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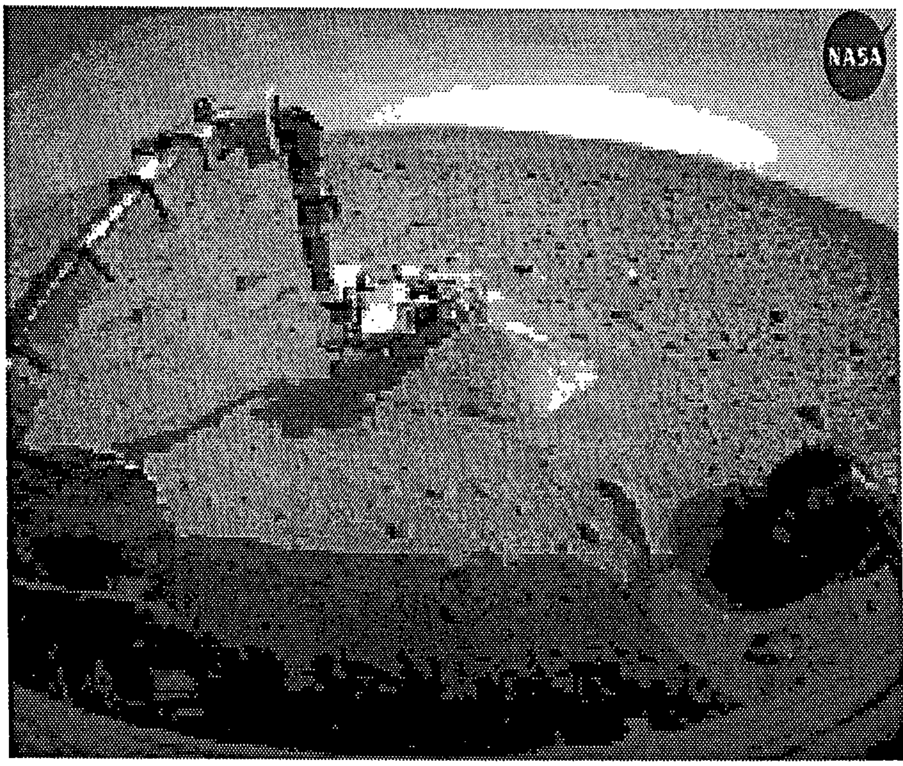

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EDITORS

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June 28 - July 1, 2004
Seville, Spain

ABOUT THE WAC 2004 CD

WAC 2004 is dedicated to Professor **Javier Aracil** of the Universidad De Sevilla, Spain and Professor **Pedro Albertos** of Universidad Politecnica De Valencia, Spain for their immense contributions to automatic control systems, to national and international leaderships and dissemination of the fields of automation and control.

At this beginning of the 21st Century information technology continues to be a benefactor of intelligent paradigms with lasting impacts on the lives of all mankind. Machine intelligence through applications of AI and soft computing continue to re-define the design problem in robotics, autonomous navigation, robotic geology, Nano-technology, MEMS, manufacturing, financial engineering and automation. This volume of TSI Press Series on Intelligent Automation and Soft Computing on CD ROM constitutes a report on the research papers presented for the Fifth Biannual World Automation Congress (WAC 2004) in Seville, Spain from June 28-July 1, 2004.

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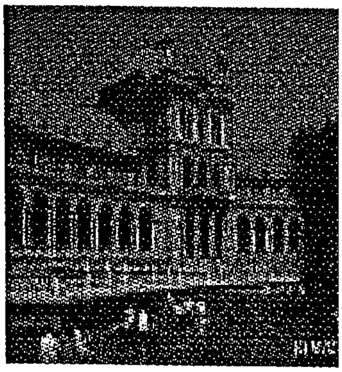

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Cooperative Perception For Fire Monitoring

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COOPERATIVE PERCEPTION FOR FIRE MONITORING

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ABSTRACT

This paper presents techniques for cooperative fire perception using vision. Algorithms for fire characteristics extraction using a single camera (infrared or visual) are summarized, including techniques for fire segmentation, characterization and measurement. Then, techniques for data association and fusion when several cameras of different modalities are observing the scene are presented. Finally, some strategies for cooperative perception when using autonomous vehicles with perception capabilities are presented.

KEYWORDS: Fire monitoring, cooperative perception, data fusion, data association.

1. INTRODUCTION

Fire monitoring, in the field of fire fighting, could be defined as the computation in real-time of the dynamic evolution of several important parameters related to the fire, such as the shape of the fire front, the maximum height of the flames and others [13]. This has been done traditionally by experts seeing the fire. Also, photogrametric techniques has been applied to images taken of a fire for analysis afterwards.

