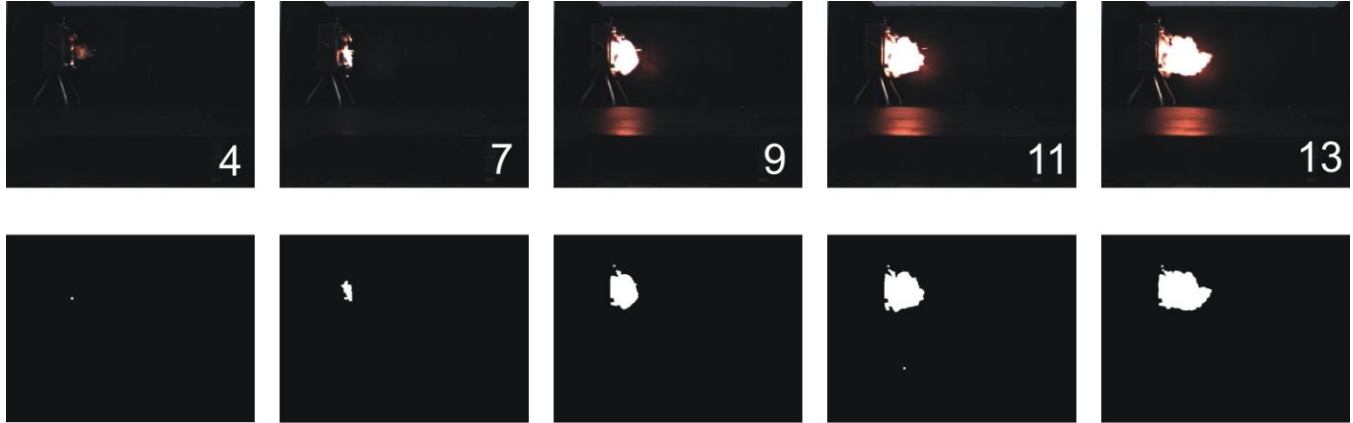

Fig. 6. First row: Deflagration sequence, number indicates frame (total duration 48 ms); second row: Deflagration segmentation using eqs. (4), (5) and (6) with $I_T = 0.34$ and $\Delta I_T = 0.1$

As it can be seen in figure 5, the first stage of the algorithm clearly detects the fireball of the deflagration. The simultaneously occurring light reflections and the backlight in the upper part of the images have no influence on detection.

The corresponding curve of the number of selected pixels is displayed in figure 7. The red curve indicates the ratio according to eq. (7) as it is used for the second stage of the algorithm. With an increasing number of pixels the ratio first increases considerably and later decreases gradually down to zero due to high-pass filtering. The large increase ratio μ indicates a fast formation of the deflagration. Depending on the value of the threshold μ_T an alarm or an extinguishing signal is generated. In the case of the shown deflagration, a threshold between 0.1 and 0.2 is sufficient.
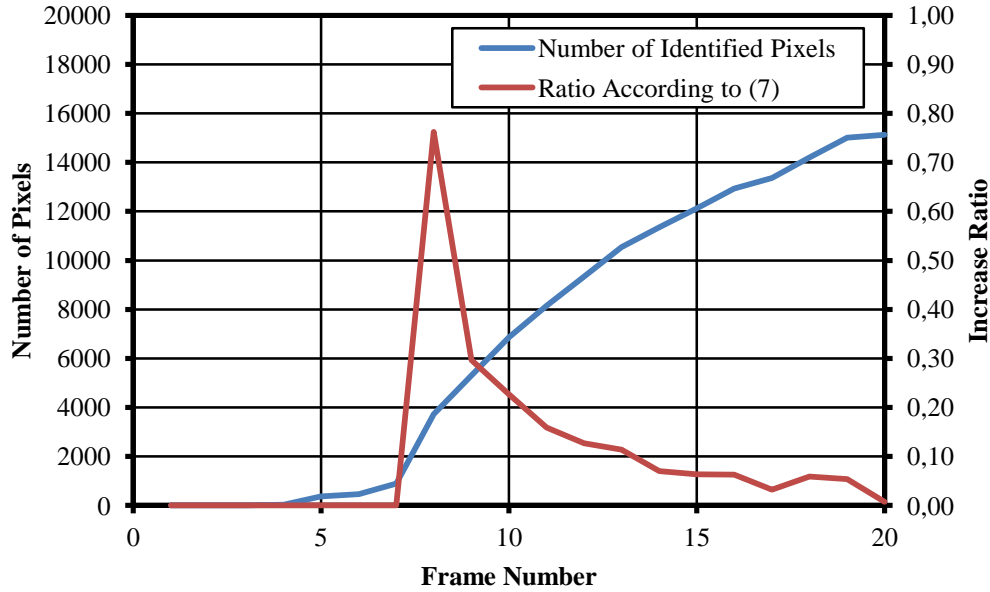
Fig. 7. Evaluation of the deflagration shown in figure 6, increase ratio according to eq. (7), $m_T = 900$

