Fuzzy Controller for Dynamic Vergence in a Stereo Head

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Abstract

The control of vergence behavior has become an essential component of any active vision system. In this paper we propose a new fuzzy controller which operates on a set of correlation measures obtained from a multiresolution representation of the image. Real-time experiments have been conducted on a mobile robot endowed with a 3 d.o.f. stereo head. We present encouraging results over different real world scenarios.

1 Introduction

Eye movements are an essential aspect of visual perception in biological visual systems. The ability to stabilize the retina with regard to the outside world is crucial to effective vision. Many vertebrates are endowed with gaze stabilization and gaze shifting mechanisms that guide them in their interaction with their dynamical environment [1]. As in living organisms, visual system in robots should incorporate motor capacities to achieve effective adaptation of their sensors in relation to the changing world.

In recent years, computer vision community has begun taking interest in the role of action in visual perception. Among other approaches, active vision [2][3] and animate vision [4] have opened new research lines emphasizing the importance of action in visual perception.

The main motivation of our work is the exploration of dynamic relationships between perceptual and motor processes. Our approach is founded on the idea that a robot and its environment form a dynamical system where balanced and unbalanced situations alternate. This changing situation should affect the robot behavior in such a way that perceptual and motor processes co-operate to reach an effective interaction with the environment. From this view, we are working on the modeling of oculomotor processes in a mobile robot endowed with a stereo head. In this paper, we focus on the development of a vergence control system.

Several techniques have been proposed dealing with the vergence control problem [5][6][7]. Our approach mainly differs from them in the use of fuzzy reasoning to drive the control. This technique provides a simple way of describing the system behavior, allowing a real-time implementation with low computational cost.

In 1963 Zadeh points out that the precise defined mathematics of functions, points, sets, etc. difficult the study of biological systems. He suggests "the mathematics of fuzzy or cloudy quantities which are not describable in terms of probability distributions" [8]. In 1965 introduces the fuzzy subset concept [9], allowing Mamdani and Assilian to implement, in 1975, the first fuzzy controller [10]. Since then there have been numerous fuzzy control theory and application studies [11].

To design a fuzzy logic based control it is necessary to define a complete map of input/output variables. This map consists on a set of fuzzy conditional rules implemented via a linguistic reasoning about the causal relation between one input fuzzy partition region and its logical/causal output. In the particular case of a PI type controller the rules have the following typical form: IF (e is PH) AND (Δe is NM) THEN Δu is PL, we can read so: if the error is positive high and the derivative of the error is negative medium, then the derivative of the control signal must be positive low. For the rule system to be complete it is needed to design NM rules, being N the number of fuzzy sets of the fuzzy partition over e, and M the number of fuzzy sets of the fuzzy partition over Δe. From this it follows that the number of rules grows exponentially with the number of variable inputs. Some mathematical strategies have been proposed to reduce this complexity, as for example decomposing the system in subsystems of lower dimensionality [12].

We propose in this work a new strategy to cope with this problem. The final controller will have a $3N$ order linear complexity. To do this two fuzzy rule subsystems must be designed: the first one of N rules whose output is the amplitude of the control signal, and the second one of $2N$ rules whose output is the sign of the control signal.

The paper is organized as follows. Section 2 describes the general strategy employed for our vergence system. In section 3, the proposed controller is presented in detail. The outcomes obtained from several real experiments are shown in section 4. Finally, section 5 summarizes the main conclusions of this paper.

2 Vergence Control

Vergence movements are crucial in human vision. They allow fixating regions of interest in the visual space, providing a mechanism for tracking visual targets as they vary in distance from the observer [1].

A vergence control system must provide a stable binocular fixation and a smooth and accurate response to changes in the environment. The design of a control strategy for such a system has to take into account these two factors in the definition of the input signals that will drive the system behavior. Binocular fixation can be quantified using a similarity measure of the images captured by the cameras. Changes in the environment can be detected by changes in time of that similarity measure. Therefore vergence control can be guided by two input signals: a similarity measure and its derivative.

