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AN INFRARED VISION SYSTEM FOR FIELD ROBOTICS APPLICATIONS

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Abstract: This paper presents a general infrared vision system to be used in robotic applications in natural outdoor environments. In these applications the robustness of the vision system and the automatic settings of the infrared cameras are very important issues. A piecewise linear model of the infrared camera has been identified. This model is used for the design and development of a fuzzy control method by applying visual feedback techniques. The vision system also includes a new fuzzy-multiresolution threshold computation method, which considers knowledge on the application and information on the illumination conditions to select an appropriate threshold for the segmentation of the object of interest. The paper describes the application of the proposed system for surveillance and includes some experiments.

Keywords: infrared detectors, robotics vision, computer controlled systems, computer vision, fuzzy control.

1. INTRODUCTION

Infrared imagery is an appropriate technology for a large number of outdoor robotic applications such as robots for the maintenance of electrical lines (Peñín, *et al.*, 1999), surveillance, and fire fighting. The development of uncooled infrared cameras has contributed to decrease their costs significantly, permitting its extension to a considerable number of applications, (Unewisse, *et al.*, 1995). Furthermore, new advances in their miniaturization (Raytheon, 2001) permits an explosion of new applications including those using unmanned aerial vehicles.

However, infrared images show high sensitivity to illumination conditions, and particularly to solar illumination, (Hudson, 1969), (Arrue, *et al.*, 2000). This high sensitivity makes difficult their application in autonomous robots.

Several strategies have been developed in computer vision to deal with changes in illumination (Horn, 1986). Some of them aim to design algorithms robust to changes in illumination conditions, (Gonzalez and Woods, 1993). Other approaches consist in adapting the camera settings in order to control the visibility conditions of the images. The application of infrared vision systems in autonomous field robotics requires the adaptation of the settings of the infrared camera in order to control the visibility conditions of the images.

This paper presents a general infrared vision system to be used in natural outdoor environments. In order to achieve robust behavior, the system makes use of several tools. The system includes functions to adapt the settings of an infrared camera in order to control the visibility conditions of the images. The identification of infrared cameras reveals piecewise linear expressions, which are used to design and develop control schemes using visual feedback techniques.

The presented vision system employs a threshold-based method for the segmentation of objects from the background. However, threshold selection exhibits critical sensitivity to illumination conditions and particularly in outdoor scenarios with unpredictable changes in the illumination conditions (Gonzalez and Woods, 1993). Then, the proposed vision system includes a fuzzy-multiresolution threshold selection method, which considers knowledge on the application and information on illumination conditions to select automatically an adequate threshold value for the segmentation of the object of interest. This new method shows high robustness to illumination changes, being appropriate for outdoor applications.

The vision system has been implemented in several infrared detection and tracking systems for applications in natural outdoor environments.

The paper is organized as follows: Section 2 presents the general structure of the system. Section 3 and 4 present the modeling and fuzzy control of an infrared camera. In Section 5 the robust threshold selection algorithm is briefly described. In Section 6 the proposed computer vision system is particularized to object tracking. Finally, Section 7 describes the conclusions and future work.

2. THE INFRARED VISION SYSTEM

Infrared cameras provide images in which each pixel expresses a punctual measurement of radiation or temperature. Most infrared cameras have two basic settings: Gain and Pedestal (Hudson, 1969). Gain can be defined as the amplitude constant that multiplies the radiation value captured by the infrared sensors. Pedestal can be defined as the radiation in the infrared sensor that is transformed in black level intensity in the image. For instance, the camera Mitsubishi IRM300, which has been used for the experiments shown in this paper, has 5 discrete Gain values and a continuous range of Pedestal.

Fig. 1 depicts the general scheme of the proposed infrared computer vision system for outdoor applications. The settings of the infrared camera are adapted to control visibility parameters such as image bright and contrast. The inputs of the controller are the actual values of the visibility conditions, which are estimated by sensorial functions, and the reference values, which are provided from the knowledge database. The objective of the controller is to minimize the errors between the reference values and the values estimated from the images, so that the images have known stabilised illumination conditions according with the information provided by the knowledge database.

