Object Discrimination by Infrared Image Processing*

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Abstract. Signal processing applied to pixel by pixel infrared image processing has been frequently used as a tool for fire detection in different scenarios. However, when processing the images pixel by pixel, the geometrical or spatial characteristics of the objects under test are not considered, thus increasing the probability of false alarms. In this paper we use classical techniques of image processing in the characterization of objects in infrared images. While applying image processing to thermal images it is possible to detect groups of hotspots representing possible objects of interest and extract the most suitable features to distinguish between them. Several parameters to characterize objects geometrically, such as fires, cars or people, have been considered and it has been shown their utility to reduce the probability of false alarms of the pixel by pixel signal processing techniques.

1 Introduction

Infrared images are often used in different studies, representing a tool of special relevance. We can mention applications like non-destructive testing [1], face recognition [2], medical characterization of blood vessels [3], medical breast cancer detection [4], land mine detection [5], etc.

Forest fire surveillance and preservation of natural heritage have a great impact on environment. For this reason, in recent years, several of our works have been focused on applying signal processing techniques to thermal images in order to detect early forest fires. In these works, the proposed algorithms are based on a pixel by pixel processing [6], [7], [8]. Besides the good results obtained, there could be a number of false alarms detected because of the existence of a number of factors in the scene that can affect temperature and hence thermal contrast, such as cloud cover, wind and precipitation. These effects alter the signal, making it more difficult to interpret and causing false detections. Moreover, the presence of other kind of high temperature objects can also complicate the identification of fires.

* This work was supported by the national R+D program under grant TEC2008-02975 (Spain) and FEDER programme.

J. Mira et al. (Eds.): IWINAC 2009, Part II, LNCS 5602, pp. 30–40, 2009.

In this work we will analyze the possibility of using image processing to complement the detection systems, working with objects and not only with hotspots. We study a set of images in order to extract characteristics of different kinds of objects and distinguish between them.

This work is structured as follows. In section 2 we will describe the process employed and the descriptors used. In section 3 we will show some examples of results obtained and, finally in section 4, conclusions will be presented.

2 The Proposed Infrared Processing Method

The proposed method, based on infrared image processing, can be divided in three steps (figure 1):

The first task to do is to get the set of images from the thermal video. Next, a phase of segmentation is implemented in order to extract the objects of interest from the global image. Finally, a set of characteristics from each one of the chosen objects is calculated and different graphs are plotted, with the aim of getting some parameters that let us distinguish between the different objects of the scene.

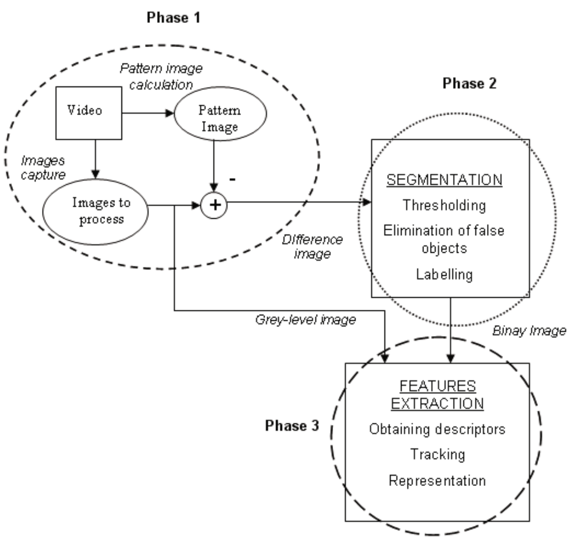


Fig. 1. General scheme

2.1 Obtaining Images

The first operation is the selection of the set of images to work with. In infrared images, each level of gray corresponds to one value of temperature due to the emissivity and reflectivity of the objects, which depend on the wavelength. The time interval between images is chosen depending on the type of video, taking

