# A Proposal of a Homeostatic-Adaptive Control for a Robotic System

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# A Proposal of a Homeostatic-Adaptive Control for a Robotic System*

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## Abstract

In this work, we present a hybrid control structure for a mobile robotic system which combines concepts from homeostatic control and adaptive behavior. The homeostatic control consists of a set of control loops operating on state variables. These variables are 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 homeostatic 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. To validate this proposal we have carried out some experiments using a mobile robot which performs a line following task under variable lighting conditions.

## 1 Introduction

Most of living beings are endowed with internal regulation mechanisms to keep what Ashby named as essential variables [3] within physiological limits. This equilibrium state is normally related to the survival of the organism and is generally referred to as homeostatic regulation.

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 understimulated. 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* which take as inputs the variables to control and their desired values modifying accordingly the behavior of the system to restore the homeostatic regime.

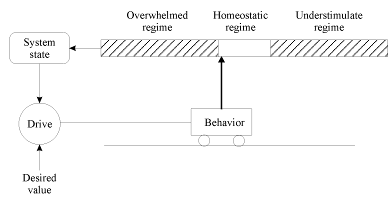


Figure 1: Homeostatic regulation mechanism

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 tempera-

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ture. A similar idea is proposed by Hsiang et al. [10].

In the neurophysiological field, 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 primary or innate emotions as homeostatic regulation has been used by some other authors. Velasquez [13], 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.

The works reviewed above are mainly related to robotics since robots possess elements (effectors) to act on the environment. However, since the introduction of the Active Vision paradigm [1], 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 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 always get the best performance.

Some important considerations must be taken into account when putting homeostatic regulation into practice. Initially, an homeostasis control system can be configured as a set of independent drives or control loops operating at a predefined frequency. However, in practice the execution of some loops can affect others requiring certain level of coordination to avoid undesired effects. On the other hand, active-vision and mobile robotic applications are usually implemented as a set of multiple periodic tasks executing concurrently on limited resources systems [7, 5]. 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 [12]. A worst-case off-line analysis is a typical solution for guaranteeing response times in hard real-time systems with perfectly calibrated tasks. This alternative, however, is not feasible for soft real-time applications, where system resources become most of time infra-utilized leading to low performance. So, there is a need for high-level adaptation control rules that permit a smooth degradation of system performance when available resources are not enough to respond to system demands, and a controlled recovering to nominal values whenever possible. Some alternatives that have been proposed for adaptation include any-time processing scheme [14], imprecise computation [9] or variable frequency [6].

In our context, adaptation should deal with several aspects such as low-level homeostatic loop coordination, inter-level coordination, priority-based degradation, resource management (CPU processing time, memory, energy), etc. Additionally, we have try to design an adaptive control that manages uniformly both low-level homeostatic loops and high level application tasks. The solution adopted takes the form of a prioritized fuzzy rule controller that operates on state variable values and errors to generate execution parameters configurations as outputs.

This paper explores the introduction of a homeostatic regulation mechanism, described in section 2, for an active-vision robotic system. This basic control is complemented with a high-level hierarchical adaptive control that will be presented in section 3. Section 4 illustrates the experiments that have been carried out on a mobile robotic platform equipped with an on-board color camera performing a simple line following task under varying lighting conditions. Finally the conclusions are outlined.

## 2 A homeostatic regulation for a robotic system

The performance in most of the computer vision systems relies heavily on the quality of the images supplied by the acquisition subsystem. 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 $\delta$ is the one which maximizes the performance of the system under the environmental conditions $E$ (solid line). If the environment changes to $E'$ (dashed line), for example due to different lighting conditions, the performance of the system will be maximum for another set of camera parameters $\delta'$. 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 $\delta$, and we must rely on an external agent to readjust the parameter set to $\delta'$.

