2010 IEEE International Conference on Robotics and Automation
Anchorage Convention District
May 3-8, 2010, Anchorage, Alaska, USA

A Mobile Robotic Platform Exploiting the Navigational Capabilities of the *Carassius auratus* using a Natural Interface

Dino Accoto†, Luca Lucibello†, Domenico Campolo* and Eugenio Guglielmelli†

***Abstract*— This paper reports on an autonomous mobile robot embodying a simple instantiation of the *Double Hybrid Control* Architecture, with a living animal in the control loop for improving robot navigational capabilities.**

In particular, a *Carassius auratus* (common *Goldfish*) receives a natural visual feedback from the environment, while its motor reactions, acquired by a digital camera and adequately processed, are mapped into motor commands, which are fed as inputs to the robot controller.

Both the hardware and the software required for robot control is presented, as well as preliminary experimental data demonstrating the viability of the proposed approach.

***Index Terms*— Biorobotics; double hybrid control architecture; exploratory robotics.**

I. INTRODUCTION

Robots are indispensable in scenarios that may be intolerably dangerous or non viable for humans, such as in space exploration or in hostile environments. Autonomous robots are also helpful in the exploration of impervious small cavities, e.g. through debris in rescue operations.

In such scenarios it is desired that robots exhibit autonomous and effective navigational capabilities, adapting their behaviour according to the unpredictable and complex features of the unstructured environment.

If we consider nature, we see that even simple animal forms exhibit remarkable navigational skills with a striking robustness. Such performance is often unparalleled by existing control strategies. A possible approach to reduce the performance gap between the biological realm and robotics, pursued in this paper, consists in *embedding* animals capabilities in a robot, by physically integrating a biological organism in a proper control scheme. Once all relevant ethical issues related to the use of living animals are properly taken into account, a number of technical challenges must be considered. In particular, in order to harvest the potentials of the animal intelligence, it is necessary to provide it with a proper sensory flow. Then, it is necessary to adequately interface the animal to the robot in order to extract a sequence of motor commands coherent with the data processing occurred in the animal's brain.

In this paper we show that the proper choice of the animal can simplify the design of the robot in the case sensory information can be directly gathered by the animal sensory apparatus and motor commands can be decoded from animal's motions by means of a minimally invasive visual inspection.

The robot described in this paper comprises a platform hosting a transparent fish-bowl, where a *Carassius auratus* (*Goldfish*) is free to move according to the environmental visual cues it perceives. The motion of the Goldfish is captured by a digital camera mounted on the same platform and it is mapped into motor commands fed to the platform controller. We show that with this simple scheme the platform is able to move according to the fish intentions, exhibiting useful navigational behaviours (namely, obstacle avoidance) with no need for algorithmic computation.

A quick overview of the state of the art on control architectures with animal in the loop is provided in Sec. II. The actual prototype used to perform preliminary tests is described in Sec. III, while preliminary experimental data are reported in Sec. IV. Finally, a discussion about the prototype developed and future work is presented in Sec. V.

II. BACKGROUND ON ANIMAL-MACHINE INTERFACES

A *neural interface* comprises a number of electrodes implanted into the nervous system. As such, it is an invasive interface, implying non trivial ethical issues, that impacts the integrity of the animal and, expectedly, its capability to behave and/or process information in a natural way.

On the contrary, a *natural interface* may be regarded as a synthetic environment that is minimally invasive to the animal, which is free to react to external stimuli according to its neural processes. The natural interface maps the robot's sensors data into a sensory flow that is natural and intelligible for the animal; on the other way, the interface maps animal's behaviours into proper motor commands sent to the robot.

To our knowledge, only one example of natural interfaces used for robot navigation tasks has been presented so far. The robot, developed at the Concept Lab at the University of California at Irvine [2], is a mobile platform equipped with distance sensors. It hosts an insect of the *Blattaria* order (cockroach) held by a rigid support over a trackball, which is put in motion by insect legs. The trackball codes animal's movements into electric signals, which are used as motor commands for the robotic platform. A LCD panel provides to the (photophobe) insect a coherent mapping of the external environment, perceived through the robotic platform sensors.

