Flame Verification using Motion Orientation and Temporal Persistency

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ABSTRACT

This paper proposes a flame verification algorithm using motion and spatial persistency. Most previous vision-based methods using color information and temporal variations of pixels produce frequent false alarms due to the use of many heuristic features. To solve these problems, we used a Bayesian Networks. In addition, since the shape of flame changes upwards irregularly due to the airflow caused by wind or burning material, we distinct real flame from moving objects by checking the motion orientation and temporal persistency of flame regions to remove the misclassification. As a result, the use of two verification steps and a Bayesian inference improved the detection performance and reduced the missing rate.

Keywords: Bayesian networks, motion, temporal persistency,

1. INTRODUCTION

Video surveillance in image sequences is one of the most interesting subjects in computer vision and many practical application fields have been researched over the past couple of years. Along with general video surveillance based on CCD camera, flame detection using video cameras has also become an important area of research. Most current flame alarm systems are based on infrared sensors, optical sensors, or ion sensors that depend on certain characteristics of flame, such as smoke, heat, or radiation. Especially, the most commonly used uncooled infrared sensor has become much cheaper in recent years and provides a very useful tool for industry [1].

However, these traditional flame alarm systems are not alerted until the particles actually reach the sensors, and usually are unable to provide any additional information, such as the location and size of the flame and the degree of burning. In contrast, vision sensor-based flame detection systems offer following several advantages [1,3].

- the equipment cost is lower
- the response time for flame and smoke detection is faster
- it can monitor the larger area

Various studies have recently investigated for flame detection and applied a variety of visual features, such as color, motion, edge and the shape of a flame region. Toreyin and Cetin[2] used Markov models representing the flam and flame colored ordinary moving objects to distinguish temporal flame from flame-colored moving objects. Celik *et al.*[3] proposed a real-time flame detector that combines foreground object information with color pixel statistics for flame. The foreground information is extracted using an adaptive background subtraction algorithm, and then verified using a statistical flame color model. Ko *et al.*[1] proposed a Support Vector Machine (SVM)-based flame detection method using color and temporal variation of pixels.

In this paper, we update our previous flame detection research [4] using omni-directional camera and Bayesian Networks. Here, we focus on flame verification method after flame detection using spatial motion orientation and temporal block variation.

The remainder of this paper is organized as follows. Section 2 describes the detection of flame detection based on Bayesian Networks, then the flame-pixel verification using motion orientation and spatial persistency is introduced in Section 3. Section 4 evaluates the accuracy and applicability of the proposed flame detection method based on experiments, and some final conclusions and areas for future work are presented in Section 5.

2. FLAME DETECTION BASED ON BAYESIAN NETWORKS

Most previous vision-based methods using color information and temporal variations of pixels produce frequent false alarms due to the use of many heuristic features. Plus, there is usually a computation delay for accurate flame detection. Thus, in our previous research [4], candidate flame regions were first detected using a background model and color model of flame.

The parameters of the distribution functions need to be learned from training data. However since the shape of flame changes irregularly due to the airflow caused by wind or burning material as distinct from a moving object, it is very difficult to make a probability model. In general, supervised learning is based on the assumption that the forms of the underlying density functions are known. However, since features that do not follow known distribution and parametric densities may be multimodal densities rather than unimodal, the probability density functions of each node are estimated using a non-parametric method. In the present case, the conditional probabilities of leaf nodes are directly learned from image sequences based on the temporal variation of pixels and probability density functions using a non-parametric method. The probability density functions for each node are modeled using the skewness of the color red, green, blue and three high frequency components obtained from a wavelet transform. Thus, these models are applied to a Bayesian Network. Our previous research used a three-level Bayesian Network that contains intermediate nodes, and uses six probability density functions for evidence at each node. In this paper, we inserted additional intermediate node N_1 and three leaf nodes, $N_{1\text{-}1}$, $N_{1\text{-}2}$ and $N_{1\text{-}3}$ respectively as shown in Figure 1. At Figure1, $N_{1\text{-}1}$ node is the observation node and has the probability distribution on Red color. $N_{1\text{-}2}$ and $N_{1\text{-}3}$ has the probability distribution on Green color and Blue color. The likelihood of N_1 is calculated by following joint probability function.

