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A video-based smoke detection using smoke flow pattern and spatial-temporal energy analyses for alarm systems

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ABSTRACT

Detecting smoke during the initial stages is vital for preventing fire events. This study proposes a video-based approach for alarm systems that detects smoke based on temporal features extracted from optical smoke flow pattern analysis and spatial-temporal energy analysis. To do this, it considers various optical characteristics such as the diffusion, color, and semi-transparency of smoke. In the proposed model, smoke-colored pixels are identified via masking in the HSV color space and a temporal frame difference is applied. To extract the temporal feature vectors, we propose a new method that determines the optical flow of smoke by using distinguished texture information by applying a Gabor filter bank with preferred orientations. In addition, when applied to an image that has been temporal-differenced, the energy of the spatial frequencies is fed as another feature into the feature vector. Finally, these features are fed to a support vector machine (SVM) to discriminate our data more thoroughly and provide accurate detection of smoke. Experiments are carried out with benchmark datasets, which show that the proposed approach can work effectively without false alarms.

1. Introduction

Smoke appears mostly as a prelude to fire; therefore, it can acts as a forewarning to potentially catastrophic events. Thus, early detection of smoke can serve as an effective alarm to the occurrence of fire, which can help saving lives, the environment, and prevent costly damage to infrastructure. Hence, smoke detection is a very important problem; accidents related to fire inevitably cause economic and ecological impairment. Research works investigating smoke sensors that detect the heat of smoke for early identification are limited by the fact that these smoke sensors inherently suffer from transport delay (i.e., the time it takes for smoke to move from the fire to the sensor), which makes them inappropriate for early detection. Moreover, these systems serve as point sensors in space, which makes them inefficient at monitoring larger areas (unless many sensors are used) because smoke propagates in multiple directions [20].

The limitations of current smoke sensors have prompted investigations into vision-based methods for detecting smoke. These sensors use the visual signatures of smoke such as its color, motion, and texture information. Vision-based systems provide efficient results for larger areas and can be easily integrated into existing closed-circuit surveillance systems. However, these systems are currently limited by a great number of technical challenges because many characteristics have to be

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considered; these factors include the variability in smoke density, the color of the smoke, obscuration characteristics, illumination, the non-rigid and changeable shape of smoke, and diverse backgrounds that can be similar to the color of smoke [6].

Many researchers have investigated computer vision-based smoke detection technologies. Most of these are based on multistage pattern recognition, which basically consists of three stages [2–5,8,10,12,14–19]: the *preprocessing stage* (PPS), *feature extraction* (FE), and *classification* (CLASSIFY). The PPS is the fundamental task used to determine the region of interest (ROI) in the input video frames by identifying smoke pixels and analyzing the eligible regions [8]. For segmenting the ROI from the input (derived from the static cameras), color segmentation (CS) [2,4,5,12,14,15,17,19] methods have been used by many researchers in various color spaces. This is commonly done by converting the RGB space into the HSV [2], YUV [12], YCbCr [17], or HSI [14] color spaces. The HSV color space emphasizes visual perception in terms of variations in the hue, saturation, and intensity values of an image pixel, which makes segmentation easier to accomplish. However, the analysis of eligible regions is done by detecting temporal changes, which is done mostly by frame differencing [18], optical flow analysis [5,10], and Gaussian mixture modelling [4,19]. Though the information obtained from simple frame differencing can provide powerful cues to capture the motion characteristics of smoke, it has trouble differentiating moving objects that are similar in color to smoke, which can decrease its accuracy in smoke detection. To address this issue, many researchers have analyzed regions of smoke by extracting features from spatial-temporal wavelet analysis [2,10,15,19] and dynamic texture analysis by means of mathematical models [7,16]. In [2], spatiotemporal analysis, smoke motion modeling, and dynamic texture recognition are used to discern smoke from smoke-colored moving objects. Alternatively, in [15], smoke is distinguished through Eigen values that are calculated using wavelet transformations and optical flow. However, this wavelet analysis alone cannot overcome the aforementioned issues because it can only determine the high frequency components. Moreover, smoke characteristics vary with density in subsequent frames, which necessitates the use of texture analysis. In [15], dynamic textures are modeled by estimating LDSs (linear dynamic systems) to extract the appearance and features. The authors in [7] proposed a model that extracts texture by mapping each pixel to node of complex network to produce spatial and temporal degrees from network transformations in order to extract appearance and motion features, respectively. The authors in [9] utilized a 2D Gabor filter, which has the ability to decompose an image with preferred directional properties, to improve the biomedical diagnostic accuracy and obtain efficient representation of the visual texture properties.

Similarly, smoke displays optical flow characteristics at different orientation angles in between video frames. Therefore, for subsequent images with discontinuities, when there is a linear combination of spatial wavelet energy and statistical features derived from the directional transforms of Gabor-filtered images, the classification from smoke to non-smoke frames can be improved. Thus, researchers have employed Gabor filters and the wavelet energy to extract potential spatial-temporal features from optical smoke flow, which allows smoke classification to be accomplished via support vector machines (SVM) [2,9,17,19]. Though there are many classification techniques, artificial neural networks (ANNs) [8,14] and SVMs are popular among them. We are considering SVM based classification because fewer hyper parameters are enough, number of training data samples are less required to get high accuracy and require less grid searching to get a reasonably accurate model. Moreover, this classification method is suitable to our application scenario.

In this paper, we propose an algorithm that utilizes an image processing system that uses the combined features of energy components of spatial-temporal frequencies derived from wavelet transforms and the statistical information of directional transforms obtained from Gabor-filtered temporal images. Though spatial-temporal energy coefficients are extensively used as informative smoke features, this information is not sufficient to determine the notorious characteristics of smoke. However, combining the Gabor filter with optical texture discrimination in preferred orientations can offer flow characteristics. Thus, we combine the spatiotemporal energy component of the frame and directional information extracted from Gabor filter banks to create a feature vector to detect smoke. Finally, classification is accomplished with an SVM.

The rest of this paper is organized as follows. Section 2 provides detailed information about the procedure used to determine the optical features of smoke and its differentiation from non-smoke image sequences. Section 3 analyzes the performance of the application and its efficiency. Finally, Section 4 concludes this paper.

2. Proposed optical smoke detection approach

The proposed approach addresses the characteristic features of smoke, such as the diffusion-based dynamic behavior, the color ranges of smoke, the semi-transparent properties, and smoke texture patterns. To evaluate the performance of our proposed model, we referred to many real-time smoke detection models and used the following three-stage methodology: PPS, FE, and CLASSIFY. The steps of the proposed approach are depicted in Fig. 1 and are discussed in greater detail below.

2.1. Pre-processing stage

2.1.1. Color analysis

Under appropriate conditions, fuels tend to combine with oxygen in air and combust, leaving behind some residues and generating flame and smoke. The characteristics of smoke vary depending on the burning temperature, chemical composure of the material/fuel, and the supply of oxygen. In most common cases, the color of the smoke that is generated varies from bluish-white to white when the smoke temperature is low. With rising temperature, the color can change from grayish–black to black until combustion occurs [5]. In addition, the external environment near the recording device also has an