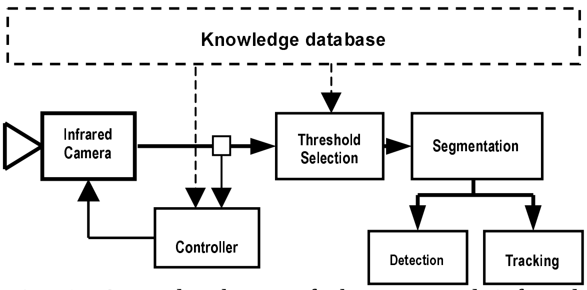


Fig. 1. General scheme of the proposed infrared computer vision system.

The images are processed by several blocks. Typically, the objects of interest have different radiation properties from the background and exhibit different intensity levels in infrared images. In many of these cases, simple threshold application is enough to perform correct segmentation. However, threshold selection normally is highly dependent on the application and is very sensitive to illumination conditions. The proposed threshold selection method employs heuristic knowledge of the application to compute an appropriate threshold value to segment the desired objects. Section 5 is devoted to the description of this method.

Algorithms insensitive to illumination conditions have a wide set of applications. They can be applied in completely autonomous systems as well as in cooperative hybrid operator-computer systems, in which the operator can change system settings and parameters without affecting the automatic image-processing algorithms. Notice that both strategies are complementary and can be applied simultaneously to increase robustness. Furthermore, it is also possible to make use of their synergies by establishing co-operative procedures to cope with certain illumination conditions and situations. These properties make the presented vision system appropriate for autonomous and tele-operated field robotic systems.

The database contains knowledge of the application, which is employed to set the desired reference values for image visibility control and to select adequate segmentation threshold values.

The following general steps depicted in Fig. 1 are: threshold-based segmentation, detection and tracking functions. The description of these blocks is not the object of this paper.

3. VISIBILITY MODELING OF AN INFRARED CAMERA

3.1 Infrared Camera Modeling

Consider that the model of an infrared camera can be decomposed in a static component and a dynamic one. The identification of the static component, which can be considered as a first step towards the identification of the complete model, consists in finding out the expressions that relate the changes in the camera settings with the changes in the image pixels intensity values.

Most infrared cameras aim to provide estimations of the radiation intensity and, thus, normally use linear functions in the image formation process. Thus, static identification can be achieved applying simple identifications techniques based on Least Squares criterion.

Let $\mathrm{Im}_1(x, y)$ and $\mathrm{Im}_2(x, y)$ be two infrared images of the same scene but taken with different settings, i.e. Gain=G1 and Pedestal=P1 for $\mathrm{Im}_1(x, y)$ and Gain=G2 and Pedestal=P2 for $\mathrm{Im}_2(x, y)$. A large set of experiments has been carried out revealing the following expressions (Martinez-de Dios, 2001):

$$\mathrm{Im}_2 = m(\Delta G)\,\mathrm{Im}_1 + y_0(G_1, \Delta G, \Delta P)\,, \qquad (1)$$

where $y_0(G, \Delta G, \Delta P)$ is shown in the following expression:

$$y_0(G_1, \Delta G, \Delta P) = m(\Delta G) f_A(G_1)\Delta P + f_B(\Delta G)\,, \quad (2)$$

For the infrared camera Mitsubishi IRM-300, used for the experiments presented in this paper, the following expressions were experimentally identified:

$$m(\Delta G) = (1'96)^{\Delta G} \quad (3)$$

$$f_A(G_1) = -192\,(1'96)^{G_1} \quad (4)$$

$$f_B(\Delta G) = \begin{cases} -73'34 \sum_{i=1}^{\Delta G} (1'96)^{i-1} & \text{If } \Delta G > 0 \\ 0 & \text{If } \Delta G = 0\,, \\ 73'34 \sum_{i=-1}^{\Delta G} (1'96)^{i} & \text{If } \Delta G < 0 \end{cases} \quad (5)$$

where $\Delta G = G2 - G1$ and $\Delta P = P2 - P1$.

