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Hot Topics in Video Fire Surveillance

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1. Introduction

Fire is one of the most powerful forces of nature. Nowadays it is the leading hazard affecting everyday life around the world. The sooner the fire is detected, the better the chances are for survival. Today's fire alarm systems, such as smoke and heat sensors, however still pose many problems. They are generally limited to indoors; require a close proximity to the fire; and most of them cannot provide additional information about fire circumstances. In order to provide faster, more complete and more reliable information, video fire detection (VFD) is becoming more and more interesting.

Current research (Verstockt et al., 2009) shows that video-based fire detection promises fast detection and can be a viable alternative for the more traditional techniques. Especially in large and open spaces, such as shopping malls, parking lots, and airports, video fire detection can make the difference. The reason for this expected success is that the majority of detection systems that are used in these places today suffer with a lot of problems which VFD do not have, e.g., a transport- and threshold delay. As soon as smoke or flames occur in one of the camera views, fire can be detected. However, due to the variability of shape, motion, transparency, colors, and patterns of smoke and flames, existing approaches are still vulnerable to false alarms. On the other hand, video-based fire alarm systems mostly only detect the presence of fire. To understand the fire, however, detection is not enough. Effective response to fire requires accurate and timely information of its evolution. As an answer to both problems a multi-sensor fire detector and a multi-view fire analysis framework (Verstockt et al., 2010a) are proposed in this chapter, which can be seen as the first steps towards more valuable and accurate video fire detection.

Although different sensors can be used for multi-sensor fire detection, we believe that the added value of IR cameras in the long wave IR range (LWIR) will be the highest. Various facts support this idea. First of all, existing VFD algorithms have inherent limitations, such as the need for sufficient and specific lighting conditions. Thermal IR imaging sensors image emitted light, not reflected light, and do not have this limitation. Also, the further one goes in the IR spectrum the more the visual perceptibility decreases and the thermal perceptibility increases. As such, hot objects like flames will be best visible and less disturbed by other objects in the LWIR spectral range. By combining the thermal and visual

characteristics of moving objects in registered LWIR, as well as visual images, more robust fire detection can be achieved. Since visual misdetections can be corrected by LWIR detections and vice versa, fewer false alarms will occur.

Due to the transparency of smoke in LWIR images, its absence can be used to distinguish between smoke and smoke-like moving objects. Since ordinary moving objects produce similar silhouettes in background-subtracted visual and thermal IR images, the coverage between these images is quasi constant. Smoke, contrarily, will only be detected in the visual images, and as such the coverage will start to decrease. Due to the dynamic character of the smoke, the visual silhouette will also show a high degree of disorder. By focusing on both coverage behaviors, smoke can be detected. On the basis of all these facts, the use of LWIR in combination with ordinary VFD is considered to be a win-win, as is confirmed by our experiments, in which the fused detectors perform better than either sensor alone.

In order to actually understand and interpret the fire, however, detection is not enough. It is also important to have a clear understanding of the fire development and the location. This information is essential for safety analysis and fire fighting/mitigation, and plays an important role in assessing the risk of escalation. Nevertheless, the majority of the detectors that are currently in use only detect the presence of fire, and are not able to model fire evolution. In order to accomplish more valuable fire analysis, the proposed video fire analysis framework fuses VFD results of multiple cameras by homographic projection onto multiple horizontal and vertical planes, which slice the scene. The crossings of these slices create a 3D grid of virtual sensor points. Using this grid, information about the location of the fire, its size and its propagation can be instantly extracted.

The remainder of this chapter is organized as follows: Section 2 presents the state-of-the-art detection methods in the visible and infrared spectral range, with a particular focus on the underlying features which can be of use in multi-sensor flame and smoke detection. Based on the analysis of the existing approaches, Section 3 proposes the novel multi-sensor flame and smoke detector. The multi-sensor detectors combine the multi-modal information of low-cost visual and thermal infrared detection results. Experiments on fire and non-fire multi-sensor sequences indicate that the combined detector yields more accurate results, with fewer false alarms, than either detector alone. Subsequently, Section 4 discusses the multi-view fire analysis framework (Verstockt et al., 2010a), which main goal is to overcome the lack in a video-based fire analysis tool to detect valuable fire characteristics at the early stage of the fire. Next, Section 5 gives suggestions on how the resulting fire progress information of the analysis framework can be used for video-driven fire spread forecasting. Finally, Section 6 lists the conclusions.

2. State-of-the-art in video fire detection (VFD)

2.1 VFD in visible light

The number of papers about fire detection in the computer vision literature is rather limited. As is, this relatively new subject in vision research has still a long way to go. Nevertheless, the results from existing work already seem very promising. The majority of the fire detection algorithms detects flames or smoke by analyzing one or more fire features in visible light. In the following, we will discuss the most widely used of these features.

Color was one of the first features used in VFD and is still by far the most popular (Celik & Demirel, 2008). The majority of the color-based approaches in VFD makes use of RGB color space, sometimes in combination with the saturation of HSI (Hue-Saturation-Intensity) color

space (Chen et al., 2004; Qi & Ebert, 2009). The main reason for using RGB is the equality in RGB values of smoke pixels and the easily distinguishable red-yellow range of flames. Although the test results in the referenced work seems promising at first, the variability in color, density, lighting, and background do raise questions about the applicability of RGB in real world detection systems. In (Verstockt et al., 2009) the authors discuss the detection of chrominance decrease as a superior method.

Other frequently used fire features are flickering (Qi & Ebert, 2009; Marbach et al., 2006) and energy variation (Calderara et al., 2008; Toreyin et al., 2006). Both focus on the temporal behavior of flames and smoke. Flickering refers to the temporal behaviour with which pixels appear and disappear at the edges of turbulent flames. Energy variation refers to the temporal disorder of pixels in the high-pass components of the discrete wavelet transformed images of the camera. Fire also has the unique characteristic that it does not remain a steady color, i.e., the flames are composed of several varying colors within a small area. Spatial difference analysis (Qi & Ebert, 2009; Toreyin et al., 2005) focuses on this feature and analyses the spatial color variations in pixel values to eliminate ordinary fire-colored objects with a solid flame color.

Also an interesting feature for fire detection is the disorder of smoke and flame regions over time. Some examples of frequently used metrics to measure this disorder are randomness of area size (Borges et al., 2008), boundary roughness (Toreyin et al., 2006), and turbulence variance (Xiong et al, 2007). Although not directly related to fire characteristics, motion is also used in most VFD systems as a feature to simplify and improve the detection process, i.e., to eliminate the disturbance of stationary non-fire objects. In order to detect possible motion, possibly caused by the fire, the moving part in the current video frame is detected by means of motion segmentation (Calderara et al., 2008; Toreyin et al., 2006).