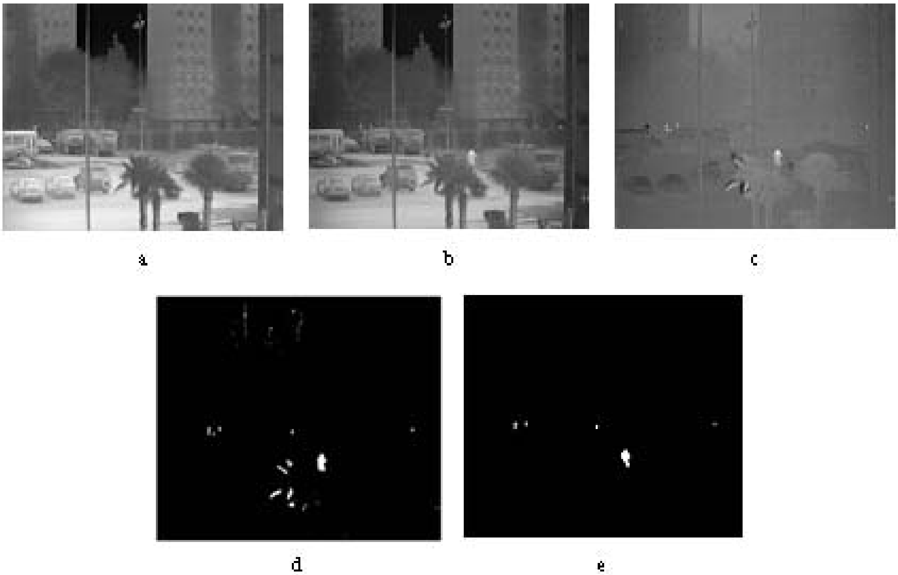


Fig. 2. Pattern image (a), selected image (b), difference image (c), binary image as a result of the thresholding (d) and binary image as a result of selecting RONI before thresholding and using morphological operations after it

into account the possible movement of the objects. For instance, when we focus on forest fires with a slow progress, a suitable interval could be one image per second, but if we focus on vehicles and we want to have enough frames to study, the interval has to be smaller, in the order of milliseconds.

In these images, only objects containing hotspots are considered as an area of interest, like people, vehicles or fires; the rest of the image has been considered as a noise (image background). For this reason, a pattern image (figure 2a) representing the noise (or everything that remains constant over time) is calculated and subtracted from each one of the images previously selected (an example of these images is shown in figure 2b). The pattern image is obtained using a number of images equal to N, acquired when the scenery has invariable conditions, and it is calculated, pixel by pixel, as the median of those N values. As a result of the subtraction a new image is obtained (figure 2c), where possible objects of interest appear with a higher intensity.

2.2 Segmentation

The next step is to separate highly brightened values, corresponding to possible objects of interest, from the background of the image. The Otsus method [9] is chosen as a thresholding technique (the result is shown in figure 2d). In order to reduce the computational complexity of the algorithm, it could be interesting to select areas not being evaluated. Those areas or RONI (Regions Of Non Interest) would be selected depending on the kind of object that we are focused on. For instance, being interested in studying vehicles, it would not make sense to study the area corresponding to the sky or buildings. After thresholding, a set of bright pixels that do not belong to any object could have been selected. The fact of continuing processing those pixels would involve an unnecessary computational use. For that reason, a morphological opening using as structuring element a circle of radius 2 has been used to remove or reduce the number of isolated pixels (figure 2e) [9],[10]. Finally, the binary image obtained is labelled, so as to be able to identify and work with each one of the remaining objects independently.

2.3 Feature Extraction: A Review of Descriptors

Once the objects have been separated from the background, extraction of characteristics can take place. Among the different kinds of descriptors studied, the ones that allow a better distinction between different objects are intensity, signature and orientation.

