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# Real Time Video Based Smoke Detection Using Double Optical Flow Estimation

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***Abstract*—In this paper, we present a video based smoke detection algorithm based on TVL1 optical flow estimation. The main part of the algorithm is an accumulating system for motion angles and upward motion speed of the flow field. We optimized the usage of TVL1 flow estimation for the detection of smoke with very low smoke density. Therefore, we use adapted flow parameters and estimate the flow field on difference images. We show in theory and in evaluation that this improves the performance of smoke detection significantly. We evaluate the smoke algorithm using videos with different smoke densities and different backgrounds. We show that smoke detection is very reliable in varying scenarios. Further we verify that our algorithm is very robust towards crowded scenes disturbance videos.

***Keywords*—Low density, optical flow, upward smoke motion, video based smoke detection.

## I. Introduction

DETECTING smoke with video cameras can improve fire detection time significantly and can prevent damage. Conventional smoke detection systems typically are installed under the ceiling of a room or hall. Much time can pass until the smoke density at the detector is high enough to trigger alarm. Video based smoke detection systems are able to detect smoke directly at the fire source. However, smoke is very turbulent and the inner structure of smoke is varying continuously. Thus, video based detection of smoke is challenging. In previous works, different kinds of features are used for smoke detection. In most cases, smoke detection algorithms use combination of color or motion segmentation, texture or energy analysis or features measuring the disorder of smoke. Good summaries of features used frequently for smoke detection can be found in the work of Verstockt et al. [1] and Cetin et al. [2].

The algorithm presented in this paper is based on smoke motion estimation. As the temperature of smoke is higher as the temperature of the surrounding air, smoke generally is moving upward. The upward motion frequently is the most explicit visual characteristic of smoke and is visible in almost all videos containing smoke.

Motion estimation takes high computational power compared to other features which were used for smoke detection mostly. However, with increasing computational power and more efficient flow algorithms, motion estimation can be used for smoke detection.

In some previous works, motion analysis was used for smoke detection. Yu et al. [3], [4] perform statistical motion analysis of smoke regions. For motion analysis, they use the optical flow estimation method they use the method proposed by Lucas and Kanade [5]. Yuan et al. [6] and Alejandro et al. [7] propose a block motion orientation model and use histogram analysis for verification. They accumulate the motion of smoke over time. However, they use motion estimation algorithms which produce sparse flow results, which can lead to detection problems inside of smoke regions. Koselov et al. [8] propose a dense optical flow estimation method that is adjusted to the physical behavior of smoke. However, all the methods have problems with detection of smoke with very low smoke density. In this paper, we present a motion accumulation based method that especially is adapted to the detection of smoke with very low smoke density.

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## II. Algorithm Concept

The algorithm we present for smoke detection is mainly based on two criteria. The first criterion is an accumulation model for motion vectors. The second criterion is based on brightness transitions over time. In a verification step, the algorithm analyzes if smoke alarm candidates persist over a certain verification time period.

### A. Smoke Motion Accumulation

We estimate the motion using TVL1 optical flow algorithm proposed in [9] and [10]. The TVL1 flow estimation takes less than 50 ms on an up-to-date computer processor with quality settings sufficient for the further parts of the smoke detection algorithm[1]. It provides a dense flow field allowing discontinuities, what is important to segment smoke motion exactly. The usage of other flow algorithms is also possible, if the computation takes comparable time and they allow discontinuities in flow field.

For further processing of the optical flow field, at first we treat flow vectors $\vec{v}_{x,y}[n]$ at position $x, y$ and frame number $n$ individually.

We split up the motion in two components; the motion angle and the motion velocity. First, the criterion $c1_{x,y}[n]$ for motion velocity $\vartheta_{x,y}[n]$ is defined as

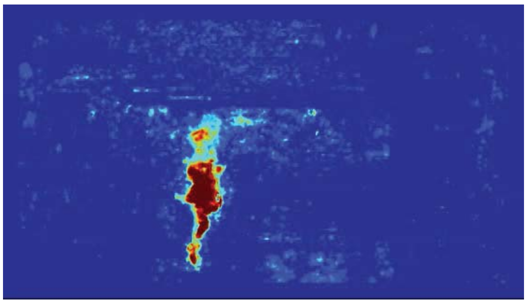
$$c1_{x,y}[n] \quad = \quad \begin{cases} 1 & if\ b_1 \le \vartheta_{x,y}[n] \le b_2 \\ 0 & else \end{cases} . \qquad (1)$$

The flow vector $\vec{v}_{x,y}[n]$ is allowed for further processing if its length lies between the boundaries $b_1$ and $b_2$. Otherwise it will not be considered for the current frame.

