Fire Safety Journal 65 (2014) 1–10

Contents lists available at ScienceDirect

Fire Safety Journal

journal homepage: www.elsevier.com/locate/firesaf

Image processing based deflagration detection using fuzzy logic classification

Thomas Schröder [a,*], Klaus Krüger [a], Felix Kümmerlen [b]

[a] Institute of Automation Technology, Helmut Schmidt University Hamburg, Holstenhofweg 85, 22043 Hamburg, Germany
[b] Bundeswehr Research Institute for Protective Technologies and NBC Protection, Humboldstrasse, 29633 Munster, Germany

ARTICLE INFO

Article history:
Received 27 November 2013
Received in revised form
4 February 2014
Accepted 22 February 2014
Available online 15 March 2014

Keywords:
Deflagration detection
Image processing
Fire detection
Fuzzy classification

ABSTRACT

Image processing-based deflagration detection is currently a novel application with a considerable development potential. Moreover, this technology could replace the commonly used infrared photodiode-based detection sensors and can help to avoid tunnel disasters or accidents in chemical plants more reliably. Today's deflagration detection systems only provide a detection signal without any further information concerning the triggering event. In addition, these systems are not able to distinguish between a hazardous deflagration and a less dangerous fire-like process.

This paper proposes a two-stage algorithm for deflagration detection in order to obtain this valuable information. The first stage identifies probable deflagration-like or fire-like pixels by their chromatic characteristics and dynamic intensity behaviour. The following stage evaluates the temporal expansion of the counted pixels using a defined spatial expansion parameter (SEP). In parallel to this, the oscillating change in the number of identified pixels over time is transformed into the frequency domain. The analysis of the frequency spectrum facilitates identifying fires by their typical flicker frequency. The proposed detection method uses fuzzy logic classification for each stage. Thereby no static thresholds are necessary, which yields more setting options in order to increase algorithm flexibility.

Finally, the entire algorithm is tested in different realistic scenarios with focus on deflagrations. As a general result of the performance tests, the algorithm is able to detect and distinguish deflagrations and fires with high accuracy. Furthermore, the expansion of the detected combustion processes is described quantitatively.

1. Introduction

The detection of deflagrations is a very special field within the large area of combustion processes' detection. In contrast to fire detection, as one of the widely used detection applications, today's deflagration detection systems primarily focus on the fast identification of the hazard. This means that deflagrations must be detected in their initial stage before they can unfold their endangering potential. Consequently, the sooner a deflagration is detected the higher are the chances to suppress the following effects such as fast increasing pressure and high temperatures.

The early detection of an expanding deflagration is achieved by using simple infrared photodiodes in combination with wavelength filters, which allows for monitoring the radiation of hydrocarbon-based combustion products. Photodiode-based sensors are able to detect deflagrations within 10 ms, which is sufficient time to suppress them. However, due to the required fast detection time, other characteristics of the event such as scale, hazard or localisation are neglected.

Today's photodiode-based deflagration detection systems are mostly used for certain monitoring applications in small rooms, for example in the manufacturing of explosive materials. One example of an application is an ultra-high speed digital fire and flame detector, which senses radiant energy in the ultraviolet, visible and infrared spectrum bands supported by a microprocessor based algorithm [1]. Another application of deflagration detectors is the monitoring of a military vehicle's crew compartment. During an attack, soldiers within such a vehicle are at a particularly high risk to suffer serious injuries caused by deflagrations. Deflagration detectors in combination with a very fast extinguishing system ensure the suppression of a deflagration within 150 ms [2]. However, many potentially disturbing sources inside the vehicle can lead to false alarms, which result in an unwanted activation of the one-time usable extinguishing system. Thus, the reliability of the deflagration detection is at least as important as a high detection speed. A reliable detection process includes the ability

* Corresponding author. Tel.: +44 40 6541 2189/+49 4065412189; fax: +44 40 6541 2004.
E-mail addresses: schroeder@hsu-hh.de (T. Schröder), klaus.krueger@hsu-hh.de (K. Krüger), felixkuemmerlen@bundeswehr.org (F. Kümmerlen).

http://dx.doi.org/10.1016/j.firesaf.2014.02.004
0379-7112

to differentiate between certain combustion processes and to ignore potentially disturbing sources. Due to their mode of action, photodiode-based detectors cannot distinguish between a hazardous deflagration and a less dangerous fire-like process. Both events emit radiation in the monitored wavelengths, making it very difficult for the detector to discriminate between combustion processes and disturbing sources such as welding, lighter or cigarette fires.

Additional information such as differentiation of the identified hazard, its location or dimension will help to avoid false alarms and it will improve the effectiveness of the extinguishing process. The effectiveness of non-chemical based extinguishing agents, in particular the optimum droplet size of water mist, are partly dependent on the potential size of the fire [3]. Accordingly, additional information provided by the detector, e.g. the size of the hazard can help to fully replace current chemical extinguishing agents with environmental friendly water mist based agents.

