8

Multi-UAV Experiments: Application to Forest Fires

J.R. Martínez-de-Dios[1], Luis Merino[2], Aníbal Ollero[1], Luis M. Ribeiro[3], and Xavier Viegas[3]

[1] Robotics, Vision and Control Group, University of Seville, Camino de los Descubrimientos s/n, 41092 Seville (Spain)
{jdedios,aollero}@cartuja.us.es
[2] Pablo de Olavide University, Crta. Utrera km. 1, 41013 Seville (Spain)
lmercab@upo.es
[3] Universidade de Coimbra, Apartado 10131, 3030 Coimbra (Portugal)
luisr1@netcabo.pt,xavier.viegas@dem.uc.pt

Summary. This Chapter presents the application of a multi-UAV system to forest fires. Particularly the experiments carried out with the COMETS system will be presented. After the introduction and motivation, the UAVs, sensors and basic methods are presented. The third section deals with the general description of the fire detection, localization and monitoring. The next sections are devoted to the multi-UAV surveillance and fire alarm detection, fire observation and monitoring, and cooperative fire monitoring. These sections include short summaries of experiments carried out in the Lousã airfield and the Serra de Gestosa, near Coimbra (Portugal).

8.1 Introduction and Motivation

Forest fire is an appropriate scenario for the demonstration of multi-UAV capabilities and performance. Forest fires are highly complex, non-structured environments, where the use of multiple sources of information at different locations is essential. Besides, fire evolution, which is very difficult to be predicted, and the presence of smoke occluding the images requires flexible re-planning and rescheduling of UAVs, which makes this environment a suitable scenario for testing multi-UAV performance.

Forest fires are a serious problem in many countries with high socioeconomic and environmental impacts and also with global consequences on greenhouse effect, desertification and climate change. In the last years, forest fire applications have attracted significant R&D efforts and several new technologies and platforms have been researched and applied including satellite systems [10, 12], conventional piloted aircrafts and ground stations [2, 4, 13].

However, none of these technologies offer a solution to the problem. For instance, satellite-based systems often have low spatial and temporal resolutions. Although they are successfully applied in uniform and low populated areas, they are not appropriate for regions with intensive human activities such as the European Mediterranean basin. Ground stations and conventional piloted aircrafts

A. Ollero and I. Maza (Eds.): Mult. Hetero. Unmanned Aerial Vehi., STAR 37, pp. 207–228, 2007.
springerlink.com

also have drawbacks. The application of more flexible and effective technologies and particularly its usage in operational forest fire fighting conditions is still a strong need.

Besides, forest fire fighting is a dangerous task which originates many casualties every year. The application of UAVs is convenient to reduce the presence of firemen brigades and to provide information to better organize the fire attack.

In [1] the application of a Medium Altitude (27000 feet) Long Endurance (30/40 hours) UAV with 450 lbs payload, was demonstrated in fire experiments. The data received at the ground station were geo-referenced. The process time from data acquisition aboard the UAV, through satellite uplink/downlink, processing into a geo-referenced image data file, to a fire manager in a remote control center was less than an hour.

In the COMETS project, instead of using a single powerful UAV with significant on-board resources but also with high cost, the application of a fleet of lower cost UAVs for forest fire fighting is proposed. These UAVs can be used as local flying sensors providing images and data at short distance.

This Chapter presents experimental results of multi-UAV forest surveillance, forest fire detection, localization and confirmation as well as fire observation and measurement obtained in the COMETS project. Although there is still need of research and development, the results represent a significant step towards the application of UAVs in forest fire operational conditions.

8.2 A Multi-UAV System for Forest Fire Applications

The experiments described in this Chapter were performed in the Serra de Gestosa (see Fig. 8.1) and the airfield of Lousã (Portugal) in May 2004 and 2005. In the region of Centro (Portugal), Lousã is located at one relevant forested areas of Portugal. The experiments were carried out with real fires controlled by firemen in close-to-operational conditions. The ADAI group of the University of Coimbra (Portugal) coordinated the arrangements of fire experiments. Figure 8.2 shows a map and an aerial photograph of the Lousã airfield.

8.2.1 Descriptions of the UAVs

The experiments considered a fleet of three heterogeneous UAVs: the helicopter MARVIN [11], the helicopter Helivision-GRVC [9] and, the airship Karma [5]. These UAVs are presented in Chaps. 5, 6 and 7, respectively. Figure 8.3 shows MARVIN, Helivision-GRVC and Karma UAVs in forest fire experiments at the Lousã airfield.

The heterogeneity of these UAVs is manifold. Complementary platforms are considered: helicopters have high maneuverability and hovering ability, and are suited to agile target tracking tasks and inspection and monitoring tasks that require to maintain a position and to obtain detailed views. Airships have less manoeuvrability but can be used to provide global views or to act as communication relays. Besides, these UAVs are also heterogeneous in terms of on-board

Fig. 8.1. Left: Location of Lousã on general map of Portugal. Top right: Aerial view of Serra de Gestosa (Portugal). The rectangular plots burned in the experiments can be observed in the images. Bottom right: Helivision-GRVC in forest fire experiments at Serra de Gestosa in May 2004.

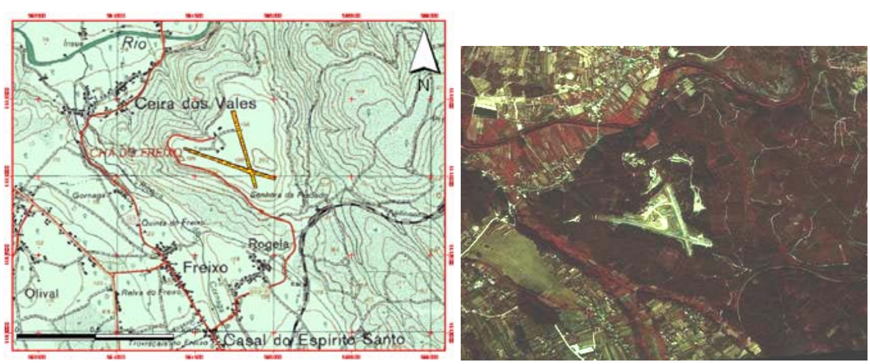

Fig. 8.2. Map and aerial photograph of Lousã airfield

processing capabilities, ranging from fully autonomous aerial systems to conventional radio controlled systems with minimal on-board capabilities required to record and transmit information.