Another performance test is shown in figure 8. Here, an image sequence of a burning candle simulates a static fire process. The algorithm detects the flame and counts the fire-colored pixels as well as the pixels with a high intensity slope. The curves remain on constant levels without any considerable increases. Due to the missing significant variation in intensity the algorithm does not detect a deflagration or anything similar. Thus, the algorithm can distinguish between static and dynamic fire-colored processes.
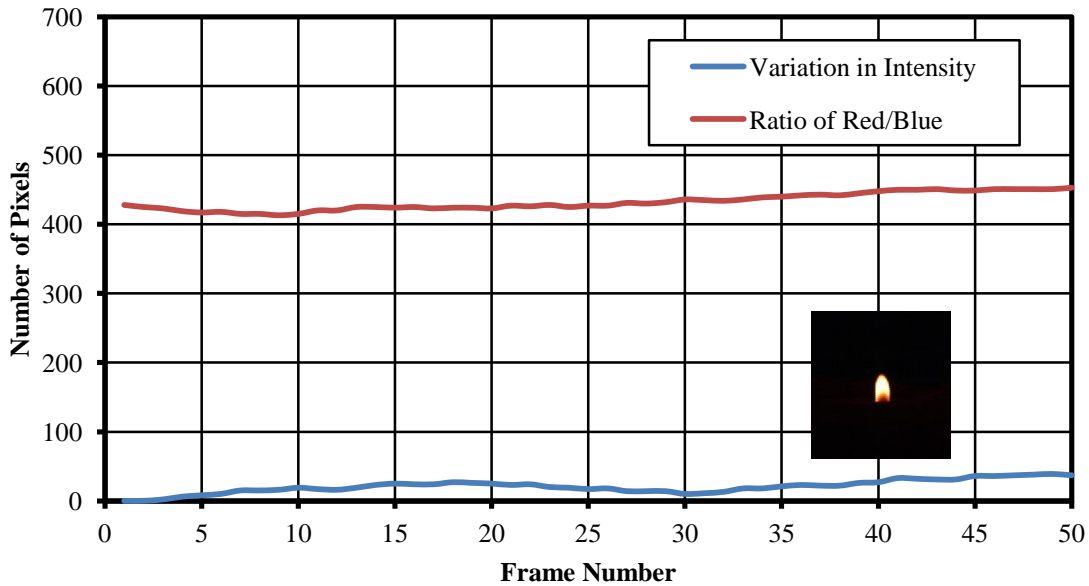

Fig. 8. Number of pixels identified by eqs. (4) and (6) with $\Delta I_T = 0.1$

An example for a deflagration recorded with a low exposure time is displayed in figure 9. This deflagration does not show a typical fireball within the first ten frames. However, the algorithm is able to detect part of the deflagration until the fireball occurs. The intensity of the image decreases with exposure time. Thus detection thresholds have to be adapted.
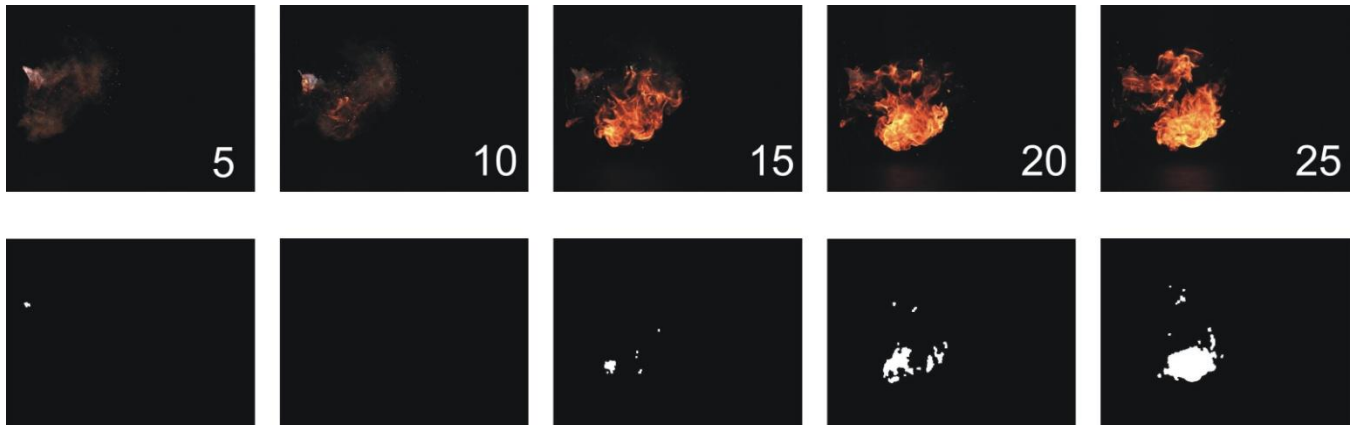

