The Smoke Detection for Early Fire-Alarming System Base on Video Processing

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Abstract

The paper presents an smoke-detection method for early fire-alarming system based on video processing. The basic strategy of smoke-pixel judgment is composed of two decision rules: a chromaticity-based static decision rule and a diffusion-based dynamic characteristic decision rule. The chromatic decision rule is deduced by grayish color of smoke and dynamic decision rule is dependent on the spreading attributes of smoke. Experimental results show that the proposed method can provide an early alarm at a lower false alarm rate before the fire burns up, and hence is very attractive for the important military, social security, commercial applications, and so on.

1. Introduction

1.1. Motivation

Generally, the fire accident usually causes economical and ecological damage as well as endangering people's lives. To avoid the fire's disasters, many early fire-detection techniques have been explored and most of them are based on particle sampling, temperature sampling, relative humidity sampling, air transparency testing, in addition to the traditional ultraviolet and infrared fire detectors. However, most of the objects will generate smoke before it catches fire and this motivates that the smoke-detection is employed to provide an early alarm of fire accident. Almost all traditional smoke-detectors either must be set in the proximity of a fire or can't provide the additional information about the process of burning, such as fire location, size, growing rate, and so on. Hence, they are not always reliable because energy emission of non-fires or byproducts of combustion, which can be yielded in other ways, may be detected by misadventure. This frequently results in false alarms. To provide more reliable information about smoke-detection, the visual-based approach is becoming more and more interesting.

Most of video-based fire-detection techniques [1] - [8] are aimed at flame detection for the purpose of giving a fire alarm. In many practical situations, smoke-detection will offer a more early alarm than flame-detection. To avoid being interfered by smoke-aliases, both chromatic recognition and disorder measurement are employed to improve the verification of a real fire [9]. For reducing false alarm rate, a more effective smoke decision function in dynamic characteristic is developed in this paper to enhance the reliability of early fire-alarming. From analyses on static and dynamic features of smoke, we propose a two-stage checking process of smoke detection. The basic strategy is to extract smoke pixels by chromatic checking in the static feature and then these pixels are further verified through the dynamic diffusion checking.

2. Features of smoke

Most fuels will burn under appropriate conditions, reacting with oxygen from the air, generating combustion products, and displaying flame and smoke. The smoke is that the material is burnt and decomposed into the gaseous state, liquid state and solid-state materials and their mixture with the air, which contains a large amount of heat. It is mainly composed of the completely burned small charcoal particles and the incomplete burned dust. The constituent and quantity of the smoke depend on the chemical components of the combustible material, the burning temperature, the supply of oxygen, and so on. If the material is completely burnt, the major components of smoke include carbon dioxide, carbon monoxide, vapor, etc. When the material is

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incompletely burnt, not only the above combustion products but also the organic compounds, such as alcohol, ether, etc., are generated. For many combustible materials, the smoke color will range from white-bluish to white when the temperature of smoke is low. On the other hand, the smoke color will range from black-grayish to black when the temperature rises until it catches fire, because there will be dehydrating phenomenon and thus it produces a large number of charcoal particles dissociated. For most of smokes, they usually display grayish colors, as shown in Figure 1.

Unfortunately, some smoke like regions in an image may have the same colors as the smoke, and these smoke-similar areas are usually extracted as the real smoke from an image. These smoke aliases are generated in two cases: non-smoke objects with the same colors as smoke and background with illumination of smoke-like light sources. In the first case, the object with grayish colors may cause a false extraction of smokes. The second reason of wrong smoke-extraction is that the background illumination has a serious influence on extraction, making the process complex and unreliable. To validate the real smoke, in addition to using chromatics, dynamic features are usually adopted to distinguish other smoke aliases. These smoke's dynamic attributes include diffusion motion, changeable shapes, and growing rate.

(a) Light-gray smoke (b) Dark-gray smoke

Figure 1. Different grayish colors of smokes.