Based on the analysis of our own experiments (Verstockt et al., 2010b) and the discussed state-of-the-art, a low-cost flame detector is presented in (Fig. 1). The detector starts with a dynamic background subtraction, which extracts moving objects by subtracting the video frames with everything in the scene that remains constant over time, i.e. the estimated background. To avoid unnecessary computational work and to decrease the number of false alarms caused by noisy objects, a morphological opening, which filters out the noise, is performed after the dynamic background subtraction. Each of the remaining foreground (FG) objects in the video images is then further analyzed using a set of visual flame features. In case of a fire object, the selected features, i.e. spatial flame color disorder, principal orientation disorder and bounding box disorder, vary considerably over time. Due to this high degree of disorder, extrema analysis is chosen as a technique to easily distinguish between flames and other objects. For more detailed information the reader is referred to (Verstockt et al., 2010b).
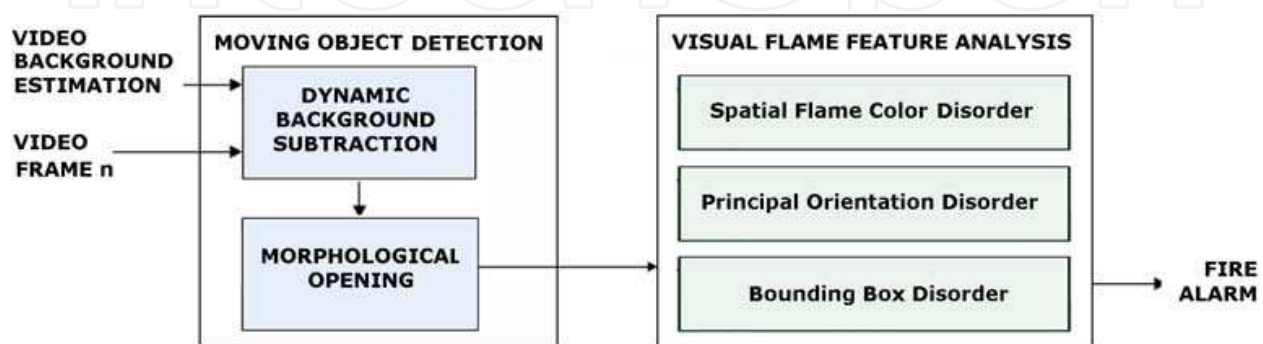

Fig. 1. Low-cost visual flame detector.

2.2 VFD in invisible light

Due to the fact that IR imaging is heading in the direction of higher resolution, increased sensitivity and higher speed, it is already used successfully as an alternative for ordinary video in many video surveillance applications, e.g., traffic safety, pedestrian detection, airport security, detection of elevated body temperature, and material inspection. As manufacturers ensure steady price-reduction, it is even expected that this number of IR imaging applications will increase significantly in the near future (Arrue et al., 2008).

Although the trend towards IR-based video analysis is noticeable, the number of papers about IR-based fire detection in the computer vision literature is still limited. As is, this relatively new subject in vision research has still a long way to go. Nevertheless, the results from existing work already seem very promising and ensure the feasibility of IR video in fire detection. (Owrutsky et al., 2005) work in the near infrared (NIR) spectral range and compare the global luminosity L, which is the sum of the pixel intensities of the current frame, to a reference luminosity L_b and a threshold L_{th}. If the number of consecutive frames where $L > L_b + L_{th}$ exceeds a persistence criterion, the system goes into alarm. Although this fairly simple algorithm seems to produce good results in the reported experiments its limited constraints do raise questions about its applicability in large and open uncontrolled public places with varying backgrounds and a lot of ordinary moving objects. (Toreyin et al., 2007) detect flames in infrared by searching for bright-looking moving objects with rapid time-varying contours. A wavelet domain analysis of the 1D-curve representation of the contours is used to detect the high frequency nature of the boundary of a fire region. In addition, the temporal behavior of the region is analyzed using a Hidden Markov Model. The combination of both temporal and spatial clues seems more appropriate than the luminosity approach and, according to Toreyin et al., greatly reduces false alarms caused by ordinary bright moving objects.

A similar combination of temporal and spatial features is also used by (Bosch et al., 2009). Hotspots, i.e., candidate flame regions, are detected by automatic histogram-based image thresholding. By analyzing the intensity, signature, and orientation of these resulting hot objects' regions, discrimination between flames and other objects is made. The IR-based fire detector (Fig. 2), proposed by the authors in (Verstockt et al., 2010c), mainly follows the latter feature-based strategy, but contrary to Bosch's work a dynamic background subtraction method is used which is more suitable to cope with the time-varying characteristics of dynamic scenes. Also, by changing the set of features and combining their probabilities into a global classifier, a decrease in computational complexity and execution time is achieved with no negative effect on the detection results.
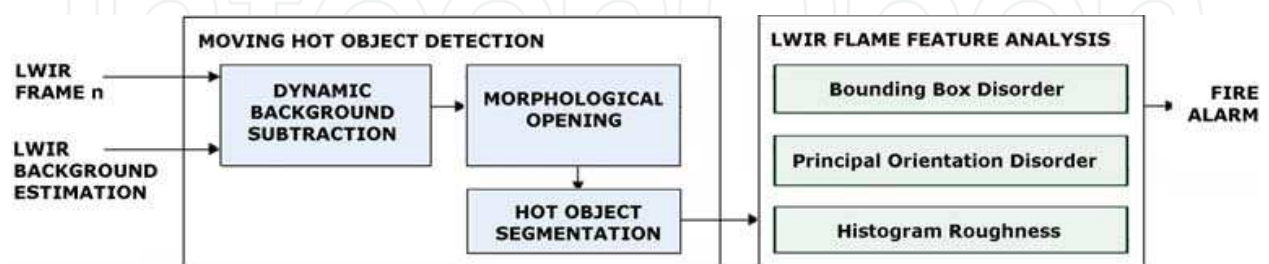

Fig. 2. Low-cost LWIR flame detector.

Similar to the visual flame detector, the LWIR detector starts with a dynamic background subtraction (Fig. 3 a-c) and morphological filtering. Then, it automatically extracts hot objects (Fig. 3 d) from the foreground thermal images by histogram-based segmentation, which is based on Otsu's method (Otsu, 1979).
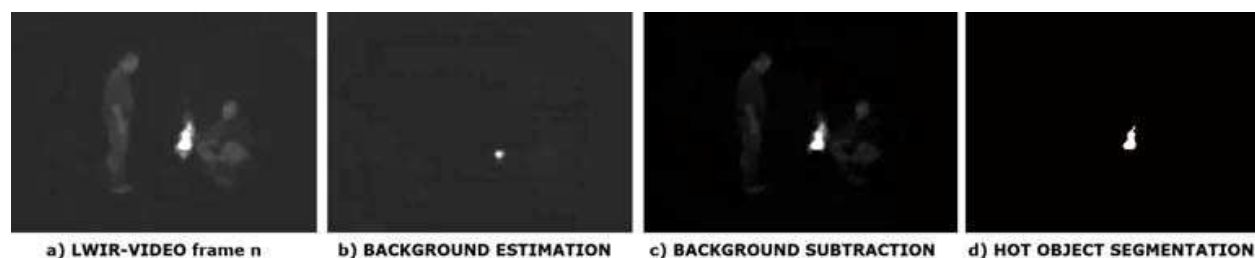
a) LWIR-VIDEO frame n   b) BACKGROUND ESTIMATION   c) BACKGROUND SUBTRACTION   d) HOT OBJECT SEGMENTATION

Fig. 3. Therrnal filtering: moving hot object segmentation.

After this thermal filtering, only the relevant hot objects in the scene remain foreground. These objects are then further analyzed using a set of three LWIR fire features: bounding box disorder, principal orientation disorder, and histogram roughness. The set of features is based on the distinctive geometric, temporal and spatial disorder characteristics of bright flame regions, which are easily detectable in LWIR thermal images. By combining the probabilities of these fast retrievable local flame features we are able to detect the fire at an early stage. Experiments with different LWIR fire/non-fire sequences show already good results, as indicated in (Table 1) by the flame detection rate, i.e. the percentage of correctly detected fire frames, compared to the manually annotated ground truth (GT).

