FIRE DETECTION USING AUTONOMOUS AERIAL VEHICLES WITH INFRARED AND VISUAL CAMERAS.

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Abstract: The paper presents a system for automatic fire detection based on the use of autonomous aerial vehicles. Particularly, the application of a helicopter with infrared and visual cameras is described. The paper presents the techniques used for fire segmentation in visual and infrared cameras, and the procedures to fuse the data obtained from both of them. Furthermore the paper presents the techniques for automatic geolocation of the detected fire alarms. Experimental results are shown.

Keywords: data fusion, infrared detectors, autonomous vehicles, helicopters.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have been proposed for surveillance and monitoring applications in different scenarios. These applications require the development of perception systems to perform autonomously detection and tracking functions. Fire detection is a significant function in many scenarios in which UAVs could play an important role.

Particularly, forest fires represent one of the most relevant environmental disasters in many countries involving high economical and ecological damages as well as hazard to people. Several fire detection systems have been developed based on various platforms such as satellite systems (Gonzalo, 1998), and ground stations (Gandia *et al.*, 1994; Den Breejen *et al.*, 1998). Ground-based detection systems using infrared and visual cameras with high resolution have demonstrated good performance for early detection (Arrue *et al.*, 2000). However, the main disadvantage of these systems is the limitation in having direct vision of the fire due to the terrain or vegetation. The use of UAVs could overcome this drawback.

Another limitation of automatic fire detection systems is the considerable rate of false alarms. Arrue *et al.* (2000) also showed that the combination of infrared and visual images is very useful to provide robust fire detection with high detection probability and low false alarm rate. This paper deals with the application of UAVs equipped with infrared and visual cameras to the automatic detection of fires. Particularly, the application of a helicopter with infrared and visual camera is presented.

The objective is to obtain robust fire detection by combining the results obtained from the analysis of different information and sensor data. Fire detection estimations are obtained from the processing of both infrared and visual images. Also, using the navigation sensors onboard the UAV, the position of the alarm is computed.

The work presented in this paper has been carried out in the framework of the project COMETS (IST-2001-34304). This project, funded by the IST Programme of the European Commission, aims to design and implement a distributed control system for cooperative detection and monitoring using heterogeneous UAVs. The COMETS project is being demonstrated in forest fire detection and monitoring among other applications, such as terrain mapping.

For a fire detection mission, the UAV fleet is endowed with a tasks consisting of patrolling an area. The task planner takes into account the characteristics of the UAV (payload and time of flight) and the on-board sensors (field of view) to compute the paths to be assigned to each one. Then, the autonomous detection relies on the ability of the system to detect the fire in the images provided by the UAVs and to localise the alarm. These functionalities are the main subject of this paper.

The paper is organized as follows: section 2 presents a brief description of the hardware and software components of the system considered. Then, sections 3 and 4 deal with the processing of infrared and visual images provided by the cameras for fire detection. Section 5 describes the data fusion techniques employed, and deals with geolocation. Section 6 describes some experimental results carried out with small fires. The last section is devoted to the conclusions.

2. GENERAL DESCRIPTION OF THE SYSTEM

The COMETS system includes heterogeneous UAVs (see Figure 1 left). Currently two helicopters and one airship have been integrated. Fixed wing aircrafts could be also integrated in the future. COMETS can integrate both fully autonomous UAVs and teleoperated UAVs. The results presented in this paper have been obtained by using a teleoperated helicopter. However, the same techniques can be applied in a fully autonomous system such as the MARVIN helicopter, also integrated in COMETS, or the autonomous helicopter developed at the University of Seville.

Figure 1 right shows the hardware components of the system considered in the paper. The helicopter-type UAV is equipped with a compass, a Lassen SKII GPS, an IMU (Microstrain 3DM-G with a piezoelectric gyroscope for each of the 3 axes), an electronic box with a Rabbit BL2000 microcontroller, one teleoperation camera, one visual camera and one miniaturized infrared camera. The infrared camera is a Raytheon 2000AS. It uses a FPA with 160x120 infrared detectors in the bandwidth range of 7-14 μm. The visual camera is a Camtronics PC-420DPB with 752x582 sensors and lens of 6 mm. focal distance.

