Fire Safety Journal 66 (2014) 1–7

Contents lists available at ScienceDirect

Fire Safety Journal

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

Comparison of intensity flickering features for video based flame detection algorithms

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ARTICLE INFO

Article history:
Received 4 July 2013
Received in revised form
28 February 2014
Accepted 7 March 2014
Available online 29 April 2014

Keywords:
Video fire detection
Flames
Flickering analysis
Feature comparison

ABSTRACT

Flickering is the most explicit visual characteristic of flames. Flames flicker in height, size and in brightness. Video based flame detection algorithms often analyze flickering of pixel intensities over time to detect flames. In this study we investigate five different pixel intensity flickering features based on methods presented in previous work. We compare the classification rates that features achieve on a large video database containing flames and non-flame objects. We depict differences of the features to each other and explain how these differences affect the classification rates. We point out components that should be considered for the design of flickering features.

1. Introduction

Conventional point smoke detectors require a minimum density of smoke at the location of the detector. Much time can pass until this smoke density is reached, especially in high rooms. Fire alarm is triggered late whereby injuries and property damages occur. Early detection methods can prevent those injuries and damages. Commonly, flames and smoke are visible earlier than alarm is triggered by conventional fire detection systems. This leads to the idea of using video cameras for fire detection. Video fire detection systems also allow fire surveillance of areas which cannot be kept under surveillance by conventional systems like big halls or outdoor areas. Additionally, cameras provide supplemental information that can be used for firefighting such as fuel or fire location and they allow to verify alarms. Furthermore video fire detection algorithms can be integrated in other video content analysis systems.

Video fire detection as a field of research can be separated in two parts – smoke detection and flame detection. For flame occurrence a sufficient temperature and oxygen supply is required and a fuel must be available which emits enough energy in short time. In this paper we focus on flame detection and treat it as a two-class classification problem, containing the classes *Flame* and *Disturbance*. The *Disturbance* class contains all not-flame objects.

In previous work diverse video flame detection features were presented. A comprehensive overview of the state of the art in video fire detection can be found in the work of Cetin et al. [1] and Verstockt et al. [2]. Features used in these works can be subsumed to features groups. One feature group, used by flame detection systems, analyzes flame color properties. Flame color filtering can be performed in different color spaces by distinct methods. One approach is the combination of threshold filters, as implemented by Chen et al. [3], Celik and Demirel [4], and Chen et al. [5]. In other approaches, color filtering is applied by color models. Toreyin et al. [6], Ko et al. [7], and Zhao et al. [8] apply Gaussian models for color analysis.

Besides color, shape information often is used for object detection. Since fire has no characteristic static shape, dynamic shape analysis can be used to discriminate between flames and disturbances. Zhang et al. [9], Borges and Izquierdo [10], and Xiaoling et al. [11] presented methods to analyze the roughness of flame boundaries and flame apexes.

In another group of features the intensity variations caused by flames are analyzed. Flames flicker in height and size strongly. If flames are small, the background is still visible at image positions above the fire source. If flames are big, they cover image positions above the fire source and the background is not visible any more. As flames are brighter than the background, flickering of flames causes strong intensity variations at image positions above the fire source.

In this paper we call these variations over time as *intensity flickering*. High flickering rates of flames can be used to distinguish between flames and disturbances. Various methods were presented in previous work to analyze intensity flickering. In this

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http://dx.doi.org/10.1016/j.firesaf.2014.03.001
0379-7112/

paper we compare features based on methods proposed in Chen et al. [5], Toreyin et al. [6], Zhao et al. [8], Zhang et al. [9], Marbach et al. [12] and Dedeoglu et al. [13]. We analyze and evaluate their capability to discriminate flames from non-flame moving objects.

In Section 2 we describe the flickering features which we compare. Since different flickering features are used for different purposes, they are not comparable directly. Therefore we present a procedure to make different features comparable. In Section 3 we describe the database and compare the classification rates of different features. In Section 4 we discuss the classification rates of different features and point out the reasons for high and low rates.

2. Flickering features and optimization method

At first, in Section 2.1, we depict five different intensity flickering features. We define a trivial feature and compare it with four features proposed in previous work.

Proposed features were used to fulfill different purposes in complete flame detection algorithms. For instance they can be used to segment fire candidate regions [12] or they can be part of a classifier Zhang et al. [9]. Thus different flickering features are not comparable directly. In Section 2.2, we present a method which, on the one hand, makes the features comparable directly, and, on the other hand, optimizes features regarding classification rates.