Video sequence	# frames	# fire frames (GT)	# detected fire frames	mean P(flames)	# false detections	Flame detection rate*
Attic (fire)	337	264	255	0,91	9	0,93
Attic (fire and moving people)	2123	1461	1296	0,86	34	0,86
Attic (moving people)	886	0	14	0,24	14	-
Lab (bunsen burner)	115	98	77	0,83	0	0,79
Corridor (moving person + hot object)	184	0	8	0,29	8	-

* Detection rate = (# detected fire frames - # false detections)/#fire frames

Table 1. Experimental results of LWIR-based video fire detection

3. Multi-sensor smoke and fire detection

Recently, the fusion of visible and infrared images is starting to be explored as a way to improve detection performance in video surveillance applications. The combination of both types of imagery yields information about the scene that is rich in color, motion and thermal detail, as can be seen by comparing the LWIR and visual objects in (Fig.4). Once the images are registered, i.e. aligned, such information can be used to successfully detect and analyze activity in the scene. To detect fire, one can also take advantage of this multi-sensor benefit.
The proposed multi-sensor flame and smoke detection can be split up into two consecutive parts: the registration of the multi-modal images and the detection itself. In the following subsections each of these parts will be discussed more in detail.

3.1 Image registration
The image registration process (Fig. 5) detects the geometric parameters which are needed to overlay images of the same scene taken by different sensors. The registration starts with a moving object silhouette extraction (Chen & Varshney, 2002) to separate the calibration objects, i.e. the moving foreground, from the static background. Key components are the dynamic background (BG) subtraction, automatic thresholding and morphological filtering.

Then, 1D contour vectors are generated from the resulting IR/visual silhouettes using silhouette boundary extraction, cartesian to polar transform and radial vector analysis. Next, to retrieve the rotation angle (~ contour alignment) and the scale factor between the LWIR and visual image, the contours are mapped onto each other using circular cross correlation (Hamici, 2006) and contour scaling. Finally, the translation between the two images is calculated using maximization of binary correlation.

Fig. 4. Comparison of corresponding LWIR and visual objects.
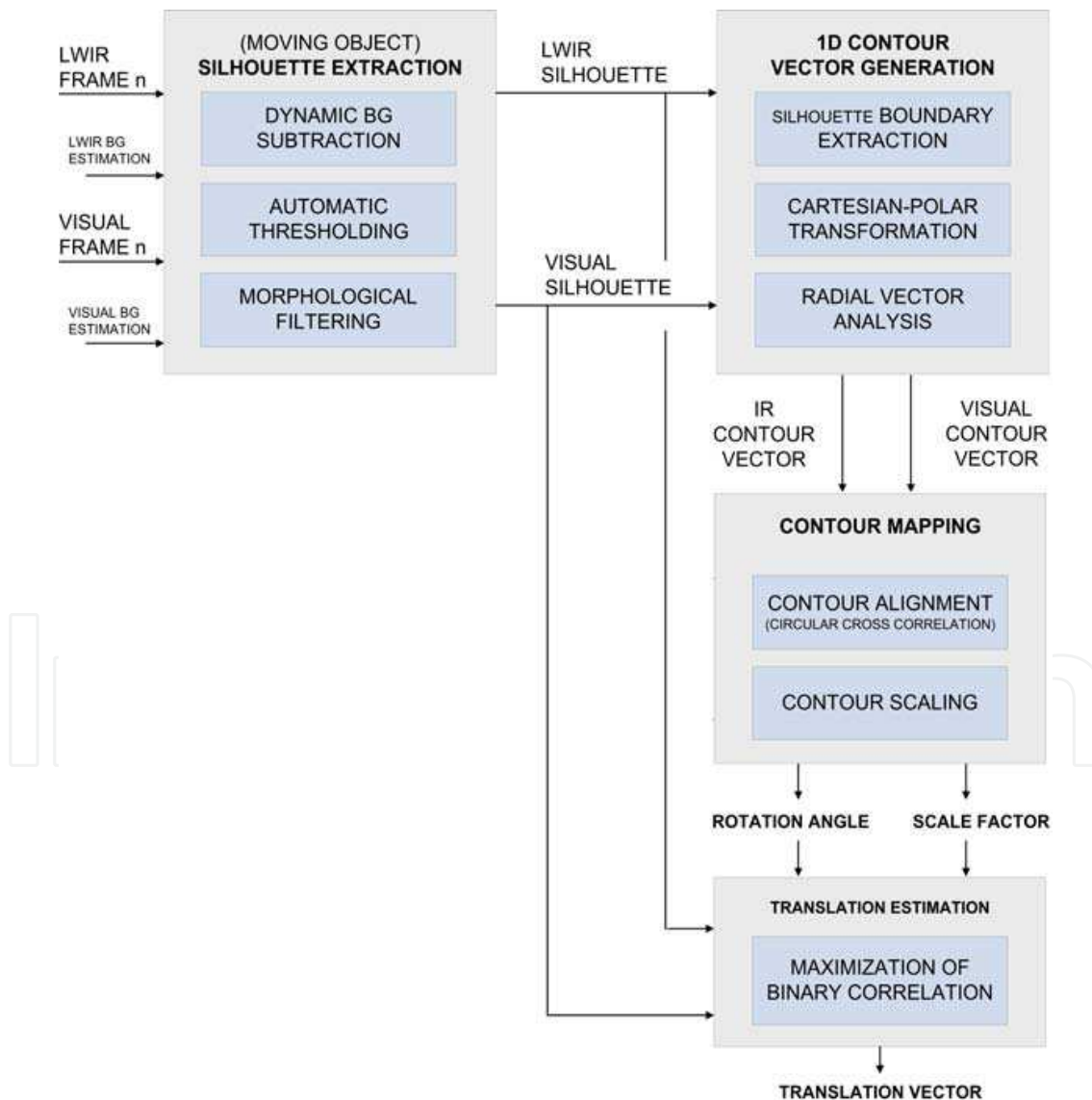
Fig. 5. LWIR-visual image registration.

3.2 Multi-sensor flame detection

The multi-sensor flame detection (Fig. 6) first searches for candidate flame objects in both LWIR and visual images by using moving object detection and flame feature analysis. These steps are already discussed in Section 2. Next, it uses the registration information, i.e. rotation angle, scale factor and translation vector, to map the LWIR and visual candidate flame objects on each other. Finally, the global classifier analyzes the probabilities of the mapped objects. In case objects are detected with a high combined multi-sensor probability, fire alarm is given.