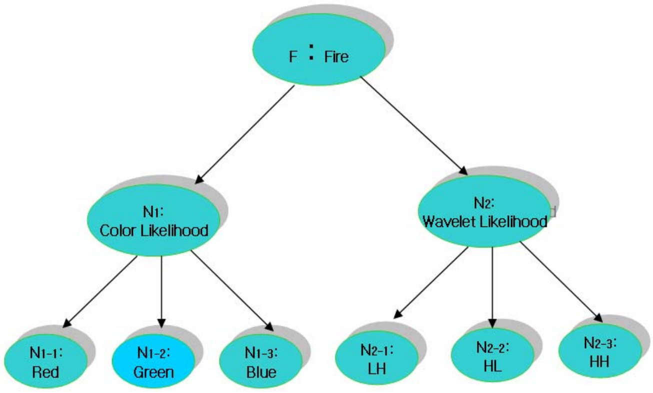


Fig. 1: Bayesian Networks for flame detection

$$\begin{aligned} p(N_{1-1}, N_{1-2}, N_{1-3}, N_1) &= p(N_{1-1}, N_{1-2}, N_{1-3} \mid N_1) \\ &= p(N_{1-1} \mid N_1) \cdot p(N_{1-2} \mid N_1) \cdot p(N_{1-3} \mid N_1) \cdot P(N_1) \\ &= \prod_{i=1}^{3} p(N_{1-i} \mid p(N_1)) \cdot P(N_1) \end{aligned} \tag{1}$$

To prevent truncate long double number, equation (1) is rewritten as follows:

$$\begin{aligned} p(N_{1-1}, N_{1-2}, N_{1-3}, N_1) &= \prod_{i=1}^{3} p(N_{1-i} \mid p(N_1)) \cdot P(N_1) \\ &= \sum_{i=1}^{3} \log(p(N_{i-i} \mid p(N_1)) \cdot P(N_1) \end{aligned} \tag{2}$$

Thus, when using the six probability distributions, Bayesian inference classifies whether a candidate flame pixel is a real flame pixel or not using equation (3).

$$P(F \mid N_1, N_2) = \frac{P(N_1, N_2 \mid F)P(F)}{P(N_1, N_2 \mid F)P(F) + P(N_1, N_2 \mid \neg F)P(\neg F)} \tag{3}$$

Figure 2 shows the flame detection procedures involved in the proposed algorithm.

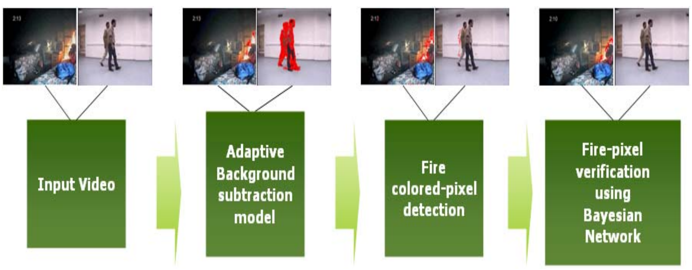


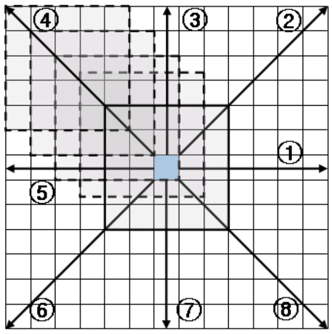
Fig. 2: Flame detection procedures involved in proposed method

3. FLAME VERIFICATION USING MOTION ORIENTATION AND TEMPORAL VARIATION

Although flame pixels are detected using a previous research, some noises which are appeared and disappeared at irregular interval can be misclassified as flame. Therefore, we add two verification algorithms by using the fact that flame usually drifts upwards continually by hot airflows [5].

3.1 Motion Orientation Persistency

Since the shape of flame changes upwards irregularly due to the airflow caused by wind or burning material, we can distinct real flame from moving objects. By using this fact, we first estimate the motion orientation from candidate flame pixels. Firstly, to reduce the error of noise pixels and reduce the computational complexity, we divide an image into nxn blocks and select flame blocks which including candidate flame pixels. Then, motion vectors are estimated using a block matching algorithm from every frame regardless of flame and saved in buffer. Even though block matching needs amount of computational time, our method only estimate motion vector from 5x5 blocks and calculate matching distance from only 25 blocks. These discrete directions are coded as 1, 2, 3, 4, 5, 6, 7 and 8, respectively. Since flame region usually changes upwards continually, we check the persistency of motion during previous N frames.