[1]Image Size 640x360, 10 Iterations, Intel Xeon E5-1650

(a)

(b)



(c)

Fig. 1 (a) Original video, (b) Optical flow visualization, (c) Smoke motion accumulation

Second, we define the weight $c2_{x,y}[n]$ for the motion angle $\varphi_{x,y}[n]$ as

$$c2_{x,y}[n] = \begin{cases} \frac{1}{\pi}\left(\pi - |\varphi_{x,y}[n]|\right) & if\ \varphi_{x,y}[n] \le \frac{\pi}{4} \\ 0 & else \end{cases} \quad (2)$$

The algorithm allows motion in the upper quarter of the circle and weights them with the angle deviation from upward motion. The criteria are visualized in Fig. 2 (a).

As fire is a chaotic process, the motion of smoke is irregular and small turbulences occur inside the smoke plume. The main motion direction, however, is upward. Therefore, we implement a accumulation model for motion vectors. The accumulation model is defined as

$$\hat{s}_{x,y}[n] = c1_{x,y}[n] \cdot c2_{x,y}[n], \quad (3)$$

$$s_{x,y}[n] = \alpha \cdot \hat{s}_{x,y}[n] + (1-\alpha) \cdot s_{x,y}[n-1] \quad (4)$$

with a smoothing constant

$$\alpha = 1 - \exp\left(-\frac{1}{\tau}\right). \quad (5)$$

The time constant $\tau$ is set to $25$, corresponding to $4s$ at $6.25fps$. In image regions, where upward motion vectors occur frequently, the $s_{x,y}[n]$ reaches high values. In regions, where upward motion vectors occur just sporadically, $s_{x,y}[n]$ stays low. A typical example for an exemplary progress of accumulation values over time is visualized in Fig. 2 (b).

The accumulation value $s_{x,y}[n]$ is treated as motion alarm candidate $mac_{x,y}[n]$, if exceeds the threshold $t$ according to

$$s_{x,y}[n] \ge t. \quad (6)$$

$$mac_{x,y}[n] = \begin{cases} 1 & if\ s_{x,y}[n] \ge t \\ 0 & else \end{cases}. \quad (7)$$

Fig. 1 (a) shows an example video image of a smoke cartridge burning in a garage. Smoke is moving upward. Fig. 1 (b) shows the corresponding visualization of optical flow. Fig. 1 (c) shows an image of accumulation values $s_{x,y}[n]$. In smoke regions accumulation values $s_{x,y}[n]$ are high, in non-smoke regions, values for $s_{x,y}[n]$ stay low.

### *B. Intensity Transitions*

Beside motion another visual characteristic of smoke is its transparency. Through its transparency, in smoke plumes no large intensity jumps occur. The temporal derivative of intensity

$$\dot{I}_{x,y}[n] = I_{x,y}[n] - I_{x,y}[n-1] \quad (8)$$

is low for smoke regions. In non-smoke regions $\dot{I}_{x,y}[n]$ can be significantly higher. We define a criterion

$$c3_{x,y}[n] = \begin{cases} 1 & if\ \dot{I}_{x,y}[n] \le b_3 \\ 0 & else \end{cases} \quad (9)$$

to filter out intensity jumps over time. Image positions $x, y$ where, $c3_{x,y}[n] = 0$ are disabled for smoke detection for time $\tau$. This is achieved by

$$d_{x,y}[n] = \begin{cases} d_{x,y}[n-1] - 1 & if\ c3_{x,y}[n] = 1 \\ \tau & else \end{cases} \quad (10)$$

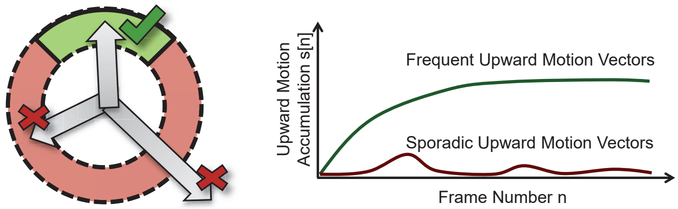
$$iac_{x,y}[n] = \begin{cases} 1 & if\ d_{x,y}[n] \le 0 \\ 0 & else \end{cases} \quad (11)$$

with $iac_{x,y}[n]$ specifying intensity transition alarm candidates.