An example of neural interfacing is presented in [3], where biolectrical signals from a moth are read by implantable electrodes and mapped into motor commands. The insect

† Biomedical Robotics and Biomicrosystems Lab, Università Campus Bio-Medico di Roma, Via A. del Portillo, 21, 00128 Roma, Italy d.accoto@unicampus.it

∗ School of Mechanical & Aerospace Engineering Nanyang Technological University 50 Nanyang Avenue Singapore 639798 d.campolo@ntu.edu.sg

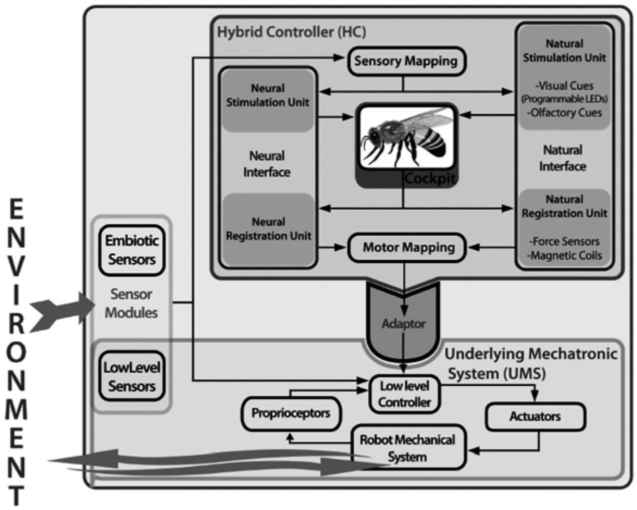

Fig. 1. Block diagram representing the elements oft the Double hybrid architecture.

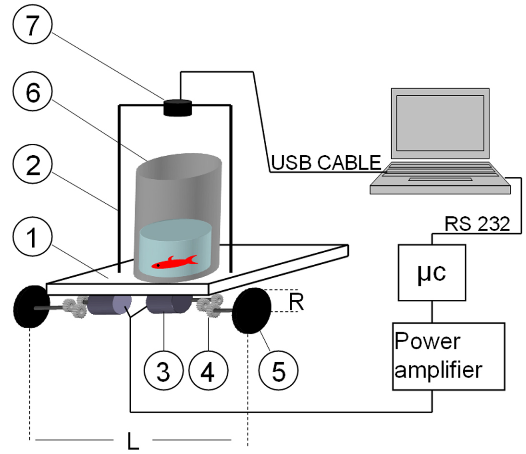

Fig. 2. Schematic of the system.

is provided with a desired sensory input flow through a revolving wall with vertical stripes.

The two mentioned examples are very interesting because they successfully attempt at harvesting insects pre-developed intelligence for navigation purposes. Nevertheless, it must be recognized that important advances in artificial intelligence and mechatronics occurred over the past years. It is therefore expected that the full potentiality of robots with animal-in-the-loop control will be better harvested when an optimal interaction will be achieved between the artificial and the biological systems.

A theoretical investigation on how achieving this goal has been recently reported, with the introduction of the concept of Double Hybrid Architecture [1]. The name of the proposed architecture refers to two hybridity relations: *deliberative-reactive* and *animal-machine*. As known, the deliberative-reactive paradigm seeks the emergence of complex behaviours with no need for global planning, which is critical in unstructured environments.

In the Double Hybrid Control Architecture, deliberative and reactive control functions are respectively demanded to the biological and the artificial components, which bidirectionally exchange information as shown in fig. 1. In the most general case, the information exchange can be achieved by concurrently using neural and natural interfaces, while an executive controller takes care of fusing and managing the outputs from the low-level and high-level controllers.

