A Biologically Inspired Neural Network for Navigation with Obstacle avoidance in Autonomous Underwater and Surface Vehicles

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***Abstract*—This paper describes a neural network model for the reactive behavioural navigation of an autonomous underwater vehicle (AUV) in which an innovative, neurobiological inspired sensorization control system and a hardware architectures are being implemented. The AUV has been with several types of environmental and oceanographic instruments such as CTD sensors, chlorophyll, turbidity, optical dissolved oxygen (YSI V6600 sonde) and nitrate analyzer (SUNA) together with ADCP, side scan sonar and video camera, in a flexible configuration to provide a water quality monitoring platform with mapping capabilities. This neurobiological inspired control architecture for autonomous intelligent navigation was implemented on an AUV capable of operating during large periods of time for observation and monitoring. In this work, the autonomy of the AUV is evaluated in several scenarios.**

***Index Terms*—Autonomous under vehicle (AUV), neural networks, obstacle avoidance, robot navigation, learning control adaptive behaviour.**

I. INTRODUCTION

The need of autonomous underwater robots has become increasingly apparent as the world pays great attention on environmental and resources issues as well as scientific and military tasks. Many autonomous underwater robots have been developed to overcome scientific challenges and engineering problems caused by the unstructured and hazardous underwater environment.

With continuous advances in control, navigation, artificial intelligence, material science, computer, sensor and communication, autonomous underwater vehicles (AUVs) have become very attractive for various underwater tasks. The autonomy is one of the most critical issues in developing AUVs. The design, development, navigation, and control process of an AUV is a complex and expensive task. Various control architectures have been studied to help increase the autonomy of AUVs [1, 2].

There are a large number of researches underway to investigate enabling technologies pacing further development of autonomous underwater robot systems. Control of AUV in uncertain and non structured environments is a complex process involving non-lineal dynamics behavior. Various advanced underwater robot control systems have been proposed such as sliding mode control (SMC) by Yoerger and Slotine in 1984 [3], nonlinear control by Nakamura and Savant in 1992 [4], adaptive control by Antonelli et al. in 2001 [5], neural network control by Lorenz and Yuh in 1996 and Porto and Fogel in 1992 [6, 7], fuzzy control by Smith et al. [8], and visual servo control by Silpa-Anan et al. in 2001 [9].

Trajectory generation with obstacle avoidance is a fundamentally important issue in robotics. Real-time collision-free trajectory generation becomes more difficult when robots are in a dynamic, unstructured environment. There are a lot of studies on trajectory generation for robots using various approaches problem (e.g. [10, 11]). Some of the previous models (e.g. , [12, 13]) use global methods to search the possible paths in the workspace, which normally deal with static environment only and are computationally expensive when the environment is complex. Seshadri and Ghosh [1] proposed a new path planning model using an iterative approach. However this model is computationally complicated, particularly in a complex environment. Li and Bui [2] proposed a fluid model for robot path planning in a static environment. Oriolo et al. [10] proposed a model for real-time map building and navigation for a mobile robot, where a global path planning plus a local graph search algorithm and several cost functions are used.

Several neural network models (e.g., [11—14]) were proposed to generate realtime trajectories through learning. Ritter et al. [13] proposed a Kohonen's selforganizing mapping algorithm based neural network model to learn the transformation from Cartesian workspace to the robot manipulator joint space. Fujii et al. [11] proposed a multilayer reinforcement learning based model for path planning with a complicated collision avoidance algorithm. However, the generated trajectories using learning based approaches are not optimal, particularly during the initial learning phase.

Several papers [2, 13-22] examine the application of neural network (NN) to the navigation and control of AUVs using a well-known back-propagation algorithm and its variants since it is not possible to accurately express the dynamics of an AUV as linear in the unknown parameters. Unfortunately, the backpropagation-based NN weight tuning is proven to have convergence and stability problems [22]. Further, an offline learning phase, which is quite expensive, is required with the NN controllers [2, 11, 16].