As can be seen in (Table 2), the multi-sensor flame detector yields better results than the LWIR detector alone (~ Table 1). In particular for uncontrolled fires, a higher flame detection rate with fewer false alarms is achieved. Compared to the rather limited results of standalone visual flame detectors, the multi-sensor detection results are also more positive. As such, the combined detector is a win-win. As the experiments (Fig. 7) show, only objects which are detected as fire by both sensors do raise the fire alarm.
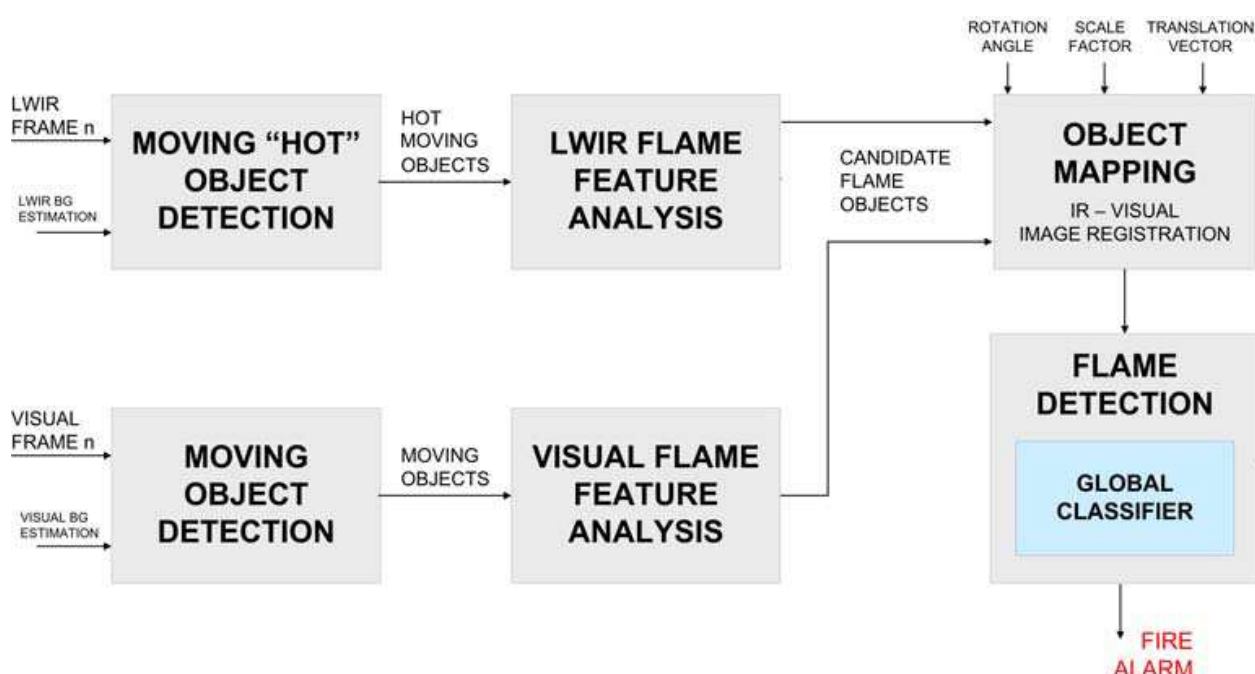

Fig. 6. Multi-sensor flame detection.

Video sequence	# frames	# fire frames	# detected fire frames	mean P(flames)	# false detections	Flame detection rate*
Attic (fire)	337	264	259	0.92	6	0.96
Attic (fire and moving people)	2123	1461	1352	0.84	19	0.91
Attic (moving people)	886	0	5	0.22	5	-
Lab (bunsen burner)	115	98	74	0.77	0	0.75
Corridor (moving person + hot object)	184	0	3	0.28	3	-

* Detection rate = (# detected fire frames - # false detections)/#fire frames

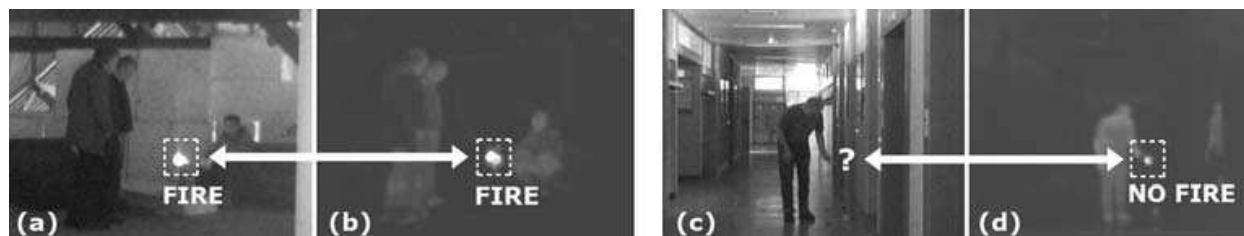Table 2. Experimental results of multi-sensor video fire detection.

Fig. 7. LWIR fire detection experiments.

3.2 Multi-sensor smoke detection

The multi-sensor smoke detector makes use of the invisibility of smoke in LWIR. Smoke, contrarily to ordinary moving objects, is only detected in visual images. As such, the coverage of moving objects their LWIR and visual silhouettes starts to decrease in case of smoke. Due to the dynamic character of smoke, the visual smoke silhouette also shows a high degree of disorder. By focusing on both silhouette behaviors, the system is able to accurately detect the smoke.

The silhouette coverage analysis (Fig. 8) also starts with the moving object silhouette extraction. Then, it uses the registration information, i.e. rotation angle, scale factor and translation vector, to map the IR and visual silhouette images on each other. As soon as this mapping is finished, the LWIR-visual silhouette map is analyzed over time using a two-phase decision algorithm. The first phase focuses on the silhouette coverage of the thermal-visual registered images and gives a kind of first smoke warning when a decrease in
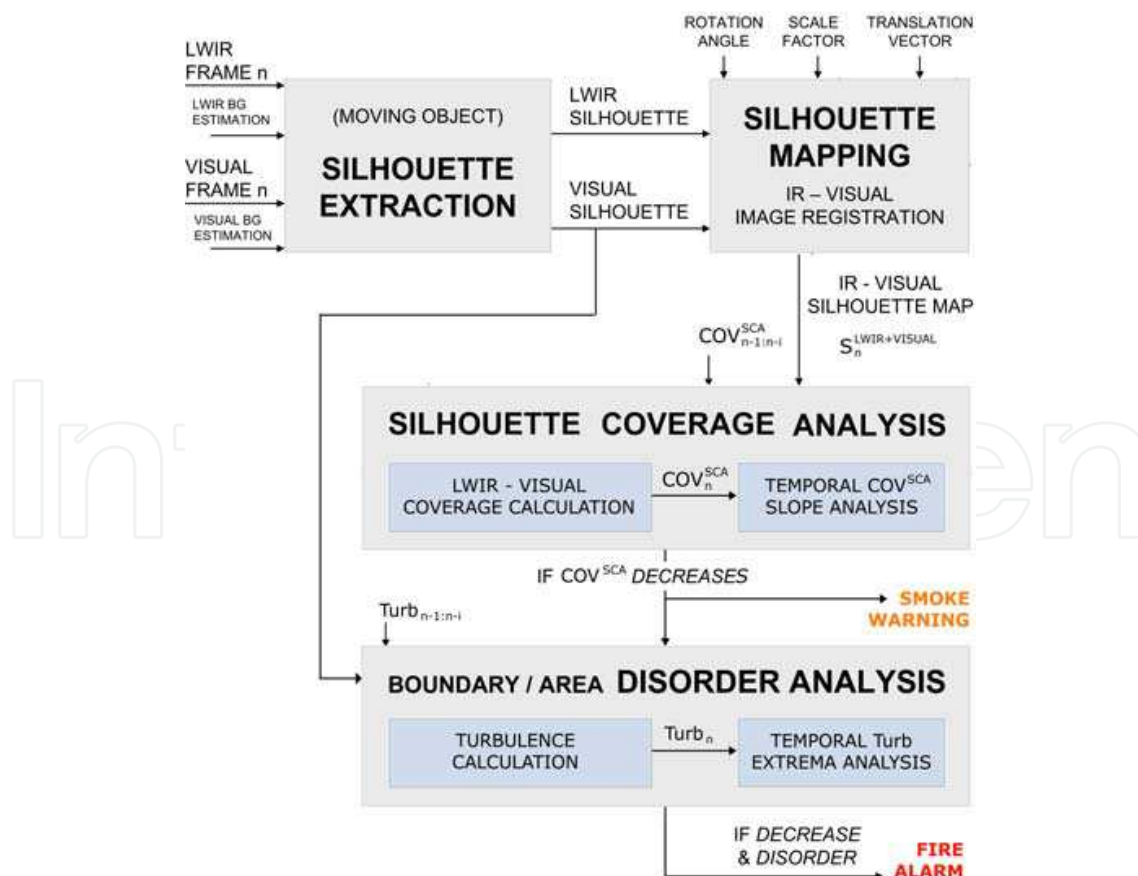

Fig. 8. Multi-sensor smoke detection.

silhouette coverage occurs. This decrease is detected using a sequence/scene independent technique based on slope analysis of the linear fit, i.e. trend line, over the most recent silhouette coverage values. If the slope of this trend line is negative and decreases continuously, smoke warning is given. In the second phase, which is only executed if a smoke warning is given, the visual silhouette is further investigated by temporal disorder analysis to distinguish true detections from false alarms, such as shadows. If this silhouette shows a high degree of turbulence disorder (Xiong et al., 2007), fire alarm is raised.

