Smoke Detection in Videos Using Non-Redundant Local Binary Pattern-Based Features

Hongda Tian, Wanqing Li, Philip Ogunbona, Duc Thanh Nguyen, Ce Zhan

Advanced Multimedia Research Lab, ICT Research Institute
School of Computer Science and Software Engineering
University of Wollongong, Australia
{ht615, wanqing, philipo, dtn156, cz847}@uow.edu.au

***Abstract*—This paper presents a novel and low complexity method for real-time video-based smoke detection. As a local texture operator, Non-Redundant Local Binary Pattern (NRLBP) is more discriminative and robust to illumination changes in comparison with original Local Binary Pattern (LBP), thus is employed to encode the appearance information of smoke. Non-Redundant Local Motion Binary Pattern (NRLMBP), which is computed on the difference image of consecutive frames, is introduced to capture the motion information of smoke. Experimental results show that NRLBP outperforms the original LBP in the smoke detection task. Furthermore, the combination of NRLBP and NRLMBP, which can be considered as a spatial-temporal descriptor of smoke, can lead to remarkable improvement on detection performance.**

I. Introduction

Smoke detection has many potential applications including early warning of fire events and alarm triggering during traffic accidents in tunnels. For conventional point smoke detectors, this task is accomplished through detecting the presence of certain particles generated by smoke and fire. Thus it means that the smoke detectors need a close proximity of smoke. Another disadvantage of traditional smoke detectors is that they could not provide additional information about smoke such as location and size. To overcome these limitations, vision-based smoke detection has received an attention in recent years.

Generally speaking, existing vision-based smoke detection methods make use of such visual signatures as motion, color, edge and texture of smoke regions. Kopilovic et al. [1] presented a method through detecting irregularities in the optical velocity field due to smoke motion. Yuan [2] proposed an accumulative motion model to extract motion characteristics of smoke. In [3], optimal mass transport was introduced into optical flow computation in order to obtain better optical flow field model for smoke. Based on the fact that the color of smoke is usually grayish, Chen et al. [4] extracted chromatic features of smoke according to a set of decision rules. The potential color range of smoke in the RGB color space was also assigned in [2]. According to the observation that smoke could blur edges, Toreyin et al. [5] proposed edge-based method to perform smoke detection. Yu et al. [6] made use of gray level co-occurrence matrices (GLCM) [7] to perform texture analysis on smoke. However, GLCM-based methods depend greatly on illumination conditions. Recently, Yuan [8] adopted local binary pattern (LBP) and local binary pattern variance (LBPV) to perform video-based smoke detection. However, this method has some drawbacks. First of all, the original LBP is sensitive to the relative changes between the background and foreground [9]. Secondly, as a texture descriptor of static images, the original LBP could not include motion information of smoke. Finally, the dimension of the feature vector in [8] is 210. Such complexity will lead to slow processing speed and high requirement about storage, which may be a problem for real-time video-based applications.

As smoke is distributed dispersively, texture is promising feature to characterize smoke. Motivated by the discriminative power of local patterns, in this paper a video-based smoke detection method is proposed with the following contributions. Firstly, Non-Redundant Local Binary Pattern (NRLBP), which has been successfully applied to object detection [9], is introduced to represent smoke appearance. Although it is a variant of original LBP, it is more discriminative and robust to illumination changes. From the perspective of computational complexity and storage requirement, it is more efficient as well. Secondly, the motion pattern of smoke is described by Non-Redundant Local Motion Binary Pattern (NRLMBP) which is computed on the difference image of consecutive frames. Experimental results show that NRLBP is insensitive to the relative changes between the background and foreground and has better performance in our smoke detection task compared with the original LBP. Furthermore, integrating NRLBP and NRLMBP will lead to a superior detection performance almost without increasing storage cost.

The remainder of this paper is organized as follows. Section II presents the proposed smoke detection algorithm in detail. Experimental results and discussions are shown in section III. Finally, the paper is concluded in section IV.

II. Proposed Algorithm

The structure of our smoke detection algorithm follows a typical pattern recognition approach with preprocessing, feature extraction and classification.

978-1-4577-1434-4/11/$26.00 ©2011 IEEE

A. Preprocessing

For video-based smoke detection, background subtraction is used to perform foreground detection. As adaptive Gaussian Mixture Model (GMM) [10] can deal well with lighting changes, repetitive motion from clutter, and long-term scene changes, it is adopted to perform background modeling. Block-based processing is another technique employed at this stage. Each frame image is divided into non-overlapped blocks with the same size. After background subtraction using GMM, the number of foreground pixels in each block can be calculated. If a certain amount of pixels in one block are detected as foreground pixels, this block will be considered as a candidate block. And the block-based feature extraction will be proceeded next.