To compute the degree of similarity between the two images, the normalized correlation coefficient [13] has been used. The main property of this index is its invariance to changes in brightness between the two cameras, which makes it suitable for our application. This correlation coefficient is defined by the following expression:

$$C = \frac{1}{2} + \frac{\sum_{i,j}(I_r(i,j) - \overline{I_r})(I_l(i,j) - \overline{I_l})}{2\sqrt{\sum_{i,j}(I_r(i,j) - \overline{I_r})^2 \sum_{i,j}(I_l(i,j) - \overline{I_l})^2}} \quad (1)$$

where I_r and I_l are the images to be compared and $\overline{I_r}$ and $\overline{I_l}$ represent their mean gray level values.

The coefficient of equation 1 takes values in the rank $[0, 1]$, where a correlation value of 1 indicates the equality of the compared images. To exploit the complete rank of this coefficient, once the measure is obtained, it is normalized by the expression of equation 2, being c_{min} and c_{max} the minimum and maximum correlation values estimated from previous measures.

$$c(k) = \frac{C(k) - c_{min}(k)}{c_{max}(k) - c_{min}(k)} \quad (2)$$

The function of vergence movements is the fixation of a target in a central subregion (called fovea in biological vision) of both image planes. Hence, vergence control can be treated as a problem of maximization of the correlation coefficient measured over a central window of the two images. Now then, the right size of that central window is dependent on the properties of the visual world, which makes it necessary the control of a new parameter: the size of the correlation window. Our proposal for this problem is based on the use of multiresolutional image decomposition [14]. The main idea of this approach is selecting a resolution level for the correlation window, instead of controlling its size. This method requires the formation of a hierarchical structure composed by subimages of fixed size extracted from the original image at different scales. Figure 1 shows this idea.

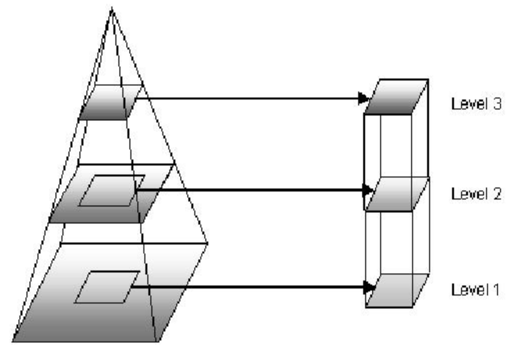

Figure 1: *Multiscale structure formation*

This multiscale scheme allows extracting information of the binocular fixation at different extents of the visual space. It gives the possibility of contrasting the correlation values of the different levels, providing a mechanism for estimating accurately the goodness of the current vergence position. To exploit the features of this scheme, each level must act according to a global measure of correlation. Our studies have been centered on a selection method based on the mean value of the correlation coefficients of every level. This global index determines which level is the most suitable for guiding the control taking into account the following remarks:

- High levels are less sensitive to small changes of vergence, providing a smoother correlation function than low levels (figure 2). It makes them suitable for low mean correlation values, since they allow avoiding local maxima that may appear in the correlation function of low levels.
- Low levels present higher values than subsequent levels at the global maximum of their correlation functions (figure 2). They give more precise information about the right vergence position and hence they must act for high mean correlation values.

From these remarks, the proposed selection method has been design to associate low mean correlation values to high levels of the multiscale structure and high mean values to low levels. Once

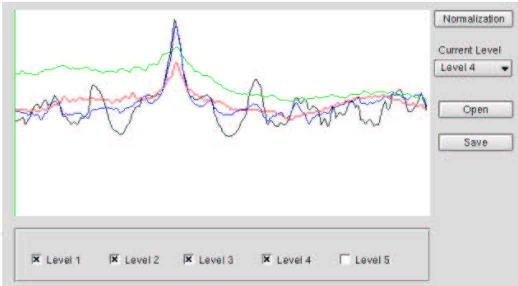

Figure 2: *Correlation value at different vergence angles obtained from a real scene. Dark lines correspond to low levels of the multiscale structure and light lines to high levels*

the current level has been selected, the correlation coefficient (referred to as c) and correlation derivative (labeled as Δc) for that level act as the input variables of the system. These signals are then used by the controller to produce appropriate changes ($\Delta\theta$) in the vergence angle θ (figure 3).

