Orientation system in Robots: Merging Allothetic and Idiothetic Estimations

Christophe Giovannangeli and Philippe Gaussier
CNRS UMR8051 ETIS
Neurocybernetic Team
Université de Cergy-Pontoise - ENSEA
2, avenue Adolphe-Chauvin
95312 Cergy-Pontoise, France
Email: giovannangeli@ensea.fr

***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 landmark is associated with the shift between its position in the visual field and a direction of reference. The projection and the integration of these data on a one dimensional neural field allow 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 the integration of 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 have 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 cells (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 the integration of 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 the autonomous navigation and/or the orientation estimation. Next, we propose a bio-inspired architecture for visual navigation and we provide some results of route learning through 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 the magnetic compass, 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 the 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 an 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 cases [4], [5], almost all the algorithms(SLAM, GPS algorithms, snapshot model derivations [6], appearance-based approaches ...) has to solve this problem.

In the early 80's, ethologists [6] put forward the role of the visual landmarks in the navigation of insects and proposed a model, called the snapshot model. Several following models 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. [7] proposes an implementation of a solar compass and a simplified version of the snapshot model: the ALV. In 2000, we showed a by-product of a neural network for view recognition could be used as a visual compass [8]. [9] 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 face 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): SLAM approaches (as weel as GPS-based approaches) generaly tries try to jointly estimate the position and the orientation by means of EKF (Extended Kalman Filter) approaches for example (the state vector being $[x, y, \theta]$). In metrical approaches, the estimation of the orientation in SLAM approaches can even be derived from the estimation of the position (two successive positions provide an estimation of the orientation) but its accuracy is then directly linked with the precision of the position estimation. In visual SLAM approches, the position of the visual cues are generally considered as some variables of the state vector but can also be used during a correction phase [10]. Finally, a priori information can help to solve ambiguous situations but such simplifications are blamed for not being enought robust in case of envrionnemental changes. The technics we propose differs from SLAM algorithms since neither topological nor metrical maps are computed but they aim at building a sensory-motor dynamics (which is closer to the learning of a policy of action).

Actually, the design of an efficient path integration system, anchored in the visual space in order to guaranty a bound of the drift, remains a difficult problem. [11] 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 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, [13] proposed a hippocampal model of the place cell in which the vision (of a distant light for example) enables to reset the idiothetic integrator ([13] also proposes an interesting review of the biological models of HD-cells until [14]). Unfortunately, the construction of the local reference is not explained in [13]. In fact, most of the algorithms that provide an estimation of the robot orientation based on vision, do not address 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 ([13] is a rare example). Inspired by results in psychology [15], [16] and mammal neurobiology [17] (especially the rodent), [18] 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 [19], [20], pro-active navigation (with planning capability) [21], multiple degree of freedom actuator control (robotic arm), temporal sequence learning, gaze direction control... In the context of local navigation, the PerAc architecture requires a local reference usually provided by a magnetic compass. [8] proposed to use a parallel PerAc loop in order to center the gaze on a particular object by associating visual features with their angular distance from the center of the object. A visual compass can be derived from this system by associating landmarks with their angular distance from a given local reference. Our paper brings some primarily results on its use in online and real time sensory-motor tasks like learning to reproduce a route. We also investigate how this visual compass can be used as a calibrator for a 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) [13].

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 [19], [22].