The silhouette maps in (Fig. 9) show that the proposed approach achieves good performance for image registration between color and thermal image sequences. The visual and IR silhouette of the person are coarsely mapped on each other. Due to the individual sensor limitations, such as shadows in visual images, thermal reflections and soft thermal boundaries in LWIR, small artifacts at the boundary of the merged silhouettes can be noticed. This is also the reason why the LWIR-visual silhouette coverage for ordinary moving objects is between 0.8 and 0.9, and not equal to 1.
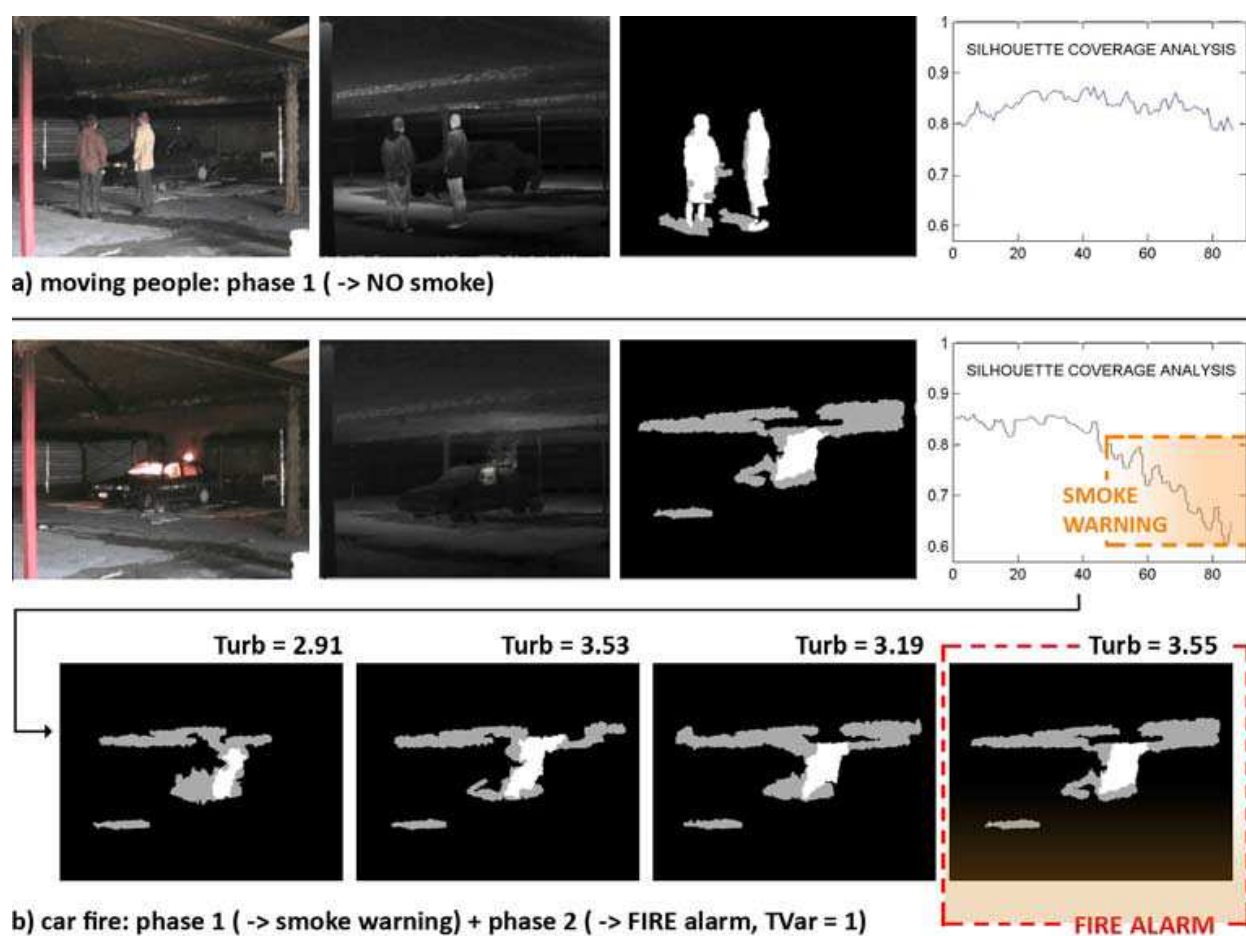
Fig. 9. Experimental results: silhouette coverage analysis.

As the results in (Fig. 9) show, the moving people sequence has a quasi constant silhouette coverage, and as such, no smoke warning is given and phase 2, i.e. the visual disorder analysis, is not performed. Contrarily, the silhouette coverage of the smoke sequence shows a high decrease after 45 frames, which activates the smoke warning. As a reaction to this warning, phase 2 of the detector is activated and analyzes the turbulence disorder of the visual silhouette objects. Since this disorder for the largest object is high, fire alarm is given.

Compared to the results of any individual visual or infrared detector, the proposed 2-phase multi-sensor detector is able to detect the smoke more accurate, i.e. with less misdetections and false alarms. Due to the low-cost of the silhouette coverage analysis and the visual turbulence disorder, which is only performed if smoke warning is given, the algorithm is also less computational expensive as many of the individual detectors.

4. Multi-view fire analysis

Only a few of the existing VFD systems (Yasmin, 2009; Akhloufi & Rossi, 2009) are capable of providing additional information on the fire circumstances, such as size and location. Despite the good performance reported in the papers, the results of these approaches are still limited and interpretation of the provided information is not straightforward. As such, one of the main goals of our work is to provide an easy-to-use and information-rich framework for video fire analysis, which is discussed briefly. For more details, readers are referred to (Verstockt et al., 2010a).

Using the localization framework shown in (Fig. 10), information about the fire location and (growing) size can be generated very accurately. First, the framework detects the fire, i.e. smoke and/or flames, in each single view. An appropriate single-view smoke or flame detector can be chosen out of the numerous approaches already proposed in Section 2. It is even possible to use the multi-sensor detectors. The only constraint is that the detector produces a binary image as output, in which white regions are fire/smoke FG regions and black regions are non-fire/non-smoke BG.

Secondly, the single-view detection results of the available cameras are projected by homography (Hartley & Zisserman, 2004) onto horizontal and vertical planes which slice the scene. For optimal performance it is assumed that the camera views overlap. Overlapping multi-camera views provide elements of redundancy, i.e., each point is seen by multiple cameras, that help to minimize ambiguities like occlusions, i.e. visual obstructions, and improve the accuracy in the determination of the position and size of the flames and smoke.

