Geographic Reasoning on Multi-Modal Fire Spread Data

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Abstract

This paper presents the general architecture of a multi-sensor GIS platform, i.e., fireGIS, which serves as a guideline for effective use of sensor data and geographic information in systems for fire incident management. The proposed platform allows the generation of real-time heatmaps that show the space-time distribution of fire risk levels across an area of concern based on multi-modal sensing. Such levels are to assist the decision makers in taking actions and aims at facilitating quick fire emergency response. Results of real fire experiments in a large-scale road tunnel show the feasibility of our approach.

Introduction

Geo-data is stored and used almost daily in many organizations, i.e., Geo-ICT is in growing expansion and changing in nature. In the context of disaster management, location identification and GEO-ICT is becoming increasingly effective, having a major role in the decision making process [1]. However, the real utilization of geo-information, such as road/building maps and real-time traffic data, and its combination with geotagged fire incident data is still limited in the analysis of fire emergency situations [2]. Geographic reasoning about fire events from heterogeneous multi-modal observations, i.e. the research topic of this paper, will help the fire crew in their decision-making process by fast on-site collaborative data collection and dynamic incident map creation on which space-time visual analysis can be performed [3].

The proposed fireGIS platform builds further on the multi-modal/multi-sensor fire detection work that has been performed at Ghent University during the past years [4, 5, 6] and extends it with the spatio-temporal mapping of the sensor data into real-time heatmaps that show the space-time distribution of fire risk levels. There are three major steps involved in the fireGIS process: (1) collection of low-cost multi-sensor data for the fire risk assessment, (2) fire maps creation and (3) spatio-temporal fire risk analysis. Within this paper, we will discuss each of these steps in more detail and illustrate their application by means of large-scale road tunnel fire experiments performed in Antwerp, Belgium by the end of 2014 (Figure 1). Real pool fires are ignited to analyze the propagation of the smoke and to show the smoke space-time spreading using the fireGIS platform. In these experiments, different types of cameras were used to monitor visibility-based smoke features.

Before going into detail concerning the architecture of the fireGIS platform, we discuss the importance of smoke reading, which is facilitated by the platform.

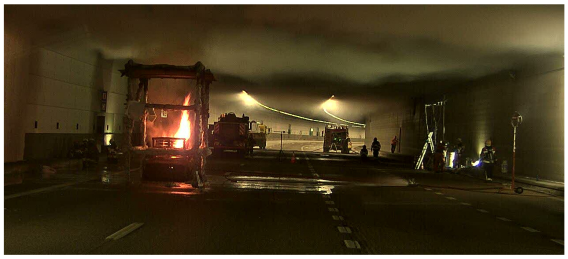

Figure 1 – fireGIS experiments at Craeybeckxtunnel in Antwerp, Belgium (November 2014).

Smoke reading

The location, the size, and the thickness of smoke can change the action plan for how to fight the fire. Furthermore, smoke is an important factor for evacuation of people. As such, reading smoke is essential for early warning and prediction of the fire behavior [7, 8]. By observing the spreading characteristics of smoke, firefighters can have a better understanding of the conditions that they will face. The speed of the smoke, for example, will give an indication about the pressure built up inside the building and the movement of the smoke will indicate if there is a large pressure inside. Combined with the turbulence this will give an impression of the possibility of a flash-over or ignition of the fire. However, not only the speed and movement but also the thickness of the smoke will give a lot of information about the fire. The smoke density or the thickness indicates if further burning is possible and with thick, black smoke, i.e., a very bad visibility, victims' chances of survival decrease rapidly. A low-visibility will also make the work of a fire crew very hard to find the victims. A fast evacuation of these regions will be necessary to increase the chance to survive. In this paper, the fireGIS platform will be used to automatically measure this visibility and visualize it on a spatio-temporal map of the environment.