The development of an automatic system based on vision for fire monitoring would be very helpful, and there have been some approaches using cameras placed on ground [10]. However, monitoring real fires poses some strong problems, such as the possibility of place sensors in the correct location. Usually, helicopters are used to approach the fire in fire fighting activities. However, they are expensive, and there is a high risk for humans involved in the operation. One solution would be the deploying of cameras on board of autonomous vehicles, such as Unmanned Aerial Vehicles (UAVs). UAVs can avoid accessibility problems. This situation is a key issue in the COMETS multi-UAV project [9]. This paper presents techniques for cooperative fire monitoring that are being used in the framework of the COMETS and SPREAD projects funded by the European Commission.

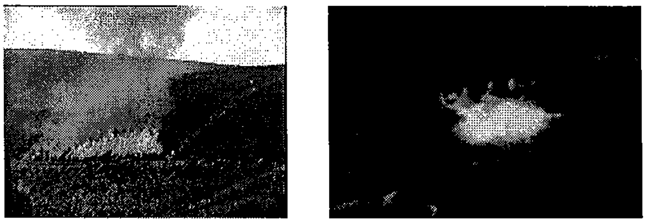

Figure 1. Two images of a fire. Left: visual. Rigth: infrared.

The paper is organized as follows: section 2 summarizes the parameters to be computed and presents techniques for fire segmentation and characterization for single cameras (infrared and

visual). Then, section 3 presents geolocation techniques for measurement. Section 4 shows how data association and fusion can be carried out when several cameras are presented. Finally, some cooperative strategies are presented.
Related to this work, artificial vision and image processing techniques have been developed mainly for forest fire detection (see for example [1], [3]). Furthermore, satellite-based systems have been proposed for forest fire monitoring [11]. In [10] techniques developed by the authors for fire monitoring using cameras fixed in the ground are presented. Also, the application of robots for fire fighting has been proposed (see for example [2]). A very interesting work on cooperative perception for robots using vision can be seen in [12].

2. FIRE SEGMENTATION AND CHARACTERIZATION

We have to deal with non-commensurate data, such as infrared and visual images. Thus, for each view a set of common features related to the fire are extracted and the fusion procedure is applied over these features. This section presents the algorithmic procedures to obtain these fire features in infrared and visual images.

2.1 Fire model

The objective of the image processing is to build a 3D model of the fire. The fire is a 3D object delimited by the fire base (with a certain width) and the top of the flames. The model considered consists of a set of triads of points: the points corresponding to the backward and forward fire front and the point on the top of the flame. Once this model has been computed, several parameters can be obtained, such as the fire front shape, the evolution of the maximum distance to a given point or line, the height of the flames and others. A scheme of the model considered can be seen in Figure 2.

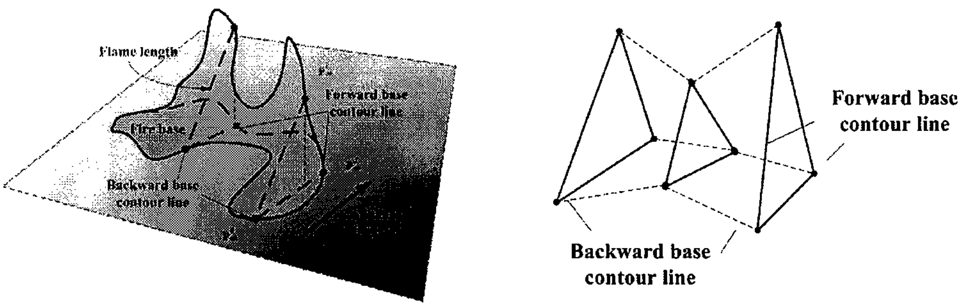

Figure 2. Left: Scheme of the 3D fire model. Right: the model is stored as a list of triads of points.

2.2 Fire segmentation

The first stage consists of segmenting the fire from the background in the images taken from the scene. In fire applications, infrared and visual cameras are usually considered.
Infrared cameras generate black and white images that provide estimations of the radiation intensity of the scene. For fire images in natural environments, fire is the source that originates the highest radiation intensity. Thus, it is reasonable to consider a threshold-based criteria for its segmentation from the background. Also, the radiation intensity of the fire base is higher than of the flames. Thus, the intensity values in infrared images of the pixels corresponding to the flames are lower than the intensity values of the pixels corresponding to the fire base, and then a threshold value could be determined to differentiate flames and fire base. The infrared threshold value is computed by using a fuzzy multi-resolution algorithm [7].
For visual images, the segmentation algorithm is based on the fact that visual colour images of fire have high magnitude components in the red component of the RGB coordinates. More details on the algorithm can be seen in [10]. Figure 3 shows some results on colour and infrared images.