The images from all the three cameras are digitized on board with an AXIS 2400 video server and sent to the ground station by wireless Ethernet 802.11 protocol. The microcontroller reads the data from all the sensors and sends them by using also the wireless data link. In the current implementation, the images and data are processed in a laptop place on ground.

Fig. 1. Left, two UAVs of the COMETS fleet. Right: Electronic box and pan and tilt with the infrared and visual camera.

One of the objectives of the system is to be able to detect fire alarms and to obtain its position in geographical coordinates by using the data gathered by the different sensors.

Fire detection algorithms are individually applied to infrared and visual images in order to obtain independent fire detection estimations. These estimations are fused to increase the performance and robustness of the system (i.e. increase the detection probability and reduce the false alarm ratio). As a result, a set of fire alarms will be generated by the image processing modules.

The GPS, IMU and pan and tilt encoders of the camera positioning system (see Figure 1 right) allow obtaining the camera position and heading. Then, if the cameras are calibrated, it is possible to geolocate the fire alarms detected by means of projecting them over a known elevation map.

3. PROCESSING OF INFRARED IMAGES

As it has been mentioned, the system considers non commensurate data (infrared and visual images). Before data fusion can be applied, common features should be extracted from both images. These features will be binary images with potential fire alarms. This section presents the algorithms used for infrared images.

The aim of the processing of infrared images is to produce binary images containing fire alarms while discarding false alarms. The processing of infrared images consist in computing a threshold value since fires appear in infrared images as high intensity regions, and applying some heuristic rules to discriminate false alarms.

The threshold selection method should take into account the particular conditions of the application to discard false alarms. Although the temperature of fire (often over 900ºC) is much higher than the temperature of the image background, temperature-based criteria can not be used for thresholding since the measures of temperature are influenced by the emmissivity indices of the materials, which are very difficult to estimate in such an unstructured environment. A problem of the processing of images from miniaturized infrared cameras is that in the current state of technology these

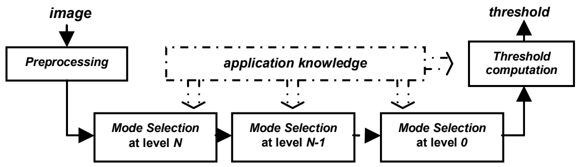


Fig. 2. Schemes of the proposed training-based threshold selection method.

cameras have low sensitivity. Thus, they require high detector exposure periods to generate the images and the high frequency vibrations of the UAVs often originate blurs in the images. These particularities should be considered in the thresholding method used.

The system uses a training-based threshold selection method described by Martinez-de Dios and Ollero (2004). This method uses knowledge of the specific computer-vision problem to supervise a multiresolution analysis. The method performs a coarse-to-fine selection (see Figure 2) of the mode or modes corresponding to the object of interest. At each step it identifies the histogram modes of interest by analyzing histograms descriptions at different level of resolution (low-pass wavelet decomposition at different level of scale).

Figure 2 shows the scheme of the proposed threshold selection method. *Mode Selection* at level l decomposes the histogram description at level l in histogram modes and selects the modes that are likely to correspond to the object of interest according to the knowledge of the application. The modes selected at level l are analyzed at the immediate finer level of resolution (level l-1). This analysis is repeated until the finest level (level 0). Finally, threshold computation is carried out by taking simple considerations on the selected histogram regions at level l=0.

The introduction of the knowledge of the specific application in the algorithm is carried out by a training process. The knowledge is extracted from a set of pairs (training image, desired threshold value) computed by an operator and incorporated in a fuzzy system by applying *ANFIS* algorithm (Jang, 1993). Further information can be found in (Martinez-de Dios and Ollero, 2004).