This paper presents a simplified instantiation of the Double Hybrid Architecture, where only motor mapping is required: the animal receives inputs from the environment using its own eyes, and no invasive interfaces are used. By exploring the responses of the animal to external stimuli while embedded in a moving platform it is possible to experimentally investigate which behaviours emerge that can be exploited for enhancing navigational capabilities. Such information provide the necessary design hints for the development of the mechatronic system, inclusive of navigation algorithms.

III. ROBOT DESIGN

A. Choice of the biological component

The *Carassius auratus* (*goldfish*) has a relatively complex and pliant to environmental changes cognitive apparatus [4] and even basic calculation capabilities [5]. Although it elaborates no abstract models of previous experiences, it can keep short term memories of episodes, classifying them as negative (e.g. dangers) or positive (e.g. food).

While navigating, many fishes are able to recognize both geometrical and featural environment cues [7]. Such capabilities have also been demonstrated for the *Carassius auratus* [10], which can react to static and dynamic aspects of the visually perceived environment. Fishes in general have lateral eyes allowing an almost $360°$ visual field [6]. Anyhow, the angle of stereoscopic vision is comparatively small: about $\pm 15°$. As a consequence, the head of the fish is always oriented towards the object that is stereoscopically observed. This feature simplifies the understanding of where the attention of the animal is most likely being directed during demanding tasks.

B. Robotic platform

A schematic of the hardware is shown in fig. 2. The battery-operated robotic platform is assembled using a development kit (Robotech s.r.l., model RDS-X01). The platform has a horizontal rectangular surface ($20\ cm \times 40\ cm$) supporting the fish-bowl (glass cylinder, internal diameter: $15\ cm$). The fish-bowl is placed symmetrically on the platform and its axis intersects the axis of the wheels. In this way, the rotation of the platform does not cause any inertial effect on the water, which is only slightly perturbed by small viscous effects.

The bottom part of the horizontal surface hosts: two DC gearmotors (reduction ratio 100:1) connected to the driving wheels; an idle wheel providing mechanical support; a microcontroller (PIC 16F877A); a power amplifier; four batteries ($1,5\,V$). A camera (352×288 pixels, 30 $frame\ s^{-1}$) is

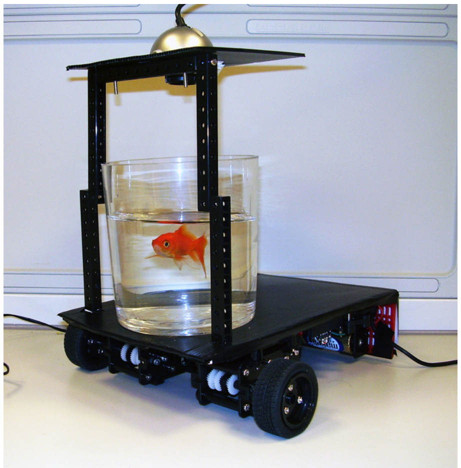

Fig. 3. Overview of the actual system.

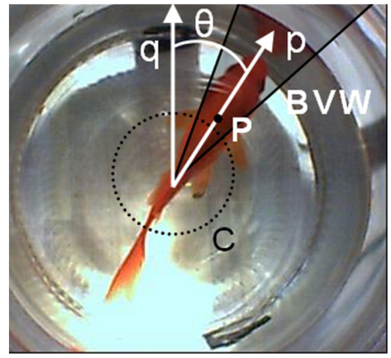

Fig. 4. Example frame reporting the variables used for motor mapping strategy.

supported by a frame connected to the base in such a way it has a horizontal view plane, overlooking the fish-bowl. The frames are sent to a PC via USB connection. Motor commands are sent from the PC to the microcontroller via RS232.