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Proceedings of the 2nd IAFSS European Symposium of Fire Safety Science

General fireGIS architecture

The general architecture of the fireGIS platform is shown in Figure 2. In order to start the fireGIS analysis, the platform needs to get metadata input about the sensors and the environment which needs to be monitored. For each of the available sensors, a link to the sensor data stream and the location information, i.e., position, orientation and field of view (FOV), needs to be registered in the fireGIS platform. In our tunnel experiments, this information was provided by the Agency for Roads and Traffic (AWV) and the Flemish Tunnel and Control Center (VTC). In Figure 3, an overview is given about the data which was provided by both agencies. It is important to remark that, in its current form, the data is difficult to import in the fireGIS architecture directly and some pre-processing is needed. In the future, better guidelines should be developed describing how to deliver this kind of data in an efficient way. Finally, the user also needs to choose on which mapping service, e.g., Google Maps and OpenStreetMap (OSM), the spatio-temporal fireGIS detection results need to be shown.

Next, when all input is provided, the low-cost detection algorithms will start analyzing the data streams. In this paper, we only discuss the use of video data, but the generic character of the framework also allows other sensor types to be included. Subsequently, the single sensor detection results are projected to a 2D or 3D map of the environment using the location information of the sensors (Figure 3). In order to give an indication of the fire risk, different color codes ranging from green to red are used, corresponding to the detected smoke/visibility at each monitored point/region. For the tunnel experiments, mapping is done to a 2D representation of the environment, however, 3D mappings are also possible and have been investigated in previous work [9]. Finally, by analyzing the generated fire risk maps over time, a spatio-temporal analysis can be performed on the spreading of the fire. This can be very useful real-time information for fire incident management, but can also be used for post fire analysis and the validation/comparison with fire models.

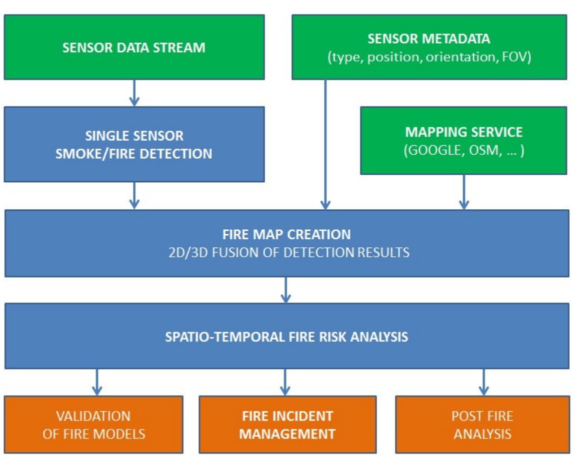
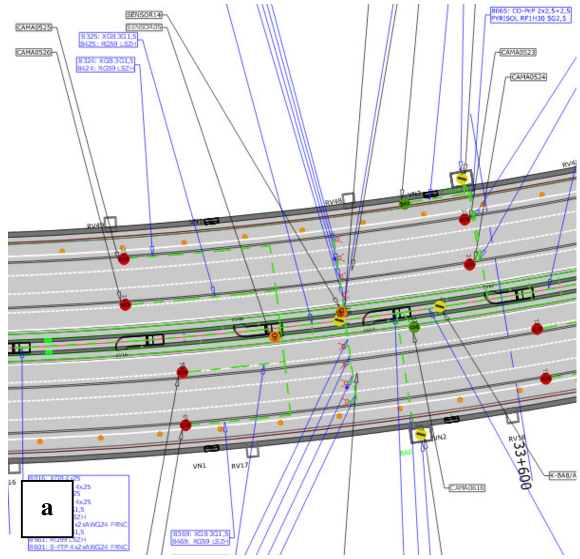


Figure 2 – Generic fireGIS architecture for spatio-temporal fire risk analysis.



