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Learning VOR-like stabilization reflexes in robots

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Abstract

We present a binocular robot that learns compensatory camera movements for image stabilization purposes. Most essential in achieving satisfactory image stabilization performance is the exploitation/integration of different self-motion information. In our robot, self-motion is measured inertially through an artificial vestibular apparatus and visually using basic motion detection algorithms. The first sensory system codes rotations and translations of the robot's head, the second, the shift of the visual world across the image plane. An adaptive neural network learns to map these sensory signals to motor commands, transforming non homogeneous self-motion information into compensatory camera movements. We describe the network architecture, the convergence of the learning scheme and the performance of the stabilization reflex evaluated quantitatively by means of direct measurements on the image plane.

1. Introduction

When moving through the environment it is of paramount importance to avoid degradation of visual functions. In humans and animals, degradation does not occur owing to an efficient image stabilization mechanism. In many species, visual stabilization is obtained through reflex eye movements and intriguingly enough, these movements are already present in the early period of the life [1]. The goal of the compensatory movements is to maintain the image on the retina stable, irrespective of the observer's movements. The brain circuitry responsible for this stabilization mechanism is the vestibulo-ocular reflex (VOR). One remarkable aspect of such circuitry is its plasticity, driven by any change which degrades image stabilization performance. Whatever the change, an error signal is created which informs the brain that the VOR is not working properly. As a result the system recalibrates itself [2]. This type of motor learning has been studied from different perspectives and models of the learning process and sites of learning have been proposed [3]. The neural region that seems responsible for these kind of recalibration is the cerebellum [4]. The gain of the VOR reflex is nominally 1.0 and it is kept close to this value by a parametric-adaptive control system [5].

In robotics, image stabilization techniques dealing with multi sensory integration have received little attention so far. Since a decade, a growing number of studies have concentrated on active control of camera movements [6], [7], [8], [9], [10], [11], [12]. Most of these systems are very efficient [13], [14] and perform well as static observers. Pursuit and saccades are the oculomotor control patterns that enable exploration, tracking and detection behaviors. It is worth noting that robust performance when the agent plays as static observer in a "structured" environment, could be completely disrupted when operating in "disturbed, non-structured" conditions. In others words, how much of the robot's performance would be modified in presence of external sources of disturbances? To what extent the programmed functionalities would fail if the vision system were onboard a vehicle moving on a rough terrain? What solution could possibly be envisaged to avoid the degradation of robot's visual functionalities? In fact, although many such systems have been engineered to a high level of performance, oculomotor control driven on the base of "pure" visual processing it is easily exposed to failure. Latencies and delays strongly degrades the robot's performance if the system has to face external unpredictable source of movements. On the contrary, oculomotor control architecture integrating inertial sensory information has the advantage to be more robust. Visual functionalities, like motion detection or time to contact, are kept unaltered even when external disturbances are present [15]. Tracking abilities do not degrade, saccades are more efficient, even in presence of external unpredictable movements [16]. Recently, Shibata and Schaal proposed an example of visuo-inertial integrated approach. Reproducing an accurate computational model of the biological VOR-OKR system, the authors show that a monocular robot can learn compensatory oculomotor reflexes fast and optimally [17]. On the other hand, optimal stabilization requires the system to account for fixation distance. In a previous work, dealing with geometric and computational issues, we have shown that optimal stabilization strategies (i.e. fine tuning of the oculomotor gains) can be implemented considering the geometry of the robot's binocular system (i.e. baseline, relative positions of eye and neck rotational axes) and the knowledge of actual gaze configuration (the gaze distance and direction) [16].

In this work we propose to embed in the system some of the required distance related knowledge through the learning of a sensory-motor map which codes adaptively oculomotor reflexes. A Growing Neural Gas (GNG) network interpolates two separate motion related sensory cues (i.e. the vestibular information and the retinal motion information) and adjusts its parameters to generate optimal motor commands. The result of the learning is the construction of a motor map which codes adaptively compensatory stabilization reflexes. The only basic assumptions made at the beginning of the learning process are that the robot must be able to compute some form of retinal slip and have access to inertial information.