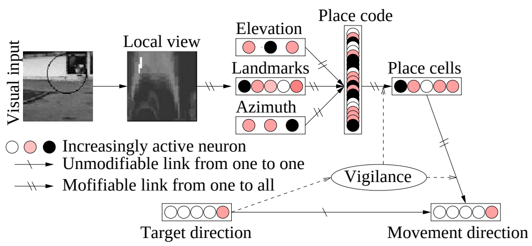
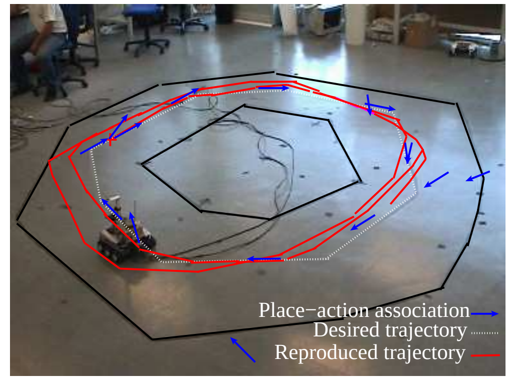


Fig. 1. Block diagram of the PerAc architecture for local navigation: it is composed of a visual system that focuses on points of interest and extracts small images in log-polar coordinates (called local views), a merging layer that compresses *what* and *where* information, a place recognition layer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

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 views, 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 [15]. A simple associative learning between places and actions enables to generate a sensory-motor dynamics approximating a homing or a route following behavior. 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 [23] 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 developped 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 positions in the neighborhood of the learned path.

Although this architecture can achieve really precise sensory-motor tasks, 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.

a)



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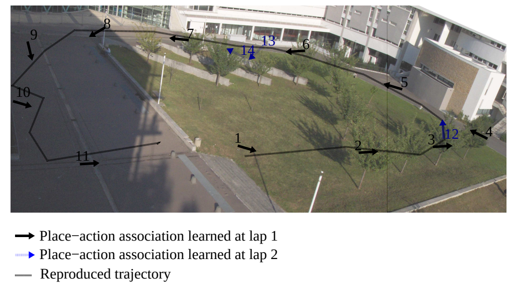

Fig. 2. a) Indoor experiment: the robot is guided by a human operator. Three laps are sufficient to train the robot to perform the task within the road defined by the black borders. b) Same experiment of visual path learning outside our lab. Two laps of proscriptive learning (14 place-action associations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

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 the location. To free the system from the magnetic compass, we proposed to associate the landmarks to their angular distance with an arbitrary direction which will stand for a local reference. In [8], the same underlying mechanism was proved to efficiently center the gaze of the robot on the learned object. In this paper, we give primarily results showing the usability of the visual compass in a dynamical context.

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 $\hat{\theta}_{L/C}$ (see architecture on fig. 3)according to the following equation (ω_{ij} is initially null):

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

In this equation, ω_{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 θ_C and $\theta_{L/C}$. The predicted shift

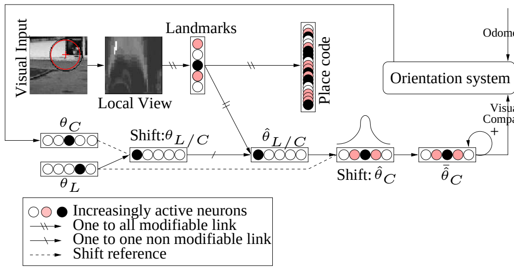

Fig. 3. Block diagram of the visual compass: The current orientation estimation θ_C provided by the global orientation system and the position of the current landmark θ_L in the visual field enable to compute the shift θ_{L-C}. This shift is associated to the landmark and can be predicted as $\hat{\theta}_{L-C}$ 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 $\bar{\hat{\theta}}_C$ which can feed a global orientation system.

is simply computed as $\hat{\theta}_{L/C}(j) = \sum_{i=1}^{N_L} \omega_{ij}^{\theta_{L/C}}.L_i$, 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 θ_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 θ_1 and θ_2 and the same variance σ are close ($|\theta_1 - \theta_2| < 2\sigma$), the sum provided an average curves and a single maximum of the activity on the neural field correspond to $\frac{\theta_1+\theta_2}{2}$: the peaks of the two Gaussian curves are merged. Otherwise, when two Gaussian curves are more distant ($|\theta_1 - \theta_2| > 2\sigma$), their peaks of activity are not merged and the two maxima remains in θ_1 and θ_2: in $\frac{\theta_1+\theta_2}{2}$ a local minimum is present corresponding to a bifurcation in the decision making. Hence, a wide Gaussian curve enhances the generalization capability but reduces 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 and defined as the visual compass $\bar{\hat{\theta}}_C$.