b

Filename	Link	Orientation	Positio
CAMA0592.mov	link	SO	4
CAMA0624p.mov	link	PTZ	3.5
CAMA0590.mov	link	SA	3
			2.5
CAMA0588.mov	link	SA	2
CAMA0586.mov	link	SA	1
CAMA0622p.mov	link	PTZ	0.5
			0
CAMA0582.mov	link	SO	-1
			-1.5
CAMA0580.mov	link	SO	-2
C[illegible]0578.mov	link	SO	-3
C[illegible]0620p.mov	link	PTZ	-3.5
C[illegible]0576.mov	link	SO	-4

Figure 3 – Sensor and environment input provided by the Agency for Roads and Traffic (AWV) and the Flemish Tunnel and Control Center (VTC). a) road map with sensor locations and b) links to sensor data streams and additional positioning/orientation information.

Tunnel fire experiments

Before going more into detail on the video fire detection (which was used to demonstrate the fireGIS platform), this section provides some additional information on the tunnel fire experiments.

The Craeybeckxtunnel is a tunnel between Brussel and Antwerp (N 51.1005, E 4.2406) in Belgium. To investigate the impact of the ventilation system on the propagation of the smoke, real pool fire tests were performed by the end of 2014. Besides the monitoring of the visibility metrics and the fire spread in case of a car fire, the recorded video images can also be used for validation of CFD simulations, which were performed prior to the tests (as shown in Figure 4). It is also important to remark that the ventilation system in the tunnel is transversal to the drive direction. This is not common and gives the opportunity to analyze smoke movement in such circumstances.

Figure 4 – Comparison of CFD temperature field and Craeybeckxtunnel video measurements.

Prior to the tests, decisions were also made related to the fire power. On the one hand, the fire power needed to be limited to avoid severe damage to the tunnel. On the other hand, the power of the fire needs to be realistic to get a similar dynamic in the smoke movement. In our tests, a 20 minutes fire of 3 MW was generated, which was representative for a modern car fire between 4 and 6 MW [10].

Different measurements were performed related to temperature, air flow and smoke/visibility. In this paper, however, we only focus on the latter one, since only the video sensors were able to monitor the whole tunnel for space-time fire risk analysis. In the next section, we describe the visibility-based algorithm that is used for measuring the smoke/fire risk level.

Low-cost video smoke detection

Video based fire detection with cameras is a hot topic that is discussed several times in literature over the past years [11]. However, the focus has mainly been on detection. The propagation of the smoke, the height of the smoke layer and the visibility is not commonly investigated with cameras. To further investigate these topics and to optimize the evacuation of casualties when a fire strikes, we evaluated several video-based visibility metrics in our tunnel experiments and developed a quantitative measure which can be used in fire incident management to adapt the tactics of the fire brigades.

The most common features to detect the visibility in an image are based on analysis and classification of the brightness, saturation, and contrast pixel values [12]. In order to easily get these values, a conversion of RGB to HSV color space can be performed [13]. Additionally, the visibility can be measured by looking for the number/strength of visible edges in the image. If these edges are georeferenced, i.e., labelled with the real distance, it is also possible to say how far it is possible to see. In [14], for example, they use something similar to measure the sharpness of an image. If the number of edges in a particular image block is higher than a pre-defined threshold value, then the block could be seen as a good visible part. In our work, the opposite approach could be used to detect a decrease in visibility, i.e., smoke. Finally, it is also possible to use frequency domain analysis techniques to measure the sharpness or visibility. Figure 5, for example, shows the Fast Fourier Transform (FFT) of two of the Craeybeckxtunnel video frames. A large spectrum contains less or no smoke, while a small spectrum could indicate smoke. In order to use each of these techniques, however, some video-based training of the environment will be needed [15].