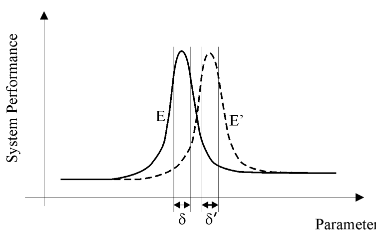


Figure 2: System performance vs camera parameters

In section 1, we have presented the concept of homeostasis 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 environmental conditions change, endowing the vision system with a homeostatic regulation mechanism. In a vision system, changes in the environmental conditions affect the quality of the acquired image. For example, if the temperature of the light source varies, the white balance changes. Thus, the homeostatic regulation tries to compensate for these effects on the image quality making use of the configurable parameters of the camera (iris, focus, zoom, white balance, ...).

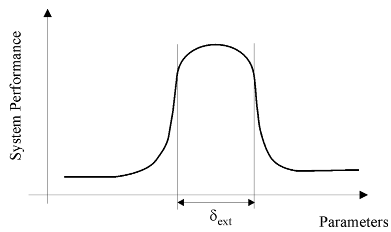


Figure 3: System performance with the introduction of the homeostatic regulation

Taking the performance-environment analysis (Fig. 2) up again, the effect of introducing the homeostatic regulation mechanisms in the system can be seen as a spreading of the range of admissible environmental conditions (Fig. 3). In this extended range, the system will be able to give an acceptable performance without the aid of external assistance.

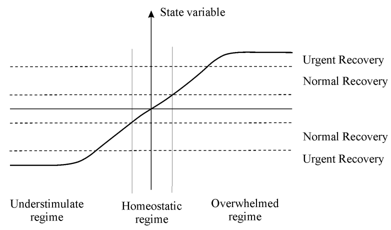


Figure 4: Mapping of the difference between desired and real value of the state variable

Due to the variability of the different measures, we have introduced a normalization phase to get the error value into the range [-1,+1], making use then of a sigmoid function (Fig. 4) to map error and recovery actions. With the error value restricted to [-1,+1] we can define the same recovery threshold for all the state variables independently of the nature of the measure they are computed from. Five different regions have been defined according to the error value: a homeostatic region, two recovery regions and two urgent recovery regions.

The split of the recovery region into two different ones will allow to implement a discretized proportional control strategy, giving more strength to control action when the error value is in the urgent recovery region than when in the normal recovery region. In this work, the homeostatic regulation is based on two state variables directly obtained from the images (*h_luminance* and *h_whitebalance*). This variables will be referenced as homeostatic variables which reflect the internal state of the vision system.

**Luminance** The *h_luminance* homeostatic variable is computed from the luminance of the image by dividing the image into five regions: upper (upper region ) and lower strip (lower region) and the central strip divides into three regions (left, central and right region); similarly to the method proposed by Lee et al. [8].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.

**White Balance** For applications based on color it is necessary to have a certain constancy because depending on the color temperature of the light source the same color appears different in the image. This situation can be dealt with using 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* [11] assumption which tries to make the average amount of green, blue and red in the image equal, by adjusting the red and blue gain parameters.

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. In some cases, this can be achieved by using a proportional controller as it was commented earlier. When the local solution is not enough, it is necessary to give less priority to other tasks. To accomplish this, we have used a high-level adaptive behavior, that will be described in the following section.

## 3 Adaptive control

The basic homeostatic control described previously has been complemented with a higher level adaptive control in order to both improve performance and fit the special characteristics of mobile robotic systems. On one hand, the homeostatic regulation loops precise an external supervision to avoid undesirable results. 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 extend settling times. In other cases, it simply makes not sense executing some loops when others are far out from their desired regime values (e.g. focussing on a very dark image). Additionally, some high processing level tasks depend on the stabilization of the homeostatic level to produce valid results, so their execution should be conditioned to this situation.

On the other hand, targeting mobile robotic systems implies that adaptive control must deal with a multiple-task shared-resource system. The global system operation normally requires the execution of multiple homeostatic control control loops as well as high-level application tasks concurrently. In case of resource shortage, low priority tasks have to be slowed-down or postponed, releasing resources for higher priority tasks. Another interesting policy that we can implement in our adaptive controller is a relaxation behavior to save resources when variable levels are inside homeostatic regime.

As previously sketched in the introduction, multiple objectives are pursued with the addition of adaptive control. The most relevant are the following: homeostatic loop and inter-level coordination, shared resource management, uniform multilevel structure and priority-based control. We will analyze these characteristics here in more detail. The figure

5 shows the control scheme combining homeostasis and adaptation.

