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Conference Paper · January 2004

Source: DBLP

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Proceedings of the 4th International Workshop on Pattern Recognition in Information Systems,
PRIS 2004, Ana Fred (ed.), pp. 5-14, Porto (Portugal), April 13-14, 2004

Introduction of Homeostatic Regulation in Face Detection

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Abstract. In this paper the introduction of a homeostatic mechanism in a vision system is proposed. This homeostatic mechanism is based on artificial hormones for which five different states have been defined. The goal is to keep the system into a regime where the performance were acceptable for the task and to recover it when the environmental conditions change. For a face detection task we have propose the control of the luminance, white balance, contrast and size of the face. The introduction of the artificial hormones will allow to implement simple control strategies and with the definition of different states for each hormone we will be able to introduce adaptation depending on the deviation from the optimal regime. Finally we realize a set of experiments to test the proposed mechanism on a face detection system and using as performance measure the rate of detected faces.

Keywords: Emotion-based Systems, Face Detection, Human-Computer Interaction

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 organism in an environment making sure that it gets enough to eat or it does not overheat or freeze. Thus, organisms are endowed with regulation mechanisms, generally referred to as homeostatic regulation, in order to maintain this state of equilibrium. Homeostatic regulation is responsible for 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

* This work has been partially supported by the University of Las Palmas de Gran Canaria under Research Projects UNI2002/16 and UNI2003/06, and by the Regional Canary Islands Goverment under Research Projects PI2003/165 and PI2003/160

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 response.

In Figure 1 the outline of a homeostatic regulation mechanism is shown. The state of the system is considered to fall into one of three categories: homeostatic, overwhelmed and understimulate. The goal 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 controlled variables and according to them, they modify the system behavior in order to restore the homeostatic regime.

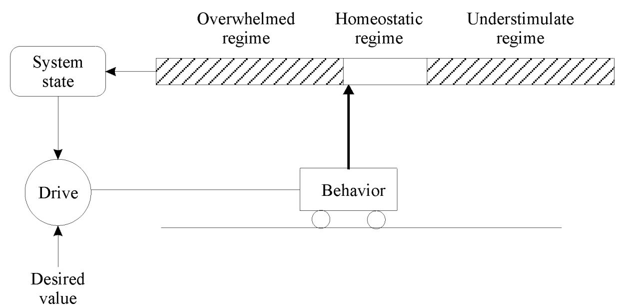

Fig. 1. Homeostatic regulation mechanism

This idea has been used by some authors in the construction of systems that carry out 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] 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 the welfare or survival of the agent. Some authors as Cañamero [5] or Breazeal [6] consider homeostasis as a motivational mechanism 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. Gadanho and Hallam [10] propose an emotion-based architecture to learn actions which relies on a set of internal needs that have to be satisfied by the robot. 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.

The works reviewed above are mainly related to robotics since robots posses elements (effectors) to modify its behavior in the environment. However, with the introduction of the Active Vision paradigm [11], the vision systems include perception strategies which are controlled by the interaction with the environment when a specific goal is pursued. Thus, we can consider the inclusion of a homeostatic regulation in such vision systems because they share with the described robotics 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.

Here we explore the introduction of a homeostatic regulation mechanism from a affective computing framework to study how it influence the system performance. In the next section the homeostatic mechanism is presented and a description of the methods implemented to compute the controlled variables . In section 3 the results obtained with the introduction of proposed mechanism in a face detection system are presented.

2 A homeostatic regulation mechanism for a vision system

In most of the computer vision systems, the performance depends 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 affected 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 images are initially tuned to get the best performance. This is illustrated in Figure 2 where the set of camera parameters δ 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 δ' as it is shown in Figure 3. So if the system can not detect the new environment E', its performance will drop because it will continue using the initial parameter set δ, and we must rely on an external agent to readjust the parameter set to δ'.

