A Homeostatic-Adaptive Approach for Controlling Robotic Systems ⋆

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Extended Abstract

In this work, we present a hybrid mechanism for controlling a mobile robotic system which combines concepts from homeostatic control and adaptive behavior. The homeostatic control is inspired by an emotional approach consisting of a set of artificial hormones [2] computed from pre-categorical sensory data and also from high-level application results. The adaptive behavior is implemented by a fuzzy controller whose rules dynamically modify several system parameters, using the same structure to control both low-level hormonal loops and high-level application tasks. The objective of this proposal is twofold: guarantee an acceptable image quality keeping the perceptual data into a homeostatic regime, and use the adaptive behavior to obtain a better resource management and dynamic response.

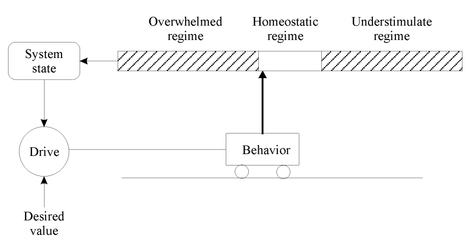

Fig. 1. Homeostatic regulation mechanism

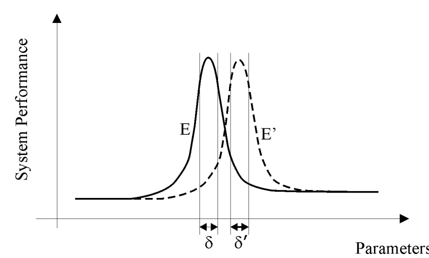

Fig. 2. Set of camera parameters

In Figure 1 the outline of a homeostatic regulation mechanism is shown. The state of the system is considered to fall into one of these categories: homeostatic, overwhelmed and understimulated. The objective is to keep the system in the homeostatic regime modifying its behavior toward this goal. In computer vision applications, for example, where the environment changes from a controlled conditions E to E' (Fig. 2) the performance of the system will be maximum for another set of camera parameters δ'. So if the system does not own a mechanism to detect the new environment, its performance will drop since 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 our proposal, the homeostatic regulation is based on different hormones: some directly obtained from the images (h_luminance, h_whitebalance) and others from the

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results of the visual task (h_size). The h_luminance hormone, for example, is computed from the luminance of the image by dividing the image into five regions similarly to the method proposed by Lee et al. [3].These five regions allow us to get different AutoExposure (AE) strategies according to the nature of the object of interest giving different weights to the average luminance in each region. For computing the h_whitebalance hormone we adopt the *Grey World* [4] assumption which tries to make the average amount of green, blue and red in the image equal, by adjusting the gain parameters.

At low level, control loops should be coordinated to take into account interdependencies, as several homeostatic loops executing simultaneously can produce side effects on each other that make the settling times larger than if execution sequence is supervised. In other cases, simply it makes not sense executing some loops when others are far out from their desired regime values (e.g. focusing on a very dark image).

On the other hand, active-vision [1] and mobile robotic applications are usually implemented as a set of multiple periodic tasks executing concurrently on limited resources systems. If not properly managed, this contention could lead to poor performance, threatening system security or even blocking its operation, when competing by CPU time, for example [5].