C. Mapping strategy

The motor mapping module is based on the analysis of the images of fish motions, as better described in Sec. III-D. Several motor mapping strategies can be devised and have been experimentally tested. We limit our description to the one actually implemented. Unfortunately, there is no available literature on how inferring fishes' cognitive mechanisms from their movements. Nonetheless, it can be observed that the fish, besides standing still, exhibits two basic behaviours: quick rotation in place (up to $\pm 180°$) and straight swimming. The chosen motor strategy hinges around the detection of such behaviours. The validity of the choice is confirmed *a posteriori* by observing how the implemented motor mapping strategy actually leads to useful behaviours (i.e. escape from approaching obstacles, as better detailed in Sec. IV).

In order to describe the selected motor mapping strategy, we first need to introduce a few symbols.

- BVW (Binocular Vision Window): is the narrow ($\pm 15°$) angular sector where the fish has binocular vision capability;
- $\mathbf{p}$ is the orientation vector parallel to BVW median axis and oriented in the tail-to-head direction;
- $\mathbf{q}$ is the vector oriented as the longitudinal axis of the robot;
- ϑ is the (smallest) angle between $\mathbf{p}$ and $\mathbf{q}$;
- R is the inner radius of the cylindrical fish-bowl;
- r is the radius of the circle C centred with the fish-bowl, $r < R$;
- P is the center of mass of the fish.

The above mentioned basic behaviours exhibited by the fish can be replicated in the robotic platform using the following strategy. If $\mathbf{q}$ is outside BVW, the robot rotates around a vertical axis coincident with the fish-bowl axis, until $\mathbf{q}$ is within BVW[1]. Then, two cases may occur. If P is in C (i.e. far from the fish-bowl wall), the robot does not move, otherwise it translates along p with constant speed. In this way the robot moves only if fish head is sufficiently close to the fish-bowl wall, otherwise (i.e. if P is in C and the head is far from the wall) the fish is not expectedly focusing on a specific target in the environment, and therefore there is presumably no need for moving.

In summary, three basic behaviours, resembling those exhibited by the fish, are allowed to the robot: 1. standing still; 2. turning around a vertical axis; 3. straight moving with constant speed.

D. Image analysis

An example frame acquired by the camera is shown in fig. 4. The objective of the image processing module is to extract the geometric features necessary for robot motion control, namely ϑ, P and ($\mathbf{p}$).

The first step consists in detecting fish body. Each acquired frame is a RGB image, structured as an array of three 352×288 matrices, denoted by the symbols: F^R, F^G and F^B, where the superscripts stand for the corresponding colour (*Red*, *Green* or *Blue*). The fish body corresponds to the frame region where the red colour is dominant. The original frame is filtered to produce a binary matrix D given by the boolean assignment:

$$D_{i,j} = \left(F^R_{i,j} > \alpha_1 F^G_{i,j} + \alpha_2 F^B_{i,j}\right)$$

where the coefficients α_1 and α_2 have been experimentally determined ($\alpha_1 = \alpha_2 = 1.0$) in order to minimize the effect of spurious optical effects (e.g. reflections).

The dominantly red pixels in the original RGB image (F) correspond to the non-zero elements of the resulting matrix D. Such filtering is computationally efficient[2] and robust with regards to environmental lightning changes. Image ground noise is then filtered by eliminating clusters of less

[1] $\mathbf{q}$ reaches the closest boundary of the BVW with a non zero speed; the resulting overshoot assures that $\mathbf{q}$ actually enters BVW.

[2] The time required for processing each frame on an Intel Core 2 duo processor, 1.66 GHz, 2 Gb RAM is about 3 ms.

than 200 pixels using the Matlab *bwareopen* command. The center of mass P and the angle ϑ are retrieved from D using the *regionsprops* Matlab command. The extraction of such features requires about $25\,ms$.

Orientation vector $\mathbf{p}$ is calculated by first localizing the position of fish head with respect to the caudal fin. The head is localized by exploiting body asymmetry (head is quite larger than caudal fin) using a morphological manipulation of the image, based on dilatation and erosion operations, using a disc shaped structuring element that is approximately equal in size to fish head. The orientation of $\mathbf{p}$ is the same of the vector connecting P to the center of such disc. This operation requires about 25 ms.