However, mathematical models of neuronal systems are a link between biology and engineering. The Dynamical Neuronal Theory (DNT) builds complex architectures at local

(VITE, AVITE), regional (ART, BCS/FCS, MULITIART) and system (DIRECT, FLETE, CEREBELLUM, ...) scale [13-12]. Algorithms based on DNT provide reliable adaptive learning models to different architectures depending on the assigned tasks. Auto-organizational neural networks can solve a wide range of problems such as inverse cinematic or reactive and autonomous navigation. Neuro-biologically inspired architectures are based on hierarchical controllers acting in a parallel way.

In this paper, a Self-Organization Direction Mapping Network (SODMN) and a Neural Network for the Avoidance Behaviour (NNAB) both biological inspired are presented. The SODMN is a kinematic adaptive neuro-controller and a real-time, unsupervised neural network that learns to control autonomous underwater and surface vehicles in a nonstationary environment. The SODMN combines an associative learning and a Vector Associative Map (VAM) learning [16] to generate transformations between spatial and velocity coordinates. The transformations are learned in an unsupervised training phase, during which the vehicle moves as a result of randomly selected velocities of its actuators. The controller learns the relationship between these velocities and the resulting incremental movements. The NNB is a neural network based on animal behaviour that learns to control avoidance behaviours in autonomous vehicles based on a form of animal learning known as operant conditioning. Learning, which requires no supervision, takes place as the vehicle moves around a cluttered environment with obstacles. The NNB requires no knowledge of the geometry of the vehicle or of the quality, number, or configuration of the autonomous vehicle's sensors. Biologically inspired neural networks proposed in this paper represent a simplified way to understand in part the mechanisms that allow the brain to collect sensory input to control adaptive behaviours of autonomous navigation of the animals. This proposed control system based on a neurobiological inspired control architecture for autonomous intelligent navigation was implemented on an AUV capable of operating during large periods of time for observation and monitoring. In this work, the autonomy of the vehicle is evaluated in several scenarios

This paper is organized as follows. We first describe (Section II) the experimental platform with the navigation system, neural control system and the set of oceanographic instruments installed on the AUV-UPCT. Section III addresses the experimental results with the proposed control system for control of avoidance and approach behaviour on the AUV-UPCT. Finally, in Section IV, conclusions based on experimental results are given.

II. Description of the Experimental Platform

A. Description of the AUV-UPCT

Figures 1 and 2 show the underwater platform and its interconnection scheme of hardware control system, respectively. The vehicle has two bodies: one integrates the propellers for movement and the other integrates perception systems. The movement body has two stern thrusters for horizontal movement, two thrusters for vertical movement and a thruster to the rotation of the vehicle. The perception body integrates a vision camera, imaging sonar, and an inertial measurement unit. The vehicle has also altimeter sonar, and a side scans sonar system in the bottom of the vehicle. It weighs170kg with positive buoyancy, the maximum speed is 4 knots.

For navigation and control the vehicle incorporate an Inertial Measurement Unit (IMU) with a Navigation and Heading Reference System processor. The internal low-power signal processor runs a real-time Kalman Filter providing inertial enhanced 3D position and velocity estimates. The IMU also provides drift-free, GPS enhanced, 3D orientation estimates, as well as calibrated 3D acceleration, 3D rate of turn and 3D earth-magnetic field data.

Fig. 1. Autonomous underwater vehicle from the UPCT (AUV-UPCT)

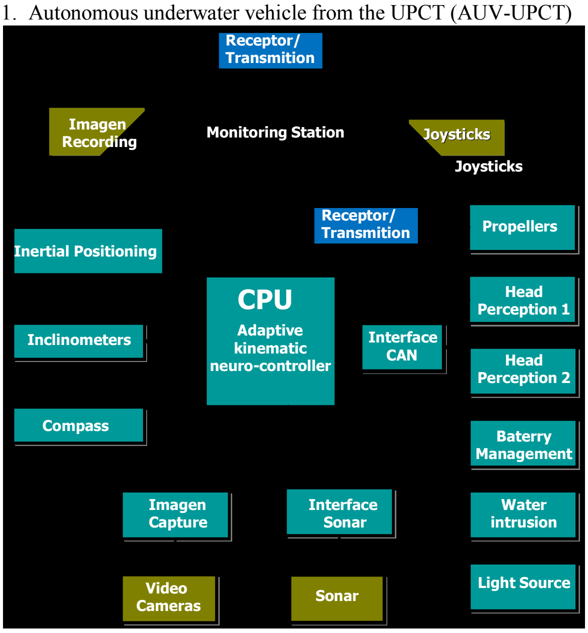

Fig. 2. Interconnection elements of hardware control system from the AUV-UPCT.