Fig. 8.3. MARVIN, Helivision-GRVC and Karma UAVs in forest fire experiments at the airfield of Lousã (Portugal) in May 2005

8.2.2 Sensors of the Fleet

The UAVs are heterogeneous also in terms of the sensors carried by them. Besides the sensors required for navigation such as DGPS, gyroscopes and Inertial Measurement Units and others, the UAVs were equipped with heterogeneous sensors for environment perception such as visual and infrared cameras and a specialized fire sensor.

Helivision-GRVC is equipped with an infrared camera and a visual video camera. The infrared camera is the low-weight (150 g) un-cooled Raytheon 2000AS camera (see Fig. 8.4 left), which operates in the far infrared band (7–14 μm). The visual camera is a low-weight Camtronics PC-420DPB with 752x582 sensors and lens with focal distance of 6 mm.

Helivision-GRVC has a motorized pan and tilt unit that allows orientating the cameras independently from the body of the vehicle (see Fig. 8.4 right). The unit has encoders to measure the pan and tilt angles.

The infrared and visual cameras of Helivision-GRVC were geometrically calibrated. The GPS, IMU and pan and tilt encoders of the camera positioning system allow obtaining the camera position and heading. These data are used to geolocate objects on the image plane by projecting them over a known elevation map as described in Chap. 4.

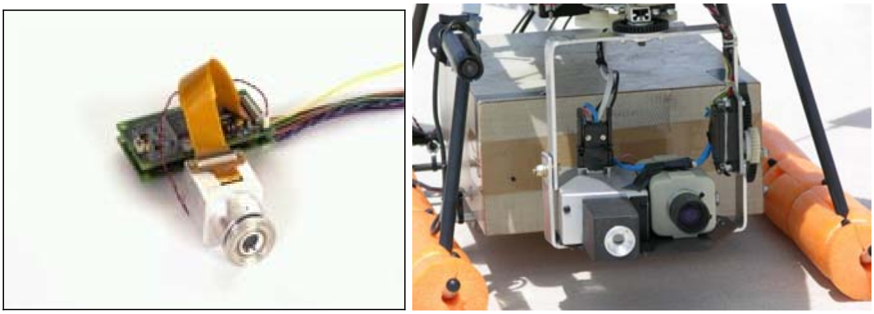

Fig. 8.4. Left: detail of the Raytheon 2000AS OEM infrared camera. Right: Infrared and visual cameras mounted on Helivision-GRVC pan and tilt unit.

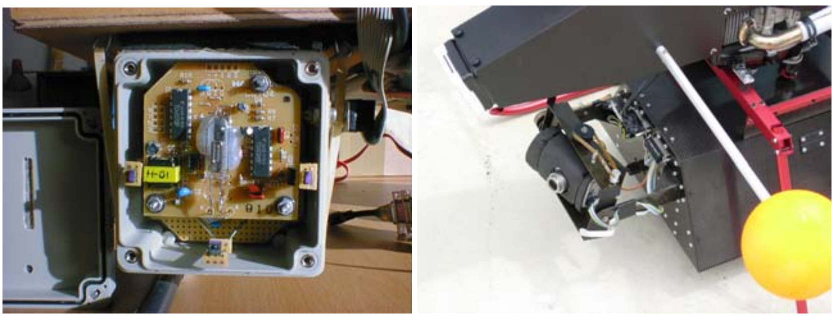

Fig. 8.5. Fire sensor (left) and digital photo camera (right) on-board MARVIN

MARVIN carries a Hamamatsu UV-Tron fire detector, whose main component is a photodiode set-up to limit its sensibility to the band of [185, 260] nm, normally associated to fires radiation. The output of the sensor is a scalar value, proportional to the radiation energy, received every two seconds. Being a magnitude sensor, it is not possible to determine if a measure is due to a big fire far away or to a nearby small fire. Also, the sensor cannot directly provide the position of the fire. MARVIN also carries a Canon Powershot S45 digital photo camera. Figure 8.5 shows the fire sensor and digital photo camera mounted on MARVIN.

Karma carries a stereo bench with two visual digital IEEE1394 colour cameras (1024x768 pixels). The stereo system is mainly applied to obtain 2D and 3D terrain maps.

8.2.3 Fire Segmentation

Forest fire perception requires algorithms capable of identifying the fire in images from the infrared and visual images and in the data generated by the fire sensor. This Section describes these segmentation techniques.

Fire Segmentation in Visual Images

The aim of the fire segmentation method is to produce binary images containing fire alarms while discarding false alarms. The technique used is a training-based algorithm similar to those described in [7, 15]. The method requires some training images in which an experienced user has previously determined which pixels correspond to the fire. In the training stage, a RGB histogram is built by adding Gaussian-type distributions centered at the RGB coordinates of the pixels considered as a fire pixel in the training images. If the pixel is considered as background in the training images, a Gaussian-type distribution centered at the RGB coordinates is subtracted from the RGB histogram.

Finally, this RGB histogram is thresholded and a look-up table for the RGB colour space is built. The look-up table contains a Boolean value indicating whether the colour represents fire or background. In the application stage, the RGB coordinates of the pixels are mapped in the trained look-up table and are considered fire pixels if the value in the look-up table is '1' and, background otherwise. Figure 8.6 shows one visual image of a Gestosa experiment and the corresponding segmented image.

Fig. 8.6. Left: original colour visual image from a Gestosa fire experiment. Right: corresponding segmented image.

Fire Segmentation in Infrared Images

The aim of the processing of infrared images is to produce binary images containing fire alarms while discarding false alarms. Since fires appear in infrared images as high intensity regions, the first step in fire segmentation is to apply a threshold value. The following step is to apply heuristic rules to discriminate false alarms.

The infrared camera used in the experiments was a low-cost OEM non-thermal camera. It does not provide temperature measures but estimations of the radiation intensity throughout the scene. Black and white colours represent low and high radiation intensities, respectively. For robust fire segmentation, the thresholding technique should consider the particularities of the application. For instance, in the current state of technology, the detectors of miniaturized infrared cameras still have low sensitivity and require high detector exposure periods to generate the images. Thus, the high frequency vibrations induced by the UAV engine often originate blurs in the infrared images.