E. Modelling and control

The replication by the mobile platform of the three desired behaviours described in par. III-C is demanded to the low level control module. Since two of the three behaviours, namely standing still and straight motion, can be trivially implemented, we focus here only on how turning behaviour, which aims at tracking fish angular position, is achieved.

DC motors are powered in PWM. Pure rotation is achieved by powering both motors with opposite voltages and the same duty cycle, which is modulated by a PD controller to regulate the angular speed.

A trial-and-error approach has been used in order to tune both the proportional (K_p) and derivative (K_d) coefficients of the PD controller. A first estimation of such parameters has been done in simulation, using a model of the system. The final tuning of the parameters has been performed on the actual hardware.

A simple electro-mechanical model for DC motors is given in eqs. (1) and (2):

$$V = R\,i + L\frac{di}{dt} + K_a\omega \tag{1}$$

$$J\dot{\omega} + b\omega = K_a i + T_m \tag{2}$$

Equation (1) relates supplied voltage (V) to armature current (i) and shaft's angular speed (ω) through the electric resistance (R), the inductance (L) and the armature constant (K_a). In (2), J is the sum of the shaft intrinsic inertia I_s, provided by the manufacturer ($I_s = 0.5\ 10^{-6}\ kg\,m^2$) and the equivalent inertia of the robot as seen at motor shaft (I_{eq}); b is the friction constant and T_m is the load torque applied to the shaft. Since only an inertial load is present during rotation, $T_m = 0$.

Not all the parameters appearing in (1) and (2) are available on the motors datasheet. Therefore, preliminary measurements were made. In particular, R was measured with a multimeter when drive shaft is blocked ($e = 0$) and electric transient is extinguished (i.e. $\frac{di}{dt} = 0$). We found: $R = 0.85\ \Omega$.

L was measured by blocking the drive shaft ($e = 0$) and applying a step voltage. L was calculated by measuring the time constant of the voltage at the brushes: $L = 3.52\ 10^{-4}\ H$.

To measure armature constant K_a, DC motors were used as dynamos: their shaft was put into rotation by an external motor controlled at constant speed ($\omega = 120\ rpm$). Being $\omega = const$, $\frac{di}{dt} = 0$. Motors were connected to a voltmeter providing V. Being $i \approx 0$, we got $K_a = V/\omega = 5\ 10^{-3}\ Vs/rad$.

Friction constant (b) was calculated by measuring i when $\frac{d\omega}{dt} = 0$ and $Tm = 0$: $b = 2.5\ 10^{-6}\ Nms$.

As it regards I_{eq}, we first evaluated the moment of inertia of the robot with respect to the rotation axis (I_r) and then its equivalent I_{eq} as seen at the shaft. Some approximations were used for evaluating I_r. During pure rotation water is fixed with respect to an inertial frame of reference[3] and therefore its mass does not contribute to robot moment of inertia (I_r). The fish-bowl is therefore modelled as a *hollow* cylinder. The other components (batteries, motors, frame, camera) are approximated to homogeneous parallelepipeds and spheres. Their moment of inertia is referred to the robot axis of rotation through Huygens-Steiner theorem. In this way we got: $I_r = 1.11\ 10^{-2} kg\,m^2$.

With reference to fig. 2, robot inertia at drive shaft (I_{eq}) can be evaluated considering the radius of the wheels (R), the distance between the wheels (L) and the reduction ratio of the gear train connected to the motors ($\tau = 100 : 1$)[4]. After simple calculations, one gets:

$$I_{eq} = 2\frac{I_r R^2}{L^2\tau^2} = 0.4\,10^{-7}\ kg\,m^2 \tag{3}$$

Therefore, $J = I_s + I_{eq} = 0.54\,10^{-6}\ kg\,m^2$.

