every 33ms. The platform then start tracking following the crude linear assumption. After about 20s of learning by tracking, the neural part of each controller becomes dominant. As shown by Figure 5, the variance of the visual error (quadratic sum of each coordinate) is significantly reduced in the right eye which is under adaptive control.

In Table 1, we show the standard deviation of the visual error with different setups. It clearly appears that the redundancy induced by the control of both the pan and the vergences is learned by the system as a nonlinearity. The residual visual error is mainly due to the 50 ms delay introduced by image acquisition and processing. Although the residual error may appear significant when evaluated in pixels, it never exceeds 2 degrees of angular error (conversion made using ESCHeR’s spatial resolution curve shown in Figure 3).

<table>
<thead>
<tr>
<th>Pan control</th>
<th>Vergence control</th>
<th>Std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not controlled</td>
<td>linear neural</td>
<td>80 22</td>
</tr>
<tr>
<td>Controlled</td>
<td>linear neural</td>
<td>50 13</td>
</tr>
</tbody>
</table>

Table 1. Standard deviation of the visual error during tracking experiments with various setups.

CONCLUSION

Whereas humans continuously learn, robots are traditionally rigidly preprogrammed. However, in case of nonlinearities and redundancies, the analytical determination of an efficient control law is not necessarily straightforward. Instead, a system that learns is potentially more capable. In this paper, we have described a modular control system based on feedback-error-learning that evolves in performance while operating: starting with a crude knowledge of its image-to-joint jacobian, ESCHeR, a gaze-platform equipped with highly distorted lenses, adapts its control while tracking a moving object. Prior random explorations are not necessary since the initial approximation guides the learning and ensures the asymptotic convergence of the control. The effectiveness of our system is shown through experimental results and without any prediction, a precision of 2 degrees is achieved.

This scheme is currently extended to address more complex active vision tasks. In particular, we intend to make both the stereo-head platform and a robot manipulator learn how to cooperate for detecting, tracking and grasping moving objects.

REFERENCES

are linear for normalizing. The hidden layer is nonlinear (arctangents). The modification of NNFC’s weights is performed by a Newton-like method.

Experimental results

Figure 4. Overall control architecture: each box is ruled by a feedback-error-learning scheme.

Figure 5. Tracking experiment after neural component has become dominant.

In our experiments, a bright object is swinging on a pendulum in front of ESCHeR. The target position is computed by a simple thresholding method and fed to the control box
EXPERIMENTAL FRAMEWORK
ESCHeR, the gaze-platform

Figure 3. ESCHeR: the vision head and its spatial resolution curve.

Designed for the purpose of studying active vision, ESCHeR (Figure 3) is a four DOF stereo-head consisting of:

- Four DC motors mounted with encoders allowing to drive pan, tilt and vergence for both cameras. Each joint is driven by the servo-controller, a transputer-based architecture which receives the asynchronous command issued from the FEL controller and converts it into a smooth, 500 Hz interpolated command for the motor.
- Two CCD cameras equipped with the human-like wide angle foveated lenses described in [2].

The redundancies between pan and vergence joint along with the high distortions of the lenses contribute to the high non-linearity of the image-to-joint transfer function.

Overall control architecture

As shown in Figure 4, our control architecture consists of a closed-loop in which the control box learns the image-to-joint transfer function. In order to reduce the complexity of the learning phase, each of ESCHeR’s four joints is independantly controlled by feedback-error-learning. Pan (respectively tilt) controller couples horizontal (respectively vertical) coordinates of both images. However, unlike animal vestibulo-ocular reflex (VOR) which stabilizes retinal images during head motion by generating compensatory (equal and opposite) eyes’s moves, pan and vergence controls are not explicitly bound. In our implementation, pan is controlled so that it minimizes the difference between left and right image horizontal coordinates. Optionnal inputs are externally computed image coordinates that correspond to a switch in the focus of attention. They are null in tracking mode.

Each CFC is a very crude linear controller with low gain (about $10^{-4}$ rads/pixel). This gain results from a tradeoff between (1) the convergence of each controller (the linear controller guides the learning of the adaptive feedback controller (NNFC)) and (2) the stability of the whole architecture (when gains are too high, delays may induce significant disturbances).

The neural controller consists of a three-layer network. Both input and output layers
Direct Inverse Modeling

Before being used as a feedforward controller, the inverse model is learned using the architecture shown in Figure 1. A set of motor commands is sent to the plant. The neural inverse model (NIM) receives the resulting position as its input. The difference between actual and NIM’s estimated commands is computed and used as a error signal for modifying NIM’s adaptive weights using a Widrow-Hoff rule (approximation of a gradient descent).

Feedback Error Learning [3]

The output of a conventional feedback controller (CFC) that models a linear approximation of the inverse-model, is propagated (dotted arrow in Figure 2) into a neural network feedback controller (NNFC) as the error signal. NNFC estimated motor command and CFC’s output are summed so that NNFC does not mimic CFC but rather acquires the nonlinearities of the plant.

Summary

The direct inverse modeling approach is very simple but exhibits critical drawbacks: (1) as far as we know, there is no mathematical guarantee that the model will follow the desired behaviour; (2) this is a two-stages approach (the inverse-model cannot be used during the training phase); (3) the choice of pertinent training sets is not obvious, especially when the transfer function is not unique (kinematic redundancies)[4].

Unlike direct-inverse-modeling’s approach, feedback error learning is achieved online. The convergence is proven (using German’s theorem and Lyapunov’s second method [5]) assuming (1) a guaranteed asymptotic convergence of the learning phase (role of the gain of the linear controller) and (2) a very small and positive-definite learning rate.

For the sake of flexibility and speed, we have chosen the feedback-error-learning approach to build a modular architecture. In the following section, we describe the overall control architecture after a brief presentation of the vision system.
A LEARNING STEREO-HEAD CONTROL SYSTEM

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ABSTRACT
Active vision tasks (such as tracking or saccadic moves) require gaze control which, in turn, depends on both the optical system and the mechanical structure. The knowledge of the image-joint jacobian is not straightforward and results traditionally from calibration procedures. Physiological studies have shown a real-time adaptation in humans’ visual system, that can be modelled by a feedback-error-learning (FEL) scheme. In this paper, we propose a FEL-based modular control system that makes a gaze-platform learn its control while tracking moving objects. The framework used to build the learning system is described along with experiments on ESCHeR - Etl Stereo Compact Head for Robot vision -. As far as the authors are aware, this is the first implementation of a real-time learning controller on an active vision system.

KEYWORDS: active vision, adaptive control, vestibulo-ocular reflex.

INTRODUCTION
For purposive robots in a complex and dynamic world, the most basic visual functions required are target detection, tracking and fixation. In order to address these issues, an active vision system based on a 4DOF gaze-platform equipped with foveated wide angle lenses has been recently implemented [1]. These so-called human-like lenses exhibit a wide field of view along with a space-varying resolution so that they facilitate both detection and close observation. However, the strong optical distortions (resulting from spatial varying resolution [2]) combined with the redundancies of the mechanical gaze-platform make an efficient control law difficult to be explicited. It is hence desirable to make the plant learn by itself the commands that produce satisfactory results.

LEARNING THE INVERSE MODEL
Finding the input that produces the desired output involves the knowledge of the inverse-model. In the following sections, we briefly describe two opposite approaches (direct inverse modeling and feedback error learning) and we justify our choice.