Extended version of Proc. of the X Conferencia de la Asociación Española de Inteligencia Artificial, vol. II, pag. 179-182. San Sebastian (Spain), November, 2003

A Proposal of a Homeostatic Regulation Mechanism for a Vision System

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Abstract. In this paper, the introduction of a homeostatic regulation mechanism in a vision system is proposed. This homeostatic mechanism takes charge of controlling the luminance, white balance, contrast and size of the object of interest in the image, using naive methods except for the contrast, for which we have implemented a method that avoids the hill climbing search for the best focus position. We carry out some experiments in order to test the possible increase in the performance of a face detection application.

1 Introduction

Homeostasis is defined in the Merriam Webster on line dictionary as "a relatively stable state of equilibrium or a tendency toward such a state between the different but interdependent elements or groups of elements of an organism, population, or group". The state of equilibrium is normally related to the survival of the animal in an environment making sure that it gets enough to eat or it does not overheat or freeze. Thus, animals have regulation mechanism, generally referred as to homeostatic regulation, in order to maintain this state of equilibrium. The homeostatic regulation is responsible of physiological changes in the body. For example, in humans the eccrine sweat glands are part of the thermoregulation mechanisms to keep the body with a temperature around 36.5 Celsius degrees, increasing sweat levels when it is hot. These glands also respond to emotional changes and that fact has been used by Healey and Picard [1] to control a wearable camera which detects emotional changes measuring the skin conductive.

In Figure 1 the outline of a homeostatic regulation mechanism is shown. The state of the system is considered into one of the three categories: homeostatic, overwhelmed and understimulate regimes. The objective is to keep the system in the homeostatic regime modifying its behavior toward this goal. The computational processes in charge of the task are normally called *drives*. Inputs to these drives are the variables to control and according to the values of them modify the behavior of the system to restore the homeostatic regime.

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* This work has been partially supported by the University of Las Palmas de Gran Canaria under Research Project UNI2002/16

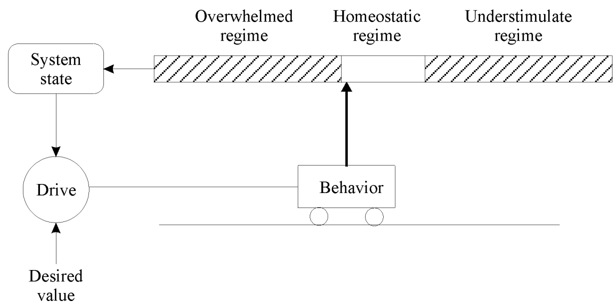

Fig. 1. Homeostatic regulation mechanism

This idea has been used by some authors in the construction of systems that have to develop their activity in a complex environment. Arkin and Balch in their AuRA architecture [2] propose a homeostatic regulation system which modifies the performance of the overall motor response according to the level of internal parameters such as battery or temperature. Another work which includes a homeostatic regulation mechanism is the proposal of Hsiang [3] who introduces it to regulate the dynamic behavior of the robot during task execution.

Damasio [4] has studied the role of emotions in the decision making process and he found that some emotions, which he called primary emotions, are in charge of taking decisions about the individual survival, so they are part of the homeostatic regulation mechanism. The idea of emotions as a way to select actions has been explored by some authors. In this case the homeostatic regulation is considered as primary or innate emotions that respond to urgent needs of the agent, normally related to welfare or survival of the agent. Some authors as Cañamero [5] or Breazeal [6] consider this mechanism as a motivational one that drives the behavior of the agent to meet bodily needs.

The idea of primary or innate emotions as homeostatic regulation has been used by some other authors. Velasquez [7, 8], introduces the concept of *drive releasers* in his Cathexis architecture as the computational systems that maintain the controlled variable, i.e. battery level in a robot, around a set point. Also in the same line but in a different context, Fujita et al. [9] propose the EGO architecture for symbol grounding. In EGO architecture the homeostatic regulation along with external stimuli select behavior for grounding symbols using visual and audio perceptions. Gadanho and Hallam [10] propose an emotion-based architecture to learn actions which relies on a set of internal needs that have to be satisfy by the robot.