3. The smoke detection

3.1. Static analysis

The smoke usually displays grayish colors during the burning process. Such a grayish color can be classified into two gray-level regions: light gray and dark-gray. This implies that three components R, G, and B of the smoke pixel are equal or so. Therefore, these grayish colors can be described with I (intensity) component of HSI color model. The intensities of light-gray and dark-gray regions range from L_1 to L_2 and D_1 to D_2 gray-levels, respectively. By the chromatic analysis, the condition $R\pm\alpha = G\pm\alpha = B\pm\alpha$ and $L_1 \leq I \leq L_2$ and $D_1 \leq I \leq D_2$ can be used as one decision function for smoke recognition. In the above condition, those values of α, L_1, L_2, D_1 and D_2 all depend on the statistical data of experiments. The range of the typical value of α is from 15 to 20. Typical values of light-gray and dark-gray range from 80 ($=D_1$) to 150 ($=D_2$) and 150 ($=L_1$) to 220 ($=L_2$), respectively. Three decision rules for extracting smoke pixels from an image are deduced in the following:

$$
\begin{aligned}
&rule\ 1: R \pm \alpha = G \pm \alpha = B \pm \alpha \\
&rule\ 2: L_1 \leq I \leq L_2 \\
&rule\ 3: D_1 \leq I \leq D_2 \\
&If\ (rule\ 1)\ AND\ \left[(rule\ 2)\ OR\ (rule\ 3)\right] = TRUE \\
&Then\ smoke-pixel \\
&Else\ not\ smoke-pixel
\end{aligned}
\tag{1}
$$

If the above condition is satisfied, it implies that the smoke may be likely a real smoke, not smoke-alias.

(a) Smoke generated by burning papers

(b) Smoke generated by burning wood

Figure 2. Different smokes generated by burning with different fuels.

3.2. Dynamic analysis

In point of dynamics, the smoke spreads out basically in a way of diffusion process. In general, airflows will seriously affect the smoke's shape, moving speed, and moving direction of those smoke particles. In the reported research [9], a disorder-based decision rule involving the quantity smoke pixels is used to verify a real smoke extracted by the color feature from the captured image sequences. However, only the measure of disorder may be not sufficient for validating a real smoke in dynamic characteristics, because the disorder can't be measured at some times. To improve the reliability of smoke detection, both the growth-rate and disorder of smoke should be considered to be involved into the decision function for smoke judgment.

Basically, airflows will make the shape of smoke to be variously changed at any time, and thus it is intractable to measure the shape. Therefore, a novel disorder measure, the ratio of circumference to area for the extracted smoke region, is introduced to improve the verification of smoke. The following decision rule can be used to detect the smoke.

$$\begin{aligned}&If\ (SEP/STP) \geq STD\\&Then\ real\ smoke\\&Else\ not\ smoke\end{aligned} \tag{2}$$

In the rule, the parameter *SEP* denotes the sums of circumferences of smoke regions segmented, *STP* is the number of smoke pixels extracted, and *STD* means a disorder threshold that distinguishes from other smoke-like objects. The ratio of *SEP/STP* defines the disorder measurement of smoke. It should be noted that the threshold *STD* is variable in various situations and dependent on the statistical data of experiments.

In addition to the disorder-based decision rule, the growth-rate is also a necessary condition for enhancing the reliability of smoke detection. Owing to the diffusion process existed in generation of smoke, the smoke region in an image sequence will gradually increase. Thus, the increment rate of the extracted smoke pixels by the chromatic decision rule (1) is defined as

$$\Delta A_{d_i} = \frac{dA}{dt} = \frac{A_{i+k} - A_i}{t_{i+k} - t_i} \tag{3.1}$$

where A_i means the smoke area at the interval between time *i+k* and time *i*. In the digital image processing, the area can be represented with the pixel quantity and the time interval will be replaced by the frame number. So, equation (3.1) can be deduced to

$$\Delta A_{d_i} = \frac{dP}{dt} = \frac{P_{i+k} - P_i}{(i+k) - i} \tag{3.2}$$

where P_i is the number of the *i*-th frame and thereby ΔA_{d_i} means the ratio of pixel quantity obtained by frame-difference between frame *i* and frame *i+k* to the frame number *k*. To obtain a more reliable measure of growth-rate, an average growth-rate is adopted and described as follows:

$$\overline{\Delta A_{d_i}} = \frac{1}{n}\sum_{i=1}^{n} \Delta A_{d_i} \tag{3.3}$$

where *n* is the number of iteratively measuring the growth-rate. Besides, it is necessary to check the average growth-rate $\overline{\Delta A_{d_i}}$ for many times because the area of smoke region is frequently affected by airflows. Therefore, the growth-based decision rule in the dynamic characteristic is described as

$$\begin{aligned}&if\ Num(D_1 < \overline{\Delta Adi} < D_2) > N_d\\&Then\ smoke\\&Else\ not\ smoke\end{aligned} \tag{4}$$

where D_1 and D_2 are the low-bound and high-bound thresholds of growth-rate, respectively, and N_d is a threshold of checking times. If the checking times of that the average growth-rate is between D_1 and D_2 are larger than N_d, it is regarded as the real smoke; otherwise, not smoke. Those thresholds of D_1, D_2 and N_d will be determined by the statistical data of experiments.