Next, the plane slicing algorithm accumulates, i.e. sums, the multi-view detection results in each of the horizontal and vertical planes. This step is a 3D extension of Arsic's work (Arsic et al., 2008). Then, a 3D grid of virtual multi-camera sensors is created at the crossings of these planes. At each sensor point of the grid, the detection results of the horizontal and vertical planes that cross in that point are analyzed and only the points with stable detections are further considered as candidate fire or smoke. Finally, 3D spatial and temporal filters clean up the grid and remove the remaining noise. The filtered grid can then be used to extract the smoke and fire location, information about the growing process and the direction of propagation.

In order to verify the proposed multi-view localization framework we performed smoke experiments in a car park. We tried to detect the location, the growing size and the propagation direction of smoke generated by a smoke machine. An example of these experiments is shown in (Fig. 11), where the upper (a-c) and the lower images (d-f) are three different camera views of the test sequences frame 4740 and 5040 respectively. Single-view fire detection results, i.e. the binary images which are the input for the homographic projection in our localization framework, were retrieved by using the chrominance-based smoke detection method proposed in (Verstockt et al., 2009). Since the framework is independent of the type of VFD, also other detectors can be used here. The only constraint is that the detector delivers a black and white binary image, as mentioned earlier. As such, it is even possible to integrate other types of sensors, such as IR-video based fire detectors or the proposed multi-sensor detectors.
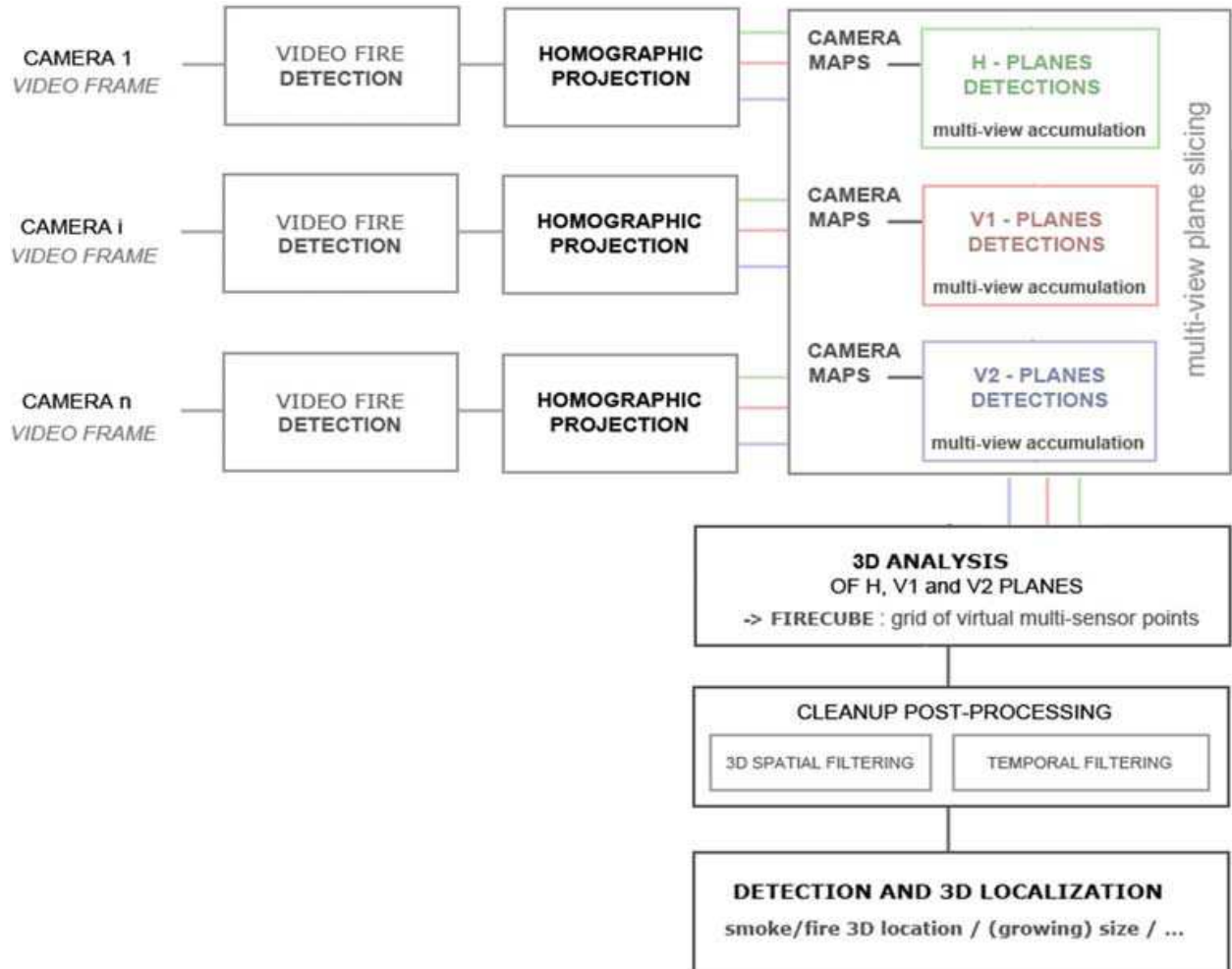
Fig. 10. Multi-view localization framework for 3D fire analysis.
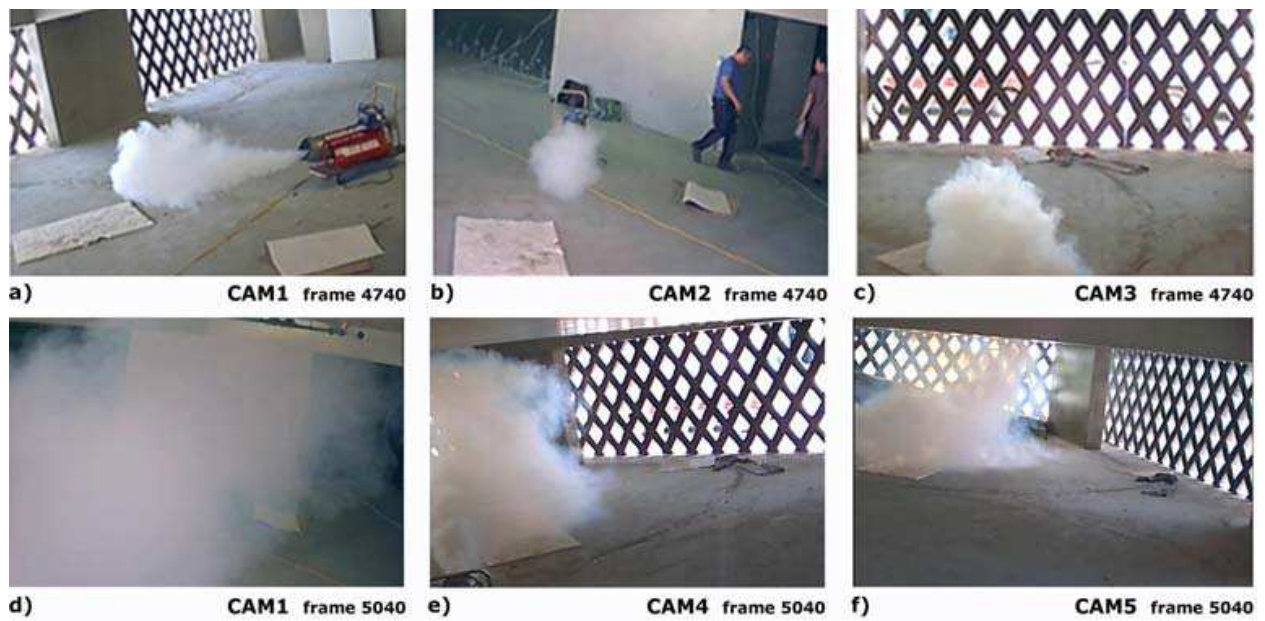

Fig. 11. Car park smoke experiments.

