

# Orientation system in Robots: Merging Allothetic and Idiothetic Estimations

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**Abstract**—For the last decade, we have developed a bio-inspired control architecture for the autonomous navigation of mobile robots. The robot is able to learn to reproduce a homing or a route following behavior by interacting with a human teacher. However, the system strongly relies on the estimation of the orientation provided by a magnetic compass. We propose in this paper a model of visual compass in order to avoid the use of a magnetic compass. Each online learned visual features characterizing a location (visual landmark) is associated with the shift between its position in the visual field and the local reference to learn. The projection and the integration of these data on a one dimensional neural field allows to build a visual compass which accurately reconstructs the local reference in the neighborhood of the locations of learning. We also investigate how this visual compass can be used to calibrate an orientation system, which could be maintained by the odometry. Finally, the global system is validated in an experiment of route learning.

## I. INTRODUCTION

Since the first algorithms for autonomous mobile robot navigation, the problem of the orientation estimation has always been a central question. The methods to estimate the orientation are various. Some methods can provide a direct estimation of the orientation such as a magnetic compass or the tracking of a very distant and non ambiguous landmark (polar star method) whereas others require the integration of rotational stimuli: odometry on the wheel encoders or accelerometers or inertial centrals or optical flow measure. Modern GPS and DGPS are also able to provide a good estimation of the direction of the movement by integrating the position of the mobile. Each method has unfortunately some drawbacks:

- The magnetic compass is not usable in planetary exploration applications (on Mars for example where no magnetic field exists) or near electrical equipments or on a ferrous ground that can deviate the magnetic field of the earth.
- A distant and non ambiguous landmark is not always visible: tracking the sun during the whole day, or finding a pertinent landmark in indoor environments seems difficult.
- The orientation estimation computed by integrating noisy rotational measurements always suffers from a cumulative drift (need of recalibration).

- GPS is not always available or can have some problems in planetary exploration applications, in urban canyon (in the environment of the fig 2 b) for instance), in indoor environments...

From the biological point of view, neuro-ethological studies has highlighted that the capability of path integration in animals relies on two different sources of information, namely allothetic information gathering the information from the external world (vision, audition, touch, smell) and idiothetic information which is endogenous (proprioception of the actuator and vestibular information) [1]. These two sources are supposed to be merged in a global path integration system. In parallel, neurobiology has also shown the existence of head direction cell (HD-cells) in different areas of the brain [2]. Some of these cells seem to provide a purely allothetic estimation of the head direction whereas others rely on idiothetic information. The discovery of the grid-cells in the entorhinal cortex of the rat [3] confirms the hypothesis that the path integration system could be calibrated by allothetic cues (a constellation of landmarks for example) and could be maintained by integrating idiothetic information. Indeed, the regular spacing of the grid even in the dark strongly suggests an integration of information coming from vestibular or proprioceptive stimuli. Moreover, the grid cells rotate linearly with the rotation of the visual cues which indicates that the path integration system is visually anchored.

This paper presents first a brief review of previous works which addressed the problems of autonomous navigation and/or orientation estimation. Then we propose a bio-inspired architecture for visual navigation and provide some results of route learning by human-robot interactions in indoor and outdoor environments with a magnetic compass used for the estimation of the orientation. In order to avoid the problems of magnetic compasses, we propose a model of a visual compass able to reconstruct an orientation by means of a set of visual landmarks. The accuracy of the allothetic estimation will be highlighted by comparing the allothetic estimation with the value of the magnetic compass. We finally address the problem of the merging of allothetic and idiothetic information in a global orientation system. The vision enables to calibrate the

orientation system which is maintained by the odometry. We finally validate our global architecture by an experiment of route learning in indoor environment.

## II. STATE OF THE ART

The problem of estimating the orientation of a robot concerns a very large class of mobile robot navigation algorithms. Excepted some rare algorithms [4], [5], almost all (SLAM algorithms, GPS algorithms, snapshot model derivations [6], appearance-based approaches ...) has to solve the problem. Biologists and psychologists consider the path integration as a result from the merging of allothetic and idiothetic information in order to provide an accurate homing vector. Whereas idiothetic integration in robotics system has been widely explored, there are only few systems providing a visual compass [7], [8]. And less numerous are the system using this visual compass as a orientation calibrator [9].