The adaptation of the method to this application was carried out by selecting training infrared images with different illumination conditions, different image

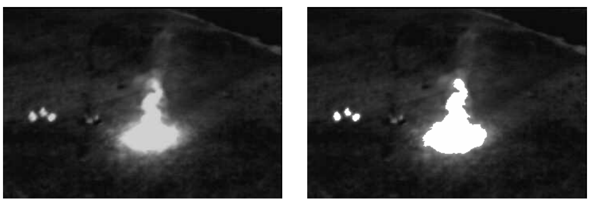
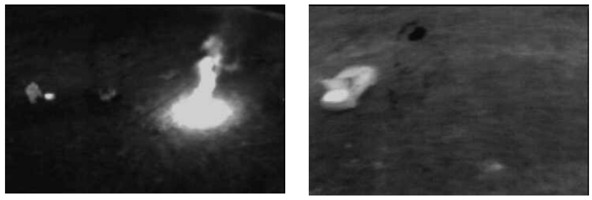


Fig. 3. Results of the infrared fire detection algorithm. Left, original image. Right, candidates of fire.



a) b)

Fig. 4. Two infrared images from a fire (a) and from a heated car engine (b).

backgrounds and different objects including fires and false alarms (i.e. heat emitting sources such as car engines).

The algorithm was trained to detect the fires and discard the false alarms. Figure 3 shows an infrared image of fire taken during field tests carried out in Seville (Spain) and the thresholded image. The image contains a fire and three small heated objects. All of them are considered fire by the thresholding method.

Some simple heuristic rules are used to discriminate false alarms. For instance, local contrast in infrared images is lower in case of false alarms originated by heated objects than in case of fire (see for instance Figure 4a of a fire and Figure 4b of a car engine). This property permits the design of rules for the discrimination of heated objects.

Consider an image with N potential alarms. The local contrast for alarm i is denoted by C_i. The fire detection estimation from local contrast ($FireEstCon_i$) is computed from C_i by the following rules:

$$IF\ \left(C_i \leq th_c\right) \text{THEN}\ FireEstCon_i = 0 \qquad (1),$$

$$IF\ \left(C_i > th_c\right) \text{ THEN }\ FireEstCon_i = 1 - Contrast_i / th_c \qquad (2)$$

where th_c behaves as a contrast value below which the region is considered as a false alarm.

4. PROCESSING OF VISUAL IMAGES

The processing of the images from the visual camera will produce binary images containing potential fire alarms.

The algorithm is based in the fact that visual colour images of fire have high absolute values in the red component of the RGB coordinates. This property permits simple threshold-based criteria on the red component of the colour images to segment fire images in natural scenarios. However, not only fire gives high values in the red component. Another characteristic of fire is the ratio between the red component and the blue and green components.

Thus, the algorithm consists of two stages. First, the pixels $\mathbf{m}=[u,v]^T$ belonging to the region of the RGB space defined by eq. 3 are selected as candidates.

$$\left.\begin{array}{l} r(u,v) - k_g \cdot g(u,v) \geq 0 \\ r(u,v) - k_b \cdot b(u,v) \geq 0 \end{array}\right\} \qquad (3)$$

Fig. 5. Colour images segmentation algorithm. Left, original image. Right, detected fire.

For the pixels selected, a method based on an analysis of the histogram of the red field is used to compute the threshold for segmenting fire. The experiments revealed that the automatic iterative thresholding algorithm described in (Ridler, 1978) applied over the red field provide good flame segmentation for most visual images. Figure 5 shows some results of the algorithm.

5. COMBINED FIRE DETECTION AND LOCALIZATION

The algorithms presented in sections 3 and 4 are used to obtain potential fire alarms on the image plane for visual and infrared images. This section presents how the potential fire alarms from both images can be fused to obtain more reliable fire detection characteristics. Also, it is presented how the geographical position of the detected alarms is computed.

5.1Registration of infrared and visual images.

Assume that both cameras of the system of figure 1 share the centre of projection. Figure 6 presents a scheme of the geometry of this configuration.