The solution adopted was to use the training-based thresholding method described in [3]. Its main idea is to extract the particularities of a computer vision application and use them to supervise a multiresolution histogram analysis. The technique is applied in two stages: training and application (see Fig. 8.7). The training stage requires a set of training images and their corresponding desired threshold values given by an experienced user. The training stage identifies the conditions under which pixels should be considered to belong to the object of interest. These particularities are introduced in a system via the ANFIS training method [6]. In the application stage, features of the image are used to determine a suitable threshold value according to these particularities. A detailed description can be found in [3].

The adaptation of the method to this application was carried out with training infrared images with different illumination conditions, different image backgrounds and different objects including fires and false alarms (i.e. heat emitting sources such as car engines).

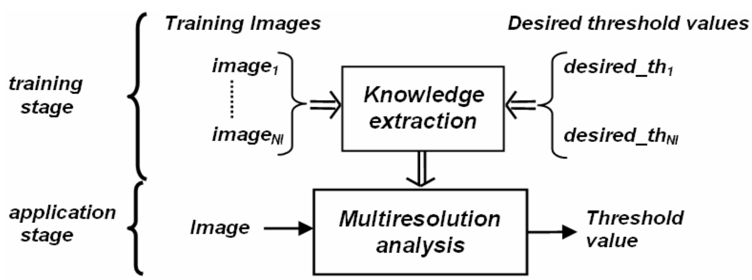

Fig. 8.7. General scheme of the training-based threshold selection

Figure 8.8 shows two examples: a fire and a heated car. In the first case, there was high contrast between the fire and its surroundings and, thus, it was considered as an actual fire and fire pixels are overlaid in white colour. In the second case, the contrast was low and this early processing discarded the alarm as false.

Fusion of Infrared and Visual Images for Fire Segmentation

Helivision-GRVC UAV carries both, an infrared and a visual camera (see Fig. 8.4). These sensors can be combined obtaining what it can be considered a “multi-spectral” camera, which can provide more robust results for fire detection purposes. This Section describes how this can be accomplished.

Assume that both cameras share the centre of projection. Figure 8.9 presents a scheme of the geometry of this configuration.

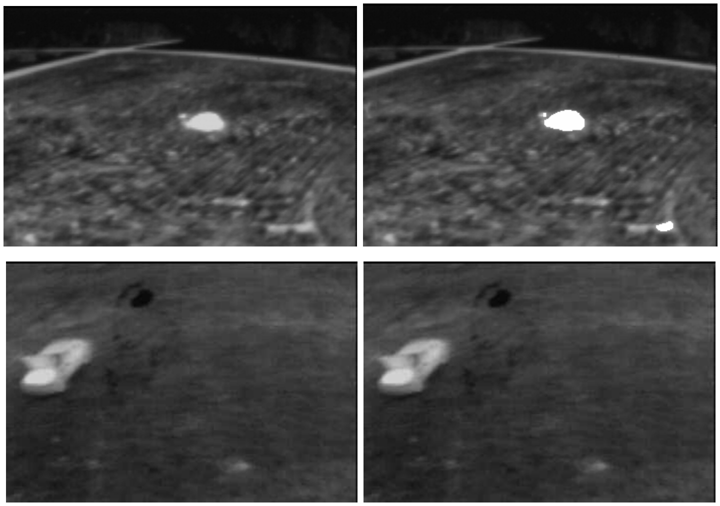

Fig. 8.8. Two infrared images from a fire (top) and from a heated car engine (bottom). Top: there is high contrast between the fire and its surroundings and the alarm is considered as fire. Bottom: the contrast is low, the alarm is discarded as false and no object is segmented.

Let $\mathbf{m}_{\mathrm{IR}} = [u\,v\,1]^T$ and $\mathbf{m}_{\mathrm{VIS}} = [u'\,v'\,1]^T$ be the images at the same instant of a point $\mathbf{X}$ in homogeneous pixel coordinates on the infrared and visual images respectively. Then, if the centres of projection of both cameras are assumed to be coincident (point $\mathbf{C}$ in Fig. 8.9), the relation between both images is given by:

$$s\mathbf{m}_{\mathrm{IR}} = H_\infty \mathbf{m}_{\mathrm{VIS}} \tag{8.1}$$

where H_∞ is a 3×3 matrix called the infinity homography and s is a scale factor. H_∞ can be calculated knowing at least four correspondences among points or lines in both images.

There are many algorithms for point matching between images of the same modality. However, this is a challenging problem when dealing with images of different modalities. For the experiments in Lousã, the calibration has been done using a known pattern that is visible on both types of cameras. It should be noticed that H_∞ is computed only once provided that the relative orientation of the cameras and their internal calibration does not change.

In the system considered, the centres of projection of both cameras will not be actually coincident, but the equations above hold if the distance between the centres of projection is small compared with the distances of the points of the scene with respect to the cameras. Figure 8.10 shows some results of the combination of infrared and visual images.

Using the technique presented above, any pixel in the infrared camera can be related to a corresponding pixel in the visual camera. This will be used to improve the results on fire detection, combining the results from the algorithms for fire segmentation in infrared and visual images.

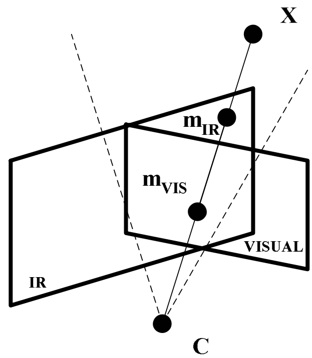

Fig. 8.9. Geometry of the configuration of the cameras

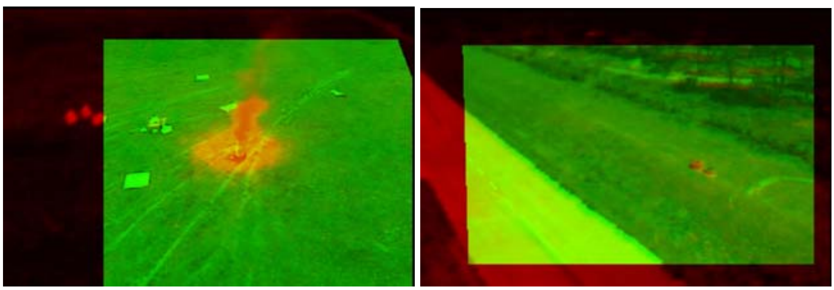

Fig. 8.10. Combination results. The infrared and visual images are presented together as the red and green fields of a colour image.