B. Feature Extraction

In this part, on the basis of LBP, NRLBP and NRLMBP are introduced to characterize smoke. All of these texture features are extracted based on block.

1) LBP: The original LBP was proposed for texture classification [11]. It is an effective descriptor to capture local appearance information. Due to its properties of highly discriminative power, robustness under illumination changes, and computational simplicity, it has been applied to smoke detection [8]. Intuitively, the LBP code of a specified pixel can be obtained by comparing its intensity with those of its neighbors. Specifically, given a pixel $c = (x_c, y_c)$, its LBP code is defined as follows:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p$$

where g_c represents the gray value of the center pixel and $g_p(p = 0, ..., P-1)$ represent the gray values of P equally spaced pixels on a circle of radius $R(R > 0)$, $s(x)$ is a Sign Function which is defined as follows:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

Similar to [8], for the trade-off between local appearance information and computational complexity, we set $P = 8$ and $R = 1$ in our experiments. Furthermore, block distance is adopted to replace the Euclidean distance in consideration of computational performance. Scanning the pixels one by one in a given block, LBP codes are accumulated into a discrete histogram called LBP histogram. And the LBP histogram distribution is considered as the feature vector. Obviously, the dimension of the feature vector is equal to the number of $LBP_{P,R}$ histogram bins (2^P).

One typical type of LBP is so-called uniform LBP which was defined in [11]. And it means there are at most two bitwise transitions from 0 to 1 and vice versa when the bit pattern is considered circular. One significant property of uniform LBPs is that uniform LBPs often represent primitive structures of the texture while non-uniform LBPs normally correspond to unexpected noises and hence are less discriminative. For instance, uniform LBPs account for slightly less than 90 percent of all patterns when $P = 8$ and $R = 1$. In this case, all non-uniform LBP patterns are stored in one single bin in the histogram computation. This can reduce the dimension of the feature vector. For example, the dimension of the feature vector is 59 when $P = 8$ and $R = 1$. In the remainder of this paper, the superscript $u2$ will be used to denote the corresponding uniform patterns. Illustratively, uniform LBP is represented by LBP^{u2}.

2) NRLBP: Although the original LBP has been widely used in applications, two drawbacks were proposed in [9]. One is that the original LBP is sensitive to the relative changes between background and foreground. As can be seen from Fig. 1, the LBP codes of the blue rectangular regions in these two images are quite different from each other. However, they describe the same spatial characteristics of smoke. The other disadvantage of the original LBP is the high requirement about computation and storage. The original $LBP_{8,1}$ requires 256 histogram bins. Even if $LBP_{8,1}^{u2}$ is adopted, 59 bins are still needed. For real-time smoke detection, we should lower the requirement of computation and storage as much as possible. Taking these two points into consideration, we employ Non-Redundant Local Binary Pattern (NRLBP) to capture the appearance information of smoke. From Fig. 1, it can be noticed that the LBP codes in the two images are complementary to each other (the sum of them is $2^P - 1$). Motivated by this fact, NRLBP is defined as follows:

$$NRLBP_{P,R}(x_c, y_c) = min\{LBP_{P,R}(x_c, y_c), 2^P - 1 - LBP_{P,R}(x_c, y_c)\}$$

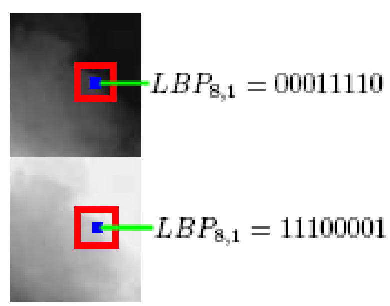

Fig. 1. Two images represent the same smoke structure with inverted background and foreground

In other words, the original LBP code and its complement are considered as the same in this case. Thus they correspond to the same bin in histogram distribution, which means that the dimension of feature vector will be reduced by half. In addition, as NRLBP reflects the relative contrast between background and foreground, it is more robust and discriminative compared with the original LBP.

3) NRLMBP: Although NRLBP has more discriminative ability and lower storage requirement compared with original

LBP, it is still a spatial texture descriptor. In other words, it only includes local appearance information. For video-based smoke detection, motion information of smoke should be utilized as well to capture the temporal characteristics of smoke. Motivated by [12] in which features were computed on the difference image between consecutive frames to encode the movement patterns of pedestrians, Non-Redundant Local Motion Binary Pattern (NRLMBP) is introduced. It is a NRLBP computed on the difference image of consecutive frames. In this case, smoke's motion information is encoded by NRLMBP.

C. Classification

After block-based features are extracted, the feature vectors of positive and negative samples are used to train a classifier which will be further used to classify new blocks. We selected Support Vector Machine (SVM) as the classifier to perform smoke detection.

