A Biologically Inspired Neural Network for Autonomous Underwater Vehicles

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Abstract. Autonomous underwater vehicles (AUVs) have great advantages for activities in deep oceans, and are expected as the attractive tool for near future underwater development or investigation. However, AUVs have various problems which should be solved for motion control, acquisition of sensors' information, behavioral decision, navigation without collision, self-localization and so on. This paper proposes an adaptive biologically inspired neural controller for trajectory tracking of AUVs in nonstationary environment. The kinematic adaptive neuro-controller is an unsupervised neural network, which is termed Self-Organization Direction Mapping Network (SODMN). The network uses an associative learning system to generate transformations between spatial coordinates and coordinates of propellers' velocity. The neurobiological inspired control architecture requires no knowledge of the geometry of the robot or of the quality, number, or configuration of the robot's sensors. The SODMN proposed in this paper represents 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. The efficiency of the proposed neurobiological inspired controller for autonomous intelligent navigation was implemented on an underwater vehicle capable of operating during large periods of time for observation and monitoring tasks.

1 Introduction

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 [1–5].

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 [2]. Some of the previous models [1–3] 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. [3] 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 [4–6] were proposed to generate real-time trajectories through learning. Ritter et al. [6] proposed a Kohonen's self-organizing mapping algorithm based neural network model to learn the transformation from Cartesian workspace to the robot manipulator joint space. Fujii et al. [4] 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 [4, 5, 7, 8] examine the application of neural network (NN) to the navigation and control of AUVs using a well-known backpropagation 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. Further, an offline learning phase, which is quite expensive, is required with the NN controllers [5].

In this paper, an unsupervised kinematic adaptive neuro-controller that can learn to guide AUVs towards a target located at an arbitrary location in a 3-D workspace is proposed. The underwater platform's movements are controlled by selecting the angular velocity of each propeller. The proposed kinematic adaptive neuro-controller requires no information about the robot's structure, is resistant to a variety of disturbances, and is based on existing neural networks of biological sensory-motor control [7]. The kinematic adaptive neuro-controller is a Self-Organization Direction Mapping Network (SODMN), and combines associative learning and Vector Associative Map (VAM) learning [8] to generate transformations between spatial coordinates and coordinates of propellers' velocity. The transformations are learned in an unsupervised training phase, during which the underwater robot moves as a result of randomly selected propellers' velocities. The robot learns the relationship between these velocities and the resulting incremental movements. The efficacy of the proposed kinematic adaptive neuro-controller is tested experimentally by an underwater vehicle capable of operating during large periods of time for observation and monitoring tasks.

This paper is organized as follows. We first describe (Section II) the neural control system for AUVs using the proposed SODMN. Section III addresses experimental results with the proposed scheme for trajectory tracking control and approach behavior over an underwater platform. Finally, in Section IV, discussion and conclusions based on experimental results are given.

2 Architecture of the Neural Control System

Figure 1 illustrates our proposed neural architecture. The trajectory tracking control without obstacles is implemented by the SODMN. The SODMN learns to control the robot through a sequence of spontaneously generated random movements. 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 [8] to generate transformations between patial 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.

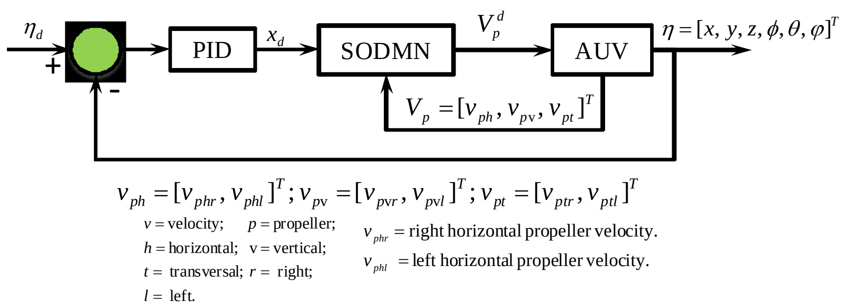

Fig. 1. Structure of adaptive biologically inspired neural controller for trajectory tracking of AUVs.

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 objetives.

2.1 Self-Organization Direction Mapping Network (SODMN)

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. 2. The tracking spatial error ($\boldsymbol{e}$) is computed to get the desired spatial direction vector ($\boldsymbol{x}_d$) 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.