The reduction gear is fabricated by serially assembling 7 moulded plastic gears, forming 6 meshes. If η_1 is the kinematic efficiency of a single mesh, the overall reduction gear efficiency is $\eta = \eta_1^6$. The actual value of η_1 is unknown and its value has been set to match model predictions with measured data. In particular, robot angular speed for different input voltages was measured and compared to model predictions. η_1 was adjusted to have a residual mean error of less than $5°/s$. With this procedure we found $\eta_1 = 0.30$.

By introducing the effect of friction, and recalling that $T_m = 0$, eq. (2) reduces to:

$$J\dot{\omega} + b\omega = \eta K_a i \tag{4}$$

F. Preliminary evaluation of control parameters by simulation

In order to get a preliminary choice of K_p and K_d, 6 constant angular positions (from 30° to 180° with increments of 30°) were provided as reference for the control. The simulated position of the robot was retrieved from the model every $100\,ms$, since this is the time interval, experimentally evaluated, required to calculate fish position by image processing (about 53 ms) and to send appropriate commands to motors (about 45 ms).

[3]The low viscosity of water assures that the moment generated by viscous shear stress during robot rotation is negligible.

[4]Wheels inertia is negligible.

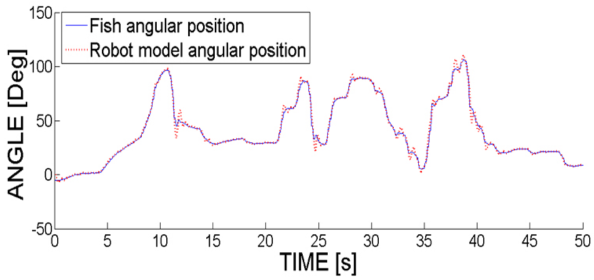

Fig. 5. Trajectory tracking using robot model.

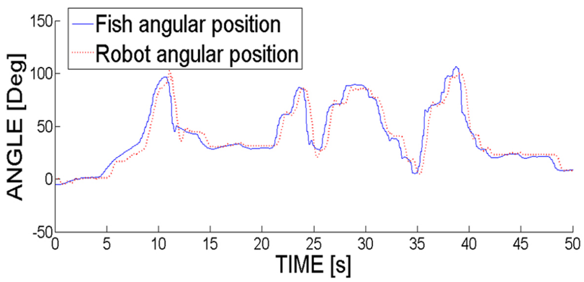

Fig. 6. Actual robot trajectory tracking.

The optimal parameters, in terms of rise time, overshoot and stability, change with step amplitude. Anyhow, a good compromise for all amplitudes occurs when $K_d \cong 0.1K_p$.

To find the actual values of the parameters, the tracking of recorded fish movements was simulated, using robot model, and looking for the least average absolute position error. The optimal values for K_p and K_d found are respectively 3.5 and 0.4, which correspond to an average absolute position error smaller than $1°$. An example plot of simulated trajectory tracking is shown in fig. 5.

IV. EXPERIMENTAL RESULTS

A first session of experimental trials was performed with the of finely tuning the control parameters. In order to have a repeatable scheme, absolute fish movements (with respect to an inertial observer) were recorded using the camera mounted on the platform for 50 s. By applying the video processing procedure, described in Sec. III-D, the absolute trajectory of the fish was calculated off-line and recorded.

Then, a printed image of the fish was connected to a fixed support and exposed to the camera. During robot rotation, the fish picture, which is fixed for an inertial observer, rotates with respect to the robot. The angular relative position is calculated on-line using the video processing procedure. This assures that the update time is the same as in the real scenario, where the processing procedure is applied on-line to the actual fish video, because the video of the (relatively) rotating fish image is processed using the same procedure that would be used if the camera was looking at the fish.

With this set-up, both fish and robot's movements are observed with respect to an inertial reference frame, and it is possible to extract ϑ. By controlling the robot using the parameters found in simulation, the mean angular error results to be about $11.5°$.