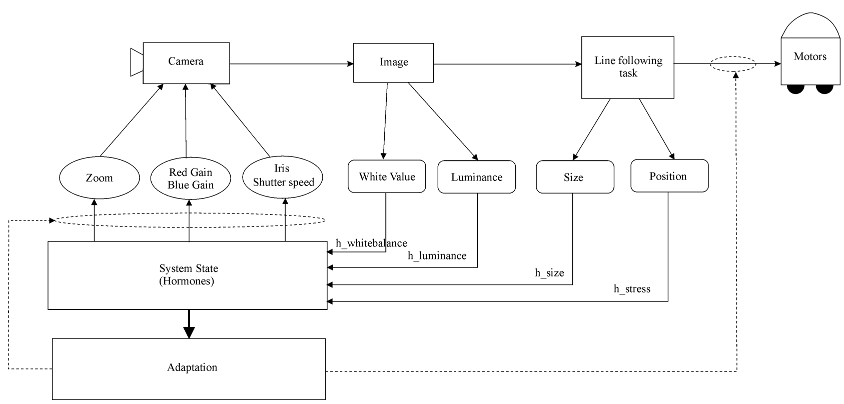

Fig. 3. Elements of the homeostatic adaptive regulation mechanism

As a consequence of this analysis, the basic homeostatic control described previously has been complemented with a higher level adaptive control in order to improve performance and also to fit the special characteristics of mobile robotic systems. We have designed a fuzzy adaptive control based on the configuration of each task in the system as a periodic process, with a desired frequency of operation to be respected whenever possible. A set of fuzzy rules take inputs from hormonal system to produce commands that can modify execution parameters. To make the control effective two types of actions are generated from fuzzy rules: quality and frequency commands. The quality signals force the output generated by a task to have a certain quality level, implicating normally a variation in the resource consumption. The frequency signals command new operation periods to the tasks, allowing also a modification on resource demands.The figure 3 shows the control scheme combining homeostasis and adaptation.

Several tests have been performed to evaluate the correct operation of the homeostatic-adaptive mechanisms on a real mobile robotic application. The goal is to follow a line traced on the floor under different lightning conditions making of two hormonal drives regulating simultaneously luminance and white balancing hormones from the image. At high-level, a control loop carries out the line following task processing the image from the camera stabilized by the hormonal loops. A “stress hormone” is computed as a function of the trajectory curvature. For the hormones the homeostatic regime is defined in the range [-0.2,+0.2].

Three sets of fuzzy rules have been defined in the adaptive controller. A “relaxation rule set” reduces the frequency of the hormonal loops when they are inside its homeostatic regime. An “image quality rule set” slows down robot motion and degrades high-level tasks when image hormones are far from their desired values. When stress hormone increases, a “stress rule set” is used to guarantee robot security, as it is approaching a curved zone.

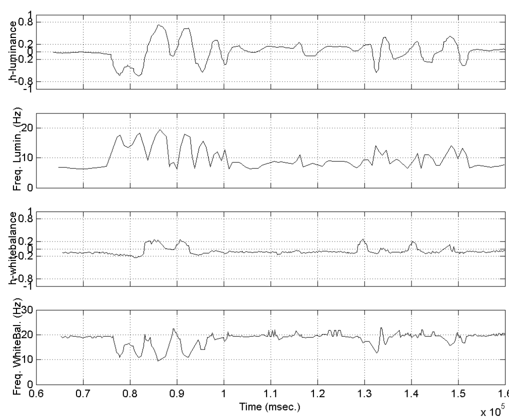

Fig. 4. Example of homeostatic-adaptive control - Internal hormones

Figures 4 and 5 show some data extracted from a test performed on an circuit consisting on two straight parallel segments connected by curved sections on both ends. The collected data correspond to a complete lap around the circuit. Lightning varies along the path, with a specially dark area near the beginning due to the existence of a kind of tunnel that the robot must traverse, so that, without homeostasis the task fails.

In Figure 4, the luminance hormone values are represented together with execution frequency values for luminance and white balance loops. As it is shown, when luminance hormone separates from homeostatic regime, luminance loop runs faster to recover image quality as soon as possible, while white balance becomes slower. This effect is specially relevant when traversing the dark zone, between seconds 75 and 100.

In homeostatic regime, white balance is allowed to execute at a higher frequency while luminance loop gets relaxed, for example when the robot is on first straight segment and first curve (seconds 100 to 125).

Figure 5 shows the stress hormone values, its effect on high-level task quality and the translation on an execution command affecting translational velocity. As we can see, the curved sections of the circuit provoke an increase in stress level that reflects in a reduction on robot velocity, for example when approaching and traversing first curve between seconds 105 and 130. At the middle of dark zone the robot near stops, waiting for the recovering of image quality by hormonal loops.

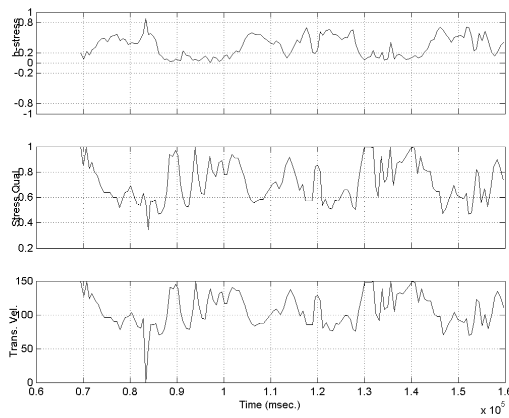

Fig. 5. Example of homeostatic-adaptive control - Application hormone

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