The works reviewed above are mainly related to robotics since robots posses elements (effectors) to modify its behavior in the environment. However, since the introduction of the Active Vision paradigm [11], vision systems include perception strategies which are controlled by the interaction with the environment when a specific goad is pursued. Thus, we can consider the inclusion of a homeostatic regulation in such vision systems because they share with the previously described systems the fact that a goal has to be achieved (survive) in a changing environment and they have to adjust their behaviors to get the best performance in the whole time.

In this work we present the introduction of a homeostatic regulation mechanism in a vision system to study how it affect to the system performance. In next Section the homeostatic regulation is presented and in Section 3 the experimental framework and the obtained results are commented.

2 A homeostatic regulation mechanism for a vision system

The performance in most of the computer vision systems relies heavily on the quality of the images supplied by the acquisition subsystem. For example face detection systems that make use of the skin color as primary clue depend on the white balance, tracking systems based on edge detection depend on image contrast and so. On the other hand, image quality is influenced by the environmental conditions, namely lighting conditions or distance from the object of interest to the camera, and the setting of the camera parameters.

In computer vision applications where the environment E is completely controlled, i.e. industrial applications, the camera parameters that define the quality of the image are initially tuned to get the best performance. This is illustrated in Figure 2 where the set of camera parameters Σ is the one which maximizes the performance of the system under the environmental conditions E. If the environment changes to E', for example due to different lighting conditions, the performance of the system will be maximum for another set of camera parameters Σ' as it is shown in Figure 3. So if the system does not have an internal mechanism to detect the new environment E', its performance will drop because it will continue using the initial parameter set Σ, and we must rely on an external agent to readjust the parameter set to Σ'.

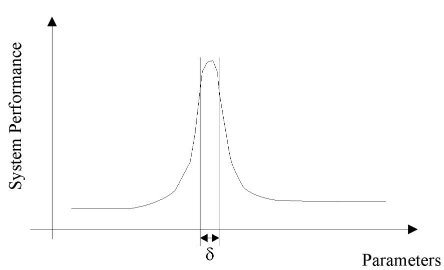

Fig. 2. Set of camera parameters for an environment E

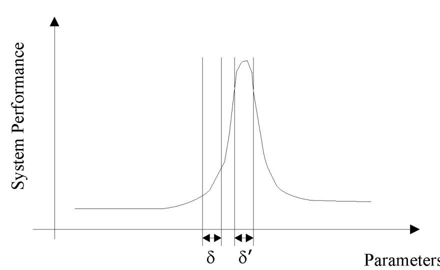

Fig. 3. Set of camera parameters for an environment E'

In the introduction, we presented the concept of homeostatic regulation as a mechanism to increase the survival opportunities of an agent in a changing environment. We can use the same concept to keep the performance of a vision system as high as possible when the environmental conditions change, endowing the vision system with a homeostatic regulation mechanism.

In a vision system the changes in the environmental conditions affect to the quality of the acquired image. For example, if the temperature of the light source varies, the white balance change or if the object of interest goes further or nearer, it can be defocussed. Thus, the homeostatic regulation tries to compensate these effects on the image quality making use of the configurable parameters of the camera.

Figure 4 shows the elements that makes up the homeostatic regulation mechanism we propose to control the quality of the acquired images. To our purposes we consider that the variables that affect to the image quality are the contrast, the luminance, size of the object of interest in the image and the white balance. For each of these variables, a homeostatic regime is defined and it is maintained by means of adjusting the camera parameters to keep the values of the variables within the homeostatic regime. In the next paragraphs the algorithms used in the system are described.