In previous work flickering rates of up to 10 Hz are assumed [6,14]. To cover even high flickering frequencies of 10 Hz, we use videos with a frame rate of 25 *frames per second*. All analyzed videos have a length of 4 s (100 frames). A time period of 4 s on the one hand is short enough to assume that fires do not grow not significantly. On the other hand 4 s is long enough to observe the flickering characteristics of flames.

2.1. Flickering features

Since pixel positions above the fire source are covered and uncovered by flame in short time intervals, strong differences in intensity occur. Fig. 1(a) shows a wood test fire with a highlighted pixel position above the fire source. Fig. 1(b) shows the corresponding intensity variation over a time period of 30 frames at the highlighted position. At subsequent frames the highlighted pixel at times is covered and not covered by flames. The intensity varies between 130 and 230. Fig. 1(c) shows the frame to frame intensity differences.

2.1.1. Continuous differences

At first, we present a trivial intensity flickering feature. It can be regarded as reference for other features. The intensity flickering measure is accomplished by summing up absolute differences of intensities, specified by

$$diff_{x,y}(t) = |I_{x,y}(t) - I_{x,y}(t-1)|, \tag{1}$$

$$D1_{x,y} = \sum_{t=1}^{100} diff_{x,y}(t). \tag{2}$$

High flickering rates cause high values of $D1_{x,y}$. The criterion to distinguish between flame and disturbance is defined by

$$D1_{x,y} \geqq SumThr1. \tag{3}$$

If $D1_{x,y}$ exceeds the threshold $SumThr1$, the pixel position $[x, y]$ will be regarded as a flame pixel, otherwise as disturbance pixel. The threshold $SumThr1$ is optimized applying the method described in Section 2.2. Subsequently this feature is called *Continuous Differences.*

2.1.2. Weighted differences

Further we implemented a feature based on a feature proposed by Marbach et al. [12]. It weights the frame to frame intensity differences by absolute intensity values. We call this feature as *Weighted Differences*. The feature is specified by

$$D2_{x,y} = \sum_{t=1}^{100} (I_{x,y}(t) \cdot diff_{x,y}(t)),$$

$$D2_{x,y} \geqq SumThr2.$$

2.1.3. Binary differences

We implemented a third flickering feature based on the feature proposed by Chen et al. [15], hereafter called *Binary Differences*. It applies a binary threshold filter before sampling. The feature is described by

$$m3_{x,y}(t) = \begin{cases} 1 & \text{if } diff_{x,y}(t) \geqq BinThr3 \\ 0 & \text{else} \end{cases}, \tag{4}$$

$$D3_{x,y} = \sum_{t=1}^{100} m3_{x,y}(t). \tag{5}$$

$$D3_{x,y} \geqq SumThr3. \tag{6}$$

In contrast to *Continuous Differences* and *Weighted Differences*, the feature *Binary Differences* depends on two parameters, $BinThr3$ and $SumThr3$. Frame to frame intensity differences have to be high enough to exceed the threshold parameter $BinThr3$ to be counted among $D3_{x,y}$.

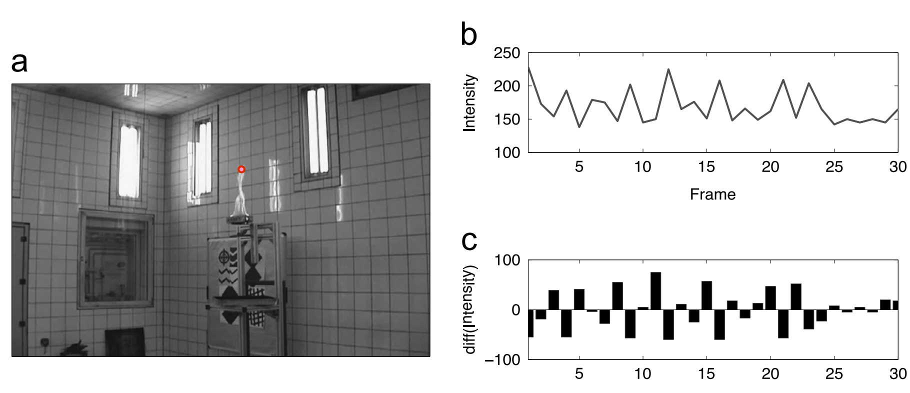

Fig. 1. (a) shows a wood test fire with marker at the point of interest (POI), (b) shows the variation of the intensity over time at POI, (c) shows the intensity differences between subsequent frames. At the POI intensities vary from 130 to 230 and frame to frame differences reach up to 80 intensity levels.