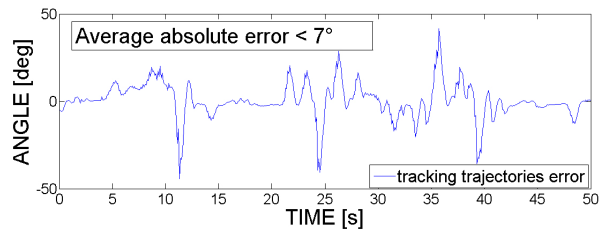

Fig. 7. Error in trajectory tracking during an experimental session with the *Carassius auratus*.

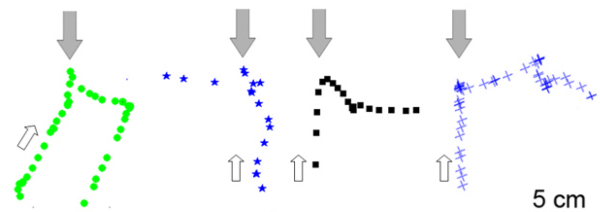

Fig. 8. Example experimental trajectories of the robot when an obstacle is approaching along the direction indicated by the grey vertical arrows. The position of the robot is extracted from a fixed videocamera every 270 ms.

A finer tuning of the control parameters (ultimately set to $K_p = 2.9$ and $K_d = 0.3$) was performed by trial-and-error until a minimum error was reached (mean value: $7.0°$; $\sigma = 7.52°$) (fig 6).

A second session of experimental trials was performed by letting the fish actually control the robot. In this session the three fish behaviours were implemented (i.e. standing still; straight motion; turning). Thanks to the low viscosity of water, the rotation of the robot does not cause any rotation of the liquid, thus assuring a minimal perturbation of the fish's environment[5].

An example plot of the tracking error corresponding to these tests is shown in fig. 7.

As shown in fig. 7 the peak error is of about $\pm 40°$. Such a high value is basically due to the ability of the fish to perform quick and large rotations (up to $180°$ in less than 1 s), while the maximum angular speed of the robot is about $120°/s$.

A final experimental session consisted in approaching coloured boxes (approx. 30 $cm \times 30$ $cm \times 30$ cm) to the robot while it was freely wandering, in order to simulate unknown dynamical obstacles. The boxes where manually moved toward the robot, with an estimated average speed of 1 m/s [6], and stopped about 10 cm from it.

Typical responses of the robot are shown in fig. 8, where obstacles' direction of motion is indicated by the vertical grey arrows.

The robot, relying on the sole response of the fish, successfully changes its trajectory in order to avoid collisions (fig. 8). As the experiment is repeated over and over, the

[5] On the contrary, linear accelerations cause perturbations in the form of non-vertical pressure gradients; anyhow linear accelerations have a short duration thanks to the high reduction ratio of the motor reduction gears.

[6] Approaching velocity does not appreciably influence the response of the robot.

response of the fish becomes less escape-oriented and, after about 5 repetitions, it appears to be *curiosity-driven*, with the fish approaching the box and even following it in case it is slowly moved away. The former escape-oriented behaviour is recovered as soon as the colour of the box is changed.

V. DISCUSSION

By comparing fig. 5 and fig. 6, we observe that the latter shows a greater residual error. This is due to a number of factors that were not taken into consideration in the modelling phase.

First of all, the robotic platform provides an angular acceleration that is too low compared to that required by the specific animal. Besides, the reduction gears used have a non negligible back-slash, that hinders prompt reactions. Moreover, fish position detection is often affected by errors caused by specific lightning condition, as well as by the undulation of the water surface, which produces spurious optical effects. Finally, static friction, not taken into consideration in (2), blocks robot motion when the voltage is below a given value, impeding small rotations.

Nonetheless, the experimental mean error ($7°$) found in tracking appears to be acceptable, because a number of tests proved that the robot was able to replicate the fish behaviour. This allows the interaction of the animal with surrounding environment in a coherent way, with particular regard to dynamic situations requiring the avoidance of approaching objects. Anyhow, a deep investigation on the actual capabilities of the *Carassius auratus* in navigational contexts, has still to be performed.