### *C. Long-Time Alarm Verification*

To reach a final alarm decision, two criteria must be fulfilled. First, motion alarm candidates and intensity transition alarm candidates must occur according to

$$c4_{x,y}[n] = m_{x,y}[n] \wedge a_{x,y}[n]. \quad (12)$$




(a) (b)

Fig. 2 (a) Motion vectors in the upper quarter with an appropriate length are allowed, others are rejected (b) Accumulation difference for frequent and sporadic upward motions

(a) (b) (c) (d) (e)

Fig. 3 (a) Image with high local contrast in background, a transparent circle is moving upwards (b) Ground truth for the corresponding flow (c) TVL1 flow (d) Difference image (e) TVL1 flow estimated on difference images



Second, at least one pixel per frame must be in alarm state for the verification time $v$ according to

$$C4\left[n\right] = \sum_{x=1}^{X}\sum_{y=1}^{Y} c4_{x,y}\left[n\right], \quad (13)$$

$$ACF\left[n\right] = \begin{cases} 1 & \Leftrightarrow C4\left[n\right] > 0 \\ 0 & else \end{cases}, \quad (14)$$

$$C5\left[n\right] = \sum_{i=0}^{v-1} AF\left[n-i\right], \quad (15)$$

$$AVF\left[n\right] = \begin{cases} 1 & \Leftrightarrow C5\left[n\right] = v \\ 0 & 0 \end{cases} \quad (16)$$

with $ACF\left[n\right]$ specifying alarm candidate frames and $AVF\left[n\right]$ specifying alarm verification frames.

## III. Detection of Thin Smoke

The smoke detection concept proposed in Section II produces reliable smoke detection for smoke with high smoke density, as we show in Section IV. However, problems can occur, if the smoke density is low, like in early fire stages. In this case the background is still visible and background texture features are dominant and optical flow algorithms are not able to estimate the smoke motion reliably.

A theoretic example therefore is shown in Fig. 3 (a). A region with varying transparency, which is characteristic for smoke, is moving upward in front of a random texture with strong local contrast. Motion ground truth is shown in Fig. 3 (b). As shown in Fig. 3 (c), the TVL1 flow algorithm is not able to estimate the upward motion of the circle reliable. However, using different images removes the background texture. Through calculating

$$dI\left[n_1\right] = I\left[n_2\right] - I\left[n_1\right], \quad (17)$$

$$dI\left[n_2\right] = I\left[n_3\right] - I\left[n_2\right] \quad (18)$$

we remove the unchanged background texture features and emphasize smoke typical regions with different transparencies. An example therefore is shown in Fig. 3 (d). The moving circle is visible clearly in difference images. Thus, the optical flow calculated on difference images, as shown in Fig. 3 (e), comes much closer to the ground truth compared to the optical flow calculated on the original images.

Our smoke detection algorithm uses a combination of flow estimation on original images and difference images for motion accumulation. A flow chart of the algorithm is shown in Fig. 4.

A typical example of the advantage of estimating optical flow on original and difference images is shown in Fig. 5. The TVL1 algorithm is not able to estimate the flow reliably on original images. In this case the alarm state stays low, as shown in Fig. 5 (b). However, if flow is estimated on difference images, the algorithm comes to alarm state reliably, as shown in Fig. 5 (c).

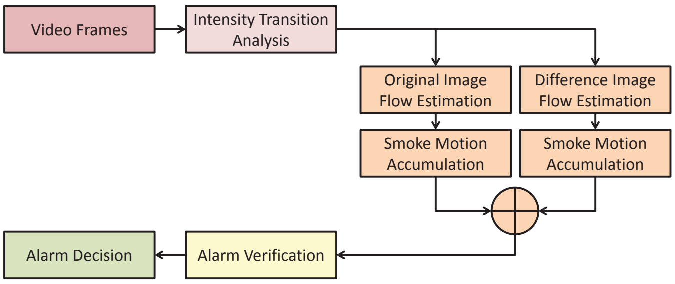
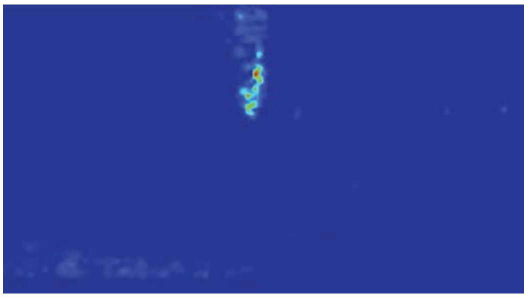
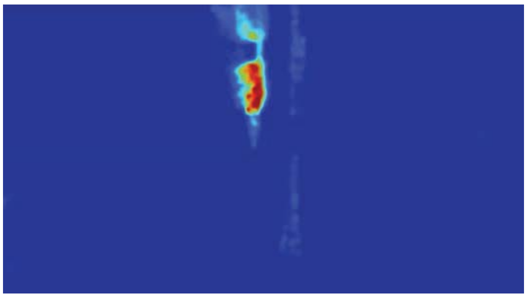



Fig. 4 Algorithm flow chart consisting of motion accumulation, intensity transistions and long-time persistence analysis

(a)



(b)



(c)

Fig. 5 (a) Thin smoke video image: The background texture features are still dominant (b) Motion accumulation based on original images (c) Motion accumulation based on difference images

## IV. Evaluation

We evaluate the algorithm on a database containing 9 videos containing various kinds of smoke in different scenarios. Small images of our smoke videos are shown in Fig. 6.