In the early 80's, ethologists [6] put forward the role of the visual landmarks in the navigation of insect and proposed a model, called the snapshot model. Several other models derived from it suggest animals and even robots could navigate to a place by performing a parallax minimization between the current place and the goal place. Most of these models require the estimation of a local reference. In this attempt, [10] proposes an implementation of a solar compass and a simplified version of the snapshot model: the ALV. In 2000, we shown a by-product of a neural network for view recognition could be used as a visual compass [11]. [7] reviews some bio-inspired architectures for mobile robot navigation and also proposes a visual compass which is unfortunately difficult to use in an online system because three non aligned panoramas must be available before computing the direction of the compass. Ethological experiments of blind homing has also proved that a homing vector can be estimated without visual cues but that the drift of this vector seems cumulative as the integration of rotational information provided by wheels encoders of a mobile robot, accelerometers, gyroscopes or inertial centrals. It seems that the nature has been confronted to the same problems robotics specialists have today. In robotics the problem of dead reckoning has early been stressed. The major problem is the cumulative drift of the computed homing vector. Hence, the need to localize precisely by means of allothetic cues has guided most of the researches on mobile robot navigation (occupancy grid, SLAM algorithm, appearance-based approaches). Yet, most of the systems require an orientation measurement performed generally by a magnetic compass or by tracking a precise distant landmark or by means of external references (GPS for instance). Whereas some systems try to jointly estimate the position and the orientation (GPS-based systems with EKF approaches for example), the design of an efficient path integration system, anchored in the visual space in order to guarantying a bound of the drift, remains a difficult problem. [8] compares two panoramic images to extract rotational information. The system tries to find the shift that minimizes the distance between the current image and the previous image. Authors insist on the fact that the system

can work without calibration and that the system is robust to translation of the robot. The main drawback is that errors are cumulative. Hence, this system suffers from the same drawback as classical odometers. Moreover, some panoramic cameras are known to induce anisotropic deformations. Hence, it seems that the system has at least to be calibrated to avoid this kind of deformations. Another recent and interesting system is the one related in [12], which aims at estimating a 3D orientation of a hand-held camera. Authors suppose that objects are at an infinite distance (which is generally true in a large outdoor environment like a street). They use an EKF (Extended Kalman Filter) to infer the 3D orientation and insist on the fact that the error remains bounded. Such a property is crucial if the visual compass is foreseen as a calibrator for a global path integration system. Inspired by neuro-ethological data, [9] proposed a hippocampal model of the place cell in which the vision (of a distant light for example) enables to reset the idiothetic integrator ([9] also proposes an interesting review of the biological models of HD-cells until [13]). Unfortunately, the construction of the local reference is not explained in [9]. In fact, the various algorithms that provide an estimation of the robot orientation based on vision, almost none has addressed the problem of the online construction and maintenance of the local reference. Moreover, the problem of merging idiothetic integration with allothetic cues has in fact rarely been stressed ([9] is a rare example).

Inspired by results in psychology [14], [15] and mammal neurobiology [16] (especially the rodent), [17] proposes a generic architecture called the PerAc architecture. This architecture can learn a sensory motor dynamics approximating a given behavior and has been used in many applications: local navigation [18], [19], pro-active navigation (with planning capability) [20], multiple degree of freedom actuator control (robotic arm) [21], temporal sequence learning [22], gaze direction control... In the context of local navigation, the PerAc architecture requires a local reference usually provided by a magnetic compass. [11] proposed to use a parallel PerAc loop in order to create a visual compass by associating each landmark with its angular distance from the local reference. The visual compass was previously used for active object recognition in order to center the pertinent object in the visual field. Our paper brings some primarily results on its use in online and real time sensory-motor task like learning to reproduce a route. We also investigate how this visual compass can be used as a calibrator for vestibular/proprioceptive integration in order to provide a global orientation system anchored in the visual space (guarantying a bounded drift) and maintained by the odometrical measurements (when the visual modality is unavailable or unreliable) [9].