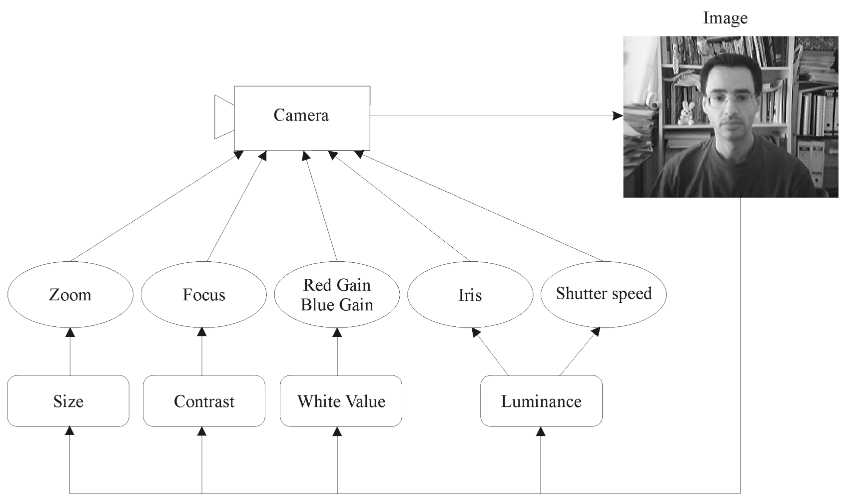

Fig. 4. Elements of the homeostatic regulation mechanism

2.1 Luminance

The luminance of the image is controlled by dividing the image into five regions (Fig. 5) similar to the proposed by Lee et al. [12]. These five regions allow us to get different AE strategies according to the nature of the object of interest giving different weights to the average luminance in each region. For example in a tracking system the object of interest will be centered in the image and *Region 2* will have more importance in the luminance than the rest of the image. Another situation is in a perceptual user interface where the individual will normally occupy *Region 2* and *Region 4* and the rest corresponds to the background.

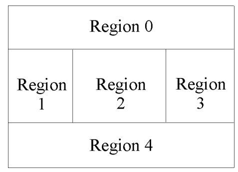

Fig. 5. Regions to compute the luminance of the image

We have tested three different strategies for auto exposure that we have called as uniform, centered and selective. The luminance for each of these strategies is computed as follows:

$$L_{uniform} = (R_0 + R_1 + R_2 + R_3 + R_4)/5 \quad (1)$$

$$L_{centered} = 0.8R_2 + 0.2(R_0 + R_1 + R_3 + R_4)/4 \quad (2)$$

$$L_{selective} = 0.8(R_2 + R_4)/2 + 0.2(R_0 + R_1 + R_3)/3 \quad (3)$$

where L is the total luminance of the image and R_i denotes the average luminance of *Region i*.

The homeostatic regulation mechanism for the luminance is going to keep the total luminance of the image around a set point, normally 127, that defines the homeostatic regime using the shutter speed and the iris of the lens.

2.2 Contrast

As focused camera gives sharp images hence the acquired image has a high contrast, we use a autofocus algorithm for regulating the contrast of the images. Since the study of complex focus algorithms is out of scope of this work, we

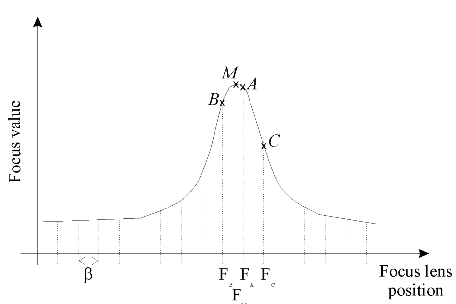

Fig. 6. Autofocus algorithm: initialization

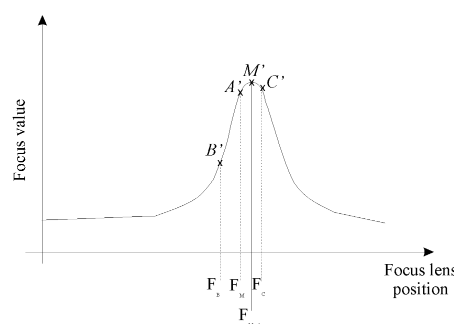

Fig. 7. Autofocus algorithm

choose a passive focus technique with a measure which exhibits a maximum when the image is at best focus proposed by Nanda and Cutler [13]. The measure of contrast is the absolute difference of a pixel with its eight neighbors, summed over all the pixels of the image. This measure exhibits a sharp and well defined peak at the position of the best focus and decreased monotonically as the defocus increases. It has the advantage that it is resistant to noise in the image.