An important difference with the system proposed in [8] is the possibility to force the system to build a specific visual reference. Indeed, the shift $\theta_{L/C}$ between the landmark position θ_L and the current orientation θ_C of the robot compels the visual compass to learn θ_C as the local reference. This mechanism will be used in the next section to keep a constant reference from one learned place to the next. 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

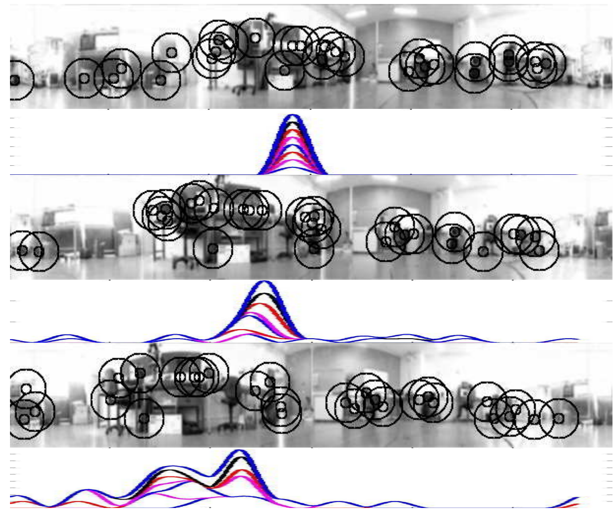

Fig. 4. Learning and prediction of the visual compass: The blacks ring on the images of the environment are the 32 extracted landmarks. The graphes under the images represent the building of the visual compass $\bar{\hat{\theta}}_C$ during the analysis of the images. Each curve corresponds to the sum 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 changes, the system provides 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 maintain the correct estimation in such an ambiguous situation.

the measurement of the magnetic compass with the predicted direction while the robot rotates on itself. The test is realized at the learned location and in surrounding locations as shown in fig. 5 (0 m, 1 m, 1.414 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 reliably substitute the magnetic compass.

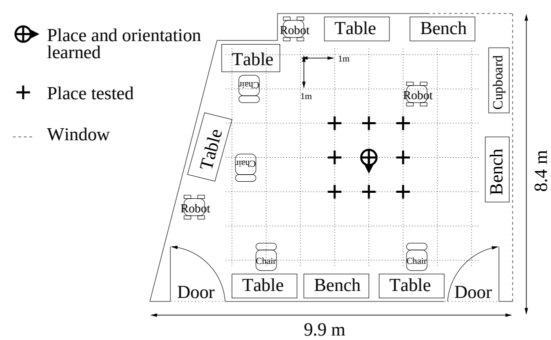

Fig. 5. Working room of the experiment of fig 6.

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.

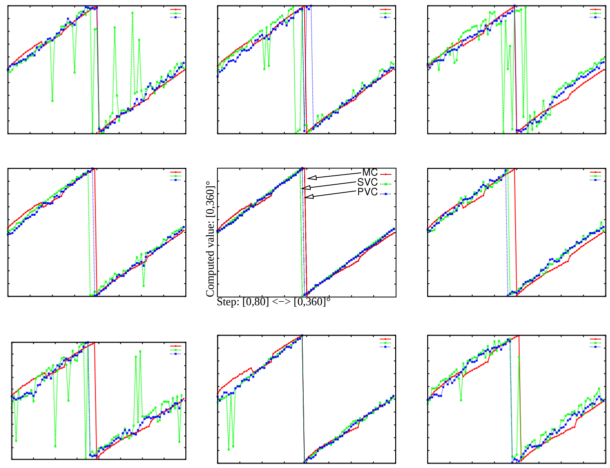

Fig. 6. Test of the visual compass in the neighborhood of the location where the local reference was learned. Three curves are displayed: the magnetic compass, the visual compass as described in the fig. 3, and the visual compass with a priming on the estimation of the orientation estimation which amplify the direction close to the previous direction and inhibits the direction to far from the previous direction. The curves are displayed according to their relative position int the environment of fig. 5. The results show that with the mechanism of priming, the visual compass is able to substitute the magnetic compass.