III. Experimental Results and Discussions

A. Experiment Setup

As there is no representative databases for smoke detection to date, some smoke video clips in [13] and [14] are chosen to test our algorithm. In our experiments, we set the block size as 16×16. In consideration of potential real-time application, for all the LBP-based features we set $P = 8$ and $R = 1$. For the classifier, kernel SVM is adopted in the experiments. As for LBP-based features, LBP^{u2}, $NRLBP^{u2}$, and $NRLMBP^{u2}$ are employed. The experimental results are presented in the following section.

B. Experimental Results and Discussions

In our experiments, 563 positive and 818 negative samples are selected to construct the training set. The testing set is composed of 50912 smoke blocks and 4083058 non-smoke blocks. The statistical detection results based on block are shown in Table I, where DR means detection rate, FAR represents false alarm rate, and MR denotes misclassification rate. Although there is a trade-off between detection rate and false alarm rate, misclassification rate can be independently regarded as an overall index to verify the algorithms. The case when LBP^{u2} is used is considered as the baseline. As can be seen from Table I, lower misclassification rate can be obtained when $NRLBP^{u2}$ is used compared with the baseline case. The reason is that NRLBP is more robust and adaptive to relative changes of background and foreground. In terms of capturing appearance information of smoke, NRLBP outperforms LBP. When the feature vectors of NRLBP and NRLMBP are concatenated to construct a spatial-temporal descriptor, the lowest misclassification rate in all the three cases is obtained. This demonstrates that NRLMBP is effective in capturing motion information of smoke.

TABLE I

STATISTICAL DETECTION RESULTS BASED ON BLOCK

Index	LBP^{u2}	$NRLBP^{u2}$	$NRLBP^{u2}+$ $NRLMBP^{u2}$
DR (%)	77.49	80.21	79.52
FAR (%)	0.4712	0.5020	0.4227
MR (%)	0.7427	0.7396	0.6698

For real-life video-based smoke detection, smoke alarm should be issued based on the whole image or frame instead of block. The reason can be explained as follows: a frame cannot be easily classified as smoke image just because of the existence of one single "smoke" block in the frame. Thus it makes sense to present the statistical detection results based on frame. Furthermore, specific rule should be provided. Here we define a rule of issuing a smoke alarm based on frame, which is named Neighboring Block Rule. When smoke appears in a frame, normally one smoke block will be detected. It is assumed that some of the neighboring blocks of this smoke block will be detected as smoke blocks as well. As can be seen from Fig. 2, take the central red block for example, when it is detected as a smoke block, a smoke alarm will be issued only if at least one of the eight neighboring blocks is also detected as smoke block. Otherwise, the central block will be considered as an isolated candidate block and no smoke alarm will be issued.

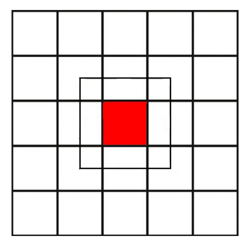

Fig. 2. Schematic representation of Neighboring Block Rule

According to Neighboring Block Rule, Table II shows us the statistical detection results based on frame. The case when LBP^{u2} is used is also considered as the baseline. Similarly, in comparison with the baseline case, reduced misclassification rate is obtained by introducing $NRLBP^{u2}$. The robustness of NRLBP is verified once again. In addition, when NRLBP and NRLMBP are integrated together, the best performance on all the three indexes can be observed. From the perspective of practical smoke detection, the effectiveness of Neighboring Block Rule is demonstrated as well.

TABLE II

STATISTICAL DETECTION RESULTS BASED ON FRAME

Index	LBP^{u2}	$NRLBP^{u2}$	$NRLBP^{u2}+$ $NRLMBP^{u2}$
DR (%)	97.23	96.58	97.69
FAR (%)	2.696	1.165	1.165
MR (%)	2.724	2.063	1.622

Fig. 3 shows us some scenarios of the video clips tested in the experiments. As can be seen, some true positive examples are displayed as well.

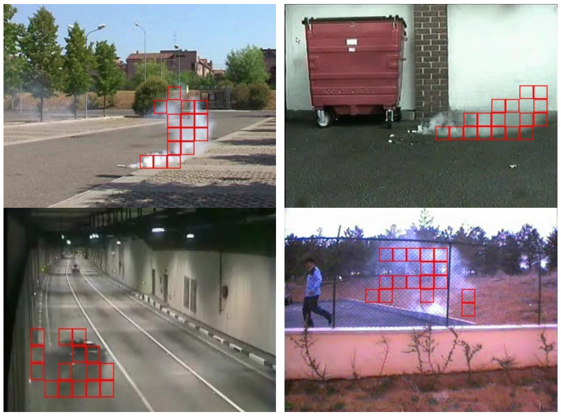

Fig. 3. True positive examples in the experiments

Inevitably, some non-smoke objects are wrongly detected as smoke, which are shown in Fig. 4.