3.3. Smoke detection flow diagram

Based on the above decision rules of both static and dynamic features of smoke, Figure2 demonstrates different smokes generated by burning with different fuels in various environments. By employing such decision rules of (1), (2) and (4), the subfigure (a) shows the light-grayish smoke generated by burning papers and the extracted smoke pixels. By the same way, the subfigure (b) shows the dark-grayish smoke generated by burning wood and the extracted smoke pixels.

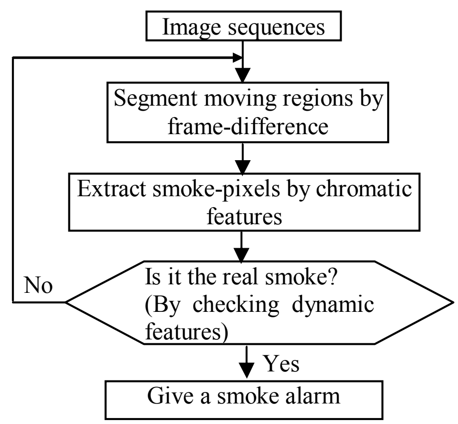


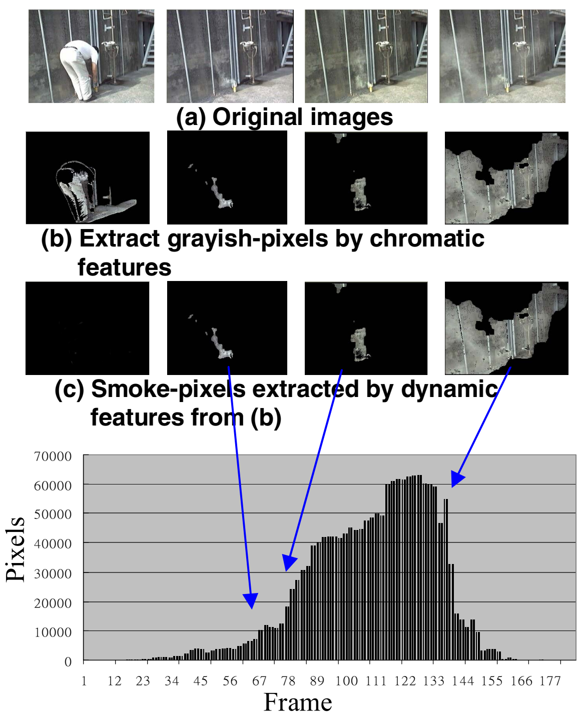
Figure 3. Smoke detection algorithm.

The proposed smoke detection algorithm is dedicated to providing an early alarm for possible fire accidents, as depicted in Figure 3. At first, the moving regions are segmented form the captured image sequences and thus used as candidates for checking if they are smokes. By chromatic features, as described in subsection 3.1, smoke-pixels will be extracted from these moving regions. Then, to distinguish form smoke-aliases, dynamic features including growth-rate and disorder are utilized for validating these smoke-pixels extracted. Finally, as room as the real smoke is confirmed, a smoke-alarm is given.

4. Experimental results

A theoretical analysis about the proposed smoke detection method has been given in the above sections, but the implementation can provide a realistic and interesting evaluation. In Figure 4, subfigure (b) shows the extracted grayish pixels by the chromatic decision rule from moving regions in the image sequence captured. It can be clearly observed that a man wearing the grayish clothes is wrongly extracted, as shown in the left image of image of subfigure (b). However, such a problem caused by only using the chromatic feature can be solved by further using the dynamic feature, as shown in the left image of subfigure (c). Obviously, the real smoke pixels are finally extracted, as shown in the subfigure (c) and these pixels and depicted in a way of histogram in the subfigure (d).

For the bright background, the smoke can be correctly extracted, but the extraction may fail in the dark environment due to the camera's capturing attributes. Nevertheless, IRC (infrared ray camera) can be used to cope with the capturing problem inherently existed in the dark surroundings.



(a) Original images

(b) Extract grayish-pixels by chromatic features

(c) Smoke-pixels extracted by dynamic features from (b)

(d) Number of smoke-pixels extracted

Figure 4. Experimental results.

5. Conclusions

This research develops a smoke-detection method based on image processing to provide an early alarm for the fire accidents. Both static and dynamic features of smoke are involved into the decision function to improve the reliability of smoke detection. Experimental results show that the proposed method can provide a reliable and cost-effective solution for smoke detection, and it may be more attractive than the conventional ways of smoke detection.

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