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

$$s\mathbf{m}_{IR} = \mathbf{H}_{\infty}\mathbf{m}_{VIS} \quad (4),$$

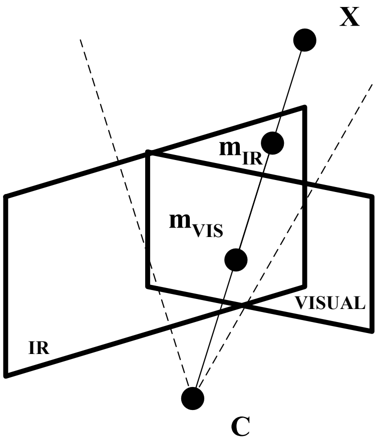


Fig. 6. Geometry of the configuration of the cameras.

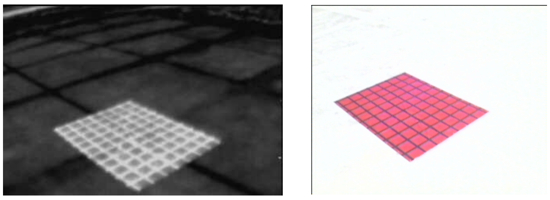


Fig. 7. Grid used for calibration of the system.

where $\mathbf{H}_{\infty}$ is a 3x3 matrix called the infinity homography and s is a scale factor. As showed in (Faugeras and Luong, 2001),

$$\mathbf{H}_{\infty} \cong \mathbf{A}_{IR}\mathbf{R}\mathbf{A}_{VIS}^{-1} \quad (5),$$

where $\mathbf{A}_{IR}$ and $\mathbf{A}_{VIS}$ are the internal calibration matrices of both cameras and $\mathbf{R}$ is the rotation matrix that relates the camera centred coordinate frames.Thus, $\mathbf{H}_{\infty}$ could be computed if the cameras are calibrated and the relative frame transformation is known. However, $\mathbf{H}_{\infty}$ can be also 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 presented in this paper, the calibration has been done using a known pattern that is visible on both types of cameras, as shown in Figure 7. It should be noticed that the relation $\mathbf{H}_{\infty}$ has to be computed only once provided that the relative orientation of the cameras and their internal calibration does not change. Caspi and Irani (2001) have presented another method that can be used to compute $\mathbf{H}_{\infty}$ from measurements on the image plane, without needed of a calibration grid.

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 shows some results of the combination of infrared and visual images.

Once $\mathbf{H}_{\infty}$ is known, both images can be registered, and thus, the detected alarms on the visual image can be transformed to the infrared image plane.

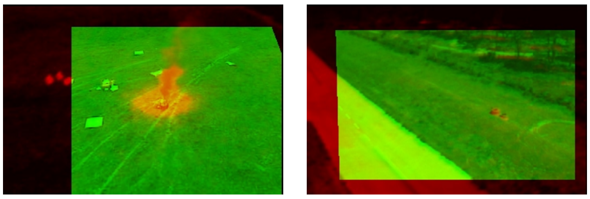


Fig. 8. Combination results. The infrared and visual images are presented together as the red and green fields of a colour image.

5.2 Data fusion

The operation of the fire detection system consists in applying the presented processing to infrared and visual images. Each processing will reach at a decision z for each pixel stating that there is fire (z=1) or not (z=0) in that position. By using $\mathbf{H}_{\infty}$, both measurements can be expressed in a common frame (see figure 9). Thus, for each pixel, there is a set of measurements $\mathbf{Z}=[z_{IR},z_{VIS}]$. The objective is to obtain a fusion rule that leads to a fused decision d for the global hypothesis T_0 (not fire) or T_1 (fire) for each pixel.

In (Gunatilaka and Baertlein, 2001) it can be seen that the likelihood ratio lr given by:

$$lr = \frac{P(\mathbf{Z}|T_1)}{P(\mathbf{Z}|T_0)} \tag{6}$$

can be used as a fusion rule that leads to the minimum Bayes risk. The objective is to find an optimum threshold th so that if $lr > th$, then d=1 (that is, hypothesis T_1, fire, is selected). Otherwise, d=0.