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 as in the following experiment of fig. 8, implies a temporal hysteresis: the set of landmark used to compute the visual reference does not belong to a single place but to the set of places occupied by the robot during the previous instants. The effect of this drift can be neglected in a straight line but it 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^o for example), these local maxima can suggest a problem (bifurction of an erroneous attractor). If the local maxima sufficiently distant from the global maximum are higher than 70% of the height of the first maximum (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 criterions 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.

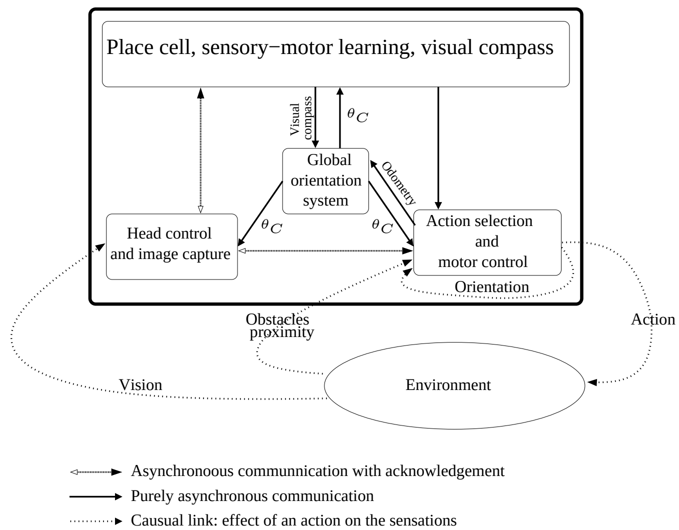

Fig. 7. Parallel control architecture for visual navigation without any magnetic compass. Most of the communications are purely asynchronous. Four neural networks are used. The block called Head control and image capture is responsible for making the pan camera rotate and for grabbing the image. The 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 θ_C according to the visual compass and the odometry. Finally, the global orientation system asynchronously sends back its estimation to each neural network.

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. Our bio-inspired orientation system is calibrated by the allothetic estimation of the orientation provided by the visual compass and maintained by the idiothetic integration comming from 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 stands 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.

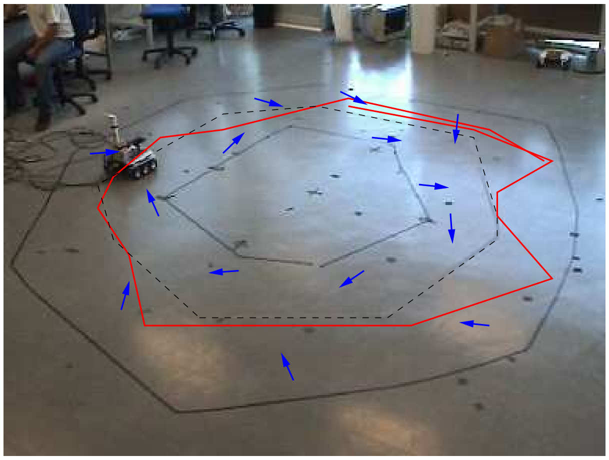

Fig. 8. Route following without magnetic compass. Each time the visual compass is correct according to the criterion previously defined, it calibrates the orientation system. Otherwise (for example in the dark or when the robot is rotating or when the visual compass potentially gives a wrong orientation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

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 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.

If enough learned landmarks are visible from the point of view of the robot, 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.

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

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