2. Image stabilization: learning oculomotor control

A target ***T*** tracked or fixated by the robot is stable within its view when the image slip is equal to zero irrespective of the robot's motion. During a translation and rotation of the head ($\underline{\omega}_H, \underline{v}_H$), if we limit our attention to rotational movements of the head around a vertical axis, $\underline{\omega}_H = (0, \Omega_y, 0)$, translation along an horizontal axis in the fronto-parallel plane, $\underline{v}_H = (V_x, 0, 0)$, in order to keep the line of sights (hereafter indicated as ($\underline{g}_L$, $\underline{g}_R$) on the target ***T***, the kinematics of the eye-in-head velocity w_y gives for the left eye:

$$w_y = -\Omega_y - \frac{1}{|\underline{g}_L|}\left[\left(Cos\mu_L \cdot a + Sin\mu_L \cdot \frac{b}{2}\right)\cdot \Omega_y + Cos\mu_L V_x\right] \tag{1}$$

where the geometric parameters of the eye-head system (a,b), the fixation distance (i.e. $|\underline{g}_L|$) and the gaze direction (i.e. the vector $\hat{\underline{g}}_L$), which in Eq. (1) is simply expressed as the eye orientation with respect to head (i.e. μ_L angle), affects the counter rotation required to stabilize optimally. Surprisingly enough, for the simple case of rotation ($V_x = 0$), most of the quantities present in equation (1) are directly available to the robot. The angular velocity Ω_y can be measured through the vestibular apparatus, the camera gaze line $\hat{\underline{g}}_L$ through the motor encoders, the distance to the target $|\underline{g}_L|$ through binocular vergence control [16]. Instead of trying to combine these quantities to obtain a feed-forward control, we observe that optic flow as a function of observer movement [18] can be written as:

$$u_0 = f_x\left[-\frac{T_x}{Z(0,0)} - W_y\right] \tag{2}$$

where T_x represent the translation along the fronto parallel image plane, W_y the rotation around a vertical axis, f_x the focal length and $Z(0,0)$ the distance to the fixation point. By substituting the term W_y with the sum of the head velocity Ω_y and the eye velocity with respect to head w_y we have:

$$\frac{u_0}{f_x} = -\frac{T_x}{Z(0,0)} - (\Omega_y + w_y) \tag{3}$$

If we compare the second member of the latter equation with Eq.(1) (i.e. kinematics of stabilization) it is evident that a direct measure of optic flow provides an indication of the error that would be performed having initiated an incorrect compensatory eye movement. To a first approximation Eq.(3) also tell us that Ω_y and u_0 variables are the most indicated to learn to generate compensatory eye movement w_y for image stabilization. We have then envisaged the use of these two variables as independent inputs to a neural network which learns to approximate a control surface representative of the optimal compensatory command w_y as given by Eq. (1).

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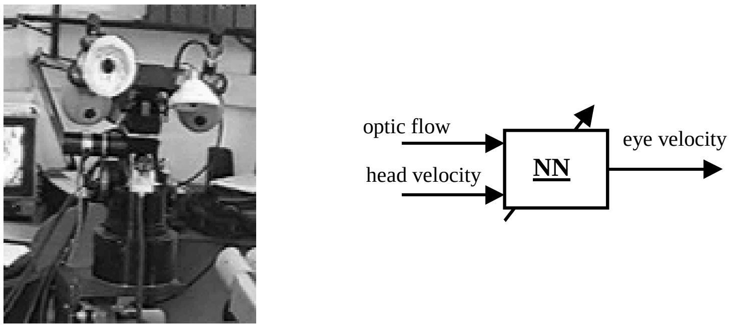

Figure 1: **The experimental setup.** Right: the robot system is a 5 DOF binocular head integrating an artificial vestibular system (i.e. the white bloc in the centre of the picture). Left: a block diagram of the NN, its inputs (optic flow, head velocity) and output (eye velocity).

3. The neural network model

The neural network which learns the oculomotor stabilization behaviour is built on a GNG-Soft architecture [19]. It combines two network models, namely, the Growing Neural Gas (GNG) model and SoftMax function network. The resulting hybrid architecture has several advantages. First, the effectiveness, typical of the GNG, in distributing the units within the multi-dimensional input space. Second, the "optimal" approximation and interpolation properties of SoftMax functions networks. Third, an interesting (with relation to our task) self-tuning capability. Structurally, the network consists of a single layer of processing elements (PEs), each characterized by a receptive field-like structure. The single PE's response can be described analytically by the following expression:

$$U_i(\xi, c_i) = \frac{G(\|\xi - c_i\|)}{\sum_j G(\|\xi - c_j\|)} \qquad (4)$$

where *G( )* is a Gaussian function, $\xi \in \Re^N$ is the input to the network and c_i the receptive field positions. The output of the network is the linear combination of a number of PEs. Analytically we have:

$$g(\xi) = \sum_i v_i U_i(\xi, c_i) \qquad (5)$$

where i extends to the number of units mapping the input space and the parameters v_i are the weights of the output layer ($g(\xi) \in \Re$). The network parameters which will be tuned during the unsupervised learning process are: $c_{i,}$ (the function's centers), v_i (the weights of the output layer), σ_i (the standard deviation of each Gaussian functions). The learning process consists of incrementally adjusting these parameters to improve/reduce a predefined "performance index" over time.

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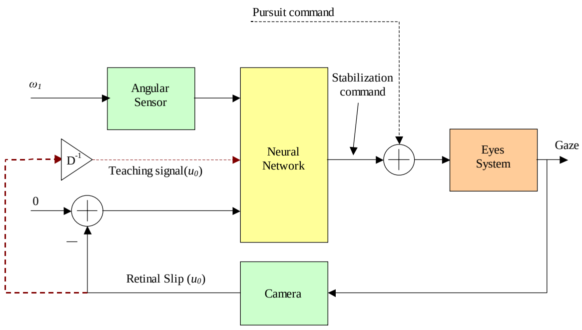

Figure 2 **Motor learning scheme.** The inertial information (angular sensor) and the retinal slip (optic flow) are combined by the NN. The teaching signal is the optic flow itself, which has to be minimized for stabilization to be effective.

3.1 Learning principle and learning scheme

In our framework the input space of the network is two-dimensional. It is defined by the instantaneous angular velocity of the head (i.e. Ω_y) and by the instantaneous optic flow (i.e. u_0) measured on each camera image plane. To adjust the network parameters, we have chosen a performance index measuring the instantaneous component of the residual optic flow (ROF) at the center of the image plane (u_0). The tuning of the network parameters has the goal of minimizing the ROF on the image plane, that is:

$$\min_{v_i,c_i}\left[-\frac{T_x}{Z(0,0)}-(\Omega_y+\sum_i v_i U_i(\xi,c_i))\right] \qquad (6)$$

Self-normalizing Hebbian rules are used to modify the PEs centers c_i, the weights v_i of the output layer according as follows:

$$\Delta c_i = \eta_1(\lambda - c_i)U_i \qquad\qquad \Delta v_i = \eta_2(\varsigma - v_i)U_i$$

A heuristic criterion is used in order to tune the Gaussian's variances σ_i. A description of this can be found elsewhere [19]. On the other hand, in order to carry on the minimization, the weights of the output layers are modified as follows:

$$\Delta v_i = \eta_2\left(\sum_j v_j U_j(\xi,c_j)+u_0-v_i\right)\cdot U_i(\xi,c_i) \qquad (7)$$

that is the target output is shifted by the quantity u_0 from the current network output. Whenever, stabilization is perfect (i.e. $u_0=0$), no adjustment is necessary and in fact $\Delta v_i \approx 0$. It is worth stressing that time, which is not explicitly indicated in equation (7), plays a fundamental role in this schema. In fact, the optic flow used as input to the network is actually one time step before of that used as stabilization measure. That

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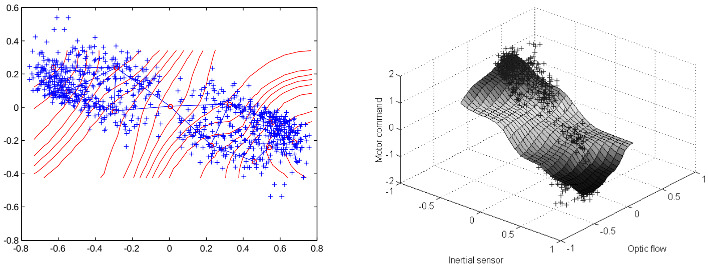

Figure 3 – **The sensory motor map of the stabilization reflex.** Left: the input space of the neural network (flow, inertial)and the network units (small circles) distribution. Right: the control surface interpolated by the network units.

is, the measure of the network performance can be obtained only one step after the network has been used to generate a motion command. A delay line in Figure 2 indicates this last point.