Fire Identification in Data from the Fire Detector

The fire sensor provides a scalar value indicating the presence of fire. This value is proportional to the amount of radiation received in a narrow band adjusted to the emissions of fire. Thus, fire is segmented by applying a threshold, so that a Boolean value is obtained, indicating that a fire is present in the field of view of the sensor.

The threshold can be adapted depending on the application. A lower threshold increases the probability of detection (which can be convenient during a detection stage), but on the other hand produces more false alarms. A higher threshold rejects more false alarms while reducing the detection capabilities (interesting for confirmation stages).

Characterization of the Fire Segmentation and Identification

The cooperative perception techniques described in Chap. 4 requires a probabilistic characterization of the fire segmentation algorithms. The algorithms are modelled by the probabilities P_D of detection and P_F of false positive outputs defined as follows:

- P_D is the ratio between the alarms correctly detected and the total number of fire alarms presented in the set of images.
- P_F is the ratio between the number of images where the algorithm detected fire incorrectly and the total number of images of the sequence.

The values shown in the table 8.1 have been experimentally computed for the three algorithms with a large set of images and data, including real fires.

Table 8.1. Characterization of fire segmentation algorithms

	Infrared camera	Visual camera	Fire detector
P_D	100%	89,2%	95%
P_F	8,9%	3,1%	1%

8.3 General Description of the Mission

The experiments carried out are instances of a general mission that performs fire detection, confirmation and precise localization with several cooperating UAVs, and that could include different combinations of UAVs and sensors. The mission is decomposed in the following stages:

- *alarm detection*,
- *alarm confirmation*,
- *fire observation and measurement*.

The main idea is to simulate the performance of forest fire fighting protocols currently applied in many countries. In fact, these three stages are common in current operational forest fire fighting operations. Forest surveillance is often carried out by experienced operators in watch towers, by aerial patrolling or by automatic fire detection systems. Detected alarms are confirmed by using additional information, which often involves that a piloted helicopter is sent for visual confirmation. If the alarm is confirmed, the fire extinguishing protocols are started. These protocols require to know the state of the forest fire including its location, its severity and several fire geometry features, which are currently visually estimated by expert firemen.

The *alarm detection* stage starts by searching potential fires. In this stage, the overall area to be surveyed by the fleet is divided in searching regions for MARVIN and Helivision-GRVC. For fire search MARVIN uses its fire sensor and Helivision-GRVC uses its infrared camera. Karma is sent to obtain a global view of the overall area. At this location Karma acts as communication relay. When any of the UAVs detects a potential fire alarm, this stage concludes and the *alarm confirmation* stage starts.

In the *alarm confirmation* stage the tasks for MARVIN and Helivision-GRVC are replanned. The UAV that detected the alarm is commanded to hover at a safety distance from the fire alarm. The other UAV is sent to the alarm location in order to confirm the alarm by using its own sensors. The data from different sensors in different UAVs are merged to confirm or discard the alarm. If the alarm is found to be false, then the *alarm confirmation* stage finishes and the *alarm detection* stage is resumed. If the alarm is confirmed as a fire, then the *fire observation* stage starts.

In the *fire observation* stage the tasks for MARVIN and Helivision-GRVC are re-planned: both are commanded to hover on to the fire alarm and to obtain stabilized images and data of the fire from different views.

Figure 8.11 shows two images taken from forest fire multi-UAV experiments. In the following sections, these stages are described with more details and illustrated with results from field experiments.

Fig. 8.11. Left: Karma and Helivision-GRVC involved in a fire experiment at the Lousã airfield (Portugal). Right: a view of the airfield from MARVIN.

8.4 Multi-UAV Surveillance and Fire Alarm Detection

This stage can be decomposed in two essential steps. In the first step, the global region to be surveyed is divided in regions for each UAV. For such a division the Control Centre takes into account the capabilities of each UAV including the flight speed and altitude of each UAV, as well as the sensing width which depends of the field of view of the cameras or detectors on-board each UAV. The UAVs cover their convex surveillance regions by describing back and forward rectilinear sweeps. The division of the overall region is carried out by minimizing the number of sweep turns, which involve significant time for the UAVs to stop, rotate and then accelerate for the following sweep (more details on can be found in [8]). Once the Control Centre has divided the global area among the UAVs, it assigns the waypoints required for each UAV to describe the assigned trajectory.

In the second step, each UAV of the fleet follows the waypoints commanded by the Control Centre and performs individual fire alarm search by applying the fire segmentation algorithms described in Sect. 8.2.3.

The data from the MARVIN fire sensor are processed to evolve a fire probability grid over the searching zone by using the techniques described in Chap. 4. The grid covers 310x400 square meters and each cell corresponds to an area of $1\,m^2$. Initially all the cells are set to a probability value of 0.5. Figure 8.12 shows the initial stages of the evolution of the probability values of the grid every 40 seconds. Each triangle represents the area covered by the fire sensor (several cells of the grid) at different time instants and, its colour represents the probability of having a fire alarm in this grid cell. Black colour is low probability and white is high probability. Connected cells with high probability (higher than 0.7) are considered as fire alarms and their locations are obtained.

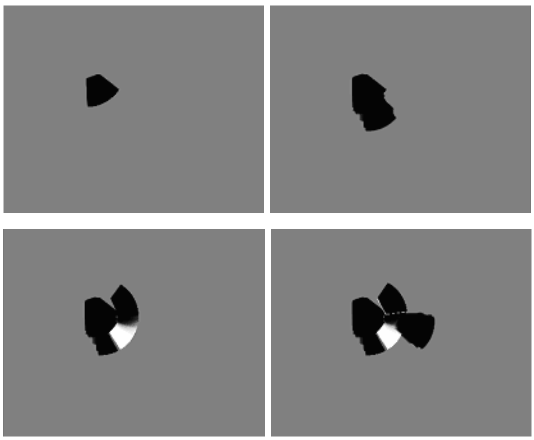

Fig. 8.12. Evolution of fire probability of the grids cells. Each triangle represents a cell of the grid. White colour indicates grid cells with high fire probability and black colour, with low probability.