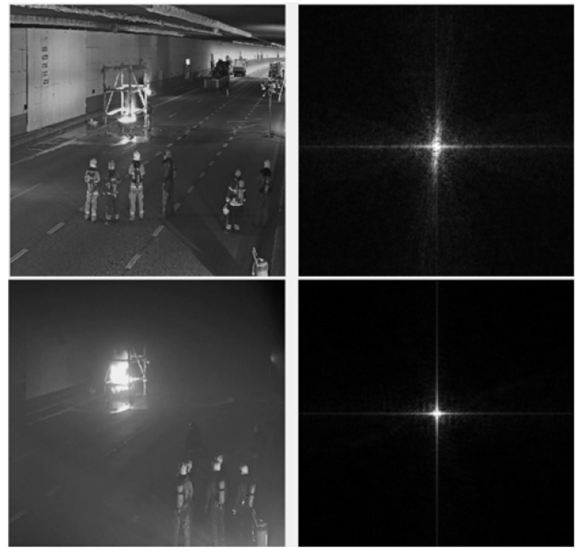


Figure 5 – FFT analysis of Craeybeckxtunnel video frames. Upper images - no smoke; lower images - smoke and smaller spectrum.

A flowchart of the proposed low-cost (i.e., computationally efficient) algorithm for video smoke detection is shown in Figure 6. The algorithm starts by converting the video to HSV color space and by filtering out the value (V) component. In this way, a change in lightning or a change in colors will not influence the algorithm [11]. Next, we use a Canny edge detector [16] to detect the prominent edges in V. This edge detector uses Gaussian filtering and hysteresis tracking, to smooth the image, remove the noise, and to suppress the weakly connected edges. Subsequently, we

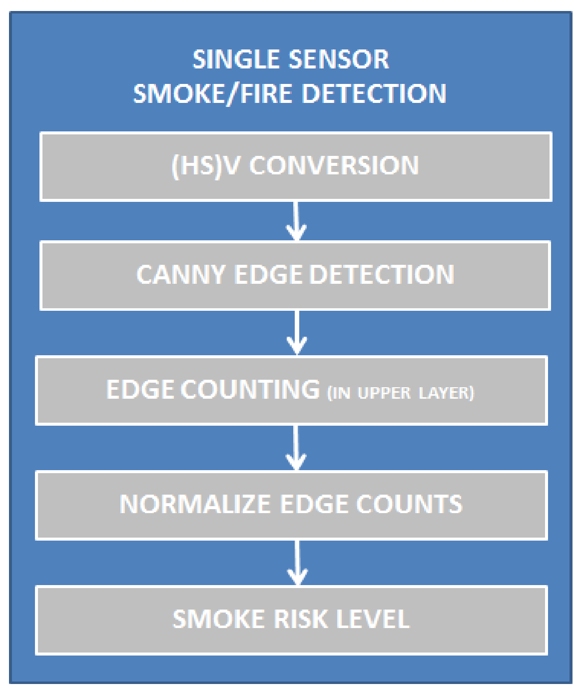
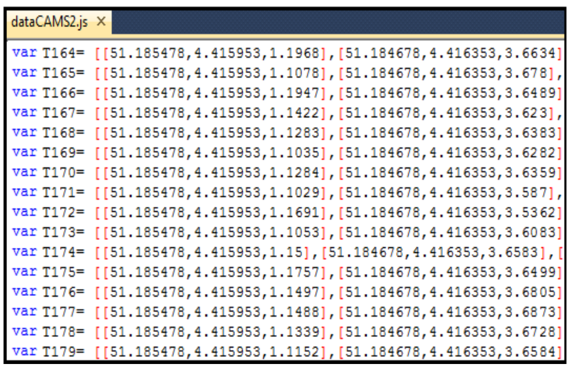


Figure 6 - Low-cost video smoke detection algorithm.

count the remaining bright pixels in the upper part of the image. This value gives a quantitative measure for the visibility in that region, i.e., an indication of the smoke level. We only focus on the upper part of the images, because of moving objects (like people and cars) in the lower part of the image, which can disturb the algorithm. Furthermore, smoke will rise, thus the upper part will contain most of the smoke. Finally, we normalize the edge counts (using edge characteristics of the video training phase) and we calculate de smoke risk level ranging from 1 to 5, i.e., high visibility and no-visibility respectively. Important to remark is that all these operations have a low computational cost, making it possible to process the video frames in real-time.