Each of the sensors can be characterized by their probabilities of correct detection $P_{Di}=P(z_i=1|T_1)$ and false positive $P_{Fi}=P(z_i=1|T_0)$. Assuming that the measurements z_i are conditionally independent, eq. (6) leads to:

$$lr = \sum_{i\in\{IR,VIS\}}\left[z_i \log\left(\frac{P_{Di}}{P_{Fi}}\right) + (1-z_i)\log\left(\frac{1-P_{Di}}{1-P_{Fi}}\right)\right] \tag{7}$$

Therefore, in order to fuse the data, the segmentation algorithms presented above should be characterized by their probabilities of detection and false positive.

Section 6 will presents the results of the data fusion algorithms for a set of images of controlled fires.

5.3 Geolocation of fire alarms.

Once a fire has been detected, its geographical position should be computed and transmitted

Fig. 9. Detected alarms. Dark, infrared alarms. Bright, visual camera generated alarms.

The sensors on board the different UAVs (GPS, gyros, etc) are used to compute the position and orientation of the cameras $[\mathbf{x}_c, \alpha_c, \beta_c, \varphi_c]$ in a global and common coordinate frame. Thus, all the images gathered are labeled with these data.

If the cameras are calibrated, knowing a digital elevation map M it is possible to obtain the position of the alarm $\mathbf{x}_a$, knowing its position on the image plane $\mathbf{m}_a$. The position $\mathbf{x}_a$ is a function of the position and orientation of the camera and also depends on the map.

$$\mathbf{x}_a = \mathbf{f}(\mathbf{m}_a, \mathbf{x}_c, \alpha_c, \beta_c, \varphi_c, M) \tag{8}$$

The function $\mathbf{f}$ encompasses the pin-hole model of the camera. Clearly, the function $\mathbf{f}$ is non-linear, and in the general case the dependence on the map M cannot be expressed explicitly.

Notice that, in the COMETS multi-UAV fleet, the map M can be previously computed by one of the UAVs in the fleet.

Once a fire alarm has been geo-localized, other terrain information could be used for increasing the robustness of fire detection, particularly, the combustibility of the terrain zone of the alarm.

6. RESULTS

One of the key issues of the COMETS project is the demonstration. The project is being demonstrated in fire detection and monitoring activities, and also for terrain mapping missions.

Several experiments with controlled small fires have been carried out at Lousa, Portugal during the years 2003 and 2004. The controlled fires used in the fire detection tests are originated by the burning of small shrubs.

A set of sequences of images containing fire alarms and potential false alarms (heated objects, etc) were recorded. The individual fire segmentation algorithms for infrared and visual cameras, and the data fusion techniques were applied over the images. For each case, the probabilities of detection P_D and false positive P_F were computed as:

- P_D as the average of the ratio between pixels detected correctly and the complete set of pixels corresponding to fire.
- P_F as the average of the ratio of detected pixels not being fire and the total number of pixels of one image.

Manually segmented images has been used as ground truth to compute these quantities. Table 1 shows the results of the fusion algorithms.

Also, the detection procedure has been applied on actual flights. Figure 9 shows a flight carried out by

Table 1 Results of the data fusion algorithms.

Algorithm	P_D	P_F
IR	0.962	0.045
Visual	0.819	0.023
Combined	0.981	0.003

the Helivision helicopter, and marked as 1 the estimated position of the alarm. With the current sensors, the estimated position is within 5 meters of the actual position (recorded by using a GPS).

7. CONCLUSIONS

This paper describes a step in the application of UAVs for forest fire detection. The paper has presented the hardware components of the helicopter-type UAV considered in the paper. The UAV is equipped with an infrared and a visual camera used for detection purposes. The infrared and visual images are processed individually in order to obtain independent fire estimations. These fire estimations are combined in order to obtain robust fire detection in terms of high detection probability and low rate of false alarm.