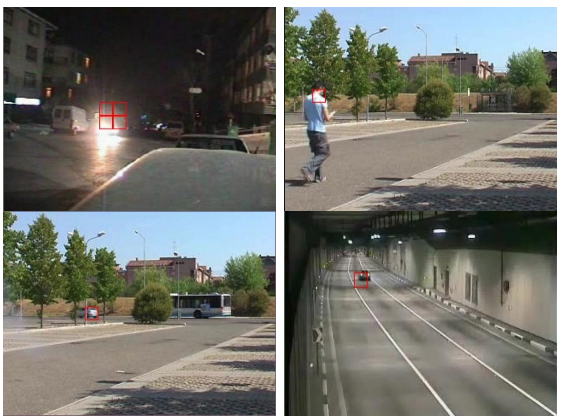

Fig. 4. False positive examples in the experiments

One concern in real-time applications is the requirement of memory. Table III shows us the dimensions of the corresponding feature vectors. Taking Table I, II, and III into consideration comprehensively, compared with LBP^{u2}, almost half dimensions are needed for $NRLBP^{u2}$ which can improve the detection performance. Noticeably, significant performance improvement can be obtained by integrating $NRLBP^{u2}$ and $NRLMBP^{u2}$ nearly without increasing storage cost.

TABLE III
THE DIMENSIONS OF FEATURE VECTORS

LBP^{u2}	$NRLBP^{u2}$	$NRLBP^{u2} + NRLMBP^{u2}$
59	30	60

IV. CONCLUSIONS

In this paper, NRLBP and NRLMBP are adopted to perform smoke detection in videos. Specifically, NRLBP describes smoke's appearance information in a discriminative and compact way. NRLMBP can effectively encode the motion patterns of smoke in videos. Thus the integration of NRLBP and NRLMBP provides an accurate spatial-temporal texture representation of smoke. Experimental results have demonstrated the effectiveness and efficiency of them in video-based smoke detection.

ACKNOWLEDGMENT

This work was partly supported by Beijing Polymer Sensing Technology Co. Ltd.

REFERENCES

[1] I. Kopilovic, B. Vagvolgyi, and T. Sziranyi, "Application of panoramic annular lens for motion analysis tasks: surveillance and smoke detection," in *Proc. International Conference on Pattern Recognition*, 2000, pp. 714–717.
[2] F. Yuan, "A fast accumulative motion orientation model based on integral image for video smoke detection," *Pattern Recognition Letters*, vol. 29, no. 7, pp. 925–932, May 2008.
[3] I. Kolesov, P. Karasev, A. Tannenbaum, and E. Haber, "Fire and smoke detection in video with optimal mass transport based optical flow and neural networks," in *Proc. IEEE International Conference on Image Processing*, 2010, pp. 761–764.
[4] T. Chen, Y. Yin, S. Huang, and Y. Ye, "The smoke detection for early fire-alarming system base on video processing," in *Proc. International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, 2006, pp. 427–430.
[5] B. U. Toreyin, Y. Dedeoglu, and A. E. Cetin, "Wavelet based real-time smoke detection in video," in *Proc. European Signal Processing Conference*, 2005.
[6] C. Yu, Y. Zhang, J. Fang, and J. Wang, "Texture analysis of smoke for real-time fire detection," in *Proc. IEEE International Workshop on Computer Science and Engineering*, 2009, pp. 511–515.
[7] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 3, no. 6, pp. 610–621, 1973.
[8] F. Yuan, "Video-based smoke detection with histogram sequence of LBP and LBPV pyramids," *Fire Safety Journal*, vol. 46, no. 3, pp. 132–139, Apr. 2011.
[9] D. T. Nguyen, Z. Zong, P. Ogunbona, and W. Li, "Object detection using non-redundant local binary patterns," in *Proc. IEEE International Conference on Image Processing*, 2010, pp. 4609–4612.
[10] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for realtime tracking," in *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1999, pp. 246–252.
[11] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, Jul. 2002.
[12] P. Viola, M. J. Jones, and D. Snow, "Detecting pedestrians using patterns of motion and appearance," *International Journal of Computer Vision*, vol. 63, no. 2, pp. 153–161, Jul. 2005.
[13] VISOR: Video Surveillance Online Repository. [Online]. Available: http://imagelab.ing.unimore.it/visor
[14] Sample fire and smoke video clips. [Online]. Available: http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SampleClips.html