## III. PERAC ARCHITECTURE FOR VISUAL NAVIGATION

This section focuses on the PerAc architecture for local navigation tasks. A model of visual place-cells is used to provide a robust localization level of the robot in indoor as well as in outdoor environments [18], [23].

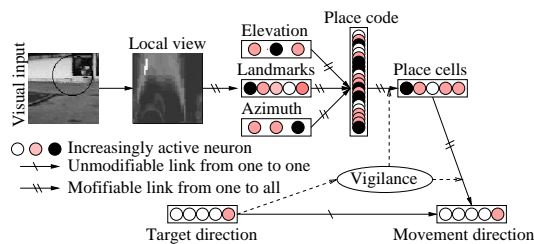


Fig. 1. Block diagram of the PerAc architecture for local navigation: it is composed of a visual system that focuses on points of interest and extracts small images in log-polar coordinates (called local views), a merging layer that compresses *what* and *where* information, a place recognition layer and a sensory-motor layer that associates places with action, creating a behavioral dynamic.

Fig. 1 summarizes the chain of processing used on our robots for the learning of behavioral attractors. A place is defined as a spatial constellation of online learned visual features (here a set of triplets *landmark-azimuth-elevation*) compressed into a place code. The constellation results from the merging a *what* information and a *where* information provided by the visual system that extracts local-view (a log-polar mapping is used to transform these local view, providing some robustness to scale and rotation variation) centered on the points of interest. Moreover, neither Cartesian nor topological map building is required for the localisation. On the contrary, the world acts as an outside memory [14]. A simple associative learning between places and actions enables to generate a sensory-motor dynamic approximating a homing or a route following behaviors. The homing is possible in the area where a minimal set of landmarks can be recognized (generalisation area). The problem of choosing an efficient policy of actions has often been stressed in the literature of reinforcement learning [24], [25] but we claim that the PerAc architecture is extremely efficient for spatial behavior learning since it embeds the problem of the state space partitioning as well has the problem of policies learning. Fig. 2 a) and b) present experiments of route learning by human-robot interactions. The real time properties of our control architecture (not developed here) enable to teach the robot in an intuitive manner how to follow a path. The learned sensory-motor associations shape an attraction basin allowing our robot to return on the path and to follow it even for position in the neighborhood of the learned path.

Although this architecture can achieve really precise sensory-motor task, it requires a local reference provided by a magnetic compass. The next section proposes a second PerAc loop in order to create a visual compass.

#### IV. LANDMARKS-BASED VISUAL COMPASS

The place recognition architecture previously introduced provides a robust gradient of localization (an activity level which decreases monotonically with the distance to the learned location). We deduce from this result that the features the visual system extract are really pertinent and characteristic of

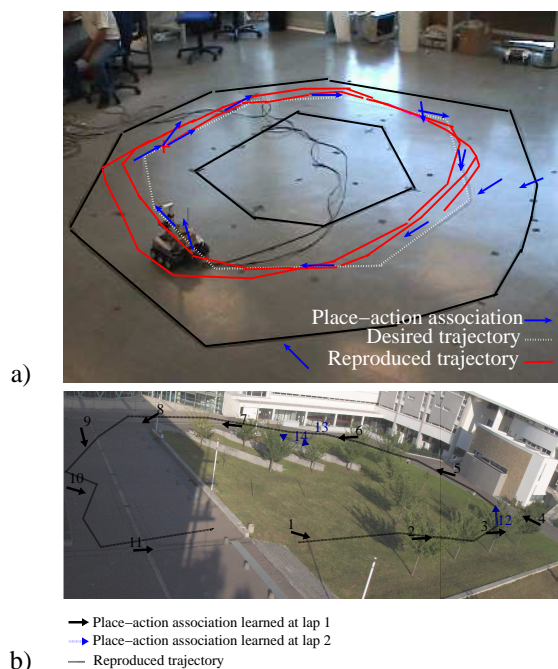


Fig. 2. a): Indoor experiment: the robot is guided by a human operator. Three laps are sufficient to train the robot to perform the task within the road defined by the black border. b): Same experiment of the visual path learning outside our lab. Two laps of proscriptive learning (14 place-action associations learned) are sufficient to teach the robot to perform again and again the same trajectory.

the location. To free the system from the magnetic compass, [11] proposed to associate the landmarks to their angular distance with an arbitrary direction which will stand for a local reference. The visual compass was proved to efficiently substitute the magnetic compass at least in the location the local reference was learned.