For providing additional information, a visual based approach for deflagration detection is a serious alternative to the conventional photodiode-based systems. The use of image processing techniques for fire detection has already been a well established method for at least two decades [4]. Most of the fire detection approaches are mainly based on the typical fire colour characteristics and the motion of the fire or the flame [5].

One of the first approaches of image processing for fire detection by Healey et al. [4] detects a fire by manually marking the fire-coloured area with a rectangle, and one of the latest detection approaches uses the fire colour features for pixel identification [6]. This shows that colour is still by far one of the most reliable features of a fire and promises successful detection results. Typically used colour spaces are the well-known RGB colour space, the YCbCr colour space, which facilitates a better discrimination of the luminance from the chrominance, and the HSI/HSV colour space for a single use of the saturation and intensity [5]. Most of the rule-based approaches use Gaussian-smoothed histograms to detect fire-coloured pixels [7]. Statistical colour models [8] or simple decision rules based on relations between the single colour channels are also commonly used [9].

After the fire-coloured pixels are detected successfully, other techniques are in use to confirm the selected pixel area as a fire. One approach is the measurement of the fire disorder [10]. Hereby, the difference in pixel quantity of the flame between two consecutive frames is evaluated and compared to an empirically determined threshold. A further technique is to check the growing rate of the number of fire pixels [9]. This allows for evaluating the increase of the fire and for automating the fire detection process.

Motion or temporal behaviour of a fire is an even more important feature for fire. Motion can be distinguished between a microscopic and a macroscopic scale. Microscopic motion refers to the variation of each pixel value, i.e. moving fire can be isolated from the background by analysing the variation of the pixel's luminance [11] or intensity [12].These methods are used to identify potential fire pixels. Macroscopic motion describes the variation of the entire fire or flame. As it is presented in Hamins et al. [13], fire or flames pulsate in a special frequency range, called flicker frequency (1–10 Hz). Fire detection approaches based on this knowledge transform the temporal variation of a fire shape into a frequency spectrum by using wavelet [12] or Fourier transform [14]. If the resulting frequencies are in the flicker range, the pixel area can be confirmed as a fire or flame.

The analysis of the detection results is done by fuzzy classification, artificial neuronal networks or a hybrid of both [15]. These so-called intelligent techniques provide an automatic fire detection system, in which the human knowledge about fire classification can be incorporated.

Nevertheless, the image-based detection of deflagrations requires algorithms, which focus on the deflagration features. In addition, recent approaches for fire detection are based on time-consuming algorithms such as several conversions between different colour spaces and sophisticated frequency analysis. Thus it is highly probable that the detection time rises considerably above the required value of less than 15 ms. Furthermore, most of the algorithms assume that the fire will grow gradually. This might not be the case during the expansion of a deflagration. Due to that, usual fire-detection algorithms are not suitable for deflagration detection [16].

2. Detection strategy

The identification of each potential deflagration-like or fire-like pixel is a challenge for every detection algorithm. Consequently, the detection strategy must be focused on typical features of the combustion processes, which are to be detected. The chromatic features of a deflagration are already presented in Schroeder et al. [17]. The most typical feature of a deflagration-like pixel is the high variation in intensity due to the emission of a huge quantity of energy in a very short time. Further features are the ratio of the red and blue value and the absolute pixel intensity.

The proposed multi-criteria deflagration detection algorithm consists of two stages, the identification of deflagration-like or fire-like pixels and the subsequent verification of the identified event. Both stages consist of purpose-developed characterising sub-algorithms and fuzzy-based classification models.

The first stage identifies pixels with a fast variation in intensity and a characteristic ratio of red and blue. Evaluating the intensity dynamics the corresponding fuzzy classification considers the dynamic range of the sensor. The subsequent evaluated ratio of red and blue is used to confirm the presence of a reddish fire-like event. Finally, all pixels of a frame, which exceed the detection conditions, are counted.

The second stage evaluates the variation in the number of identified pixels between consecutive frames by computing the first temporal derivation. This value describes the expansion of the event. Both, number of identified pixels and its first derivation are further evaluated by fuzzy classification in order to detect a deflagration. In parallel to this, the temporal curve of the number of identified pixels is transformed into a frequency spectrum. This allows for identifying the typical flicker frequency range of a fire or flame. Again, both parameters are evaluated by a fuzzy classification for detecting a fire or flame.

A first approach for a deflagration detection algorithm based on image processing is already presented [18]. This algorithm still works with static thresholds instead of flexible fuzzy models. Additionally, the thresholds are determined by empirical data, the detection rate depends on the settings of these thresholds. In the following, each stage of the algorithm is explained in detail.

2.1. Pixel identification

As described in [17] a deflagration is mainly characterised by a high variation in pixel intensity. A previous fire detection approach proposed by Marbach et al. [11] tries to detect fire-like pixels by analysing the luminance variation. However, this approach computes the exponentially smoothed cumulative variation in luminance of each pixel to identify the moving pixels of a fire. This results in the differentiation of stationary regions, which are represented by zero, and moving regions, which are indicated by non-zero pixel values. The accumulation of the absolute luminance values facilitates the detection of expanding as well as contracting areas. Thus, this approach is not usable for the detection of a