Action Selection for Single- and Multi-Robot Tasks Using Cooperative Extended Kohonen Maps

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Abstract

This paper presents an action selection framework based on an assemblage of self-organizing neural networks called *Cooperative Extended Kohonen Maps*. This framework encapsulates two features that significantly enhance a robot's action selection capability: self-organization in the continuous state and action spaces to provide smooth, efficient and fine motion control; action selection via the cooperation and competition of Extended Kohonen Maps to achieve more complex motion tasks. Qualitative and quantitative comparisons for single- and multi-robot tasks show our framework can provide better action selection than do potential fields method.

1 Introduction

A central issue in the design of behavior-based control architectures for autonomous agents is the formulation of effective action selection mechanisms (ASMs) to coordinate the behaviors. This paper describes a neural network-based ASM for autonomous non-holonomic mobile robots. Our motivation is to develop a motion control strategy that can perform distributed multi-robot surveillance in unknown, dynamic, and unpredictable environments. By implementing the ASM using an assemblage of self-organizing neural networks, it induces the following key features that significantly enhance the agent's action selection capability: *self-organization of continuous state and action spaces* to provide smooth, efficient and fine motion control, and *action selection via the cooperation and competition of Extended Kohonen Maps* to achieve more complex motion tasks.

2 Action Selection Framework

Our proposed ASM, termed *Cooperative Extended Kohonen Maps* (EKMs), is implemented by connecting an ensemble of EKMs. An EKM extends the Kohonen Self-Organizing Map. Besides encoding a set of input weights that self-organize in the sensory input space, the neurons also produce outputs that vary with the incoming sensed inputs. Our implementation extends the work of [Low *et al.*, 2002] by connecting several EKMs to form cooperative EKMs. These neural networks cooperate and compete to produce an appropriate motor action for the robot to approach targets, negotiate unforeseen, possibly concave, obstacles, and keep away from robot kins when it is tracking moving targets (Fig. 1).

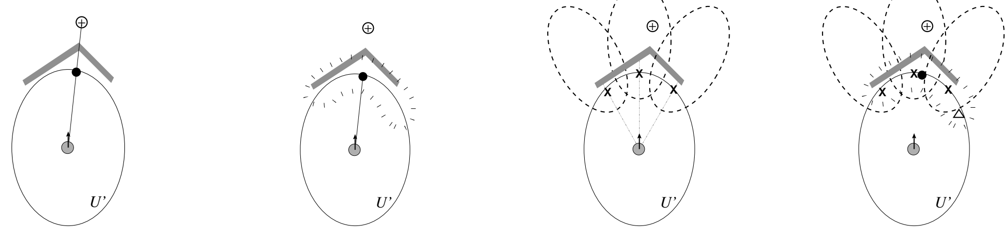
Our ASM framework consists of four types of EKMs: target localization, obstacle localization, robot kin localization, and motor control EKMs. In the presence of a target, neurons in the target localization EKM, which encodes target location in the local sensory input space $\mathcal{U}'$, are activated (Fig. 1a). A *target field* with the shape of an elongated Gaussian is produced (Fig. 1b) such that the neurons at and near the target location have the strongest activities. The elongated target field is crucial to the robot's avoidance of concave obstacles.

Similarly, the presence of an obstacle activates neurons in the obstacle localization EKMs. The neurons in these EKMs at and near the obstacle locations will be activated to produce *obstacle fields* (Fig. 1c). These obstacle fields are stretched along the obstacle directions such that neurons beyond the obstacle locations are also inhibited to indicate inaccessibility. *Robot kin fields* are activated in a similar way in the robot EKMs in the presense of robot kins.

In activating the motor control EKM, the obstacle fields are subtracted from the target field (Fig. 1d). If the target lies within the obstacle fields, the activation of the motor control EKM neurons close to the target location will be suppressed. Consequently, another neuron at a location that is not inhibited by the obstacle fields becomes most highly activated (Fig. 1d). This neuron produces a control parameter that moves the robot away from the obstacle. While the robot moves around the obstacle, the target and obstacle localization EKMs are continuously updated with the current locations and directions of the target and obstacles. Their interactions with the motor control EKM produce fine and smooth motion control of the robot to negotiate the obstacle and reach the target. In the case of multi-robot tracking of multiple targets, multiple target fields and robot kins fields are activated. The robots act like highly repulsive obstacles to other robots, thus separating them from each other.

3 Experiments and Discussions

Two qualitative tests were conducted to demonstrate the capabilities of cooperative EKMs in performing complex motion tasks. The experiments were performed using Webots, an embodied simulator for Khepera mobile robots, which incorporated 10% noise in its sensors and actuators.