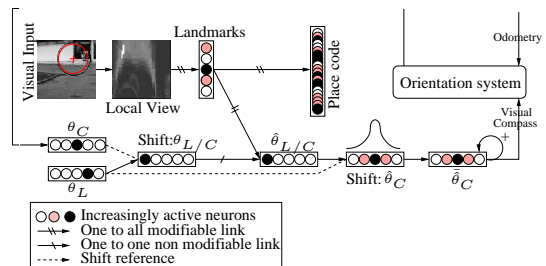


Fig. 3. Block diagram of the visual compass: The current orientation estimation  $\theta_C$  provided by the global orientation system and the position of the current landmark  $\theta_L$  in the visual field enable to compute the shift  $\theta_{L-C}$ . This shift is associated to the landmark and can be predicted as  $\hat{\theta}_{L-C}$  when the landmark is visible. Shifting this prediction with the position of the landmark enable to reconstruct the local reference in the visual field:  $\hat{\theta}_C$ . By simply summing the successive predictions after a Gaussian convolution, the system finally compute a visual estimation of the orientation  $\hat{\theta}_C$  which can feed a global orientation system.

The fig. 3 presents the architecture of the visual compass. The shift between the current orientation and the current landmark position is associated to the landmark by means

of the neural group called  $\hat{\theta}_{L/C}$  according to the following equation ( $\omega_{ij}$  is initially null):

$$\omega_{ij}(t + dt) = \omega_{ij}(t) + \epsilon \cdot S_j(t) \cdot S_i^L(t)$$

In this equation,  $\omega_{ij}$  is the synaptic weight between the  $i^{th}$  landmark neuron and the  $j^{th}$  neuron of the group  $\hat{\theta}_{L/C}$ .  $S_i^L(t) = 1$  if the landmark  $i$  is being recruited and 0 otherwise.  $S_j(t)$  is the activity of the  $j^{th}$  input neuron giving the direction of the local reference. If the learning rate  $\epsilon = 1$ , the group associates in one shot the shift between the position of the landmark and the local reference. The reconstruction of the local reference does not use  $\theta_C$  and  $\theta_{L/C}$ . The predicted shift is simply computed as  $\hat{\theta}_{L/C}(j) = \sum_{i=1}^{N_L} \omega_{ij}^{\theta_{L/C}} \cdot L_i$ , where  $L_i$  is the activity of the landmark neuron  $i$  and  $N_L$  the number of encoded landmarks.

After the learning, the system predicts the position of the local reference  $\hat{\theta}_C$  by adding the prediction of the shift  $\hat{\theta}_{L/C}$  between the local reference and the landmark position to the current landmark direction  $\theta_L$ . Fig. 3 also highlights the interest of using a convolution with a Gaussian before the temporal integration of the predicted shift. When two Gaussian curves parametrized by their mean value  $\nu_1$  and  $\nu_2$  and the same variance  $\sigma$  are close ( $|\nu_1 - \nu_2| < 2\sigma$ ), the sum provided an average curves and a single maximum of the activity on the neural field correspond to  $\frac{\nu_1 + \nu_2}{2}$ : the peaks of the two Gaussian curves are merged. Otherwise, when two Gaussian curves are more distant ( $|\nu_1 - \nu_2| > 2\sigma$ ), their peaks of activity are not merged and the two maxima remains in  $\nu_1$  and  $\nu_2$ : in  $\frac{\nu_1 + \nu_2}{2}$  a local minimum is present corresponding to a bifurcation in the decision making). Hence, a wide Gaussian curves enhance the generalization capability but reduce the precision, whereas a narrow Gaussian curves provides more accurate predictions but with less generalization capability (ie : a good precision near the location of the learning). By sequentially summing each convolved prediction, a mean orientation is computed which we defined as the visual compass  $\hat{\theta}_C$ .