Figure 3. Segmentation results for visual and infrared images..

2.3 Fire characterization

The results from the previous techniques are binary images that show the segmented fire on the image plane. The contours of these regions contain the information on the fire front shape and the height of the flames. However, in order to compute the 3D fire model of section 2.1 (see Figure 2), it is needed to distinguish, among the pixels of these contours: the subset of pixels corresponding to the backward fire base contour, the related points of the forward 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 objects. 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 the pixels corresponding to the fire base contour, a temporal low pass filter is applied over the binary images.

A further characterization is needed to compute the fire base width, identifying the pixels of the fire base corresponding to the forward and backward base contour. Analyzing also the velocity $\overline{\mathbf{v}}_b$ of the centroid of the fire base contour (see Figure 4-d) it is possible to estimate the direction of advance of the fire base on the image plane (for example, by simple difference between consecutive frames). Using the direction, it is possible to assign pixels of the backward base contour line and the forward base contour line, and thus to compute the width in pixels of the fire base. Averages along several frames are computed to obtain a robust estimation of the temporal evolution of the centroid.

a) b) c) d)

Figure 4. a) visual image of a fire. b) segmented fire. c) pixels belonging to the fire base. d)scheme of the final characterization: blue, pixels of the backward fire front, green, pixels of the forward fire front, red, pixels of the top of the flame.

Also, the estimation of the flame inclination angle on the image plane is needed to assign the pixels of the fire base contour to their corresponding pixels of the top of the flames. A rough estimation is given by the vector $\overline{\mathbf{v}}_f$, that joins the centroid of the fire base and the centroid of the set of pixels corresponding to the top of the flames. In fact, the inclination angle is not really uniform along the whole fire front, but this approximation is valid for most of experiments.

3. GEOLOCATION

The computation of the 3D fire model is done obtaining the 3D position of the pixels belonging to the forward and backward fire fronts. This geolocation procedure is implemented by means of projection of the pixels over the terrain. The relation, in homogeneous coordinates, between points in the terrain (X,Y,Z) and their corresponding pixel coordinates (u,v) in the image [1], is given by

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \mathbf{A}[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{r}_3 \quad \mathbf{t}]\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \mathbf{P}\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{1}$$

where $[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{r}_3]$ is the rotation matrix that relates a camera centered coordinate frame and the world coordinate frame, $\mathbf{t}$ is the position of the camera and $\mathbf{A}$ is the internal calibration matrix. The cameras are assumed to be calibrated (the matrix $\mathbf{A}$ is known). Thus, knowing the camera position and orientation (measured by the sensors inside the UAV) and a digital terrain map it is possible to obtain the position corresponding to one pixel on the image plane, projecting it over the terrain.

It is also important to obtain a measure of the uncertainty in the positions of the points. There are errors associated to the fire segmentation procedure. Also, the measures of the sensors are affected by errors. The relation given by Eq. (1), although linear in homogeneous coordinates, is however non-linear when computing the actual position. Thus, to propagate the uncertainties (modeled as covariance matrixes) in the camera position and orientation and in the position in pixels of the objects, the Unscented Transform [6] can be used. This approach allows us avoiding the computation of the Jacobian of the transformation. Thus, the final result a 3D fire model of all the fire objects, with the uncertainties associated to all the points of the fire contour.

4. DATA ASSOCIATION AND FUSION

4.1 Data association

Having different sources, we should perform data association before fusion. Each view provides an estimation of the shape of the fire front in 3D coordinates. First, the different fire objects are associated using a nearest neighbor strategy. The objects are associated if the distances between their centroids is lower than a threshold value.

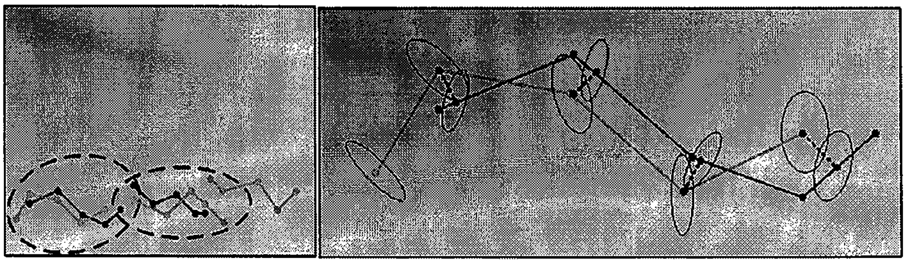

Figure 5. Data association. Left: fire fronts estimated by different cameras. The marked fronts will be associated. Right: associated points with their uncertainties represented as ellipses.

