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A simple neural network controller merging different behaviors for collector robots.

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1 Introduction

Robots are expected to become reliable partners for working in human environments. One of the tasks that they could have to perform is collecting objects and gathering/sorting them for any purposes. In such a task the robot would have to explore its environment to discover objects of interest, navigate toward them, grasp them and navigate again to a storage area to drop the object. In this paper we show how the basic principles behind these complex behaviors can be obtained from fairly simple neural network controllers.

In accordance to behavior based approaches [1], the developped architecture gathers several simple behaviors that affect the dynamic of the robot [5] to let a meaningful behavior emerge. We will first explain the different principles that enable a robot to display behaviors of exploration, tracking of a specific object and trying to catch that object. Then we present an implementation of the neural network on a mobile robot with a mounted arm.

2 A neural network generating force signals for motor control

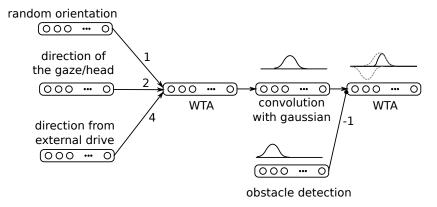


Figure 1: Architecture determining the orientation of the robot.

A preferred object recognized by its color is visually detected. The position of the object is projected in a head centered space. In fact, the head and the body of the robot are not dissociable. The head centered space is also a body centered space. A comparison between the current orientation of the gaze and the object position provides the corrective control on the orientation of the camera. The position of the object in the head/body centered space also provides a command for the control of the orientation of the robot. Three different commands are merged on the same body centered frame to control the orientation of the robot:

- 1. A random orientation which enables the robot to perform an exploration of the environment.
- 2. The attempt to align the orientation of the robot with the orientation of the object in the body-centered space. If the direction of the gaze is associated with the direction of the head, then this control corresponds to moving the body in order to decrease the torsion on the neck and align the body with the head.

3. A direct control by joystick which enables a human to influence directly the trajectory of the robot. It corresponds to the possibility to drive the robot in one direction or another like by pushing or dragging it.

Each movement strategy is weighted differently to introduce priorities in the behaviors. If no particular stimulus is perceived, the default behavior is the random exploration of the environment with a constant speed. If the preferred object is detected, navigation toward it will take precedence over the random exploration behavior. The speed of the robot is proportionnal to the distance to the object (i.e. perceived size of the object calculated as a number of pixels of the preferred color). If the object is close enough, the robot stops. Finally, physical command from an external person through the use of the joystick has the highest priority. The selected direction is always filtered by the activation of the mobile base ultrasound sensors in order to avoid obstacles.

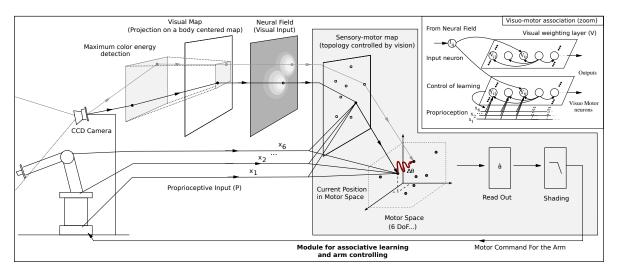


Figure 2: Model of visuo-motor association learner.

The movements of the arm are controlled by the motor controller described in [2] (Figure 2). In a first phase, the robot learns the association of visual positions with their corresponding motor positions. The visual position of the object then activates some attractors in the motor space to generate a movement allowing the gripper to reach the object.

3 Robotic implementation

The neural network architecture is implemented on a Robulab mobile platform from Robosoft. A Katana electrical 6DOF arm is mounted on the robot. Visual information is provided by a monocular camera mounted on a pan-tilt servo motor setup. In this experiment, the visual information simply corresponds to a pink color detection. Visual processing enables the robot to recognize a favorite object: a pink ball. Ultrasound sensors located around the mobile base of the robot provide range measures about obstacles. In a first phase the robot learns associations between the motor position of the arm and the visual position of its end effector (the robot is holding the pink ball to localize its gripper).

The two main behaviors are the exploration of the environment and the convergence toward the favorite object (Figure 3). In both behaviors, the robot is able to avoid obstacles for its own security. The different mechanisms that are running in parallel provide the robot with an interesting global behavior. In Figure 3, the robot that orientates itself toward the object is also trying to align the end effector of the arm with the visual position of the ball in order to catch it. Due to optical properties, a close object is perceived at a lower position in the visual field than a far object. The arm of the robot is naturally going down as the robot gets closer to the object. It is interesting to note that the system can be used by the robot to reach static objects but can also be used by the experimenter to guide the robot, since any human holding the object will be followed by the robot.

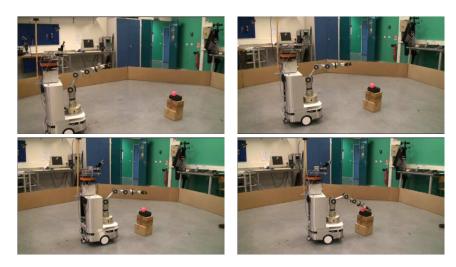


Figure 3: Robot navigating to and reaching for a pink ball on a box.



Figure 4: Obstacle avoidance while reaching for a pink ball held by a human interacting with the robot.

4 Discussion - Perspectives

The presented architecture proposes simple principles that allow the emergence of an object-seeking behavior. The robot is able to look for a specific object in the environment in order to reach and catch it. This behavior is based on simple mechanisms that can be subsumed by higher level strategies or behaviors. This kind of robotic setup could be used in future studies of multi agent cooperation on real robots [3]. Another perspective is the learning, through interaction and with reinforcement learning, of sequences of actions for both the mobile platform and the arm. After having caught the object, the robot could perform a homing navigation to a specific location to store the object. Such a sequence would require to merge spatial navigation and arm control with a planning architecture. We are working on using a multi-modal state sequence learning architecture inspired from the hippocampus [4], coupled with a cognitive map planning system, to learn and plan sequences of actions for both mobile platform and arm.

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