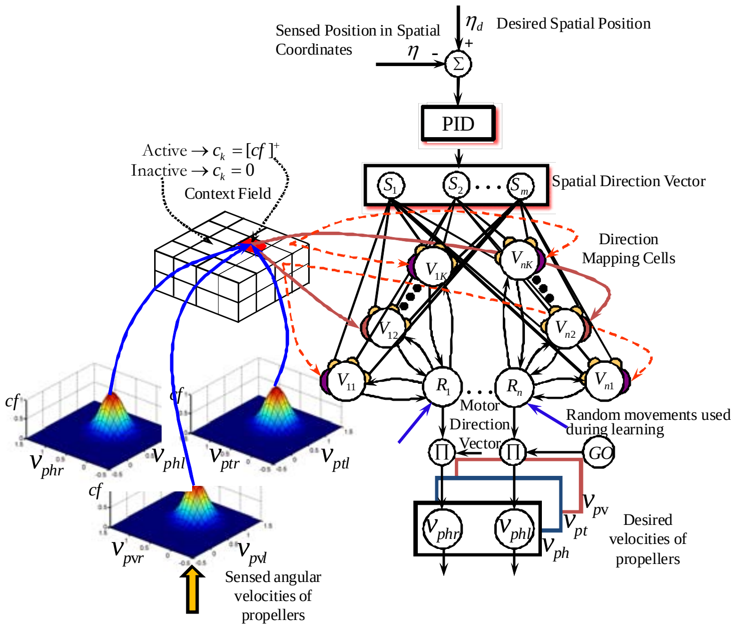

Fig. 2. Architecture of self-organization direction mapping network for autonomous robotic systems.

A speed-control GO signal acts as a nonspecific multiplicative gate and control the movement's overall speed. The GO signal is a 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_j , $j = 1, ..., m$, but connects to only one R_i cell (see Figure 2). The mechanism that is used to ensure weights converge to the correct linear mapping is similar to the VAM learning construction [9]. The direction mapping cells ($\mathbf{V} \in \mathbb{R}^{n \times k}$) 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. 2. 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 2, 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, wich decays to zero. When the k^{th} 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. 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 underwater robot as training vectors to the direction mapping network.

3 Experimental results

The proposed biologically-inspired control system is implemented on a underwater robot from the UPCT (AUV-UPCT). The rebuilt vehicle was transferred to the UPCT by the Spanish Navy. Figure 3 shows the underwater platform and the interconnection scheme of hardware components from the AUV: Battery, CPU, inertial positioning systems, compass, propulsion systems, video capture, inclinometers, water intrusion detectors, monitoring station, and sonars. It consists of a pressure resistant body with 5 motor for propulsion and manoeuverability. AUV-UPCT has a dimension of 1680 L $\times$ 600 W $\times$ 635 H (mm), a weight of 160 Kg, a maximum speed of 4 knots (48 V) and 2 knots (24 V), an operacional depth of 300 mts, two vertical thrusters, two forward thrusters and one transversal thruster. The core of central controller system is a Kontron 986LCD-M/mITX motherboard. High-level control algorithms (SODMN) are written in VC++ and run with a sampling time of 10 ms on the central controller system.

The proposed neural network model is capable of generating optimal trajectory for underwater vehicles in an arbitrarily varying enviroment. The state space is the Cartesian workspace of underwater robot. The proposed model is the applied to a trajectory generation problem for a robot to track a target (O).