The resulting smoke risk levels are stored in a comma-separated values (CSV) file, as shown in Figure 7. For each camera that is used in the tunnel experiments, we generate a comma-separated object containing the position (latitude/longitude coordinates which are stored in the sensor metadata) and the smoke risk level at timestamp *T*. Based on this CSV file, the fire maps can be generated.



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dataCAMS2.js
var T164= [[51.185478,4.415953,1.1968],[51.184678,4.416353,3.6634]
var T165= [[51.185478,4.415953,1.1078],[51.184678,4.416353,3.678],
var T166= [[51.185478,4.415953,1.1947],[51.184678,4.416353,3.6489]
var T167= [[51.185478,4.415953,1.1422],[51.184678,4.416353,3.623],
var T168= [[51.185478,4.415953,1.1283],[51.184678,4.416353,3.6383]
var T169= [[51.185478,4.415953,1.1035],[51.184678,4.416353,3.6282]
var T170= [[51.185478,4.415953,1.1284],[51.184678,4.416353,3.6359]
var T171= [[51.185478,4.415953,1.1029],[51.184678,4.416353,3.587],
var T172= [[51.185478,4.415953,1.1691],[51.184678,4.416353,3.5362]
var T173= [[51.185478,4.415953,1.1053],[51.184678,4.416353,3.6083]
var T174= [[51.185478,4.415953,1.15],[51.184678,4.416353,3.6583],[
var T175= [[51.185478,4.415953,1.1757],[51.184678,4.416353,3.6499]
var T176= [[51.185478,4.415953,1.1497],[51.184678,4.416353,3.6805]
var T177= [[51.185478,4.415953,1.1488],[51.184678,4.416353,3.6873]
var T178= [[51.185478,4.415953,1.1339],[51.184678,4.416353,3.6728]
var T179= [[51.185478,4.415953,1.1152],[51.184678,4.416353,3.6584]
```

Figure 7 – CSV files with detected smoke risk levels. For each timestamp *T*, the coordinates of the cameras and corresponding rosk levels are stored in comma- separated objects.

Fire map generation

In order to generate a 2D fire map of the smoke risk levels at timestamp *T*, we developed a dynamic JavaScript-based web page. The web page makes use of the Leaflet.heat and leaflet.js heatmap plugin, which is a tiny, simple and fast solution for heatmap generation, available from http://leafletjs.com. This plugin constructs a heatmap layer on top of a map given an array of latitude/longitude points and a point intensity, i.e., the smoke risk level in our tunnel experiments.