Average intensity gives us information about the darkness or brightness of an object. If the variable that indicates intensity it is called z_i , $p(z)$ represents the histogram of the intensity levels in a region and L is the number of possible levels of intensity, then the expression for the intensity is as follows:

$$m = \sum_{i=0}^{L-1} z_i \cdot p(z_i) \tag{1}$$

Before describing the rest of parameters it is necessary to introduce some expressions. For a generic 2D discrete function, the moments are defined as:

$$M_{jk} = \sum \sum x^j y^k I(x, y) \tag{2}$$

where function *I(x,y)* represents pixels binarized value at coordinates (x,y). The zero and first-order moments have a particular importance; particularising equation (2), we obtain:

$$M_{00} = \sum \sum I(x, y) \equiv Area \tag{3}$$

$$M_{10} = \sum \sum xI(x, y) \tag{4}$$

$$M_{01} = \sum \sum yI(x, y) \tag{5}$$

From these moments it is possible to calculate the center of mass coordinates (c_x, c_y), or centroid, as:

$$c_x = \frac{M_{10}}{M_{00}} \quad \text{and} \quad c_y = \frac{M_{01}}{M_{00}} \tag{6}$$

.

These coordinates are used in the definition of central moments, as follows:

$$\mu_{jk} = \sum \sum (x - c_x)^j (y - c_y)^k I(x, y) \tag{7}$$

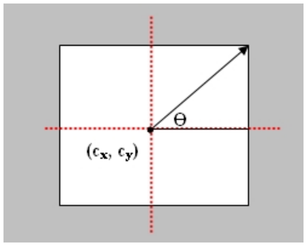


Fig. 3. Signature descriptor

Once the previous formulations have been introduced, we continue with the description of parameters.

A signature is a 1-D representation of an object boundary. To calculate it, it is necessary to compute for each angle θ the Euclidean distance between the centre of gravity or centroid, defined in equation (6), and the boundary of the region (figure 3). Changes in size of a shape result in changes in the amplitude values of the corresponding signature. As well as providing information about area changes, signatures inform us about the angular direction of those changes.

Object orientation, defined as the angle between the major axis of the object and the axis x, can be estimated using the central moments. Employing equation (7) we can calculate μ_{11}, μ_{20} and μ_{02}, and then, it is possible to obtain the expression of the inclination angle as:

$$\alpha = \frac{1}{2} arctan\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \tag{8}$$

In the next section, the results of applying these parameters to discriminate and characterize objects are shown. For each object, the evolution over time of each descriptor has been studied and represented graphically.

3 Results

The algorithm has been applied to different thermal videos. Some of them belong to a set of videos obtained from former research, where different scenarios were chosen and fires were generated under control in order to test vigilance systems. We have focused on the discrimination of vehicles, people and fires.

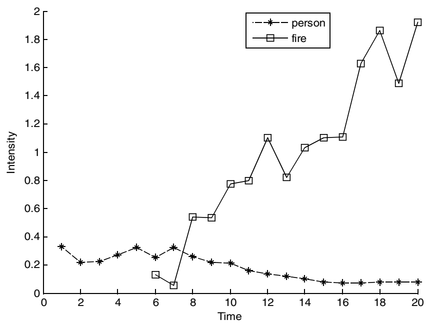
3.1 Discrimination between People and Fires

Figure 4 illustrates one of the infrared images belonging to one of the mentioned videos, where the objects under study appear bounded by boxes.

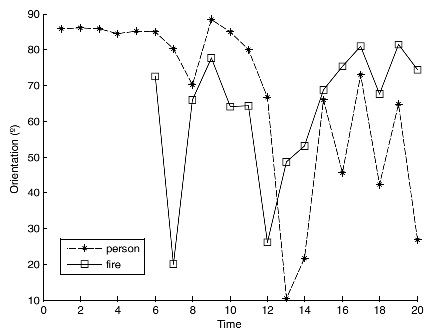
In this case, it was used the thermal camera 320V of FLIR systems. Some of its characteristics are: field of view 24°x18°, thermal sensitivity 0.1° (at 30°C), spatial resolution 320x240 pixels, spectral range 7.5–13 μm.

The algorithm is performed on a set of 20 frames to evaluate differences between a person and a fire. The graphs obtained are shown in figure 5. Figure 5a

Fig. 4. Selected image with two objects of interest: a person is bounded by a white box and a fire is bounded by a black box



a



b

Fig. 5. Representation of the descriptors intensity (a) and orientation (b) for a person and a fire

illustrates the evolution of the temperature over time. It can be seen that, while the behaviour of the intensity curve for the fire is increasing, the one for the person remains almost constant. This characteristic will let us know the temperature evolution for a detected object and determinate if there exist significant changes that can identify the object as a fire: we can expect that the temperature of a person will remain constant, but the one of a fire will be changing meaningfully.