As can be seen in the 3D model in (Fig. 12) and in the back-projections of the 3D results in (Fig.13), the framework is able to detect the location and the dimension of the smoke regions. In (Fig. 12) the smoke regions are represented by the dark gray 3D boxes, which are bounded by the minimal and maximal horizontal and vertical FG slices. As a reference, also the bounding box of the smoking machine is visualized. Even if a camera view is partially or fully occluded by smoke, like for example in frame 5040 of CAM2 (Fig. 11 d), the framework localizes the smoke, as long as it is visible from the other views. Based on the detected 3D smoke boxes, the framework generates the spatial smoke characteristics, i.e., the height, width, length, centroid, and volume of the smoke region. By analyzing this information over time, the growing size and the propagation direction are also estimated. If LWIR-visual multi-sensor cameras, like the one proposed in this paper, are used, it is even possible to also analyze the temperature evolution of the detected regions. As such, for example, temperature-based levels of warnings can be given.

SMOKE CHARACTERISTICS

loc_centroid_xy = (5.4 m, 3.1 m)

height = 0.8 m
width = 1.4 m
length = 2 m
volume = 2.24 m³

growing size = 1.4 m³/s

propagation_direction_xy = 123°

frame 4740

SMOKE CHARACTERISTICS

loc_centroid_xy = (3.9 m, 5.2 m)

height = 2.2 m
width = 5.6 m
length = 5 m
volume = 61.6 m³

growing size = 5.93 m³/s

propagation_direction_xy = 144°

frame 5040

■ SMOKE BOX   ■ V1-PLANES   ■ H-PLANES   ■ V2-PLANES   ■ SMOKING MACHINE (BOX)
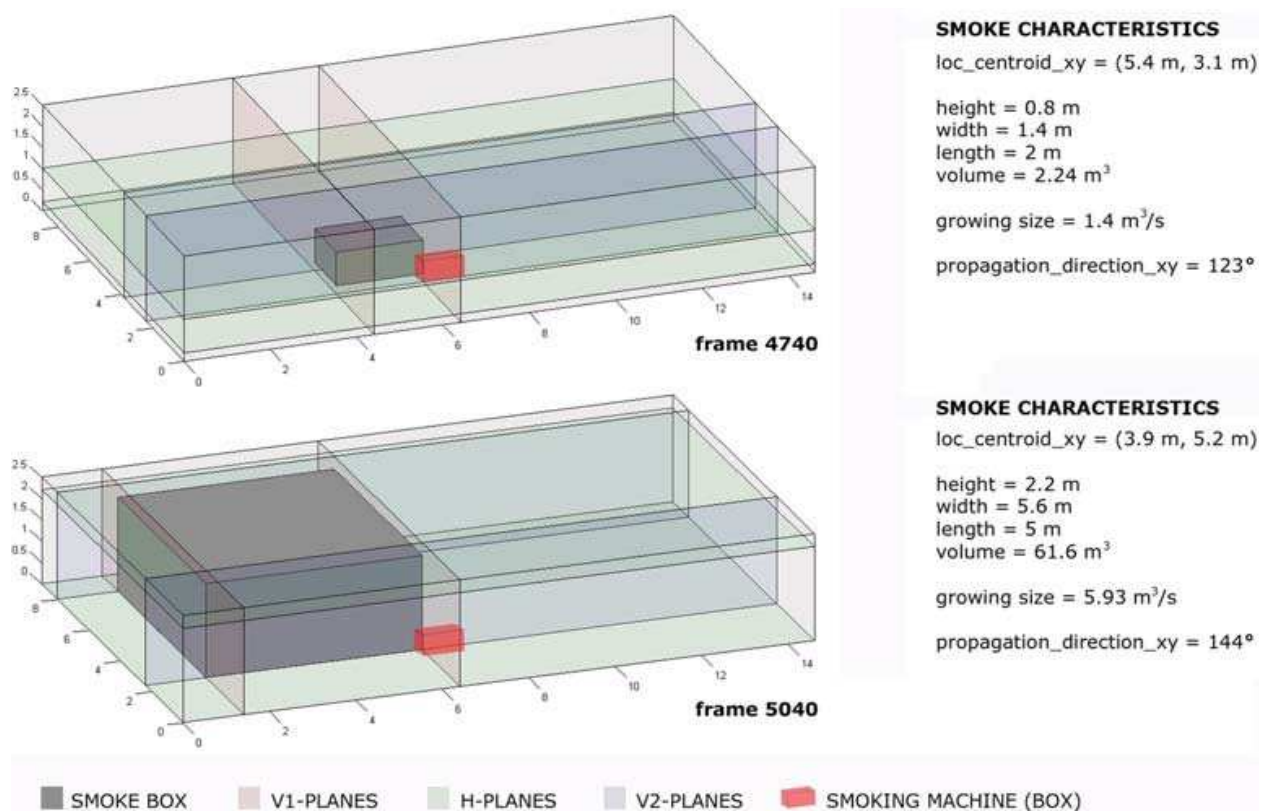
Fig. 12. Plane slicing-based smoke box localization.

The back-projections (Fig. 13) of the 3D smoke regions to the camera views show that the multi-view slicing approach produces acceptable results. Due to the fact that the number of (multi-view) video fire sequences is limited and the fact that no 3D ground truth data and widely "agree-upon" evaluation criteria of video-based fire tests are available yet, only this kind of visual validation is possible for the moment. Contrary to existing fire analysis approaches (Akhloufi & Rossi, 2009), which deliver a rather limited 3D reconstruction, the output contains valuable 3D information about the fire development.
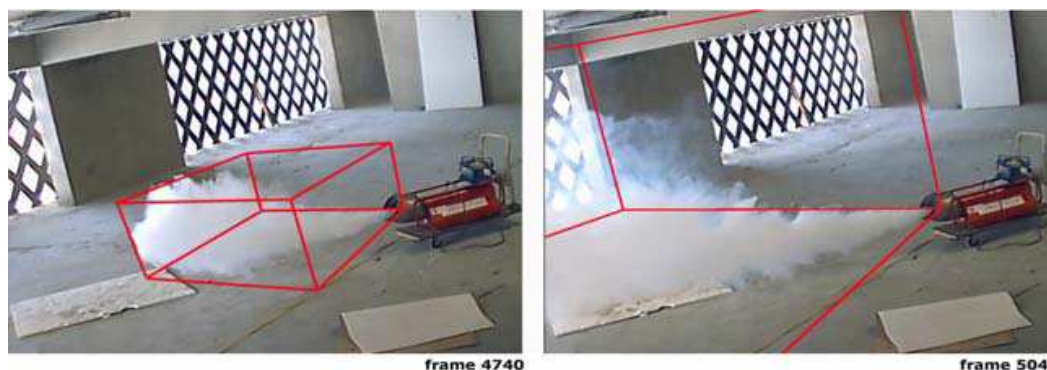
Fig. 13. Back-projection of 3D smoke box results into camera view CAM1.