The AF algorithm we have developed starts with a run along the complete range of focus lens positions with a step β (Fig. 6). Due to the discretization effect of the focus positions, the maximum value A is found at F_A whereas the actual maximum is M at position F_M. To estimate the value M, a quadratic function f_F is computed from points (F_B, B), (F_A, A) and (F_C, C) and the maximum of f_F is taken as an estimation of M. Thus, we avoid to use slow hill-climbing techniques around the point A.

After the initial focus value has been found, the system does not need to compute the focus values for the whole run of the focus positions but it only gets the focus value A' for the current position F_M and two adjacent positions $F_{B'}$ and $F_{C'}$ (Fig. 7). With these three points, the new focus value of M' is estimated and its focus position $F_{M'}$ is used as current one.

2.3 White Balance

For applications based on color it is necessary that it has a certain constancy because depending on the light source temperature the same color appears different in the image. This situation can be dealt using white balance techniques because a white surface has the same power spectrum that the one of the light source. As the white surface should appear to be white independent of the light source, we can use it to get a balance. To do it dynamically we adopt the *Grey World* [13] assumption which tries to make the amount of green, blue and red in the image equal, by adjusting the red and blue gain parameters.

2.4 Size

The last variable to control in our proposal is the size of the object of interest in the image. Here we are interested in keeping constant the aspect ratio of the object in the image. To accomplish it the zoom value is increased or decreased.

3 Experiments

To test the introduction of the homeostatic regulation in a vision system we are going to use a face detection application as test bed. This application utilizes the architecture ENCARA [14] which is based on the concatenation of naive classifiers whose inputs are weak clues about the presence of a face in the image. These classifiers have a good accuracy but with a high rate of false positives. The cascade combination of the classifiers (Fig. 8) allows to reduce the rate of false positives without increasing the rate of false negatives. Thus the face

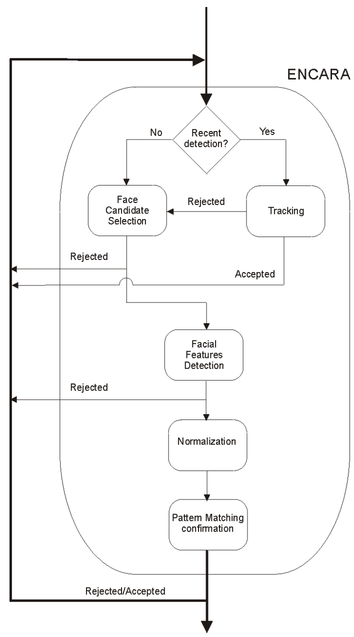

Fig. 8. Architecture of ENCARA

detection starts with a weak clue as a skin color blob and then some filters are applied based on geometric constraints, detection of facial features (eyes, nose and mouth) and implicit pattern tests that allows to accept or reject the initial blob as a face.

The input to the face detection system are color images taken with a firewire camera that has control over zoom, focus, gain, iris, shutter speed, red and blue gain, etc. The system has been developed in C++ under Microsoft Windows 2000 operative system and the OpenCV library was used for the image processing tasks.

Figures 9 and 10 show the results before and after the AF is applied. In the first phase of the AF algorithm the maximum value for the measure (value A in Fig 6) is 7359246 at a focus position 88 (point F_A in Fig 6) and with the quadratic curve fitting a maximum value of 7451958 (value M in Fig. 6) at focus position 95 (point F_M in Fig 6).

To test the introduction of the homeostatic mechanism in the face detection application, we compare the performance of the system with changing environmental conditions. The performance is measured as the number of frontal faced detected. A drawback in the test of this kind of systems (with actual environments nor simulated) is that the conditions can not be exactly reproduced in different experiments. In order to test only the effect of the homeostatic mechanism in the face detection in ENCARA we deactivate the tracking module (Fig. 8), thus only color is used to detect face candidate regions.