Figure 8 shows two example of fire maps generated for the Craeybeckxtunnel tests using the heatmap functionality. As can be seen in the first example, only small central part of the tunnel has low visibility, while the other parts of the tunnel are still smoke-free. In the second example, smoke starts spreading towards both sided of the tunnel, indicating low visibility over the entire tunnel. This information can be very useful for fire incident management, such as evacuation planning.

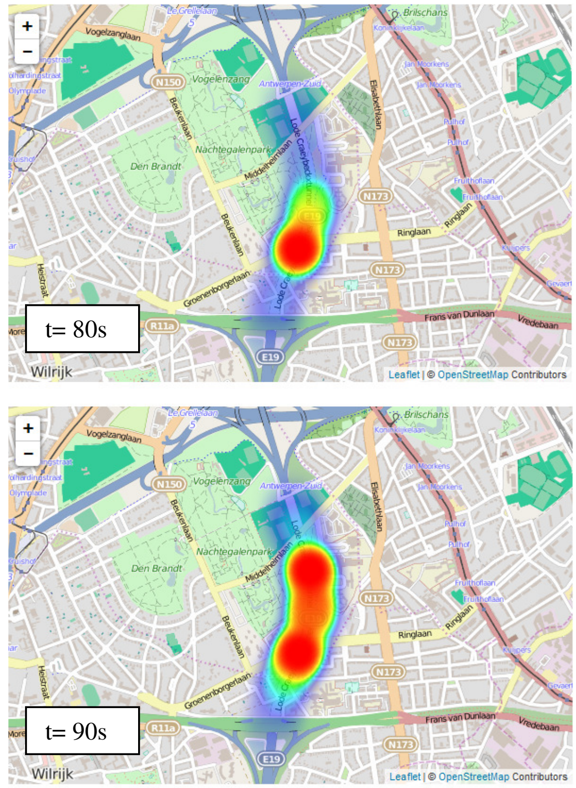
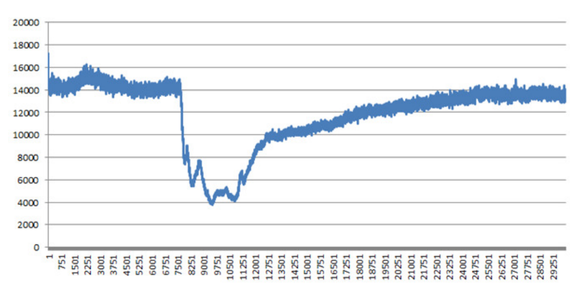


Figure 8 – Fire maps showing smoke risk level (i.e., low visibility) in Craeybeckxtunnel experiment.

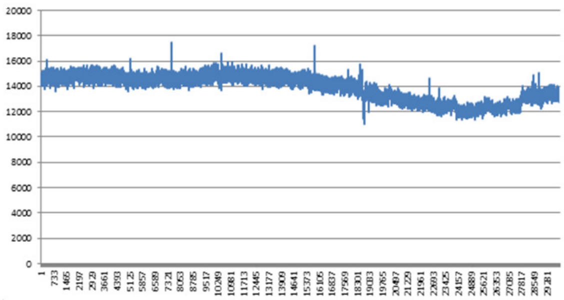
Spatio-temporal fire risk analysis.

By analyzing the fire maps (shown in Figure 8) over time, it is possible to perform a space-time analysis of the smoke spreading and to get an idea about the direction, speed and thickness of the smoke at each point in time over the entire tunnel. This can facilitate the smoke reading and decision making, as discussed in the introduction of this paper.

Using the CSV smoke risk data, the fireGIS platform can also plot temporal graphs of the smoke risk level (~ edge count) for each sensor region. Graph 1 and 2, for example, illustrate this process, showing the temporal evolution of the edge counts for two different sensors that were placed in the middle and the end of the tunnel respectively. Results are shown for the same experiment (i.e., ventilation conditions).

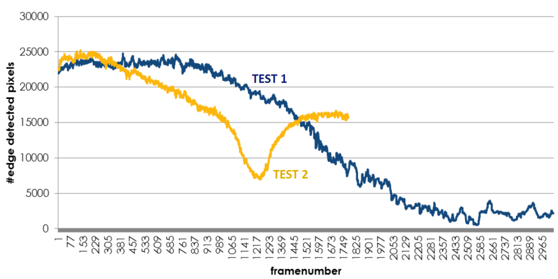


Graph 1 – Temporal evolution of edge counts (~ smoke risk level) in the middle of the tunnel.



Graph 2 – Temporal evolution of edge counts (~ smoke risk level) in the middle of the tunnel.