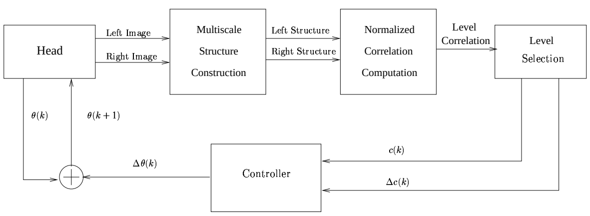

Figure 3: *Vergence system scheme*

3 The Controller

Conventional control theory is based on the construction of a mathematical model of the target system from the observation of their characteristics. For our application, such a mathematical model is very difficult to articulate because of the variability of the visual world. On the other hand, fuzzy systems have the ability to realize a complex nonlinear input-output relation through multiple simple input-output relations, supplying a simpler way of describing the system behavior. Exploiting the advantages of this kind of systems, we propose a fuzzy vergence controller, structured as it is shown in figure 4.

The proposed system computes changes in the current vergence angle (3) as result of the product of two signals, a and s (4). The first signal is the amplitude of the vergence change, i.e. it indicates how much the current vergence angle should be modified to reach the target position. The other one is a sign signal which provides the direction of the movement (convergent or divergent). This signal is obtained dynamically through the expression of equation 5, being δs

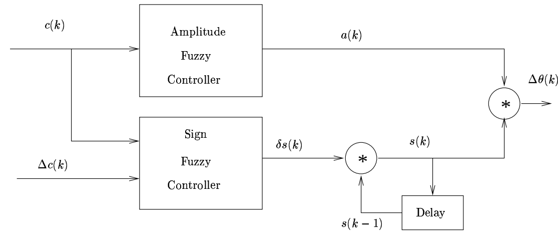

Figure 4: *Vergence controller scheme*

another signal that indicates the necessity of change in the direction of the movement.

$$\theta(k+1) = \theta(k) + \Delta\theta(k) \tag{3}$$

$$\Delta\theta(k) = a(k) * s(k) \tag{4}$$

$$s(k) = \delta s(k) * s(k-1) \tag{5}$$

Both amplitude (a) and change in sign (δs) signals are modeled by two fuzzy controllers. Their designs require the definition of a set of fuzzy rules and the assignment of a control value (consequent) to each resulting rule. To allow a smooth control, each fuzzy set has been designed to overlap adjacent areas at a certain degree. Outputs of both controllers have been determined applying the simplified fuzzy reasoning method [15]. Next subsections detail these design steps for the two fuzzy controllers of our vergence system.

3.1 The Amplitude Fuzzy Controller

The amplitude of the signal $\Delta\theta$ is a function of the current correlation value. Therefore, the different fuzzy rules (C_j) acting in the amplitude controller have to be defined according to a set of fuzzy values of the variable $c(k)$. Fuzzy sets C_j have been designed of triangular type as figure 5 shows, where c_j follows the relation of equation 6, with $c_1 = 0$, $c_N = 1$ and $k_c > 0$.

$$c_j = c_{j-1} + k_c(c_{j-1} - c_{j-2}) \tag{6}$$

The design of the consequent parts, i.e. the selection of a control value associated to each rule area, has been carried out under the assumption that the higher the correlation value is, the closer the current position is from the target. Thus, the output of each rule has been chosen taking into account that its value has to be lower than the output value of the preceding rule and higher than the output associated to the following one. Moreover, if the current correlation value is high, the system should not modify the vergence position, since the target has been reached. This situation has to be expressed assigning an output value of

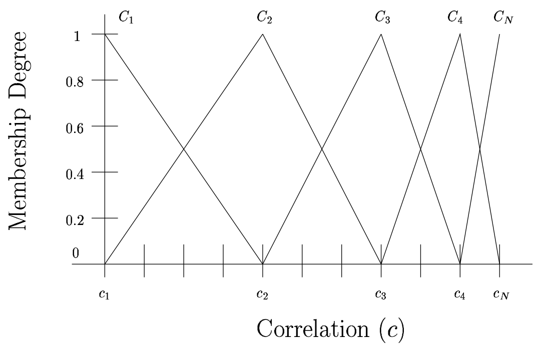

Figure 5: *Fuzzy sets for the variable c*

0 to the last rule. From these observations, we define the control output of each rule in the following way, being N the total number of rules:

IF c is C_j THEN $a = a_j$ $(j = 1..N)$

where a_j follows the relation $a_j = a_{j-1} + k_a(a_{j-1} - a_{j-2})$ with $k_a \in [0, 1)$, $a_1 = 1$, $a_N = 0$

To compute the final control output, each rule output a_i is weighted with its membership value h_{Ci}. Hence, the final output $a(k)$ is obtained as:

$$a(k) = A_{MAX} \sum_{i=1..N} h_{Ci}(c(k))a_i \qquad (7)$$

being A_{MAX} the maximum amplitude allowed for the change in the vergence position.

3.2 The Sign Fuzzy Controller

Appropriate changes in the direction of vergence movements can be determined by changes in the correlation value (Δc). In fact, if Δc is negative, it can be deduced that the system is moving away from the target position, which should induce a change in the current direction. However, depending on the current correlation value, a negative value of Δc can be interpreted as a jump from a local maximum of the correlation function. If this situation is detected, the system should maintain the direction of the movement, since the preceding position is not the target position. According to this second idea, the control of changes in the sign of the signal $\Delta\theta$ requires information about the state of two variables, the correlation coefficient (c) and its variation in time (Δc). From this remark, the set of rules acting in the sign fuzzy controller and their associated outputs have been design in the following way:

IF (c is C_j) and (Δc is D_{j1}) THEN $\delta s_{j1} = -1$

IF (c is C_j) and (Δc is D_{j2}) THEN $\delta s_{j2} = 1$

Fuzzy sets D_{j1} and D_{j2} are of trapezoidal type as figure 6 shows, where d_j follows the relation $d_j = d_{j-1} + k_d(d_{j-1} - d_{j-2})$ with $d_0 = -1$, $d_N = 0$, $k_d \in [0, 1)$.

From the membership value of c (h_{Ci}) and Δc (h_{Dij}) to each rule, the final control output is obtained by the following expression:

$$\delta s(k) = sign(\sum_{i=1..N} \sum_{j=1,2} h_{Ci} h_{Dij} \delta s_{ij}) \qquad (8)$$

where $sign(x)$ is defined as: $sign(x) = 1$ if $x \geq 0$, $sign(x) = -1$ if $x < 0$

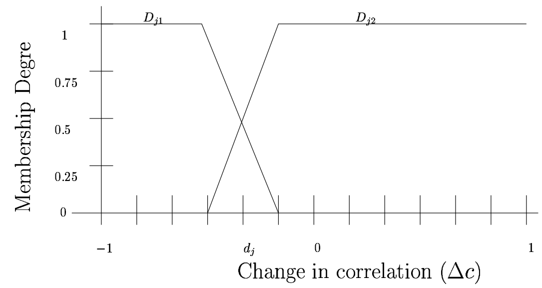

Figure 6: *Fuzzy sets for the variable Δc*

4 Experimental Results

The proposed vergence system has been proved in a mobile robot endowed with a stereo vision head (figure 7). The vision platform consists of a three degrees of freedom binocular head with digital vision sensors (Sony DFW-VL500). On the mobile platform, it has been placed a double rack containing the control hardware and a PC mainboard that runs the system software.

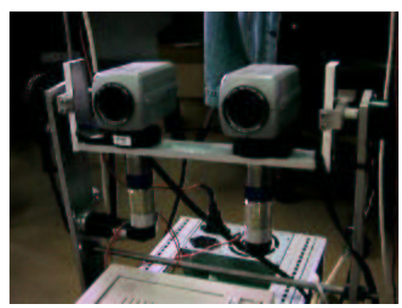

Figure 7: *Robot used to carry out the experiments*

To show the performance of the proposed vergence system at different situations, several real experiments are described in the next sections. In all the experiments, five fuzzy sets have been used for the correlation coefficient and values of 2/3, 1/2 and 1/2 have been chosen for k_c, k_a and k_d. Also, the multiscale structure has been constructed using four levels.