B. Navigation System of the AUV

The main goal of the navigation system is to achieve an appropriate level of spatial location at all times, allowing trajectory correction using a neural control algorithm, to process the corresponding corrections. Initially, consider three types of missions and each one different positioning procedure.

A global positioning system (GPS) mounted on the vehicle, as usual, will be modified for navigation in shallow waters when long time submerged operation is required. Two options are being considered: a surface-towing buoy with GPS and RF communications system or a kind trolley-pole linked to the buoy when accuracy in location is a critical factor.

When no accurate bathymetry is available or unexpected wreck can be found the proposed neural control algorithm would avoid collision risk.

In deep waters, regular emersions of the vehicle are not feasible, so the neural control system represents the most suitable system to avoid obstacles and allow the spatial location of the vehicle. Using an inertial navigation system combined with the control algorithm and a calibration of positioning bathymetric points of reference, the position of the vehicle is permanently submerged. In this case, it is important to define the benchmarks in the seabed with the utmost accuracy thus allowing the vehicle to find and modify the following path on the basis of these data. In addition, there is being implementing a complementary algorithm to allow the vehicle to be able to search and find the seafloor reference in case of lost the expected location.

In order to save the maximum level of available energy it is mandatory minimizing the number of 'search and find' operations. So it is strongly recommendable to check the course deviation in the study area before each mission. In this way, definition of the local deviation parameters and its use as inputs to calibrate the control system will minimize the tracking deviation.

C. Neural Control System

Figures 3, 4 and 5 illustrate our proposed neural architecture. The trajectory tracking control without obstacles is implemented by the SODMN and the avoidance behaviour of obstacles is implemented by a neural network of biological behaviour.

For a dynamic positioning in the path tracking a PID controller was incorporated into the architecture of control system. It allows smooth the error signal in the reaching of objectives.

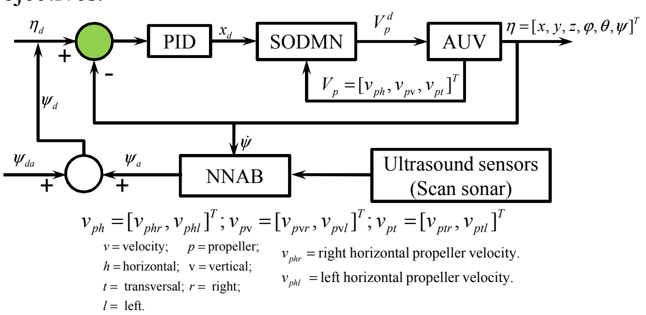

Fig. 3. Neural architecture for reactive and adaptive navigation of an AUV.

C1. Self-Organization Direction Mapping Network (SODMN)

The SODMN learns to control the robot through a sequence of spontaneously generated random movements (shown in Fig. 4). The random movements enable the neural network to learn the relationship between angular velocities applied at the propellers and the incremental displacement that ensues during a fixed time step. The proposed SODMN combines associative learning and Vector Associative Map (VAM) learning [16] to generate transformations between spatial coordinates and coordinates of propellers' velocity. The nature of the proposed kinematic adaptive neuro-controller is that continuously calculates a vectorial difference between desired and actual velocities, the underwater robot can move to arbitrary distances and angles even though during the initial training phase it has only sampled a small range of displacements.

Furthermore, the online error-correcting properties of the proposed architecture endow the controller with many useful properties, such as the ability to reach targets in spite of drastic changes of robot's parameters or other perturbations.