Figure 8.13 shows a georeferenced schematic map of the Lousã airfield. The solid polygonal object represents the concrete area where the UAVs take off and land. The axes are shifted UTM coordinates in meters. In the whole duration of this stage, three potential alarms are detected with the MARVIN fire sensor. Only one of the three fire alarms is a true fire. The position of the actual controlled fire is marked with a solid square.

Also, Helivision-GRVC applies the fire segmentation algorithm in infrared images described in Sect. 8.2.3. If a fire alarm is segmented, the fire segmentation in visual images is applied over the Helivision-GRVC visual image in order to confirm the alarm. If the same alarm is segmented in both images, then Helivision-GRVC sends the alarm to the Control Center.

Figure 8.14 top shows the original and segmented infrared images of a fire alarm detected in a field experiment in May 2004. Figure 8.14 centre shows the corresponding original and segmented visual images. Figure 8.14 bottom displays the overlapping between both segmented images.

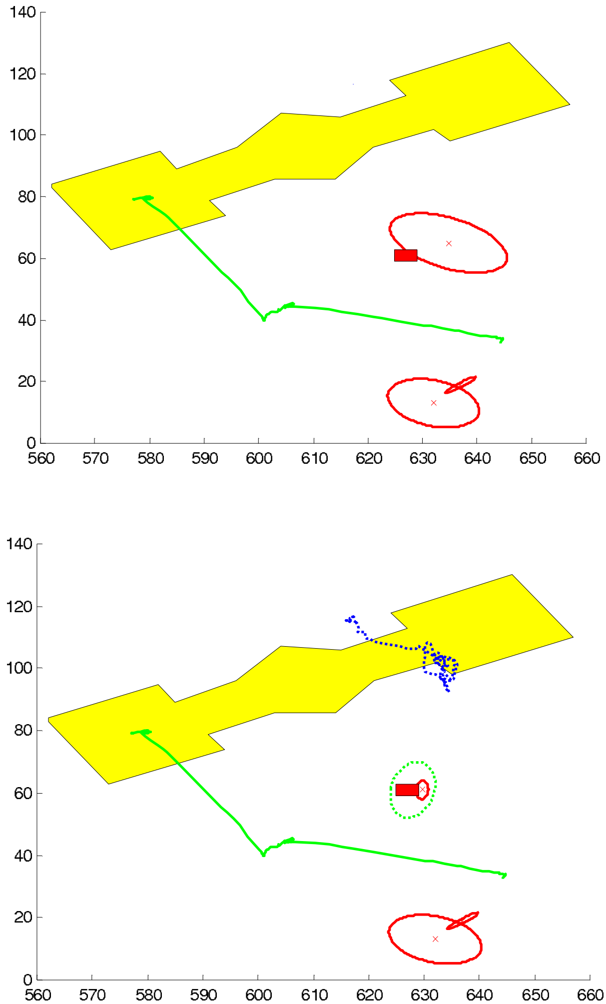

Fig. 8.13. Top: alarm detection stage. Fire alarms detected using the fire sensor. The ellipses represent the uncertainties in the computed positions of the alarms. The square indicates the actual position of the fire. The trajectory of MARVIN is shown. Bottom: alarm confirmation stage. New measures from Helivision-GRVC (dotted ellipse) are used to refine the location of the alarms. Helivision-GRVC trajectory is also shown (dotted).

When any of the UAVs of the fleet detects a fire, it georeferences the alarm by using the techniques described in Chap. 4 and sends the georeferenced location of the alarm to the Control Centre. Then, the *alarm detection* stage concludes and *alarm confirmation* starts.

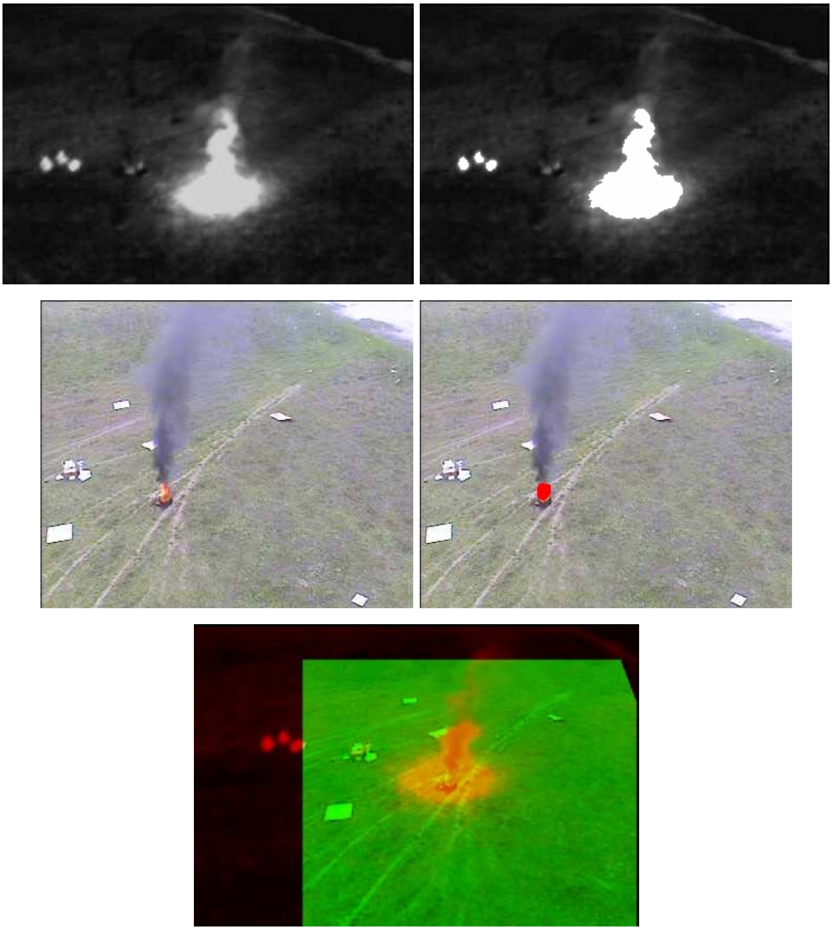

Fig. 8.14. Top: original and segmented infrared images of a fire alarm detected in a field experiment in May 2004. Centre: corresponding original and segmented visual images. Bottom: overlapping between segmented infrared (red field of the colour image) and visual images (green field of the colour image).