An important difference with the system proposed in [11] is the possibility to force the system to build a specific visual reference. Indeed, the shift  $\theta_{L/C}$  between the landmark position  $\theta_L$  and the current orientation  $\theta_C$  of the robot compels the visual compass to learn  $\theta_C$  as the local reference. This mechanism will be used in the next section to keep a constant reference from learned place to learned place. As all the landmarks in the environment will predict the same direction, the visual ambiguity on the landmarks does not appears as a problem for the reconstruction of the reference.

To demonstrate the efficiency of such a visual compass, the experiment of fig 6 and 5 is proposed: the robot learns a place and a visual orientation is arbitrarily chosen. We compare the measurement of the magnetic compass with the predicted direction while the robot rotates on him-self. The test is realized at the learned location and in surrounding locations as shown in fig. 5 (0 m, 1 m, 1.141 m). Fig 6 shows that the prediction remains pertinent even in the neighborhood of the learned location. It seems that such a visual compass could

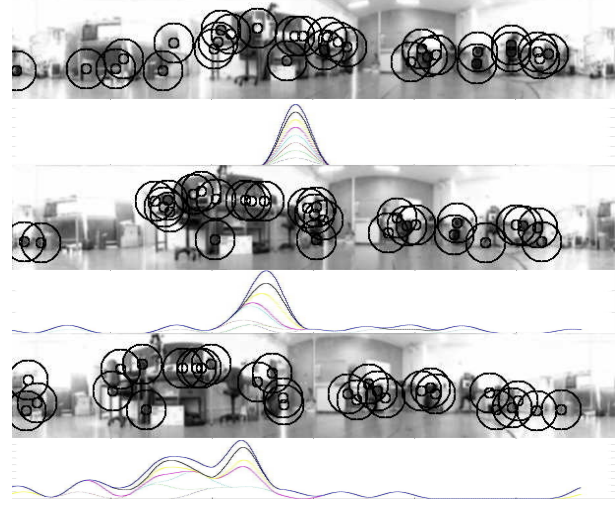


Fig. 4. Learning and prediction of the visual compass: The blacks ring on the images of the environment are the 32 extracted landmarks. The graphs under the images represent the building of the visual compass  $\hat{\theta}_C$  during the analysis of the images. Each curves correspond to the sum of the prediction of the analysis of 4, 8, 12, ... 32 landmarks. Between the first place where the visual compass and the landmarks are learned, and the third place, the robot moves forward and rotates. In spite of the visual changement, the system provide an accurate estimation of the local reference. However, in the last place, two max are plausible and it can be dangerous to randomly choose one of them. The odometry could to maintain the correct estimation in such an ambiguous situation.

reliably substitute the magnetic compass.

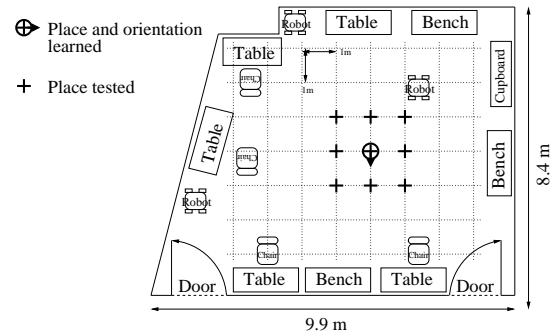


Fig. 5. Working room of the experiment of fig 6.

However, the experiment of fig. 6 does not guaranty the usability of the system in an online and real time application. The next section proposes a global orientation system that uses the visual compass as a calibrator and odometry to maintain the local reference on short distance.