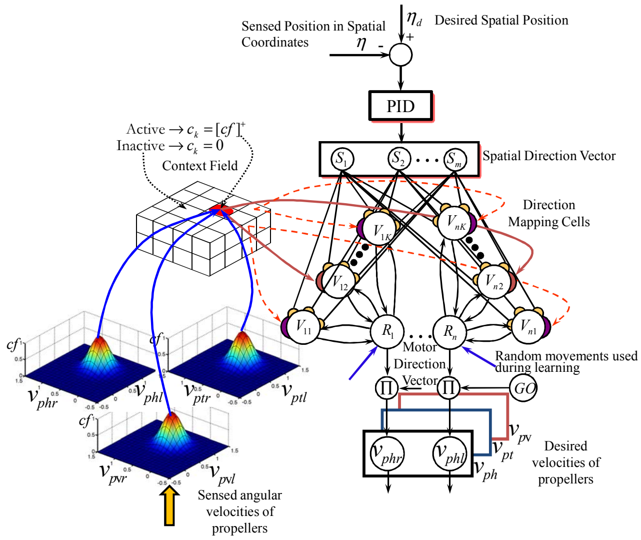

Fig. 4. Self-organization direction mapping network (SODMN) for the trajectory tracking of an AUV robot.

At a given set of angular velocities the differential relationship between underwater robot motions in spatial coordinates and angular velocities of propellers is expressed like a linear mapping. This mapping varies with the velocities of propellers.

The transformation of spatial directions to propellers' angular velocities is shown in Fig. 4. The tracking spatial error (e) is computed to get the desired spatial direction vector (x_d) and the spatial direction vector (DVs). The DVs is transformed by the direction mapping network elements V_{ik} to corresponding motor direction vector (DVm). On the other hand, a set of tonically active inhibitory cells which receive broad-based inputs that determine the context of a motor action was implemented as a context field. The context field selects the V_{ik} elements based on the propellers' angular velocities configuration.

A speed-control GO signal acts as a nonspecific multiplicative gate and controls the movement's overall speed. The GO signal is an input from a decision center in the brain, and starts at zero before movement and then grows smoothly to a positive value as the movement develops. During the learning, sensed angular velocities of propellers are fed into the DVm and the GO signal is inactive.

Activities of cells of the DVs are represented in the neural network by quantities (S_1, S_2, ⋯, S_m), while activities of the cells of the motor direction vector (DVm) are represented by quantities (R_1, R_2, ⋯, R_n). The direction mapping is formed with a field of cells with activities V_{ik}. Each V_{ik} cell receives the complete set of spatial inputs S_1, $j = 1, \cdots, m$, but connects to only one R_i cell (see Figure 4). The mechanism that is used to ensure weights converge to the correct linear mapping is similar to the VAM learning construction [16]. The direction mapping cells ($\mathbf{V} \in \mathrm{R}^{n \times k}$) compute a difference of activity between the spatial and motor direction vectors via feedback from DVm. During learning, this difference drives the adjustment of the weights. During performance, the difference drives DVm activity to the value encoded in the learned mapping.

A context field cell pauses when it recognizes a particular velocity state (*i.e.*, a velocity configuration) on its inputs, and thereby disinhibits its target cells. The target cells (direction mapping cells) are completely shut off when their context cells are inactive. This is shown in Fig. 4. Each context field cell projects to a set of direction mapping cells, one for each velocity vector component. Each velocity vector component has a set of direction mapping cells associated with it, one for each context. A cell is "*on*" for a compact region of the velocity space. It is assumed for simplicity that only one context field cell turns "*on*" at a time. In Figure 4, inactive cells in the context field are shown as white disks. The center context field cell is "*on*" when the angular velocities are in the center region of the velocity space, in this three degree-of-freedom example. The "*on*" context cell enables a subset of direction mapping cells through the inhibition variable c_k, while "*off*" context cells disable to the other subsets. When the k^{th} context cell is "*off*" or inactive (modeled as c_k=0), in its target cells, the entire input current to the soma is shunted away such that there remains only activity in the axon hillock, which decays to zero. When the kth context cell is "on" or active, c_k =1, its target cells (V_{ik}) receive normal input.