Fig. 9. First row: Deflagration sequence recorded with low exposure time; second row: Deflagration segmentation using eqs. (4), (5) and (6) with $I_T = 0.34$ and $\Delta I_T = 0.1$

Again, the algorithm detects this special deflagration both by its chromatic and dynamic features. As displayed in figure 10, the identified pixels show the typical increase at the initial stage of the deflagration, which is recognized by the increase ratio according to eq. (7).
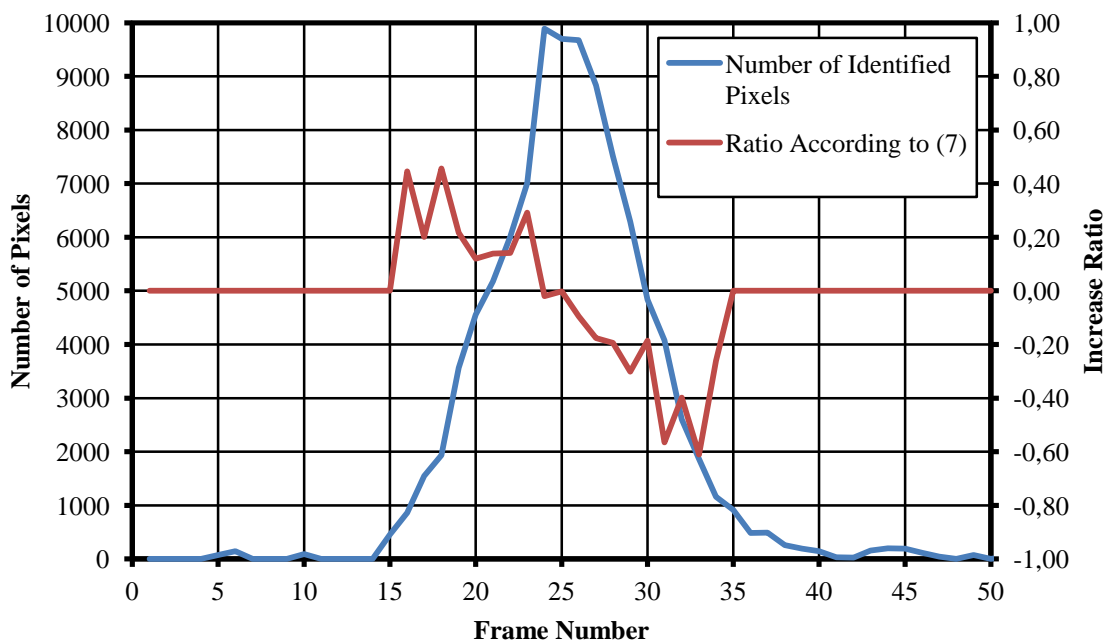

Fig. 10. Number of identified pixels for the deflagration in figure 8 and ratio according to eq. (7) with $m_T = 900$

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Conclusions and Outlook

This paper presents an algorithm for detecting a deflagration at its initial stage by using image processing. The proposed two-stage and rule-based algorithm is able to detect deflagration-like pixels with its first stage and can distinguish between static and dynamic processes by its second stage. It is planned to use the algorithm in combination with a high-speed camera within a crew compartment of an armored vehicle.

First experimental results show that the algorithm has the ability to detect a deflagration-like process without being disturbed by light reflections or other backlight sources such as daylight.

Nevertheless the proposed algorithm represents only a basis for further developments. It is necessary to analyze the exposure time settings. Moreover, the algorithm's performance should be tested in more scenarios, e.g. fast moving backlight or within a real crew compartment. For additional information about the identified process, the method has to be extended for use with more cameras. This will allow a spatial estimation of the dimension and position of the deflagration. Further fire suppression systems for armored vehicles based on water mist will be more effective by using this additional information.

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