Fig. 9. Image before autofocus

Fig. 10. Image after autofocus

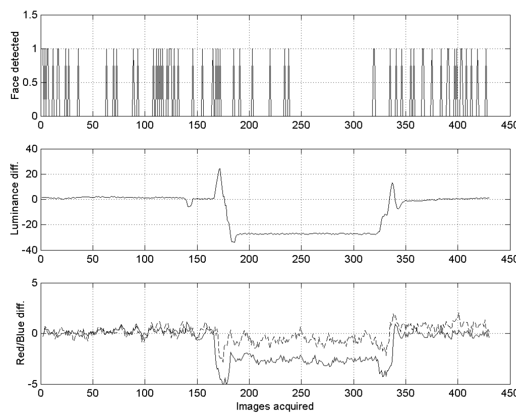

Fig. 11. Face detection without homeostatic control

Figure 11 and 12 show the obtained results without and with the homeostatic regulation mechanism respectively. The experiments were carried out with a person in front of the camera, after a while some lamps were switched off and then they were switched on to restore the initial illumination conditions. Previously to the experiment, camera parameters were adjusted to achieve a good performance. Finally, from the three luminance measures in equation (1), we choose the selective measure $L_{selective}$ since the object of interest in these experiments was a person. The autofocus is done at the begining of the experiments and the homeostatic regions for the luminance is [122,132] and for the red and blue difference is [-1,1].

In Figure 11 we can see that between images 165 and 320, when some lamps were switched off, both the luminance level and the red and blue difference in the image do not recover their initial levels so the images supplied are not good enough to detect a face and consequently a small number of frontal faces are detected. When the illumination conditions are restored, the performance is similar to the initial one.

Figure 12 shows the results we obtained when the homeostatic mechanism was activated. In this case the lamps were switched off when 150 images were acquired and then switched on after the acquisition of 320 images. Unlike the previous experiment, the number of faces detected when the lamps were switched off is greater and both the luminance and white balance is restored using the parameters of the camera after a transitory time period. The performance in this case is slightly higher due to the faces detected during the period of time the lamps were switched off since when the lamps are switched on the performance is similar in both experiments.

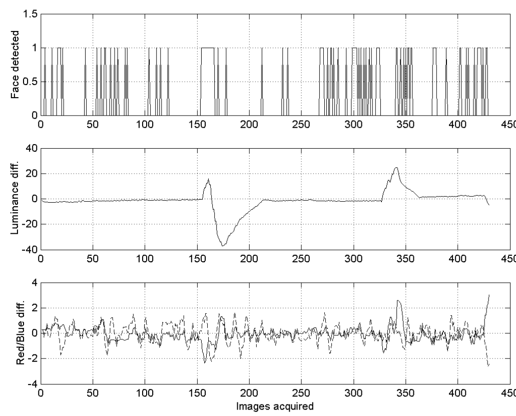

Fig. 12. Face detection with homeostatic control

4 Conclusions and Future Work

In this paper, we have initially presented a discussion about the suitability of including a homeostatic regulation mechanism in a vision system that operates in a non controlled environment, similar to the mechanisms included in mobile robots that have to develop their activity in a complex environment. Then we identify some variables to be controlled and we have proposed the architecture of a simple homeostatic mechanism to maintain them near a set point, called homeostatic regime. This homeostatic mechanism includes a two phase autofocus method based on the fitting of a quadratic function that avoids a hill climbing search to find the best focus position. In the experiments carried out with a face detection application we have found that the number of faces detected is greater when the homeostatic mechanism is activated than when it is not.

As future work, we think that the proposal has to be tested on other situations as robot vision based navigation where the robot has to travel in different environments. Besides, the controlled variables should include two more states, apart from the ones in Figure 1, that allows to implement an adaptive control of the system depending of how far are their values from the set point. This adaptive response can be done by modifying the frequency to which the camera parameters are adjusted or by using more sophisticated control strategies as a PID control.

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