3.2 Efficient learning convergence

In order to characterize the learning process, we monitored the generation of the compensatory command during a complete training session. Learning has been performed using different stimuli, changing the amplitude and the frequency of the externally imposed movement. In all such cases convergence toward a stable behavior have been achieved. To describe the convergence behavior in time, we have evaluated the transformation of the input domain at different time instants of the process. We have characterized the input domain in term of the relationship between the input signals: the residual optic flow (ROF) on the image plane and the rotational component of the imposed movement. Figure 4 shows the linear fit of these data. Intuitively, the more the system learns to compensate correctly, the smaller will be the retinal slip component (ROF) across the image. This can be evaluated numerically, by observing that the trend of the input data turns counter-clock wise toward smaller values of retinal slip (ROF). Therefore, the network operates correctly modifying its parameters to reduce retinal slip in all stimulation conditions.

4. Stabilization performance

Direct measurements on the image plane is of paramount importance if one wishes to evaluate the impact of external disturbances on the visual functionalities of the system. Therefore, stabilization performance is evaluated by means of optic flow techniques exploiting first order components estimates (see [10] for the algorithm). In all performance measurements, the same learned sensory motor map is used to generate the compensatory camera movements. Figure 5 shows on a normalized scale the inertial measurement (angular velocity) and the retinal slip velocity (u_0 component of the optic flow) corresponding to two different external movement (stimuli characteristics are respectively 0.3 Hz, 18 deg/s amplitude and 0.6 Hz, 81 deg/s amplitude). We have evaluated numerically the amount of ROF. In correspondence to

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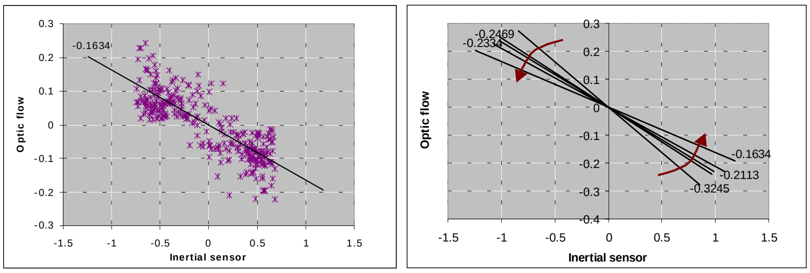

Figure 4 – Input domain of the neural controller. Left: data set distribution and linear fit. Note the ratio between the inertial information and the residual optic flow (ROF) during this initial phase of learning. Right: The linear fits of several input sets turn counter-clock wise over time.

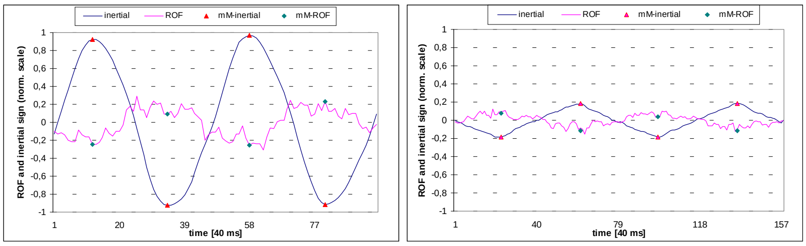

Figure 5 – Residual optic flow (ROF) during stabilization. Left: a normalized scale of the ROF measured (norm. fact. 5 pixels/frame) and the angular velocity component of the external movement (max 90 deg/s). For a rotational movement of about 80 deg/s, ROF is bounded to less than 1 pixel/frame. Right: ROF is bounded here to 0.5 pixel/frame (0.1*5 pixels/frame) for a rotational movement of 18 deg/s.

the maximum peak velocity of each stimulus, the ROF is less than 1 pixel/frame. It is worth noting that, with the second stimulus, the frequency and the amplitude of the external movement change substantially (i.e. frequency roughly doubles and amplitudes increases four times approximately), but the amount of retinal slip is still very limited.

5. Conclusion

We have described a framework for the development of oculomotor stabilization reflexes in binocular robots. Sensory information about robot self-motion are obtained using an artificial vestibular apparatus and a basic motion detection algorithm. The motion cues are integrated by means of an efficient neural controller and used to generate compensatory camera movements. An unsupervised learning scheme enables the robots to build a sensory motor map transforming self motion signals into compensatory motor commands. The learning scheme is efficient in adapting the network parameters and becomes effective after a short training period. The stabilization performance obtained with such an approach has been evaluated directly on the image plane: retinal slip remains constrained to 1 pixel/frame for different externally imposed movement of different dynamic characteristics.

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