The experiments revealed that changes in the settings modify all image pixels in the same way. Besides, the system has time-invariant behavior. It can also be noticed that no change in the settings, i.e. $\Delta G = 0$ and $\Delta P = 0$, originate no change in the images, i.e. $\mathrm{Im}_2 = \mathrm{Im}_1$. The experiments carried out demonstrated that the camera behaves like a 0-order system. The only dynamics is a dead time of negligible duration for the practical aspects considered in this paper.

3.2 Visibility Modeling

Traditionally, illumination conditions in gray-level images have been parameterized in terms of *bright* and *contrast* values, i.e.:

$$B = \frac{1}{NxM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \mathrm{Im}(x, y) \quad (6)$$

$$C = n_{max} - n_{min}\,, \quad (7)$$

where NxM is the size of the image and n_{max} and n_{min} stand for the maximum and minimum non-null intensity values of the image histogram.

It is easy to demonstrate that the relations between *bright* and *contrast* values of $\mathrm{Im}_1(x,y)$ and $\mathrm{Im}_2(x,y)$ have the following expressions:

$$C_2 = m(\Delta G)\, C_1 \quad (8)$$

$$B_2 = m(\Delta G)\, B_1 + y_0(G_1, \Delta G, \Delta P) \quad (9)$$

Notice that Eq. (8) only depends on ΔG while Eq. (9) depends both on ΔG and ΔP. With these expressions it is not difficult to design a control system with the structure shown in Fig. 2.

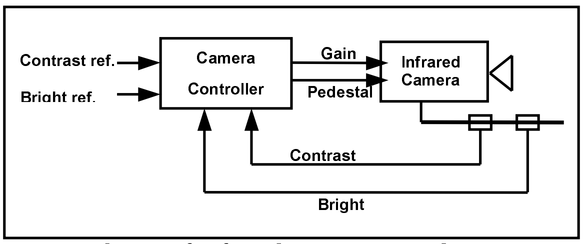


Fig. 2. Scheme of infrared camera control.

4. FUZZY CONTROL OF AN INFRARED CAMERA

The camera controller aims to compute the values of Gain and Pedestal in order to simultaneously minimize the errors between the references of *contrast* and *bright* and the values provided by the image sensors.

4.1 Contrast Control

From Eq (8) it is not difficult to obtain the following control law:

$$\Delta G = \ln\left(\frac{C_{ref}}{C_{sensor}}\right)\frac{1}{\ln(1'96)}\,, \quad (10)$$

where C_{ref} is the reference contrast value and C_{sensor} is the contrast estimation. In case $C_{ref}=C_{sensor}$, no change in Gain should be applied, i.e. $\Delta G = 0$.

In the Mitsubishi camera, Gain is a discrete parameter with 5 values. Thus, contrast control consists in selecting the value of ΔG that minimizes the error between C_{ref} and C_{sensor}, being not possible to cancel the error in the general case. The activation signals are restricted to $\Delta G = \{-1, 0, 1\}$ due to the high sensitivity of the image to ΔG, which can be observed in Eq. (1). Besides, the contrast control incorporates filtering functions to avoid noisy estimations of C_{sensor}.

Contrast control is performed by the fuzzy controller depicted in Fig. 3. The inputs of the controller are: $v_1=C_{ref}/C_{sensor})_n$, i.e. contrast ratio for current image (image n), $v_2=C_{ref}/C_{sensor})_{n-1}$, i.e. contrast ratio for image n-1, and $v_3=G_1$, which represents the current value of Gain. Fig. 4 shows the membership functions of v_1 and v_2 (Fig. 4a) and v_3 (Fig. 4b).