In the introduction, we presented the concept of homeostatic regulation as a mechanism to increase the survival opportunities of an agent in a changing

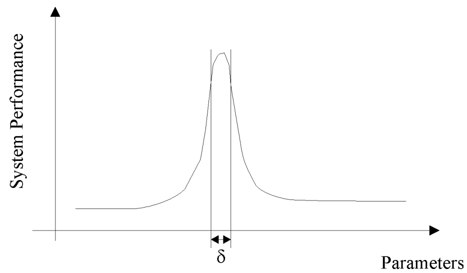

Fig. 2. Set of camera parameters for an environment E

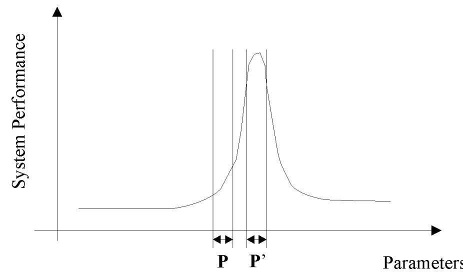

Fig. 3. Set of camera parameters for an environment E'

environment. We can use the same concept to keep the performance of a vision system as high as possible when environmental conditions change, endowing the vision system with a homeostatic regulation mechanism.

In a vision system, the changes in the environment affect the quality of the acquired image. For example, if the temperature of the light source varies, the white balance changes or if the object of interest goes further or nearer, obviously its size in the image changes. Thus, the homeostatic regulation tries to compensate for these effects on the image making use of the configurable parameters of the camera.

In the affective computing framework, systems must be "bodily" because human emotions involve both the body and the mind. Since our system does not have a body, as an anthropomorphic robot, we simulate the physiological changes that influence the homeostasis mechanism. Cañamero [5] proposes synthetic hormones to imitate physiological changes in the body of a robot which evolves in a two-dimensional world and whose motivations respond to the levels of the synthetic hormones. We adopt this approach in our system and implement some synthetic hormones that reflect the internal state of the computer system "body" (Fig. 4).

The internal state of the vision system is represented by four hormones associated to the luminance (*h_luminance*), contrast (*h_contrast*), color constancy (*h_whitebalance*) and size of the object (*h_size*). The homeostatic mechanism will be in charge of keeping this internal state into a regime which will allow the system to operate at an acceptable performance. The internal state of the system also modifies high level behaviors, as it is shown in Figure 4. For example if the image is too dark, it has no sense to realize any visual process on it.

An important element in a homeostatic mechanism is its adaptive aspect. When the internal state of the body is too far away from the desired regime, the homeostatic mechanism must recover it as soon as possible.

The adaptive response of the homeostatic mechanism is governed by the hormone levels which are computed from the controlled variables by means of a sigmoid mapping (Fig. 5). In this way, we can implement adaptive strategies more easily in the drives since the hormone levels that define the normal and

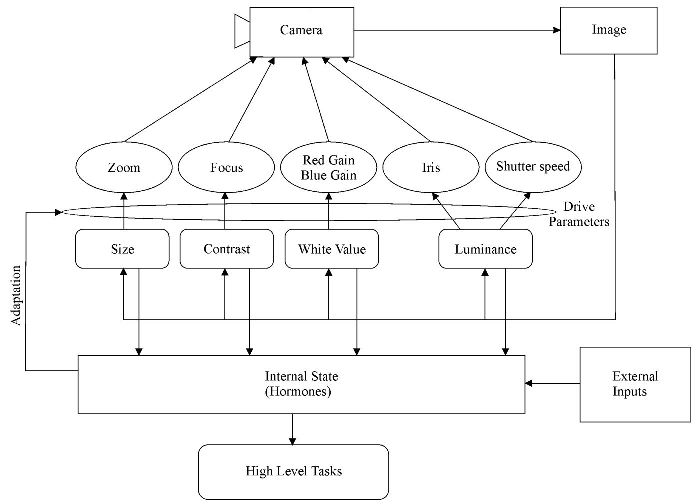

Fig. 4. Elements of the homeostatic regulation mechanism

urgent recovery zones are always the same independently of the controlled levels. Below we briefly describe the methods used to compute these variables.

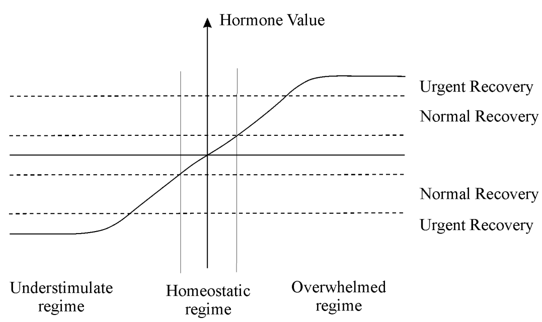

Fig. 5. Hormone value mapping from the variable of interest

2.1 Luminance

The luminance of the image is computed by dividing the image into five regions, similar to the method proposed by Lee et al. [12]: an upper strip (R_0), a lower strip (R_4) and the central strip is divided into three regions (R_1, R_2 and R_3 from left to right). These five regions allow us to define different auto exposure (AE) strategies according to the nature of the object of interest giving different weights to the average luminance in each region.