4.1 Vergence on a Motionless Target

The aim of this experiment is to test the stability of the system when no external changes occur. The results obtained are shown in figures 8 and 9. The evolution of the system during several frames is depicted in the graph of figure 8. The three curves plotted show the correlation coefficient of the active level (black line), the mean correlation value of the multiscale structure (dotted line) and the vergence angle normalized between 0 and 1 (gray line). Figure 9 shows the multiscale structure extracted from right and left images at initial frame (two first rows of images) and at frame 40 (two last rows of images).

From the curve of the vergence angle, it can be seen the stable behavior of the system at a motionless situation. Once the target is reached (approximately at frame 40) the vergence position is maintained with little variations.

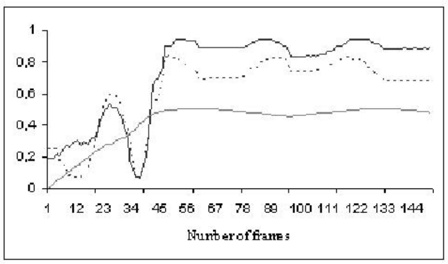

Figure 8: *Current level correlation value (black line), mean correlation value (dotted line) and vergence angle (gray line) for the first experiment*

Figure 9: *Right and left structures at initial frame (two first rows) and at frame 40 (two last rows) for the first experiment*

4.2 Tracking Moving Target

This second experiment shows the system behavior when the target is slowly moving nearer and away from the robot (figures 10 and 11). Results were obtained from the following situation: the target starts moving away from the robot approximately at frame 40. At frame 265, it begins getting closer and stops at frame 500.

Vergence curve of figure 10 shows the smooth evolution of the system to achieve the tracking of the target position. As it can be observed in this graph, the controller generates correct responses to the different changes in the correlation value.

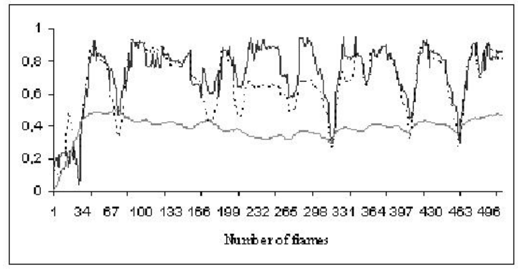

Figure 10: *Current level correlation value (black line), mean correlation value (dotted line) and vergence angle (gray line) for the second experiment*

Figure 11: *Right and left structures at frame 40 (two first rows), at frame 235 (two second rows) and at frame 490 (two last rows) for the second experiment*

4.3 Response to Sudden Depth Changes

The last experiment shows the reaction of the system to sudden changes in depth (figures 12 and 13). Initially, the robot is situated in front of a table 4 meters away. At frame 20, it verges to the right position, maintaining a correct configuration until frame 90, when an object invades the field of view. After 60 frames, the robot reaches the target. Finally, at frame 200, the object disappears and new vergence correction movements succeed to stabilize again at frame 250.

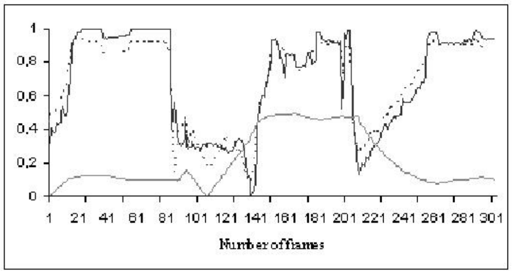

Figure 12: Current level correlation value (black line), mean correlation value (dotted line) and vergence angle (gray line) for the third experiment

Figure 13: Right and left structures at frame 25 (two first rows), at frame 160 (two second rows) and at frame 265 (two last rows) for the third experiment

5 Summary and Conclusions

Fuzzy control for the vergence problem offers two significant advantages: first, it facilitates the construction of a non linear control surface; second, it allows a very efficient implementation. The experiments conducted show that this approach can be effectively used as a building block to expand more complex oculomotor behaviors, such as gaze control and its interactions with natural dynamics of world and robot's body.

Acknowledgments

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