## V. MERGING ALLOTHETIC AND IDIOTHETIC INFORMATION

We present here our navigation architecture without a magnetic compass. In practice, even if the visual modality is rich enough to reconstruct a local reference, the permanent movement of the robot, especially without a panoramic sensor, implies a temporal hysteresis: the set of landmark used to compute the visual reference does not belong to a single place but the set of places occupied by the robot during the previous

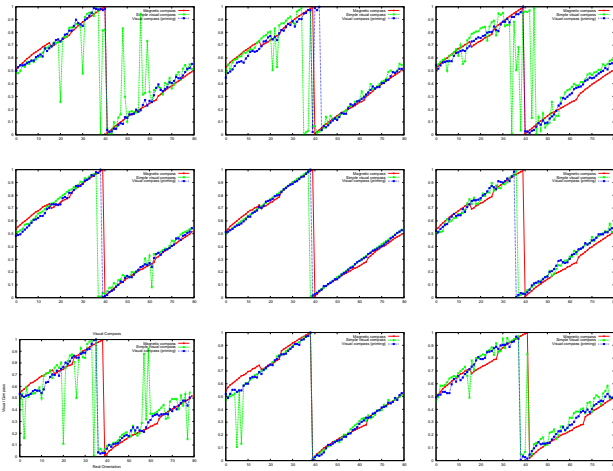


Fig. 6. Experiment of the visual compass in the neighborhood of the location where the local reference was learned. Three curves are displayed: the magnetic compass, the visual compass as described in the fig. 3, and the visual compass with a priming on the estimation of the orientation estimation which amplify the direction close to the previous direction and inhibits the direction to far from the previous direction. The results show that with the mechanism of priming, the visual compass is able to substitute the magnetic compass.

instants. The effect of this drift can be neglected in a straight line but can be important when the robot rotates. Thanks to the odometry, the robot is however able to maintain the orientation estimation quite accurately during a short period. Since this information is more precise and faster to compute than the visual compass, our architecture proposes to use the odometry to compute very quickly the orientation estimation which is re-calibrated by the visual compass.

In order to achieve the recalibration of the odometry by the means of the visual compass, several methods can be used. Our first proposition is to compute a quality measure of the estimation of the orientation: the orientation must be non-ambiguous. Obviously, the estimated orientation may have several maxima in practice. Our criterion is the following: if the activity of the neural field has local maxima far from the global maximum according to a given threshold ( $30^\circ$  for example), these local maxima can be a problem. If the local maxima sufficiently distant from the global maxima are higher than 70% of the height of the first maxima (the threshold is arbitrary), the compass is considered as erroneous. This simple mechanism enables to refrain the system to self-calibrate on a potentially wrong value. A second criterion comes from the observation of a practical problem. When the robot is rotating while currently going forward, the set of images used to compute the visual compass firstly does not belong to a single place but to the set of locations defined by the recent past position of the robot (not grabbed with the same robot orientation). Indeed, the angular value used to shift the landmarks azimuths is erroneous when the robot is rotating. Hence the estimation of the visual compass at the end of a rectilinear movement is more accurate. A simple solution is to wait that the robot does a rectilinear movement before

to recalibrate. Such calibration criterion enables the robot to robustly navigate almost as if it was using a magnetic compass. Fig 7 gives an overview of the designed parallel architecture and its asynchronous or pipelined communications.

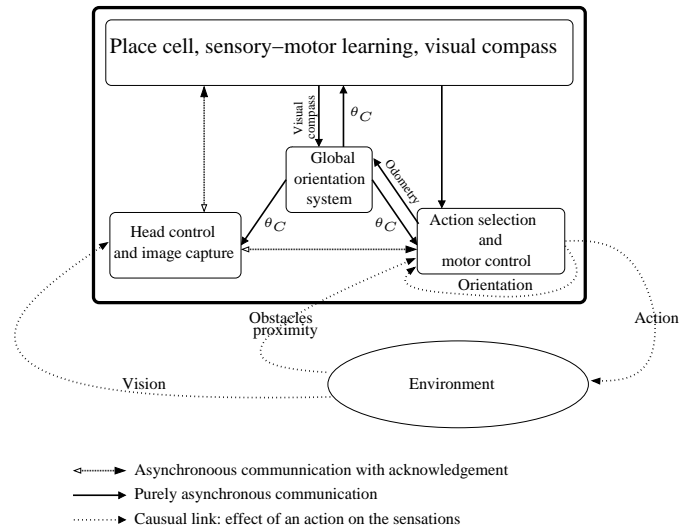
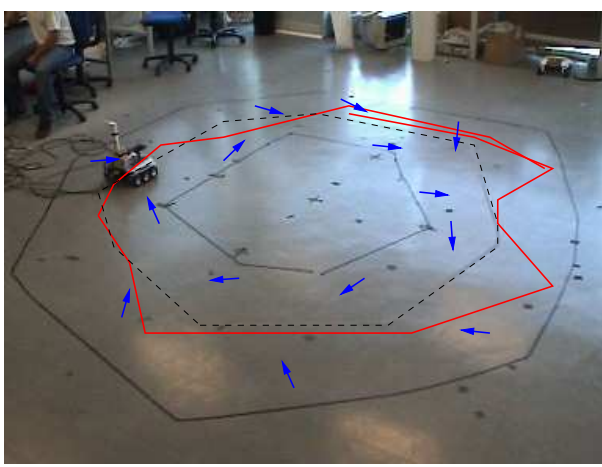