The learning is obtained by decreasing weights in proportion to the product of the presynaptic and postsynaptic activities [13-16]. Therefore, the learning rule can be obtained by using the gradient-descent algorithm. The training is done by generating random movements, and by using the resulting angular velocities and observed spatial velocities of the AUV robot as training vectors to the direction mapping network.

C2. Neural Network for the Avoidance behavior (NNAB)

The obstacle avoidance adaptive neuro-controller is a neural network that learns to control avoidance behaviors in an AUV robot based on a form of animal learning known as operant conditioning. Learning, which requires no supervision, takes place as the robot moves around a cluttered environment with obstacles. The neural network (shown in Fig. 5) requires no knowledge of the geometry of the robot or of the quality, number, or configuration of the robot's sensors. Our implementation is based in the Grossberg's conditioning circuit, which follows closely that of Grossberg & Levine [23, 26] and Chang & Gaudiano[24].

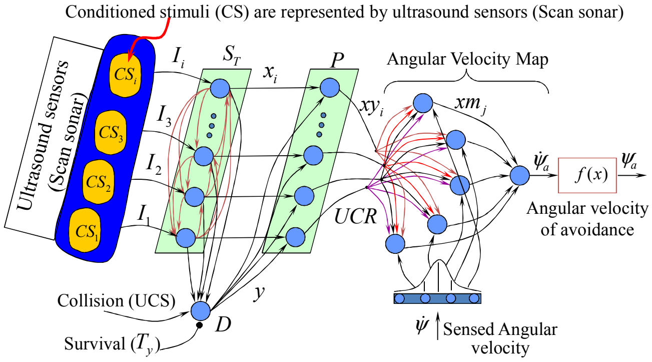

Fig. 5. Neural network for the avoidance behavior (NNAB).

In this model the sensory cues (both conditioned stimuli (CS) and unconditioned stimuli (UCS)) are stored in Short Term Memory (STM) within the population labeled S_T, which includes competitive interactions to ensure that the most salient cues are contrast enhanced and stored in STM while less salient cues are suppressed. The population S_T is modeled as a recurrent competitive field in simplified discrete-time version, which removes the inherent noise, efficiently normalizes and contrast-enhances from the ultrasound sensors activations. In the present model the CS nodes correspond to activation from the robot's ultrasound sensors. In the network I_i represents a sensor value which codes proximal objects with large values and distal objects with small values. The drive node (D) corresponds to the Reward/Punishment component of operant conditioning (an animal/robot learns the consequences of its own actions).

Learning can only occur when the drive node is active. Activation of drive node (D) is determined by the weighted sum of all the CS inputs, plus the UCS input, which is presumed to have large, fixed connection strength. The drive node is active when the robot collides with an obstacle, which could be detected through a collision sensor, or when any one of the proximity sensors indicates that an obstacle is closer than the sensor's minimum range. Then the unconditioned stimulus (USC) in this case corresponds to a collision detected by the mobile robot. The activation of the drive node and of the sensory nodes converges upon the population of polyvalent cells P. Polyvalent cells require the convergence of two types of inputs in order to become active. In particular each polyvalent cell receives input from only one sensory node, and all polyvalent cells also receive input from the drive node (D).

Finally, the neurons (xm_j) represent the response conditioned or unconditioned and are thus connected to the motor system. The motor population consists of nodes (*i.e.*, neurons) encoding desired angular velocities of avoidance, *i.e*, the activity of a given node corresponds to a particular desired angular velocity for the AUV robot. When driving the robot, activation is distributed as a Gaussian centered on the desired angular velocity of avoidance. The use of a Gaussian leads to smooth transitions in angular velocity even with few nodes.

The output of the angular velocity population is decomposed by SODMN into angular velocities of left and right horizontal thrusters. A gain term can be used to specify the maximum possible velocity. In NNAB the proximity sensors initially do not propagate activity to the motor population because the initial weights are small or zero. The robot is trained by allowing it to make random movements in a cluttered environment. Specifically, we systematically activate each node in the angular velocity map for a short time, causing the robot to cover a certain distance and rotate through a certain angle depending on which node is activated.