8.5 Cooperative Alarm Confirmation

In the *alarm confirmation* stage, the missions of the UAVs are re-planned:

- the UAV that detected the alarm is commanded to hover at the location of the alarm,
- the remaining UAVs of the fleet are commanded to go to the location of the alarm.

When the UAVs are at the location of the alarm, the images and data from all the UAVs are processed. The results of the fire segmentation algorithms are

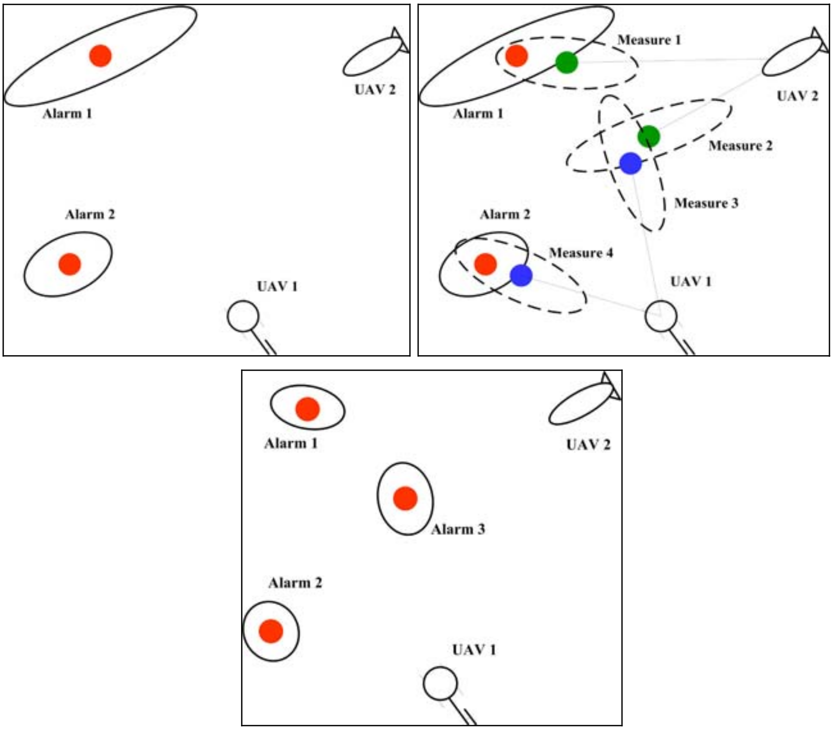

Fig. 8.15. Top left: prediction. The previous detected alarms and their uncertainties (presented as ellipses). Top right: capture of new measures. These measures are associated to the tracks of the currently detected alarms. Bottom: the update stage reduces the uncertainties of the tracks with the new data inputs. New tracks are added.

merged by using the cooperative detection technique described in Chap. 4 to confirm or discard the alarm. Figure 8.15 illustrates the scheme of cooperative alarm confirmation.

Figure 8.16 shows the fire alarms from the MARVIN fire sensor projected onto the segmented infrared images of Helivision-GRVC. The ellipses represent the uncertainty on the locations of the alarms of the fire sensor and the white patch is a region segmented as fire in the infrared image. In this example, one of the three uncertainty ellipses intersects the area of the alarm generated by the infrared images. The probability of this MARVIN alarm is enforced by the alarm of Helivision-GRVC and its probability is increased accordingly. The data of these associated alarms are used to update the probability of being fire for each alarm and also to refine the estimation of its location. The other two alarms originated by the MARVIN fire sensor are not associated to the alarm originated by the Helivision-GRVC infrared camera, and, thus, their probabilities alarms are decreased.

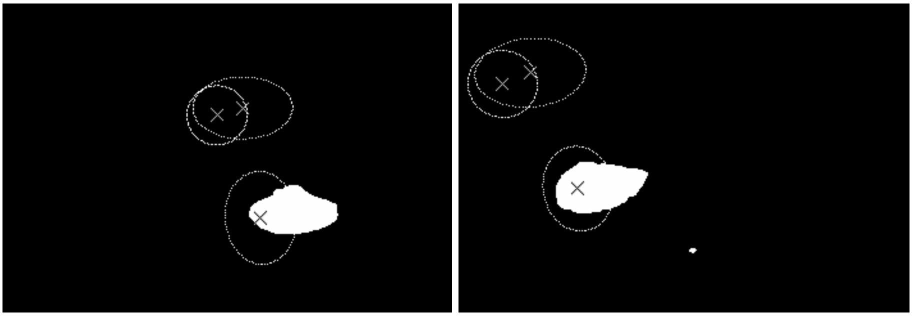

Fig. 8.16. Current alarms originated by the MARVIN fire sensor projected on the image plane of segmented Helivision-GRVC infrared images. The ellipses indicate the uncertainty on the projection.

Figure 8.17 shows how the uncertainties in the position of the true alarm are recursively reduced, while the probabilities of the false alarms drop to values close to 0, when the alarm information obtained from the fire sensor of MARVIN is combined with the data from the infrared camera of Helivision-GRVC. Table 8.2 presents the position of the fire alarm (mean and standard deviation) estimated with the fire sensor and the infrared camera. The actual location of the controlled fire measured using a GPS is also shown. The similarities between the actual and estimated position are evident.

Table 8.2. Estimated and true location of the fire and uncertainties

	Easting	Northing	Height
True location of the fire	564627	4443961	200
Final estimated location (fusion)	564628.9	4443961.4	200.04
Estimated standard deviation	1.5	2	0.28

When the alarm is confirmed as actual fire or discarded as a false alarm, the *alarm confirmation* stage finishes and the *fire observation* stage starts.

8.6 Fire Observation and Monitoring Using an UAV

Fire monitoring, in the field of forest fire fighting, could be defined as the computation in real-time of the dynamic evolution of forest fire parameters, such as the shape and location of the fire front, the maximum height of the flames and others [14]. This has been done traditionally by visual inspection carried out by experts. Also, photogrametric techniques have been applied for analysis after a fire has taken place.