Figure 5b shows the evolution of the orientation of the object over time. It can be seen that it varies with time in the case of the fire. For the person, it should remain invariable and close to 90°, denoting a vertical position; nevertheless, the graphs shows a non constant curve from the 6th temporal instant on. This fact is due to the movement of the person that makes it sometimes to be occluded with other objects. When this happens, the discrimination will be partial and difficult.

3.2 Discrimination between People and Vehicles

In order to be able to contrast results, a new thermal video was used containing both vehicles and pedestrians. In this case, the camera A20V of FLIR System was chosen, whose characteristics are: field of view 25°x19°, thermal sensitivity 0.12° (at 30°C), spatial resolution 160x120 pixels, spectral range 7.5–13 μm. Figure 6 shows one image from this thermal video. Nine frames are chosen from the video and obstructions of the objects under test are not presented. Results obtained are shown in figure 7. It can be seen that the curves remain constant for both descriptors.

The intensity of the vehicle is higher than the one of the person (figure7a). The important thing is not the specific value but the evolution over time. As far as the orientation is concerned (figure 7b), the values are 90° for the person (vertical direction) and 5° for the car (horizontal direction). This invariable behaviour of the orientation would have been the one obtained in the figure 5b if there had not happened occlusions there.

3.3 Discrimination between People, Fires and Vehicles

Using the two previous videos, we have studied the signatures of people, fires and cars. A set of 8 images is selected for the study of a person and a vehicle from the video described at point 3.2, and a set of 15 images, from the video described at point 3.1, is used in the case of the fire. In the representations, the

Fig. 6. Selected image with two objects of interest: a person is bounded by a white box and a car is bounded by a black box

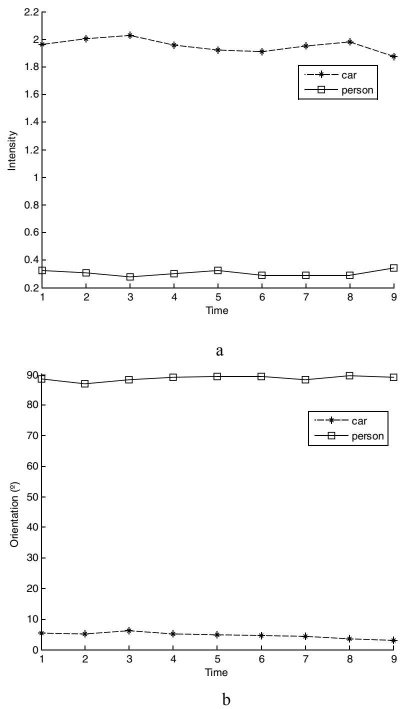


Fig. 7. Representation of the descriptors intensity (a) and orientation (b) for a person and a car

axes correspond to angle in the horizontal direction, and distance in the vertical direction. Figure 8, figure 9 and figure 10 illustrate the results obtained. It can be seen that the signature remains constant for the vehicle and the person.

In the first case (figure 8), two peaks are located in 0º and 180º, denoting a horizontal position of the object. In the second case (figure 9), two main peaks are located in 90º and 270º, denoting a vertical direction of the person. The behaviour of the peak in 270º represents the movement of the person: the angle formed by the legs changes while the person is walking. Figure 10 shows the signature of a fire. It can be seen that it has a random behaviour.

Hence, parameters extracted using image processing allow a distinction of objects. Specifically, we have focused on expanding and complementing the vigilance systems developed by our research group in order to get early forest fires detection. In this kind of scenarios, apart from fires, people and vehicles could cause false alarms due to their temperature. A better identification can be done studying their characteristics as objects or groups of pixels and not only as isolated pixels.