D. Set of Oceanographic Instruments Installed on the AUV

In order to provide a wide range of oceanographic research capabilities, the AUV-UPCT was equipped with several types of environmental and oceanographic instruments [27]. This allows the vehicle to carry out different types of missions, depending on research interests or needs. Two main areas of study with different results are supported by the vehicle operation: Shallow- and open-water missions.

Figure 6 shows the location of the areas chosen for both type of missions: The Mar Menor coastal lagoon for shallow water missions and the shelf-break off Cape Tiñoso, both located in the Region of Murcia (Spain).

Fig. 6. Map representing both research areas. Aerial view of the Mar Menor Lagoon and Cape Tiñoso in Cartagena-Murcia, Spain.

Shallow-water missions: To carry out this kind of studies the Mar Menor coastal Lagoon has been chosen. The Mar Menor is a hypersaline coastal lagoon located in the Region of Murcia (Spain) in the South Western Mediterranean Sea. Their special ecological and natural characteristics make the lagoon a unique natural, being the largest lagoon in Europe. Its General characteristics are: 6-10 meters max. depth, 135 Km^2 area, 2.5m mean depth and 42-49 P.S.U. salinity. The Figure 7 shows the Mar Menor Lagoon.

Fig. 7. Location of the study zone. Aerial view of the Mar Menor lagoon, in Murcia, Spain.

Three different mission will be developed in this environment: 1) Water quality monitoring: Using a YSI® multiparametric sonde (measuring temperature, salinity, turbidity, chlorophyll, dissolved oxygen) and a SUNA® nitrates analyzer together with an ADCP (SONTEK®) measuring currents (speed and direction). 2) Mapping: to perform high resolution bathymetries – using sonar side scanner (TRITECH®), and submerged vegetation maps using video cameras. 3) Data acquisition in order to validate high resolution 3D hydrodynamic models.

Open Water Missions: Oceanographic processes on the shelf-break off Cape Tiñoso have been chosen as case study. The area is close to Cartagena reaching 300-500 m depth in less than 6 miles off-shore with an easy access to deep water (2500 meters). In the area upwelling currents meet surface currents with high productivity thus allowing a high fisheries effort. In a first phase measurements of temperature, salinity, current velocity and direction (specially in the vertical) will be performed. Figure 8 shows area on the shelf-break where the major fisheries effort (dots) is made.

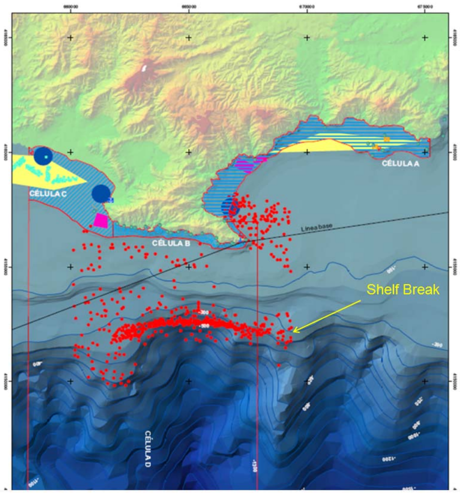

Fig. 8. Shelf-break off Cape Tiñoso. Red dots mean position where local fisheries effort is carried out.

III. Experimental Results

A. *First Navigation test of the AUV*

The first tests of navigation on the surface and immersion were performed in a pool. The robot was immersed in a controlled pool with 15 m deep in the industrial area of Fuente Álamo, Murcia-Spain. Note that the depth was recorded as positive (Z). These tests confirmed the maneuver of the vehicle and the response sensitivity of the controls in remote mode.

Navigation tests verified directional stability, turns and immersions. In all cases we were able to verify the correct response to requests from the vehicle operator. The test was developed for about an hour, at which time the battery charge did not show signs of exhaustion. It could also verify the accuracy of measurement of total displacement of the submerged vehicle, a fact which is essential to being able to properly ballast in each future operation.