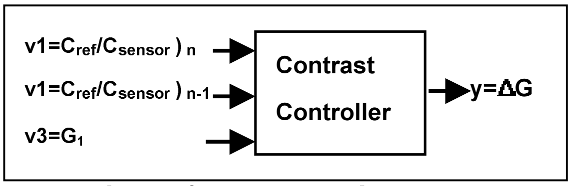


Fig. 3. Scheme of contrast control.

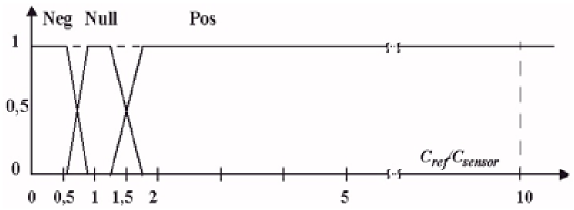
The fuzzy system has a total of 45 fuzzy rules. Two of them can be observed in the following expressions:

IF (v_1 IS **Neg**)AND(v_2 IS **Neg**)AND(v_3 IS **G1**)
THEN (ΔG IS **Negative**) (11)

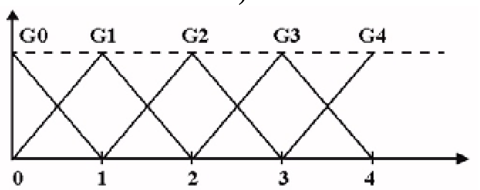
IF (v_1 IS **Pos**)AND(v_2 IS **Pos**)AND(v_3 IS **G1**)
THEN (ΔG IS **Positive**) (12)

For Eq. (11), v_1 and v_2 are **Neg**, C_{ref} <0,75 C_{sensor} for image n and n-1, and v_3 is **G1**. Thus, in order to reduce the value of C_{sensor} and minimize the error the output should be ΔG = -1. In Eq. (12) case v_1 and v_2 are **Pos**, C_{ref} >1,5 C_{sensor} for image n and n-1, and v_3 is

G1. Thus, in order to increase the value of C_{sensor} the output should be $\Delta G = 1$.



a)



b)

Fig. 4. Membership functions of input variables v_1 and v_2 (a) and v_3 (b).

4.2 Bright Control

From Eq (7) it is easy to obtain the following control law:

$$\Delta P = \frac{B_{ref} - (1'96)^{\Delta G}\ B_{sensor} - f_B(\Delta G)}{m(\Delta G)\ f_A(G_1)}, \quad (13)$$

where B_{ref} and B_{sensor} stand for the bright reference value and estimation of bright.

Bright control needs three inputs: B_{ref}, B_{sensor} and ΔG, which is computed by the contrast control block. Thus, errors in contrast control induce high sensitivity errors in bright control. Fig. 5 shows the diagram of the bright-contrast simultaneous control.

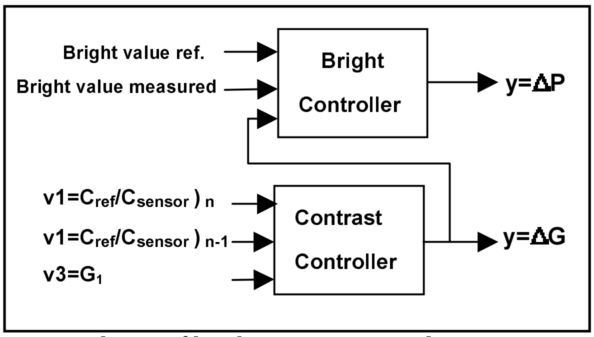


Fig. 5. Scheme of bright-contrast control.

In order to illustrate the capabilities of the control system, Fig. 6 shows the result of an experiment consisting in controlling simultaneously the bright and contrast of the infrared camera in order to fit the control references. Figure 6a and 6b show the references and the outputs obtained for bright and contrast control, respectively. They show that the error in bright control is negligible while the error in contrast control is not. The reason is that the contrast control is designed to minimize the error, without being able to cancel it in the general case. Figure 7 shows three images taken from this experiment (shown in Fig. 6) at different time instants: n=10, n=30 and n=60. These images show the same scene with gain and pedestal values adapted to fit the references. Fig. 7a shows an image with the camera configured to have low bright and low contrast values (n=10). The image in Fig. 7b (n=30) shows low bright and high contrast. For Fig. 7c the camera is configured to have high bright and low contrast (n=60).