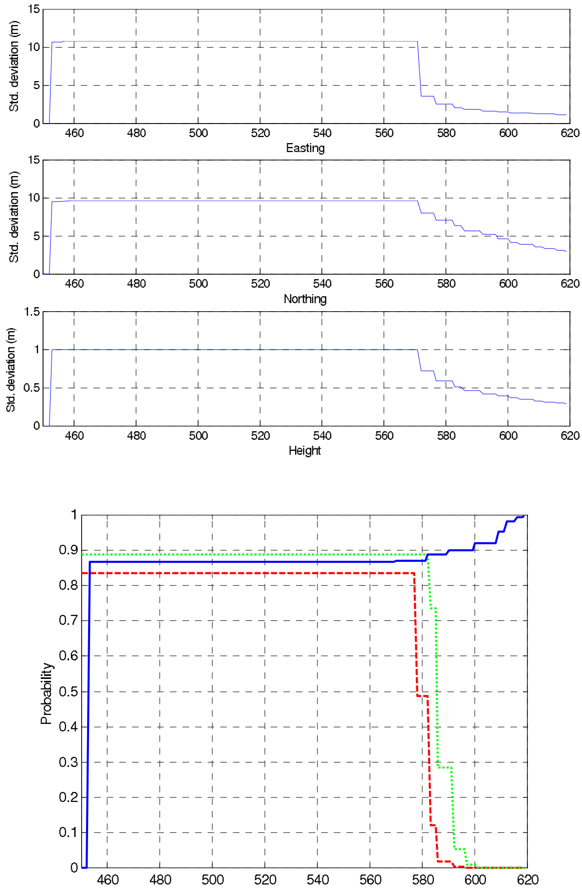

Fig. 8.17. Evolution in the localization of the alarm. Top: The graphic shows the estimated standard deviation for the location of the alarm (Easting, Northing and Height). The alarm is obtained from the fire sensor data at time 450. The initial errors are high. Around time 570, images from Helivision-GRVC are used to confirm the alarm and to refine the position. Bottom: evolution of the probabilities of the three alarms.

The development of an automatic system based on vision for online fire monitoring would be very helpful. However, monitoring real fires poses some strong problems, such as the possibility of placing sensors in the correct locations for fire observation. Usually, conventional piloted helicopters are used to approach the fire in fire fighting activities. However, these operations involve high risks. One solution would be to use cameras on board high-manoeuvrability UAVs.

In this section, a procedure for the estimation of the fire front evolution from images gathered by one UAV is briefly presented.

The fire segmentation algorithms presented in Sect. 8.2.3 are used to separate the fire from the background. The contours of the segmented regions contain the information on the fire front shape and location as well as on the height of the flames. Figure 8.18 shows the application of fire segmentation algorithms and contour computation to one visual and one infrared image gathered by an UAV in fire field experiments.

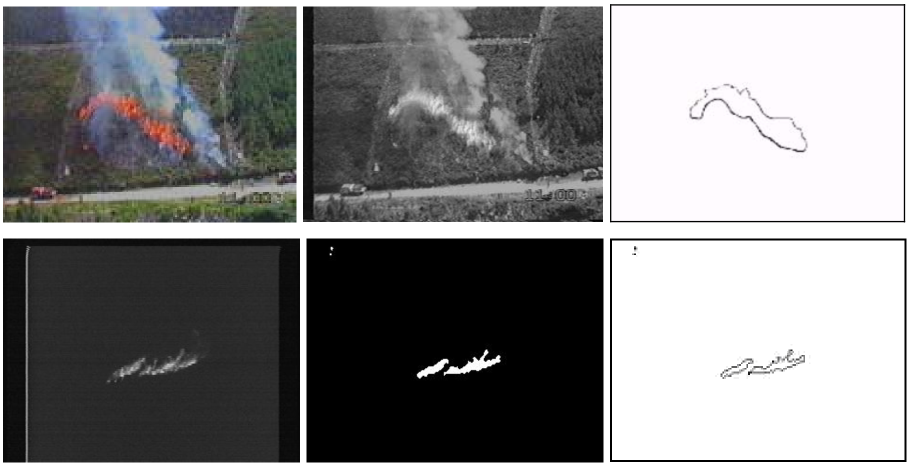

Fig. 8.18. Segmentation and contours of a visual image (Top) and an infrared image (Bottom)

In order to compute the fire front position, it is needed to distinguish, among the pixels of these contours, the subset of pixels corresponding to the fire base contour and the corresponding pixels of the top of the flames.

The dynamic characteristics of the fire are used to characterize the fire contours. In general, the pixels corresponding to the top of the flames flicker, while the pixels corresponding to the fire base move slowly. Thus, in order to determine which pixels correspond to the fire base contour and which to the flames contour, a temporal low pass filter is applied over the fire contour images.

In order to analyze these dynamic characteristics, we need to remove previously the background motion. This is accomplished by using the image stabilization procedure presented on Chap. 4. Figure 8.19 shows three images at different time instants of a forest fire experiment from a helicopter. The images have been stabilized, and the fire contour is overlaid, distinguishing between the fire front and the pixels of the top of the flames.

The computation of the fire front position is done obtaining the 3D position of the pixels belonging to the fire fronts. The geolocation procedure of Chap. 4 is used for this purpose. Figure 8.20 shows the estimated fire front position every 10 seconds for the images of the sequence of Figure 8.19. The gaps observed are due to smoke occlusions.