VI. CONCLUSIONS AND FUTURE WORK

For the first time, a higher than insect animal form, kept in ecological conditions, is inserted in a control loop. The robot presented in this paper embodies an animal-in-the-loop control architecture, which can be considered as a simplified instance of the Double Hybrid Control Architecture where input channels coincide with the animal own sensors, and motor commands are extracted by observing the animal motions (motor mapping), with no need for invasive, tethered sensors.

A detailed description of the control strategy is provided, as well as the computational technique used to extract fish's center of mass (P) and orientation ($\mathbf{p}$). Such data are fed as input to the robot control, whose objective is to have the robot replicating the basic fish movements (stand still; rotate; straight swimming). A number of experimental tests allowed the fine tuning of control parameters, as well as the evaluation of the mean tracking error (about $7°$).

Experiments have shown that the robot replicates fish's obstacle-avoidance behaviour. Quite interestingly, the learning capabilities of the fish allows the robot to discriminate erratic from repetitive dynamic obstacles. In the first case, the robot exhibits a cautious behaviour, characterized by quick trajectory changes in order to avoid the obstacle; in the second case, the robot exhibits a behaviour characterised by curiosity, getting close or even following the moving objects.

Compared to existing navigation strategies, such as those implemented in autonomous vehicles moving in fully unstructured environments or in urban sets, the behaviour of the robot is not goal-oriented, i.e. the fish is not taught a specific objective to pursue.

Anyhow, in line with the rationale of the Double Hybrid Control Architecture, robust and goal-oriented behaviours of autonomous robots can be achieved by adequately merging algorithmic capabilities, which can be embedded in the mechatronic platform, with the natural capabilities of the biological organism, especially in terms of reaction to unpredictable events.

To this aim, the preliminary investigation of animal's reactions is mandatory. One simple approach consists, as in this paper, in observing emergent behaviours while the robot merely replicates the behaviours of the animal, which is left free to explore an environment. More refined approaches can be borrowed from Ethology, which could also provide important hints for the selection of the most appropriate animal forms for specific exploratory tasks.

REFERENCES

[1] A. Benvenuto, F. Sergi, G. Di Pino, T. Seidl, D. Campolo, D. Accoto, E. Guglielmelli, "Conceptualization of an Insect/Machine hybrid controller for space applications." *Advanced Robotics* vol. 23, pp 939-953 2009.

[2] http://www.conceptlab.com/roachbot

[3] http://www.neuromorph.ece.arizona.edu.

[4] C. Briglio, "Spatial Cognition and its neural basis in teleost fishes." *Fish and Fisheries* vol.4, pp 247-255, 2003.

[5] C. Clover, "Fish can count to four - but no higher." *Environment Editor (Telegraph.co.uk)*, 2008.

[6] G.M. Wallis, L. Litherland, U.E. Siebeck, "Colour vision in coral reef fish." *Journal of Experimental Biology* vol. 211, pp 354-360, 2008.

[7] G. Vallortigara, V.A. Sovrano, A. Bisazza, "Modular and spatial reorientation in a simple mind: encoding of geometric and non geometric proprierties of a spatial environment by fish." *Animal Cognition* vol.85, B51-B59, 2002.

[8] Hermer, "Modularity and development: the case of spatial reorientation." *Animal Cognition* vol. 61, pp 195-232, 1996

[9] Hermer, "A geometric process for spatial reorientation in young children." *Nature* vol.370, pp57-59, 1994

[10] J. P. Vargas , J. C. Lopez, C. Salas, C. Thinus-Blanc, "Encoding of geometric and featural spatial information by goldfish (Carassius auratus)." *Journal of comparative psychology* vol. 118, no2, pp. 206-216, 2004.

[11] Rodriguez, Gomez, Salas, Lopez, Bingman, "Dissociation of place and cue learning by telencephalic ablation in goldfish." *Behavioural Neuroscience* vol.114, pp687-600, 2000.