Importantly, the AUV must be trained ROV mode so that the algorithm learns the maneuvers of avoidance behavior and recovery of the path to unexpected situations, in order to implement the procedures in autonomous navigation mode (unmanned AUV). By this first test we have been able to verify the feasibility of the control system. Figure 9 shows the early stages of the navigation tests.

Fig. 9. Surface navigation and successful underwater operation tests.

B. *Proposed Control System for the AUV robots*

The proposed neural network model is capable of generating optimal trajectory for underwater vehicles in an arbitrarily varying environment. The state space is the Cartesian workspace of underwater robot.

Figures 10 and 11 shows the performance of trajectory tracking controller implemented like a SODMN and these tests were carried out in Fuente Alamo-swimming pool in a 3-D workspace without any obstacle, with an initial position (P_0) at (x, y, z) = (1, 1, 1)*m* and an initial orientation as shown figures as (φ_0, θ_0, ψ_0). The trajectory carried out by the AUV in Figure 10 follows the target of $P_0 \rightarrow T_1 \rightarrow T_2 \rightarrow T_3$.

Figure 12 shows the seafloor tracking conduced in Cape Tiñoso. Altimeter sensor data are raised to avoid a collision with the seafloor. This distance is called "*Elevation Offset*" (Eoff*)*. Therefore, the underwater vehicle tracks the seafloor to 1.5 m from the line elevation (Eoff).

Figures 13 and 14 show the NNAB's performance with the presence of several obstacles. The tests were conducted in the Mar Menor Lagoon. The underwater robot starts from the initial position P_0=(10,30,1)*m* and reaches a desired position (goal). During the movements, whenever the underwater robot is approaching an obstacle, the inhibitory profile from the conditioning circuit (NNAB) changes the selected angular velocity and makes the underwater robot turn away from the obstacle. The presence of multiple obstacles at different positions in the underwater robot's sensory field causes a complex pattern of activation that steers the underwater robot between obstacles.

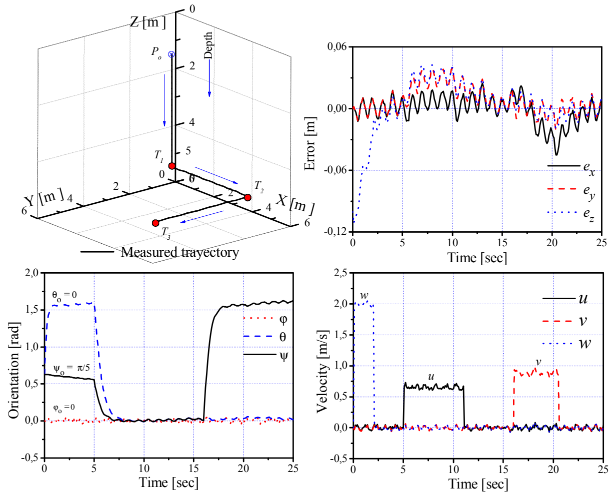

Fig. 10. Reaching of target ($P_0 \rightarrow T_1 \rightarrow T_2 \rightarrow T_3$). T_1(1,1,5)m, T_1(5,1,5)m and T_1(5,5,5)m.

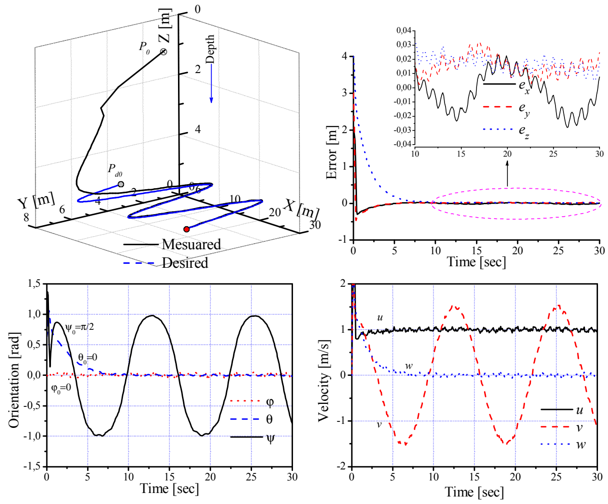

Fig. 11. Trajectory tracking.