In the Craeybeckxtunnel experiments, these temporal graphs were also used to investigate the impact of the different ventilation configurations on the smoke risk level. Graph 3, for example, shows a comparison of the temporal smoke risk level between two different tests for the same sensor. In this way, the impact of the ventilation conditions can be analyzed in straight-forward way, facilitating future decision making in case of a tunnel fire.



Graph 3 – Comparison of the temporal smoke risk level between two different tests for the same sensor.

Similar trends/evolutions as those shown in Graph 1-3 can be detected by subjectively analyzing the combined, i.e., stitched, video images in Figure 9. However, objective results, as those shown on the heat-maps and temporal smoke risk graphs, are easier and much faster to interpret compared to video images in a fast decision making process. The video streams can of course help in the evaluation of the detection algorithms and for post-fire analysis purposes.

Conclusions

This paper presents the generic architecture of the fireGIS framework, which allows the generation of real-time heatmaps that show the space-time distribution of fire risk levels. In order to show the feasibility of the proposed platform, real-fire experiments have been performed in a large-scale road tunnel. Video sensors have been used as input to feed the fireGIS system, and the visibility-based video fire detection results are mapped to spatio-temporal heatmaps. These maps can assist decision makers in taking actions and facilitate quick fire emergency response. Future work will focus on evaluating the genericity of the fireGIS framework with other/mixed types of fire sensors.

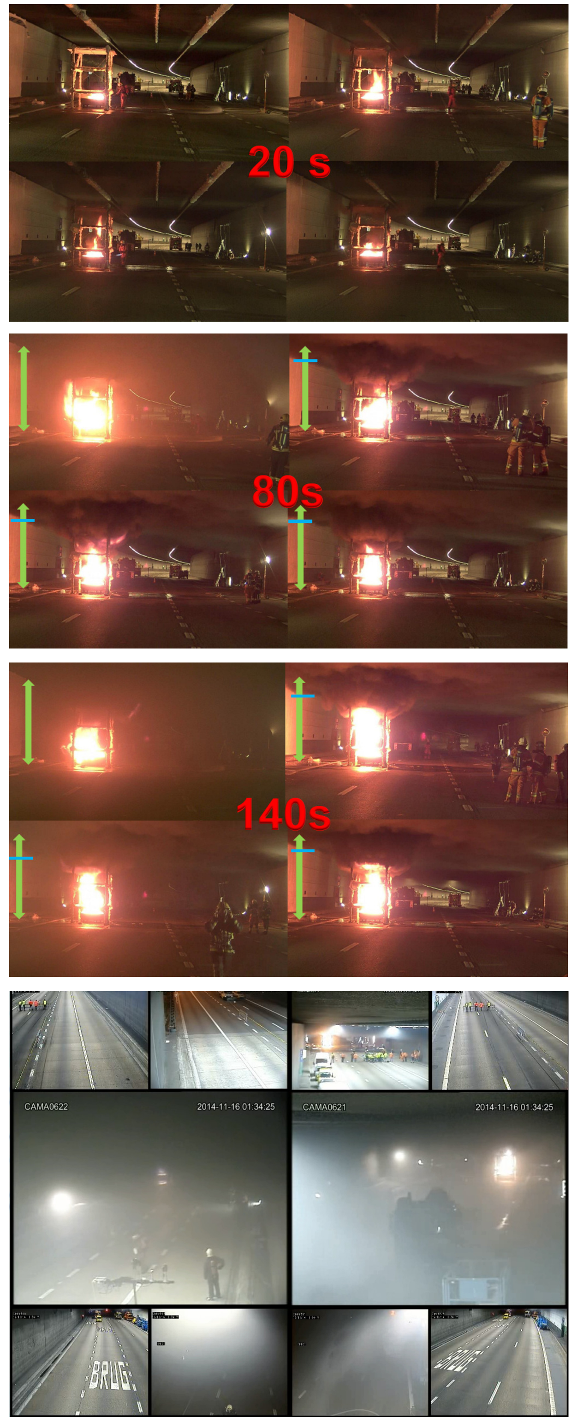


Figure 9 - Combined video images for subjective evaluation of Craeybeckxtunnel experiments.

Acknowledgements

The research activities as described in this paper were funded by Ghent University, iMinds, the Agency for Roads and Traffic (AWV), the Flemish Tunnel and Control Center (VTC), the Institute for the Promotion of Innovation by Science and Technology in Flanders (IWT), the Fund for Scientific Research-Flanders, the Belgian Federal Science Policy Office and the EU.

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