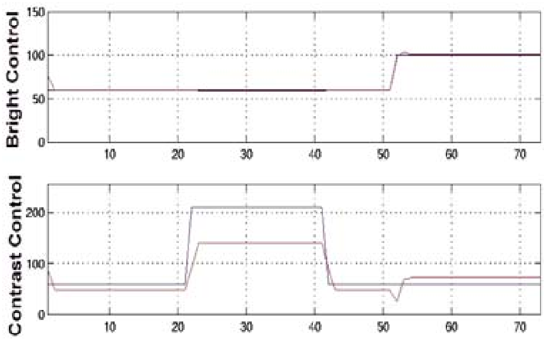
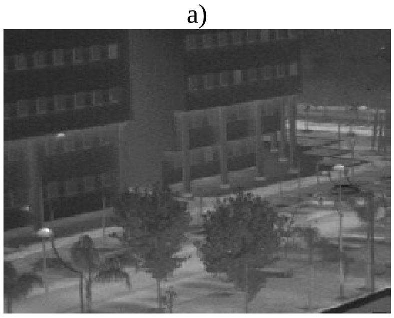
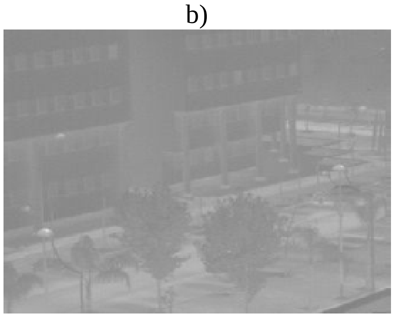


Fig. 6. Result of an experiment of bright-contrast simultaneous control of an infrared camera.

a)



b)



c)

Fig. 7. Three images taken from the experiment shown in Fig. 6 at different time instants: n=10 (a), n=30 (b) and n=60 (c).

5. ROBUST THRESHOLD SELECTION METHOD

The described threshold selection method considers the knowledge on the application and on illumination conditions to select an adequate threshold value for the segmentation of the objects of interest.

The described method assumes that the intensity values of the pixels of the objects of interest are within a certain region in the histogram, which will be called *histogram region of interest*. This hypothesis is normally assumed in most of automatic threshold selection methods (Parker, 1997).

Fig. 8 shows the scheme of the described algorithm. The method aims to identify the histogram of interest using descriptions of the histogram at several levels of resolution. The method starts making an estimation of the *histogram region of interest* using the wavelet approximation decomposition of the histogram at the coarser level of resolution, level *N*. This estimation is refined at the immediate finer level of resolution (level *N*-1) providing a new estimation. Then, this new estimation is refined at the following finer level. This process is repeated successively until the analysis is applied to the finest level of resolution (level 0). Then, once the histogram region has been estimated, the threshold selection is carried out performing simple considerations based on knowledge on the application.

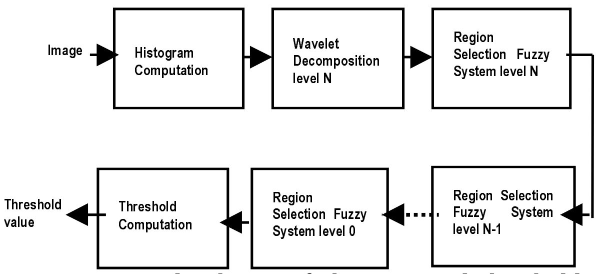


Fig. 8. General scheme of the proposed threshold selection method.

The Region Selection Fuzzy System is responsible for the selection of the histogram region at each level of resolution. This fuzzy system divides the region analyzed at each level in sub-regions, each of which corresponds to certain objects in the image. Then a fuzzy decision block, called Fuzzy Supervision Function, decides which sub-region corresponds to the object of interest. This decision block incorporates knowledge on the application and information on illumination conditions.