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:

$$L_{uniform} = (L_0 + L_1 + L_2 + L_3 + L_4)/5 \quad (1)$$
$$L_{centered} = 0.8L_2 + 0.2(L_0 + L_1 + L_3 + L_4)/4 \quad (2)$$
$$L_{selective} = 0.8(L_2 + L_4)/2 + 0.2(L_0 + L_1 + L_3)/3 \quad (3)$$

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

The $L_{centered}$ strategy is suitable for tracking tasks where the object of interest will be in the center of the image, whereas $L_{selective}$ is suitable for human-computer interaction because it considers the part of the image where normally a person appears when it is sat in front of a computer.

2.2 Contrast

A focused camera gives sharp images and hence the acquired image has a high contrast. We use an autofocus algorithm (AF) for regulating the contrast of the images. Since the study of complex focus algorithms is out of scope of this work, we choose a passive focus technique with a measure, proposed by Nanda and Cutler [13], which exhibits a maximum when the image is at the best focus. 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 decreases monotonically as the de-focus increases. It has the advantage that it exhibits a high tolerance to noise in the image.

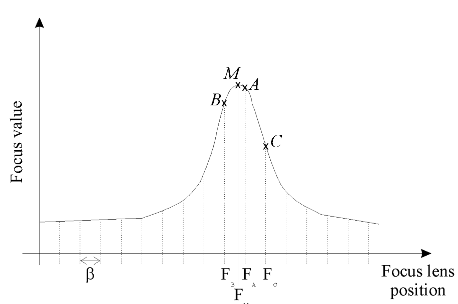

Fig. 6. Autofocus algorithm: initialization

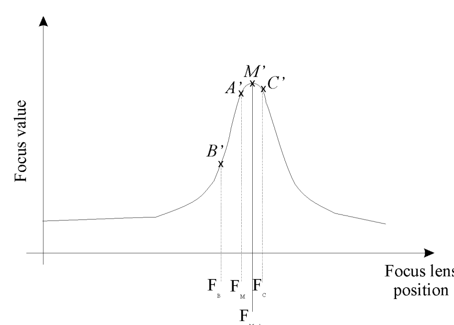

Fig. 7. Autofocus algorithm

The AF algorithm we have developed starts with a run along the whole range of focus lens positions with a step β (Fig. 6). Due to the discretization effect of the focus positions, the maximum value A could be 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 the current one.

2.3 White Balance

For applications based on color it is necessary to have a certain constancy because depending on the light source temperature the same color appears different in the image. This situation can be dealt with white balance techniques because a white surface has the same power spectrum than 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 average amount of green, blue and red in the image the same, 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. This is very important for applications such as object recognition, facial analysis,... To accomplish this, we act over the optical zoom of the camera.

3 Experiments

Now we are interested in knowing if the previously described homeostatic mechanism can improve the performance of a face detection task under changing environmental conditions. 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 allows to reduce the rate of false positives without increasing the rate of false negatives. Thus the face 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 system are color images taken with a Firewire camera that has control over zoom, focus, gain, iris, shutter speed, red and blue gain, etc.