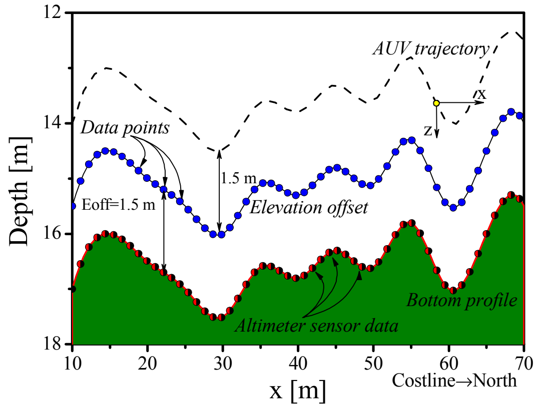

Fig. 12. Tracking of the seafloor.

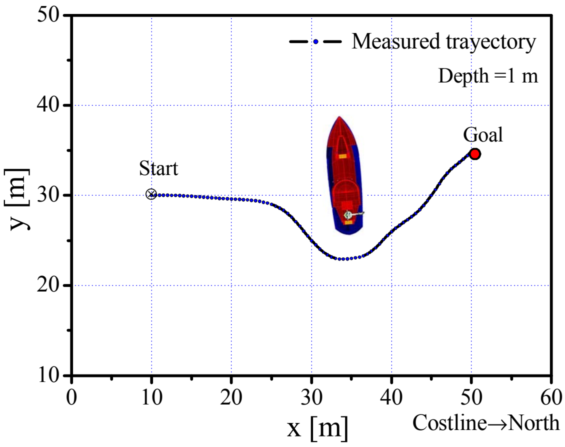

Fig. 13. Trajectory followed by the underwater robot in presence of obstacles.

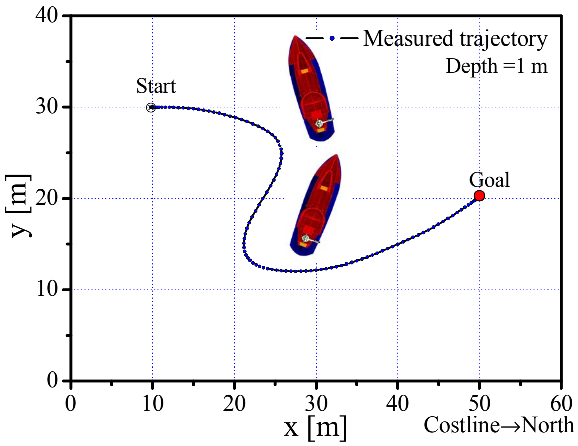

Fig. 14. Obstacle avoidance trajectory.

IV. CONCLUSIONS

In this paper, a neural architecture for trajectory tracking and avoidance behaviors of an AUV has been implemented. In addition, the hardware/software architecture was developed to allow autonomous navigation procedures for underwater vehicles. A biologically inspired neural network for the spatial reaching tracking has been developed. This neural network is implemented as a kinematic adaptive neuro-controller. The SODMN uses a context field for learning the direction mapping between spatial and angular velocity coordinates. The transformations are learned during an unsupervised training phase, during which the underwater robot moves as result of randomly selected angular velocities of propellers. It has the ability to adapt quickly for unknown states. The model algorithm is computationally efficient and the computational complexity linearly depends on the state space size of the neural network.

The avoidance behaviors of obstacles were implemented by a neural network that is based on a form of animal learning known as operant conditioning.

The efficacy of the proposed neural architecture has been successfully demonstrated in experimental results for the trajectory tracking and reaching, as well as avoidance behaviors of an underwater robot.

Tests carried out confirm the validity of the platform for its use as a multitasking vehicle for oceanographic research and missions. Due to the ability to carry out operations under remote control and autonomous, the AUV-UPCT is suitable for a wide variety of missions foreseen for the future.

The reliability of the underwater platform in an unstructured environment allows it to be a testbed for various types of control systems and instrumentation for measurements in an aquatic environment.

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