The threshold selection can be easily particularized to specific applications in contrast to most of the threshold selection methods, which are based on statistical criteria (Parker, 1997). The incorporation of knowledge can be achieved in three different ways. The first one consists in using statistical characterization of the objects of interest. However, this information is not available in many cases. The system can also employ rules provided by expert human operators. Finally, a neuro-fuzzy learning-based method has been also developed to incorporate automatically application knowledge in the algorithm, (Martinez-de Dios, 2001).

It can be demonstrated that the algorithm exhibits high robustness to the changes in the illumination conditions considered in the Fuzzy Supervision System (Martinez-de Dios, 2001). This robustness property has been tested in the wide test of experiments that have been carried out.

6. APPLICATION: TRACKING OF OBJECTS

The proposed infrared vision system is the basis for several applications in outdoor scenarios. The application described in this paper deals with surveillance at the surroundings of buildings.

The system is composed by an infrared camera mounted on an azimuth-elevation pan&tilt. The system aims to detect suspicious activities and, once detected, keep the objects of interest in the image with constant local illumination conditions.

The architecture of the system can be divided in two components: detection and tracking. The objective of the first component is to detect moving high intensity objects. Thus, the segmentation method employed is based on motion detection and thresholding. The last one is carried out by the method described in Section 5. Notice that motion segmentation avoids the detection of static high-intensity objects such as traffic lights. For detection, the references for the control of visibility conditions are kept constant in such a way that infrared images have the same visibility conditions despite solar illumination.

Object tracking involves controlling the infrared camera settings and controlling the pointing of the cameras. The pointing is not described in this paper. In order to maintain invariant local visibility conditions, predictive schemes are employed in the control structures to cancel irregularities in local illumination before they originate errors in visibility control. The tracking component of the system also includes functions to avoid partial or temporal occludings of object of interest.

The described system has been installed on the roof of the building of the School of Engineering of Seville, Spain. The computer is based on a Pentium III, 700 Mhz. The control period is 300 ms.

Fig. 10 shows four non-consecutive images taken from a detection and tracking experiment. The location of the object of interest, which is a car in this experiment, is marked with two rectangles in the images. The inner rectangle indicates the position of the segmented object, while the outer represents the predicted position for the next image in the sequence. The object of interest is detected in the image shown in Fig. 10a. In Fig. 10b, 10c and 10d the object is tracked along its trajectory. Notice that the settings have been adapted to keep the local visibility conditions around the object of interest constant along the tracking. Notice that the pan&tilt pointing for the images shown in Fig. 10a and Fig. 10b are different from Fig. 10c and 10d in order to keep the object of interest within the image. Notice that the results of the tracking and camera control are successful despite the object suffers temporal occlusion (see Fig. 10b).

a)

b)

c)

d)

Fig. 10. Images from a detection and tracking experiment.

7. CONCLUSIONS

Infrared imagery is an appropriate technology for a large number of outdoor robotic applications. However, infrared images have considerable sensitivity to illumination conditions, limiting in many cases the use of autonomous robotic systems.

This paper presents a general infrared vision system for outdoor applications. Two main approaches have been considered to solve this mentioned sensitivity to illumination conditions. The first one consists in adapting automatically the camera settings in order to control the visibility of the images. The identification of infrared cameras obtains a piecewise linear model. This model is employed to develop control schemes using visual feedback techniques.

The proposed vision system also includes a fuzzy-multiresolution threshold selection method that considers knowledge on the application and information on illumination conditions to select automatically an adequate threshold value. The adaptation of the method to specific applications can be done easily. The proposed method shows considerable robustness to illumination changes.

This vision system has been implemented in several infrared applications for outdoors, one of which is described in the paper including some examples.

Future work will include the integration in field robotics systems for applications such as surveillance and forest-fore fighting.

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