For each associated object, the points of their fire front shape should be also associated. One of the fire fronts is chosen as reference. Then, for each point of this front, the nearest neighbors in the others are obtained. If the distance is over a certain threshold, the association is discarded. This is done for all the points. The fire fronts will not match perfectly. Thus, this initial association could be used to correct the relative position between fire fronts, refining the associated points.

4.2 Data fusion

For the set points that have been associated, the different measures (the positions $\{\mathbf{x}_1, \cdots, \mathbf{x}_N\}$, being N the number of views) are fused to compute the final by means of:

$$\hat{\mathbf{x}} = (\Sigma_1^{-1} + \cdots + \Sigma_N^{-1})^{-1}(\Sigma_1^{-1}\mathbf{x}_1 + \cdots + \Sigma_N^{-1}\mathbf{x}_N) \qquad (2)$$

$$\hat{\Sigma} = (\Sigma_1^{-1} + \cdots + \Sigma_N^{-1})^{-1} \qquad (3)$$

Then, the final position is computed as a weighted averaging of all the measurements, where the weights are given by the covariance matrixes associated to each measure $\{\Sigma_1, \cdots, \Sigma_N\}$. The covariance matrix of the resultant point is given by Eq. (3). These expressions are obtained assuming that the errors in the measurements follow a Gaussian distribution, and applying the maximum likelihood criteria [8].

The above procedure is applied for the points of the fire front (forward and backward). Also, for the associated points, the heights of the flames are known in pixel coordinates. To obtain the height of the flames a triangulation procedure is used (see [2] for a review in possible triangulation methods). Figure 6 shows some results obtained by monitoring the fire of Figure 4.

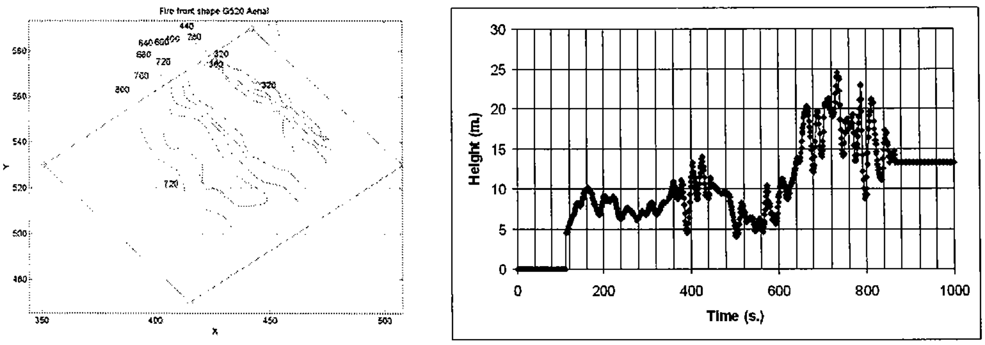

Figure 6. Results obtained monitoring the fire of Figure 4 . Left: fire front shape evolution. Right: maximum height of the flames evolution.

5. COOPERATIVE PERCEPTION

The COMETS project pursues to demonstrate cooperative perception capabilities of a fleet of heterogeneous UAVs in fire monitoring activities as illustrated in Figure 7.

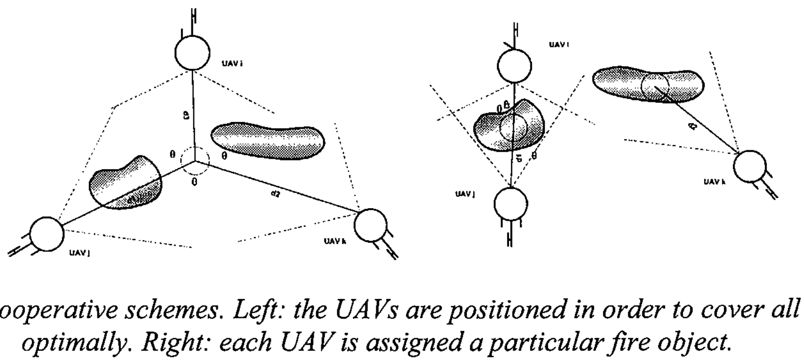

Figure 7. Cooperative schemes. Left: the UAVs are positioned in order to cover all the fire optimally. Right: each UAV is assigned a particular fire object.

Several strategies can be devised for cooperation of autonomous systems with perception capabilities for fire monitoring. In order to obtain the 3D model the best option is to deploy the cameras surrounding the fire. If there is an estimation of the centroid of the fire and of its spread, the UAVs would be distributed uniformly around it. The distance would depend on the field of view of each camera, trying to cover the whole fire (see Figure 7). Also, if the fire is large, each

UAV could be assigned to a particular fire object. An active approach will be researched in the future. Thus, a strategy based on the techniques proposed in [14] could be applied, moving the UAVs in order to reduce the uncertainty in the model that it is being obtained.

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