Fig. 8.19. Three images from a helicopter of a forest fire experiment

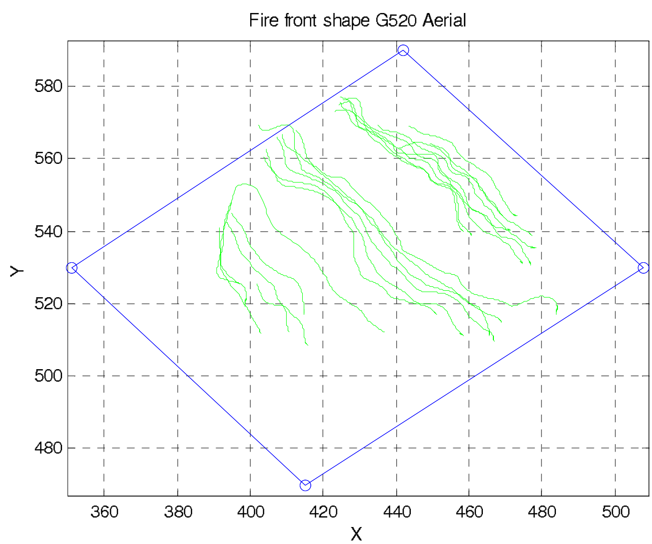

Fig. 8.20. Fire front location for the fire experiment of the images shown in Fig. 8.19. The location of the fire front is estimated every 30 seconds.

8.7 Cooperative Fire Monitoring

In this stage MARVIN and Helivision-GRVC keep on hovering on to the fire (approximately forming 120° with the fire) and sending stabilized sequences of images of the event (an operator could then observe the dynamic evolution of the fire). Figure 8.21 shows two visual images taken by Helivision-GRVC and MARVIN obtained in the *fire observation* stage.

Fig. 8.21. During the *fire observation* stage, sequences of stabilized images from different points of view are obtained by using the MARVIN and Helivision-GRVC cameras

Fig. 8.22. Fire observation by using the MARVIN and Helivision-GRVC visual cameras. The fire front shape is marked on the images.

The architecture described in Chap. 2 allows to synchronize the vehicles to send images close in time. The images are previously stabilized in real-time, using the procedures described in Chap. 4. With these stabilized images, and using the fire segmentation algorithms, it is possible to determine parameters of the fire evolution. Figure 8.22 shows images from MARVIN and Helivision-GRVC of the same fire, with the fire front marked.

8.8 Conclusions

Relevance to applications is a main issue in multi-robot systems and particularly in multi-UAV systems. This Chapter has presented the application of the COMETS multi-UAV system in a practical application with significant interest: forest fires. As far as we know this is the first experimental demonstration of the interest of a multi-UAV system in a mission consisting in fire detection, confirmation, localization and monitoring.

These experiments and demonstrations have been carried out in central Portugal, near the city of Coimbra in May 2003, 2004 and 2005. They involved the MARVIN autonomous helicopter (Chap. 5), the Karma airship (Chap. 7), and the Helivision-GRVC teleoperated helicopter (Chap. 6). The decisional architecture presented in Chap. 2, the communication system from Chap. 3 and the perception techniques described in Chap. 4 have been also applied.

The obtained results confirm the interest of the UAV technology and presented methods. It also points to the application of some of the technologies and methods presented in this book in operational forest fire conditions. These operational conditions require the use of different operational UAV platforms, including the integration in the multi-UAV system of fixed wing aircrafts and, in general, the use of UAVs platforms having more flight range, endurance and adaptation to typical forest fire scenarios with important wind velocity.

References

1. V.G. Ambrosia. Remotely piloted vehicles as fire imaging platforms: The future is here! *Wildfire Magazine*, May–June 2002.
2. B.C. Arrue, A. Ollero, and J.R. Martinez de Dios. An intelligent system for false alarm reduction in infrared forest-fire detection. *IEEE Intelligent Systems*, 15(3):64–73, 2000.
3. J.R. Martinez de Dios and A. Ollero. A multiresolution threshold selection method based on training. volume 3211 of *Lecture Notes in Computer Science*, pages 90–97. Springer, 2004.
4. D. Dierre, H. Hoff, and M. Bouchet. RAPSODI, rapid smoke detec-tion and forest fire control. In *Proceedings of the Research Special Session of the Euromediterranean Wildfire Meeting*, pages 89–96, Hyères, France, October 2000.
5. E. Hygounenc, Il-Kyun Jung, P. Souères, and S. Lacroix. The Autonomous Blimp Project of LAAS-CNRS: Achievements in Flight Control and Terrain Mapping. *The International Journal of Robotics Research*, 23(4–5):473–511, 2004.

6. Jyh-Sing Roger Jang. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23:665–684, 1993.
7. R. Kjedlsen and J. Kender. Finding skin in colour images. In *Proceedings of the International Workshop on Face and Gesture Recognition*, pages 144–150, 1996.
8. I. Maza and A. Ollero. Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms. In *Proceedings of the 7th International Symposium on Distributed Autonomous Robotic Systems (DARS)*, pages 211–220, Toulouse, France, June 2004.
9. A. Ollero, J. Alcázar, F. Cuesta, F. López-Pichaco, and C. Nogales. Helicopter teleoperation for aerial monitoring in the COMETS multi-UAV system. In *Proceedings of the 3rd IARP Workshop on Service, Assistive and Personal Robots (IARP)*, pages 137–142, Madrid, Spain, October 2003.
10. Y. Rauste. Forest fire detection with satellites for forest fire control. In *Proceedings of the XVIII Congress of the International Society for Photogrammetry and Remote Sensing*, volume XXXI, pages 584–588, Vienna, Austria, July 1996.
11. V. Remuß, M. Musial, and G. Hommel. MARVIN – an autonomous flying robot-based on mass market components. In *Proceedings of the Aerial Robotics Workshop of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 23–28, Lausanne, Switzerland, September–October 2002.
12. I.F. Tourné, J. Gonzalo, and P. Yagüe. The fuego system. In *Proceedings of the Research Special Session of the Euromediterranean Wildfire Meeting*, pages 118–122, Hyères, France, October 2000.
13. A.B. Utkin, A. Fernandes, F. Simoes, R. Vilar, and A. Lavrov. Forest fire detection by means of lidar. In *Proceedings of IV International Conference on Forest Fire Research / 2002 Wildland Fire Safety Summit*, pages 18–23, Coimbra, Portugal, November 2002.
14. D.X. Viegas. Innovations and solutions in fire behavior prediction issues. forest fires: needs and innovations. In *Proceedings of the Delfi International Symposium*, pages 164–173, Athens, Greece, 1999.
15. III Walter Phillips, Mubarak Shah, and Niels da Vitoria Lobo. Flame recognition in video. *Pattern Recogn. Lett.*, 23(1–3):319–327, 2002.