We created the smoke videos by ourselves. To verify the robustness of the algorithm against non-smoke objects, we used the complete PETS 2007 video database [11]. The PETS video material contains crowded scene sequences and slight illumination changes that could be critical for a smoke detection algorithm.

As a first evaluation step we define

$$D = \frac{1}{N} \cdot \sum_{i=1}^{N} ACF[i] \qquad (19)$$

as the percentage of alarm candidate frames, according to (14), to the total number of frames $N$. We call it $TP$ (true positive) for smoke videos and $FP$ (false positive) for non-smoke videos. Furthermore we evaluate if alarm verification frames $AVF$, according to (16), occurred in the video.

We show in the upper part of Table I the alarm candidate frame percentage $TP$ and we point out an alarm verification event occurs in the corresponding video. The lower part of of Table I shows the results for the PETS video database. Results are shown for original image motion estimation, for difference images, and for the combination of both.

Original frame based accumulation method reaches mainly high values $TP$ for videos with high smoke densities. The difference frame based method reaches high values for $TP$ in videos with low smoke density. In smoke videos the original frame based method and difference frames based motion accumulation method complement one another. The combination of both methods reaches high values for $TP$ in all videos. In all smoke videos, except the last one, alarm verification frames are detected. In the last video the smoke video endures under six seconds, so no alarm verification frame occurs.

In non-smoke videos the values for $FP$ does not crease through combination of both methods, compared to use of original frames flow method only. However the alarm frame percentage always stays below $3\%$ and still no alarm verifications event is triggered.

## V. Discussion

The theory of optical flow estimation on difference frames also works in practice. Especially in video No. 7 and No. 9 the background texture still is dominant compared to smoke. When flow estimation is performed on original images, motion of smoke is not detected. When difference frames are used the background is removed completely. The flow field solely is caused by the smoke plumes. However, calculating the flow on original images produces higher alarm candidate rate for smoke flow field for high smoke density thus allows alarm verification. The structures of smoke plumes remain.

TABLE I
ALARM MEASURES

| No. | Density | $TP(\%)$ original | $TP(\%)$ difference | $TP(\%)$ combined | *Alarm Verification occured* original | *Alarm Verification occured* difference | *Alarm Verification occured* combined |
|---|---|---|---|---|---|---|---|
| 1 | high | 58 | 45 | 58 | yes | yes | yes |
| 2 | high | 82 | 60 | 82 | yes | yes | yes |
| 3 | high | 73 | 68 | 73 | yes | yes | yes |
| 4 | mixed | 69 | 61 | 80 | yes | yes | yes |
| 5 | mixed | 74 | 80 | 92 | yes | yes | yes |
| 6 | mixed | 81 | 71 | 81 | yes | yes | yes |
| 7 | low | 2 | 78 | 78 | no | yes | yes |
| 8 | low | 50 | 69 | 69 | yes | yes | yes |
| 9 | low | 0 | 57 | 57 | no | no | no |
| | | | $FP(\%)$ | | | *Alarm Verification occured* | |
| PETS Video Database | | 3 | 0 | 3 | no | no | no |

Alarm frames percentage and persistent alarm events for smoke and non-smoke PETS sequences. Optical Flow is estimated on original frames, difference frames and a combination of both.


Fig. 6 Videos used for evaluation with various smoke densities. 1-3 high density, 4-6 mixed density, 7-9 low density

The optical flow caused by these structures is more reliable compared to the field caused by difference frames. Thus, in videos with dense smoke, alarm events are more stable using original images.

Through combination of both methods we reach high smoke detection rates for all scenarios, especially for videos where mixed smoke densities occur. In average we can improve the alarm candidate detection significantly. We expect a substantial higher robustness in long-time smoke surveillance. We can cover various background and combustibles with different smoke densities. As both methods are robust against non-smoke events, we still do not reach persistent alarm using the combination of both methods.

## VI. CONCLUSIONS

We proposed a reliable smoke detection algorithm based on a motion accumulation model. The algorithm is very robust to smoke produced in various scenarios and is capable of detecting smoke with very low smoke densities. We showed that the proposed algorithm is very robust to non-smoke disturbances.

Our algorithm estimates optical flow both on original images and difference images. Estimating the optical flow on original images is suited for smoke with high smoke density. Estimating the optical flow on difference images allows the detection of very thin smoke that otherwise would not be possible. Due to combining optical flow estimation on original images and difference images the algorithm detects smoke with various densities independently of the background.

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