5. Video-driven fire spread forecasting

Fire spread forecasting is about predicting the further evolution of a fire, in the event of the fire itself. In the world of fire research, not much experience exists on this topic (Rein et al., 2007). Based on their common use in fire modeling, CFD (Computational Fluid Dynamics; SFPE, 2002) calculations look interesting for fire forecasting at first sight. These are three-dimensional simulations where the rooms of interest are subdivided into a large amount of small cells (Fig. 14b). In each cell, the basic laws of fluid dynamics and thermodynamics (conservation of mass, total momentum and energy) are evaluated in time. These types of calculations result in quite accurate and detailed results, but they are costly, especially in calculation time. As such, CFD simulations do not seem to be the most suitable technique for fast fire forecasting. We believe, therefore, it is better to use zone models (SFPE, 2002). In a zone model, the environment is subdivided into two main zones. The smoke of the fire is in the hot zone. A cold air layer exists underneath this hot zone (Fig. 14a). The interface between these two zones is an essentially horizontal surface. The height of the interface (h_{int}) and the temperature of the hot (T_{hot}) and cold (T_{cold}) zones vary as function of time. These calculations are simple in nature. They rely on a set of experimentally derived equations for fire and smoke plumes. It usually takes between seconds and minutes to perform this kind of calculations, depending on the simulated time and the dimensions of the room or building. Therefore, it is much better suited for fire forecasting than CFD calculations.
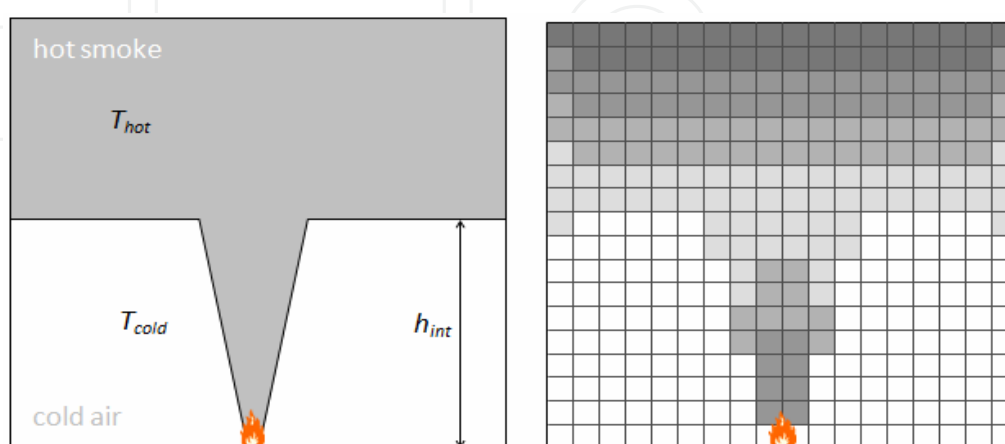

Fig. 14. Fire modeling techniques: a) zone model. b) Computational Fluid Dynamics (CFD).

The real aim of fire forecasting is to use measured data from the fire, e.g. obtained by sensors or video images in the room of interest, in order to replace or correct the model predictions (Welch et al, 2007; Jahn,2010). This process of data assimilation is illustrated in Fig. 15, which summarizes our future plans for video-driven fire forecasting. As can be seen in the graph, model predictions of smoke layer height (~ zone model interface h_{int}) are corrected at each correction point. This correction uses the measured smoke characteristics from our framework. The further we go in time, the closer the model matches the future measurements and the more accurate predictions of future smoke layer height become.

The proposed video-driven fire forecasting is a prime example of how video-based detectors will be able to do more than just generate alarms. Detectors can give information about the state of the environment, and using this information, zone model-based predictions of the future state can be improved and accelerated. By combining the information about the fire from models and real-time data we will be able to produce an estimate of the fire that is better than could be obtained from using the model or the data alone.
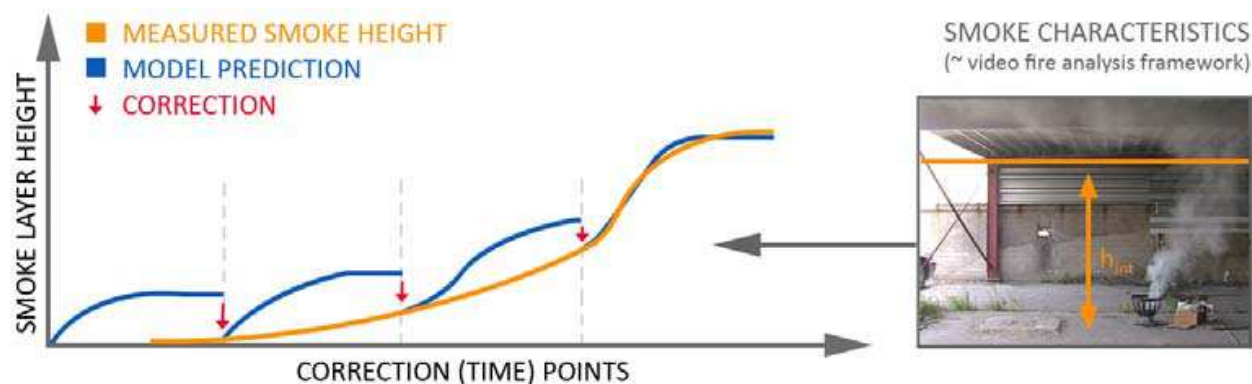

Fig. 14. Data assimilation: video-driven fire forecasting (~ Welch et al, 2007; Jahn, 2010).

6. Conclusions

To accomplish more valuable and more accurate video fire detection, this chapter has pointed out future directions and discussed first steps which are now being taken to improve the vision-based detection of smoke and flames.

Based on the analysis of existing approaches in visible and non-visible light and on our own experiments, a multi-sensor fire detector is presented which detects flames and smoke in LWIR and visual registered images. By using thermal and visual images to detect and recognize the fire, we can take advantage of the different kinds of information to improve the detection and to reduce the false alarm rate. To detect the presence of flames at an early stage, the novel multi-sensor flame detector fuses visual and non-visual flame features from moving (hot) objects in ordinary video and LWIR thermal images. By focusing on the distinctive geometric, temporal and spatial disorder characteristics of flame regions, the combined features are able to successfully detect flames.

The novel multi-sensor smoke detector, on the other hand, makes use of the smoke invisibility in LWIR. The smoke detector analyzes the silhouette coverage of moving objects in visual and LWIR registered images. In case of silhouette coverage reduction with a high degree of disorder, a fire alarm is given. Experiments on both fire and non-fire multi-sensor sequences indicate that the proposed algorithm can detect the presence of smoke and flames in most cases. Moreover, false alarms, one of the major problems of many other VFD techniques, are drastically reduced.

To provide more valuable information about the fire progress, we also present a multi-view fire analysis framework, which is mainly based on 3D extensions to homographic plane slicing. The framework merges single view VFD results of multiple cameras by homographic projection onto multiple horizontal and vertical planes which slice the scene under surveillance. At the crossings of these slices, we create a 3D grid of virtual sensor points. Using this grid, information about 3D location, size and propagation of the fire can be extracted from the video data. As prior experimental results show, this combined analysis from different viewpoints provides more valuable fire characteristics.

7. Acknowledgment

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Video Surveillance

Edited by Prof. Weiyao Lin

This book presents the latest achievements and developments in the field of video surveillance. The chapters selected for this book comprise a cross-section of topics that reflect a variety of perspectives and disciplinary backgrounds. Besides the introduction of new achievements in video surveillance, this book also presents some good overviews of the state-of-the-art technologies as well as some interesting advanced topics related to video surveillance. Summing up the wide range of issues presented in the book, it can be addressed to a quite broad audience, including both academic researchers and practitioners in halls of industries interested in scheduling theory and its applications. I believe this book can provide a clear picture of the current research status in the area of video surveillance and can also encourage the development of new achievements in this field.

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