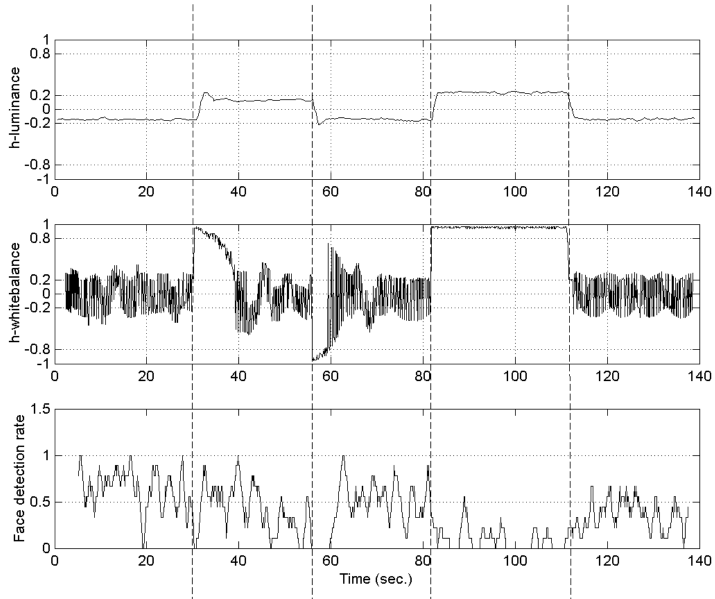

Fig. 8. Face detection rate with and without homeostatic mechanism

The system has been developed in C++ under Microsoft Windows operating system. The OpenCV library was used for the image processing tasks.

To test the introduction of the homeostatic mechanism in the face detection task, we define a performance measure as the ratio between the number of detected faces in a second and the number of images per second. As ENCARA depends on the skin color to detect the faces, we will study the influence of the luminance and white balance in the performance.

Figure 8 shows the values of the *h_luminance* and *h_whitebalance* hormones and the performance of the application. In dashed lines are marked the changes in the environmental condition (lighting).

When the system starts the performance is high and it decreases a bit when more lights are switched on (30-57 secs.). When the lights are switched on, both the *h_luminance* and *h_whitebalance* hormones go out of their desired states but the homeostatic mechanism recovers them after a delay, larger for the *h_whitebalance* hormone than for the *h_whitebalance* one.

The homeostatic mechanism is deactivated after 70 seconds, so when the conditions change again the state of the hormones is not recovered and the performance of the system decreases with a low rate of face detected.

To speed up the recovery time, we implement an adaptive strategy making use of the two recovery levels that the hormones have. So when a hormone goes into the urgent recovery zone we apply a more aggressive recovery strategy (increasing aperture of the iris or the red and blue gains) than when hormones are in the normal recovery zone (Fig. 5). We repeated the experiment, but we were only interested in the delay until the hormones return to the homeostatic regime. Figure 9 shows the results with the adaptive strategy and it can noted that the recovery time has been reduced.

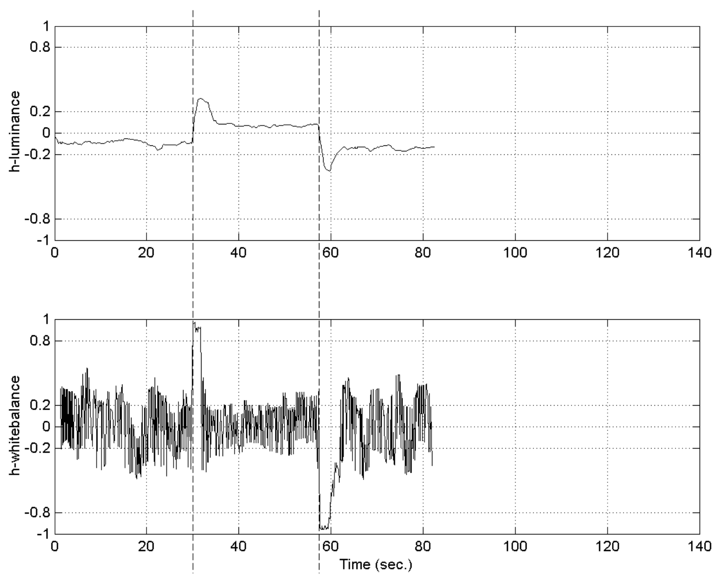

Fig. 9. Effects of the introduction of an adaptive strategy in the recovery time

4 Conclusions

In this paper, we have presented a homeostatic mechanism for vision systems based on the idea of emotion-based systems proposed by some authors. To carry it out, we have defined a set of artificial hormones related to the variables that affect the quality of the image as the luminance, white balance or contrast. To compute the values of the hormones we implement a sigmoid mapping so all the hormones have the same range of values independently of the variables they are computed from. This fact have permitted to implement simpler control strategies.

To compute the controlled variables we have implemented some techniques and we have introduced 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 task we have found that the introduction of the homeostatic mechanism reduces the effects of the changes in the lighting conditions in the rate of detected faces. Besides, the definition of two recovery threshold for the hormone values has permitted to implement an adaptive recovery strategy that decreases the time needed to achieve the homeostatic regime when the environmental conditions vary.

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