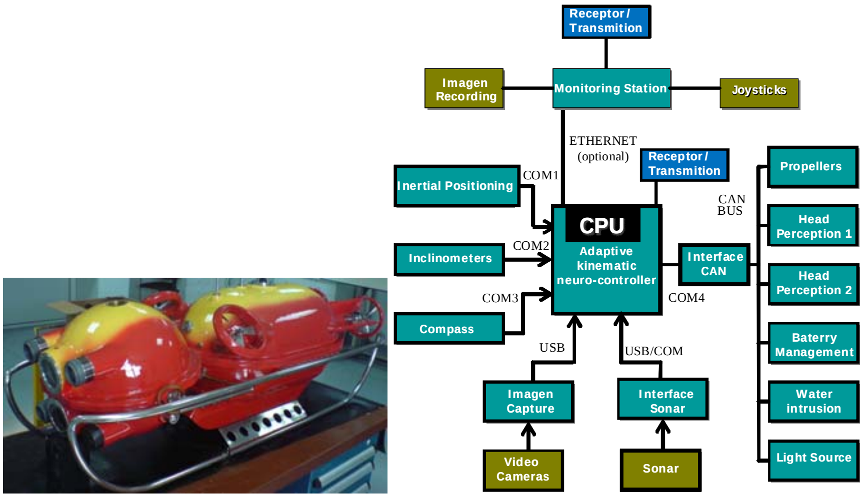

Fig. 3. Autonomous underwater vehicle from the UPCT (AUV-UPCT).

The SODMN assumes a context field structure of 100 x 100 x 10 neuron. In a 3-D workspace without any obstacle, the traveling route of the target is shown in Fig. 4(a) as indicated by circles, with an initial position at (x, y, z)= (0, 0, 4) m. 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) and that the proposed SODMN responds to the real-time location of the targets with no prior knowledge of the varying enviroment. The underwater robot starts to move from position (0, 0, 0) at a speed of 0.375 m/s. The generated trajectory of the robot is shown in Fig. 4(a) by boxes. Tracking errors of the adaptive controller system are shown in Fig. 4(b).

4 Discussion

In present model, appropriate operations are learned in an unsupervised fashion through repeated action-perception cycles by recoding proprioceptive information related to the underwater robot. The resulting solution has two interesting properties: (a) the required transformation is executed accurately over a large part of the reaching space, although few velocities are actually learned; and (b) properties of single neurons and populations closely resemble those of neurons and populations in parietal and cortical regions [10]. The activity of the population of motor cortical cells which encode movement direction appears to represent the instantaneous velocity of movement [11]. In addition, the preferred directions of individual cells shifts with the movement origin, indicating that the directional coding of motor cortex may be influenced by velocity configuration (in the model is the context field) [12], as is necessary for a Jacobian-based mapping. Correspondence between layers of the network and brain regions can be

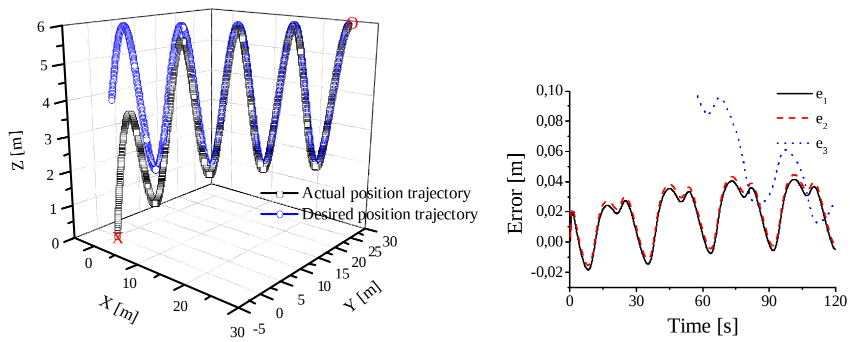

Fig. 4. Adaptive neuro-controller performance. (a) Tracking control of a desired trajectory. (b) Estimated tracking error.

made tentatively base on anatomical and physiological arguments [10, 11]. The representation of DVs could be in posterior parietal cortex (PPC) [13]. Neurons in PPC exhibit activity patterns correlated with the spatial direction of movement [14]. A candidate region for participating in the direction mapping computation is the cerebellum [15]. Also, note that there are certain similarities between the nature of the context field cells in the underwater robot movement model and the Purkinge cells of the adaptive timing model. Both types of cells are tonically active and allow a response by "pausing" this tonic activity. Thus, the possibility that a context field type of function is performed by cerebellar cortex. The proposed direction mapping model also posits a learning site separate from the context field computation, which might be a cerebellar function. In the model, motor commands were emitted by a layer containing R_i neurons, which contribute to the movement by a displacement along a direction in velocity space. The individual influence of a command neuron is proportional to its discharge level.

4.1 Conclusions

In this paper, 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 coordinates and coordinates of propellers' velocity. 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 efficacy of the proposed neural network for reaching and tracking behaviors was tested experimentally by a underwater robot.

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