Firstly, knowing the evolution of the average intensity of the objects in infrared images it is possible to determinate whether their temperature increases gradually or not. Moreover, it has been shown that geometrical descriptors give

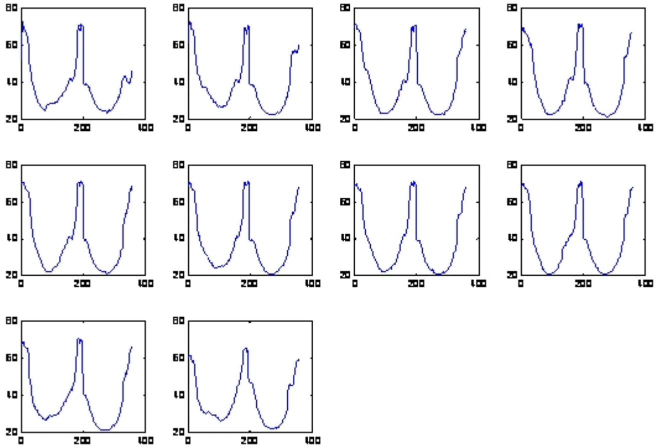


Fig. 8. Signature for a vehicle

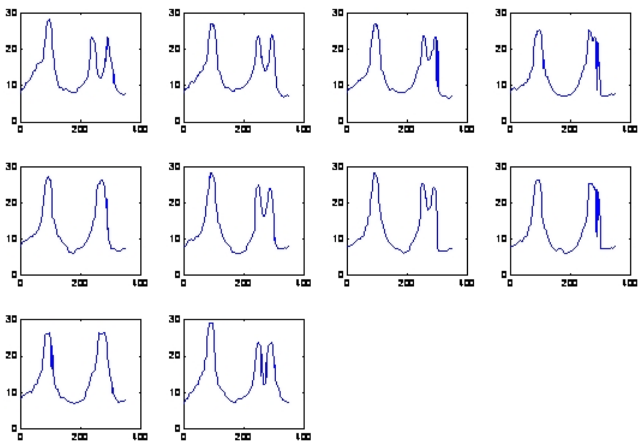


Fig. 9. Signature for a pedestrian

interesting information. Orientation let us distinguish, basing on its evolution, between fire and another kind of objects. In case of the fire, the behaviour of this parameter will be random, while it remains constant for other objects. Distinction between person and vehicle can be done with the orientation: ideally, 90^o for the person and 0^o for the vehicle. Finally, the signature parameter is also useful to provide us with another way to identify objects. Changes in shape produce changes in the amplitude of the signature over time. Objects with an invariable shape, like people and vehicles, have a constant signature, while fires have not this characteristic. Furthermore, distinction between a person, with vertical position, and a car, with horizontal position, can be done focusing on the angle where the peaks of amplitude appear.

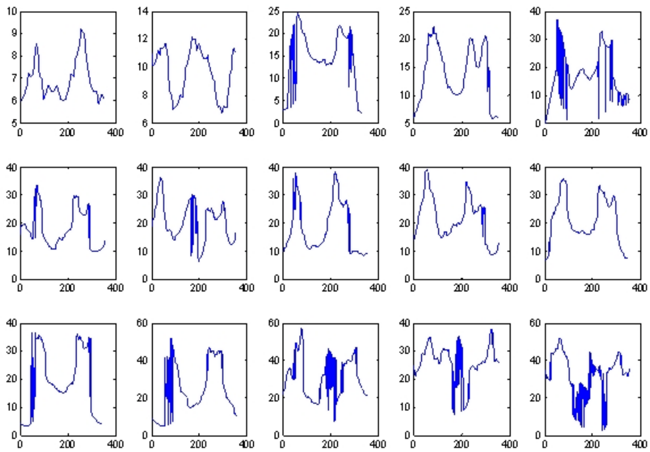


Fig. 10. Signature for a fire

4 Conclusion

In this paper, we have shown that parameters extracted from infrared image processing can be used for object discrimination and that shape descriptors provide a more accurate identification. It has been seen in some examples the behaviour of those descriptors in different objects, verifying the ability to distinguish between them. Nevertheless, it is necessary further work in order to establish statistics about the improvement of fires detection in real systems when images descriptors are incorporated.

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