(a)

(b) (c)

Fig. 3: (a) Motion estimation method (b), (c) detected motion vector

If one candidate flame block is detected at current t frame, motion histogram is generated from motion directions of past N(30) frames. Because flame usually drifts upwards continually by hot airflows, we only check the upward motions (2~4) and candidate flame block pass to next the condition if it satisfy the following motion persistency (MP) condition.

$$\begin{array}{ll} if\,(MP > T_1)\; Fire & \\ else \qquad\quad Non-fire & (1) \end{array}$$

$$MP = \frac{\sum_{c=2}^{4} h_b(c)}{N}$$

Where, MP is the ratio of the sum of frequencies at upward motion directions in the block histogram (h_b) to the sum at all frames.

3.2 Temporal Persistency

Although flame pixels are detected using previous steps, some noises which are appeared and disappeared at irregular interval can be misclassified as flame. Therefore, by modifying Dedeoglu [6]'s idea, we check the temporal persistency of flame regions to remove the misclassification. First, input image is also divided into nxn non-overlapping blocks and a counter is assigned to each block. Then, we count the number of frames during past N frames whenever candidate flame pixels are existed in corresponding past blocks. If a flame region is detected in particular block, a counter of block increases number 1. In this way, if a counter (B_c) of one block containing flame pixels exceeds one third of *N*, this block is declared as the final flame block.

$$\begin{array}{ll} if\,(B_c > N/3)\; Fire & \\ else \qquad\quad Non-fire & (2) \end{array}$$

4. EXPERIMENTAL RESULTS

The proposed flame detection system, designed to detect flame in real-time for flame monitoring, was implemented using a Pentium IV 3.2 MHz PC with a 320 x 240 image size. To validate the effectiveness of the proposed approach, the detection result of the proposed system was compared with that of Töreyin et al.[2]'s algorithm. Since the video sequences containing flame in previous researches are not publicly available except for Töreyin's research and it has dynamic videos containing flame and flame-colored moving objects, we performed performance test with Töreyin's test data and other a few flame video clips obtained from webpages. You can download the test videos from Töreyin's web-page http://signal.ee.bilkent.edu.tr/VisiFire and our web-page, http://cvpr.kmu.ac.kr.

The frame rate of the video data varied from 15Hz to 30Hz and the size of the input images was 320 by 240 pixels. In our experiment, we used 9 video sequences. First 3 videos include outdoor flames, while 3 videos include indoor flames. Flame-colored moving objects (3 videos) were also considered to check whether the proposed system could accurately classify real fire or not.

The comparative results are presented in Figure 4. Overall, the proposed approach outperforms the Töreyin's method as shown in Figure 4. In particular, Töreyin's method also gave alarms at false locations or missed flame due to light reflecting on the ground or wall from flames as shown in last figure of Figure 4-(b). However, the proposed algorithm was able to remove these false positives using flame verifying step. In the case of the first figure of Figure 4-(b), since it contained relatively small-sized flames, these small regions are considered noises and removed in Töreyin's method. However, our method also shows better detection performance than Töreyin's method.

When movies include moving objects and our method does not detect any fire, we gave 100 percent of true positive.

Thus, as seen in Figure 4, the detection performance of the proposed method showed an improvement over the other Töreyin's method.

(a) (b)

Fig. 4: Flame detection results. (a) detection results of the proposed method, (b) detection results of the Töreyin's method

5. CONCLUSION

Flame detection approaches using a camera face certain challenges, as well as offering opportunities for the development of effective flame alarming systems.

To overcome some limitations of previous researches depending on color, this paper presented a flame verification algorithm using motion and spatial persistency with a Bayesian inference to verify real flame pixels. In particular, the patterns of flame and flame-like moving objects were analyzed and probability models of flame designed using several flame feature patterns. As a result, the use of two verification steps and a Bayesian inference improved the detection performance and reduced the missing rate.

Experimental results showed that the proposed approach was more robust to noise, such as smoke, and subtle differences between consecutive frames when compared with other method. However, reducing false alarms and the missed flame regions remain as ongoing challenges for successful flame detection in a real-life environment. Our additional research also extended the proposed method to omni-directional cameras [4] instead of normal CCD cameras in order to solve the dead angle of a CCD camera. You can also see the demonstration from our web-page, http://cvpr.kmu.ac.kr.

Acknowledgement

This research was supported by the Program for the Training of Graduate Students in Regional Innovation which was conducted by the Ministry of Commerce Industry and Energy of the Korean Government.

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