### 3.1 Fuzzy control implementation

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 homeostatic system and state variables 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.

At high-level we can define some variables to module the performance of application tasks using the same adaptive scheme than for homeostatic loops. These variables have normally the purpose of characterizing environmental situations that should influence execution parameters.

#### 3.1.1 Control objects

The adaptive control scheme is implemented in terms of a set of four objects: controller, rules, inputs and loops. The *Controller* represents the basic object of the control system. It contains a set of rules that define the control strategy and a method to fuse the actions generated by each rule to obtain the resulting command. Some fusing methods that have been implemented are highest priority times certainty product and averaged command weighted by priority and certainty.

The *Rules* take the form of fuzzy implications with conditions on system inputs as antecedents, and actions on system tasks as consequents. A rule is characterized by a priority value and a method to combine the certainty of each premise to give the certainty of the rule (minimum, mean, product). Additionally, the action part is defined by the type of control action and its target either static (list of tasks) or dynamic (most CPU-demanding, most power-consuming, lowest priority, etc.).

The *Inputs* constitute storing objects to register system perceptions keeping a circular buffer with latest readings. Several input types have been considered: homeostatic variable value, homeostatic error and high level state variables. Additionally, different acquisition methods for recovering input data are available, including latest value, n-average, maximum, etc.

The *Loops* objects keep an internal representation of the different tasks in the system. Each task is characterized by a set of parameters including priority, base frequency, power consumption index or CPU load.

#### 3.1.2 Control structure

The control structure is organized hierarchically in three main areas, listed in increasing priority order: coordination of homeostatic control loops, adaptation to controllable variables and adaptation to external variables.

These areas have been introduced to meet the previously described requirements imposed on system behavior. Combined with control objects resources, they provide an effective and highly configurable framework for adaptive control. Some examples can help to illustrate these control areas in operation. When a homeostatic variable is out of its desired value some other loops can be worthless. An example is white-balancing when the scene is really dark. In this case, a coordination fuzzy rule can condition the frequency of operation of the white-balancing loop to the stability and zero error of the luminance loop.

The CPU load is a controllable variable that depends on the frequencies and individual CPU load of each executing loop. In time-pressured systems, when a maximum load is reached frequency and quality degradation orders can be commanded from adaptive rules on system tasks to reduce computing demands. Acceptable load reference levels can be established and modified dynamically, while target

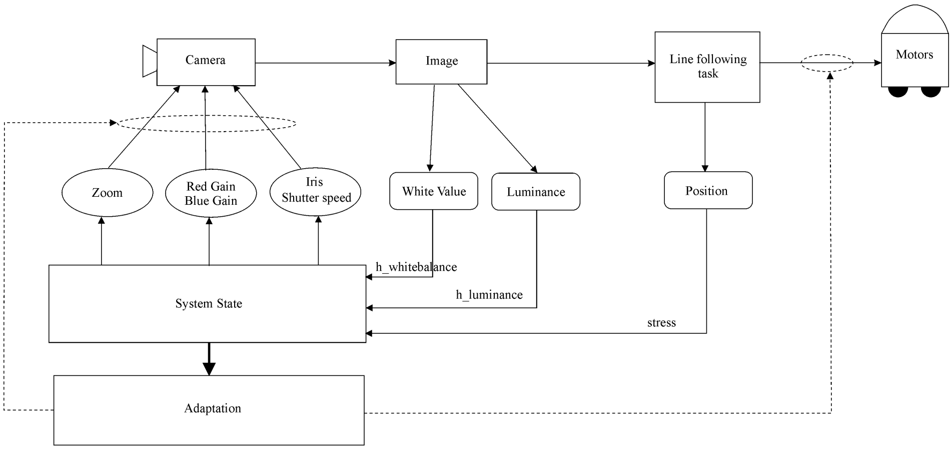


Figure 5: Elements of the homeostatic adaptive regulation mechanism

selection takes into account priority and CPU load as primary factors.