Fig. 7. Parallel control architecture for visual navigation without magnetic compass. Most of the communications are purely asynchronous. Four neural networks are used. The block called Head control and image capture is responsible for making the pan camera rotate et for grabbing the image. The upper block manages the construction of the place cells, the visual compass, and the sensory-motor learning. The right block realizes the action selection and the motor control. Finally, the global orientation system gives an orientation estimation  $\theta_C$  according to the visual compass and the odometry, and asynchronously sends to each neural network this estimation.

In the experiment of fig 8, the set of place-action associations was learned online during the guidance of the robot by the human. No magnetic compass is used but our bio-inspired orientation system calibrated by the allothetic estimation of the orientation provided by the visual compass and maintained by idiothetic integration provided by the odometrical measurement. In each learned place, a new visual orientation is associated to each landmark. As the robot stops a while before it learns the place, the current visual compass should become stable and can stand for the orientation to be learned. As compared to the results of route following with a classical magnetic compass given in fig. 2 a), the precision of the reproduced trajectory is lower. However, the fact that the robot manages the task strengthens our trust in our approach.

## VI. DISCUSSION AND CONCLUSION

Most of the modern algorithms for autonomous navigation require the estimation of a reference for the orientation. We investigated in this paper how allothetic and idiothetic information can be merged in order to provide an accurate estimation of the orientation. As the odometry is known to suffer from cumulative drifts, we propose to calibrate the orientation system by means of the vision. Vision is only correlated with the position of the robot in the environment and consequently does not suffer from any cumulative drift. If the



- - - Desired trajectory  
 — Reproduced trajectory  
 → Place-action association learned

Fig. 8. Route following without magnetic compass. Each time the visual compass is correct according to the criterion previously defined, it calibrates the orientation system. Otherwise (for example in the dark or when the robot is rotating or when the visual compass potentially gives a wrong orientation estimation), the odometrical measurements enable to maintain the estimation.

vision can sometimes predict a correct estimation, calibrating the orientation system with this estimation should be enough to bound the errors. This paper aimed at providing some result which validates this approach.

The visual compass we propose associates the landmark extracted in a place to the shift between the landmark position and a given orientation standing for the local reference to learn in the current place. If enough learned landmarks are visible, the visual compass can reconstruct the local reference in the neighborhood of the learned places, even without place recognition. However, the estimation can be erroneous especially when the robot is rotating. The global orientation system we proposed for our visual navigation architecture try to bypass the problem: the visual compass calibrates the orientation system if the robot is doing a rectilinear movement and if the estimation is non ambiguous. Otherwise, the odometry enable to maintain the estimated direction.

Our future work will focus on improving the merging of the visual compass and the odometry. We also want to investigate the behavior of our algorithm when the number of learned landmarks explodes. It will be important to identify the stable landmarks to favor their recognition and to avoid the computation of the other by means of a more sophisticated attentional vision system.

#### ACKNOWLEDGMENT

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Movies of the experiments of fig. 2 and 8 available on:  
<http://www.etis.ensea.fr/~neurocyber/giovangeli/home.htm>  
<http://www.etis.ensea.fr/~neurocyber/Videos/homing/index.html>

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