(a) (b) (c) (d)

Figure 1: Cooperative EKMs. (a) In response to the target $\oplus$, the nearest neuron (black dot) in the target localization EKM (ellipse) of the robot (gray circle) is activated. (b) The activated neuron produces a target field (dotted ellipse) in the motor control EKM. (c) Three of the robot's sensors detect obstacles and activate three neurons (crosses) in the obstacle localization EKMs, which produce the obstacle fields (dashed ellipses). (d) Subtraction of the obstacle fields from the target field results in the neuron at $\triangle$ to become the winner in the motor control EKM, which moves the robot away from the obstacle.

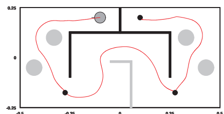


Figure 2: Motion of robot (dark gray) in an environment with unforeseen static obstacles (light gray). The robot successfully navigated through the checkpoints (small black dots) located at the doorways to reach the goal.

The environment for the first test consisted of three rooms connected by two doorways with unforeseen static obstacles (Fig. 2). The robot began in the top corner of the left-most room and was tasked to move into the narrow corner of the right-most room via checkpoints plotted by a planner. The robot with cooperative EKMs was able to move through the checkpoints to the goal by traversing between narrowly spaced convex obstacles in the first and the last room, and overcoming an concave obstacle in the middle room. A robot with potential fields would be trapped by these local minimas.

The second test (Fig. 3) illustrates how two robots endowed with cooperative EKMs cooperate to track four moving targets. When the targets were moving out of the robots' sensory range, the robot below chose to track the two targets moving to the bottom left while the robot above responded by tracking the two targets moving to the top right. In this manner, all targets could be observed by the robots. This test shows that the two robots can cooperate to track multiple moving targets without communicating with each other.

Two quantitative tests were conducted to determine the overall tracking performance of the robot team based on the following performance index:

$$\text{observation coverage} = \sum_{t=1}^{T} 100\frac{n(t)}{NT} \qquad (1)$$

where N is total number of targets, n is number of targets being tracked at time t, and the experiment lasts T amount of time. For both tests, N and T were fixed respectively as 10 targets and 1000 time steps at intervals of 128 ms.

The first test compared the mean observation coverage of robots adopting four different tracking strategies: cooperative EKMs, potential fields, fixed deployment, and random deployment. The environment or arena was an enclosed obstacle-free region that varied in size. The mobile targets were forward-moving, obstacle-avoidance vehicles that changed their direction and speed with 5% probability. Five

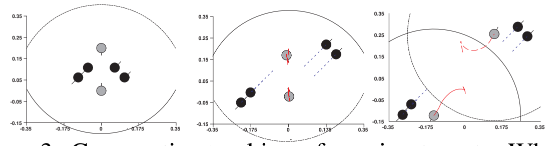
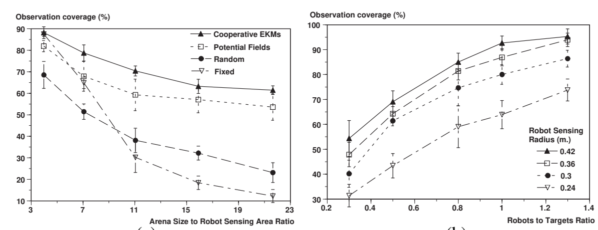


Figure 3: Cooperative tracking of moving targets. When the targets were moving out of the robots' sensory range, the robot below decided to track the targets moving to the bottom left while the robot above responded by tracking the targets moving to the top right. In this way, all targets could still be observed by the robots.



(a) (b)

Figure 4: Comparison of observation coverage for (a) robots using different tracking strategies in varying arena size, and (b) varying number of robots with different sensing ranges.

robots, each with target and robot sensing radius of 0.3 m, were deployed in this task. The fixed deployment approach distributed stationary robots uniformly over the arena. The random deployment approach allowed the robots to move randomly in a manner similar to the moving targets. Test results in Fig. 4(a) reveal that, in very large arenas, tracking strategies that respond dynamically to targets' motion (cooperative EKMs and potential fields) are significantly better than those that do not (fixed and random). In particular, cooperative EKMs offered the highest observation coverage as it could overcome local minimas posed by targets and robots.

The second test compared the mean observation coverage of the cooperative-EKM robots with different sensing ranges and number of robots. The size of the arena was 6.4 m^2, which corresponded to the largest arena used for the first test. Test results in Fig. 4(b) show that observation coverage increases with increasing number of robots and sensing range.

References

[Low *et al.*, 2002] K. H. Low, W. K. Leow, and M. H. Ang Jr. A hybrid mobile robot architecture with integrated planning and control. In *Proc. AAMAS*, pages 219–226, 2002.