The battery level is an example of external variable that forces a monotone degradation on system performance. In energy-pressured systems, a high priority rule should command adaptation orders on tasks as available power decreases. In this case, target selection is mainly driven by priority and power consumption factors.

Different target selection methods and input acquisition procedures can be combined to modify the behavior of the adaptive control. An increase on input buffer depths, for example, makes the system more cautious when recovering from degraded situations but also less reactive. The extension of the dynamic target scope, on the other hand, makes the system less selective and intensifies the control actions, at the risk of provoking oscillations.

## 4 Experiments

Several tests have been performed to evaluate the correct operation of the homeostatic-adaptive mechanisms on a real mobile robotic application, using a Pioneer robot as a base platform. The goal is to follow a line traced on the floor under different lightning conditions (figure 6). 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.

Figure 6: Experimental setup

The application consists on two homeostatic loops regulating simultaneously luminance and white balancing variables from the image. At high-level, a control loop carries out the line following task processing the image from the camera stabilized by the homeostatic loops. The homeostatic regime is defined in the range [-0.2,+0.2].

An additional state variable, *stress*, is computed from high level visual task. The *stress* variables tries to alert the robot on dangerous situations. This variable is influenced by three factors: the length of the line in the image, its angle and its displacement with respect to the center of the image x-axis. When some of these factors is unbalanced the robot decreases its translational velocity to recover the equilibrium state.

Three types of fuzzy rules have been defined in the adaptive controller:

**Relaxation** Homeostatic loops relax their frequency of operation when the variable value is inside its homeostatic regime. Here is an example:

```
if Error(h_lum) is ZERO
and Error(h_wbal) is ZERO
then DegFreq(loop_lum, loop_wbal)
```

**Image Quality** When homeostatic variables related to image quality are far from their desired values, high-level task is degraded slowing-down robot motion and thus more computational resources are reserved for homeostatic loops.

**Warning** When stress variable increases, a quality degradation rule is used to guarantee robot security, as it is approaching a curved zone.

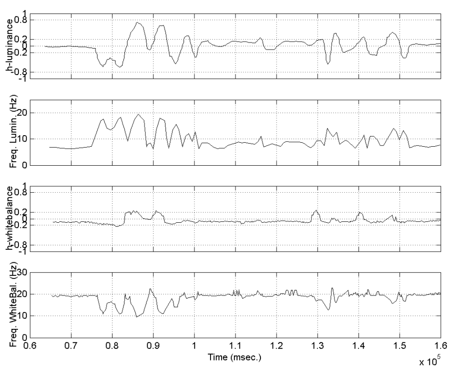


Figure 7: Example of homeostatic-adaptive control - Homeostatic variables

Figures 7 and 8 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 of the path due to the existence of a kind of tunnel that the robot must traverse, so that, without homeostasis the robot task fails.

In Figure 7, the luminance value is represented together with execution frequency values for luminance and white balance loops. As it is shown, when luminance value 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 8 shows the stress value, 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 homeostatic loops.

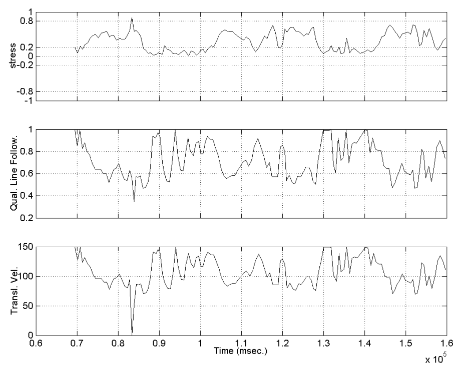


Figure 8: Example of homeostatic-adaptive control - High level variable

## 5 Conclusions

We have presented a hybrid homeostatic-adaptive control for robotic systems and its implementation on a real platform. The introduction of the homeostatic regulation mechanism improves the performance of the active-vision system, as the mean quality of the sensor data increases in dynamic environments. The combination of this low-level adaptation mechanism with a high-level fuzzy adaptive control has exhibited a better outcome under variable run-time conditions. This combination allows for a common approach for both high and low level control. In consequence, as illustrated in the experiments, we get a highly-configurable control framework that improves the system performance and extends its range of operation.

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