The algorithms to extract fire detection estimations from infrared and visual images have been described. Data fusion techniques are employed to obtain unique fire estimations. The potential alarms are geolocated in order to associate images and terrain information. The fire detection estimations obtained from image processing can be combined with terrain data and meteorological information to increase the performance and robustness of the detection. Training for fire detection at the level of fused data will be researched in the future.

The paper includes some experimental results of actual flights with small controlled fires.

In the framework of the COMETS project, fire detection can be achieved by the cooperative collaboration of a fleet of UAVs. The use of multiple UAVs for fire detection can benefit from the heterogeneous capabilities of the UAVs used (helicopter-type and blimp-type). Besides, more fire estimations can be obtained, which can reduce the uncertainties and increase the performance of the system. Collaborative activities can include strategies in which every UAV surveys different areas and, when an alarm is detected, all the UAVs are used to confirm the alarm and obtain fire detection estimations. The cooperative forest fire detection is object of current research.

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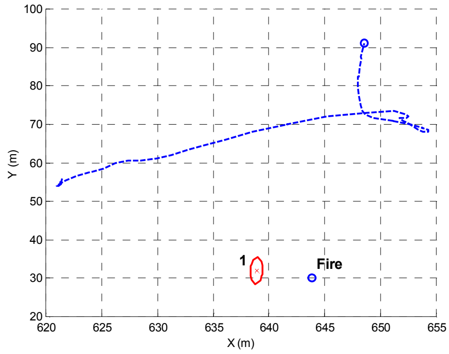

Fig. 9. Actual flight during Lousa experiments. Dashed, trajectory of the helicopter. Labelled as 1, the estimated position of the alarm. The actual position is also presented (axis in meters).

REFERENCES

Arrue, B.C., Ollero, A and Martinez de Dios, J.R., (2000). An Intelligent System for False Alarm Reduction in Infrared Forest-Fire Detection, *IEEE Intelligent Systems*, **vol. 15**, no. 3, pp-64-73.

Caspi, Y. and Irani, M. (2001). Alignment of non-overlapping sequences. *Proc. Int'l Conf. Computer Vision*, **vol. II.**, pp. 76-83, 2001.

Den Breejen E., M. Breuers, F. Cremer, R. Kemp, M. Roos, K. Schutte and De Vries, J.S. (1998). Autonomous Forest Fire Detection. In: *Proc. 3rd Int'l. Conf. on Forest Fire Research*. Luso, Portugal. November 1998. pp. 2003-2012.

Faugeras, O and Luong, Q.T. (2001). *The Geometry of Multiple Images*. The MIT Press, London, England.

Gandia A., Criado A. and Rallo M., (1994). El Sistema Bosque, Alta Tecnología en Defensa del Medio Ambiente, DYNA pp. 34-38, **n. 6**

Gonzalo J. (1998) FUEGO: A low cost service for fire detection. In: *Proc. 3rd Int'l. Conf. on Forest Fire Research*. Luso, Portugal. November 1998. pp. 2029.

Gunatilaka, A.H. and Baertlein, B.A (2001). Feature-level and decision-level fusion of noncoincidently sampled sensors for land mine detection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, **Vol. 23**, No. 6, June 2001.

J. S. R. Jang, (1993) ANFIS: Adaptive-Network-based Fuzzy Inference Systems, *IEEE Trans. Systems, Man and Cybernetics*, **Vol. 23**, no. 3, pp. 665-685, May 1993

Martinez-de Dios, J.R. and Ollero, A. (2004). A new training-based approach for robust thresholding. In: *Proc. of the World Automation Congress* WAC'2004, 28 June - 1 July, 2004, Seville, Spain.

T. W. Ridler and S. Calvard, (1978). Picture thresholding using an iterative selection method. *IEEE Trans. Systems, Man and Cybernetics*, **Vol. 8**, pp. 630-632, 1978