Modeling Representation Overlap in Motor Cortices using Self Organizing Maps

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Abstract

Understanding the functionalities of the motor cortex of the human brain has been a major focus of research in the field of neuroscience. While neuroscientific research regarding the motor cortex has shown evidence of topological preservation and self organization of motor output signals, models presented in preliminary works fail to depict such aspect and its integration into trial-and-error learning. Our research proposes a model which attempts to tackle such problem by utilizing Kohonen's self organizing map and a reinforcement learning framework.

1 Introduction

Modeling the learning process of the brain is an ever-growing field in neuroscience. The aim is to gain understanding of neurological functions by attempting to replicate synaptic activation patterns seen in the brains of animals using mathematical models. We focus primarily on the functions of the motor cortices.

Novel intuitions and knowledge obtained in such research can have significance in application, mainly in the field of treating patients with neurological illnesses. The study of motor neurons, in particular, has helped the development of treatment for motor function disorders. Additionally, electrical and software engineers have utilized such information to develop bio-inspired robots that can execute complex tasks, such as navigating through rough terrain which, in application, could aid in transportation and distribution of products.

Neurological studies in humans, apes, and rodents have shown evidence of 2 dimensional topological mapping of behaviors onto the motor cortices, mainly the primary motor cortex containing a map of body parts, each corresponding to the muscles in the area, and the premotor cortex containing actions that reflect the behavior of the subject, such as reaching the arm to grab an object in front of them or bringing food to the mouth to eat [1] [2]. Closely related body parts and behaviors are represented as neighboring neurons.

One key feature regarding the mapping in the motor cortex that has developed in the past 10 years is the notion that the behavioral and anatomical areas represented on the cortex overlap with each other instead of having clear segregation between them as suggested in preliminary works, making the boundaries of each representations blurred. This suggests that some neurons are able to control the excitation of multiple alpha motor neurons and the execution of multiple behaviors.

The aforementioned studies suggest that a topology-preserving self organization is in play as a method to obtain intrinsic information during the neurological learning process. Our study attempts to gain understanding regarding the following question: how can such self organization pattern be obtained from trial and error task learning?

As our contribution with this research, we propose a reinforcement learning framework which utilize Kohonen's self organizing maps in order to model the intrinsic representation of motor cortices, particularly the topological preservation and trial-and-error learning.

2 Background

2.1 Reinforcement learning

Reinforcement learning views control systems as a mutual interaction between an agent and an environment, which in the context of the an ethology, refer to an animal, such as an ape, and its surroundings, such as the terrain that it is on, and alters the agent's properties in order to have it complete a task. The environment outputs information regarding the relationship between the agent and the environment, such as its position relative to an origin point, as its current state, which is inputted into the agent's internal function known as the policy. The policy, given the state, outputs an action, such as the torque of all of the joints in the agent's body. The action is inputted into the environment, which in return produces a reward and an updated state. The reward indicates the performance of the agent at each timestep at completing the given task, and is used to update the policy's parameters to maximize its cumulative sum, known as the return.

A type of reinforcement algorithm that we focus on in this paper is Q-learning, which defines a q-table, or a table consisting of all combinations of states and actions and their expected return if the action in question were to be executed during the state in question.

$$Q(s_t, a_t) += r(s_t, a_t) + \gamma \max_a Q(s_{t+1}, a) \quad (1)$$

where γ is the learning rate.

2.2 Kohonen's self organizing map

Kohonen's self organizing map (SOM) is an unsupervised neural network algorithm for dimension-reduction and clustering. SOMs are composed of an input neuron and neighboring neurons. The neighboring neurons are positioned and linked together as a graph with a grid structure, where each edge dictate each neurons' neighbors. While the input neuron contains the input data, each neighboring neuron contains a weight vector with the same dimension as the dimension of the input space.

When an input vector is given and are stored in the input, it is compared with each neighboring neurons' weight vector and the neighboring neuron with the closest distance between them is selected. Since the selected neuron can be noted as a position vector within the aforementioned grid, where for example if the grid is 2 dimensional the position of the selected neuron is composed of the row number and the column number within the grid, the input vector can now be noted as a dimension-reduced vector.

$$c = \arg_i \min |w_i - x| \quad (2)$$

where x is the input vector and c is the selected neuron.

We describe the function of determining the position of the neuron c for input x.

$$position_{w_c} = SOM(x) \quad (3)$$

During training, the selected neuron and its neighboring neurons' weights are modified to reduce their euclidian distance to the input vector.

$$w_c = w_c + lr * (x - w_c) \quad (4)$$

In neuroscience, SOM in which the input data is transformed into 2 dimensions is used to model the self-organization of sensory input and motor out in the cerebral cortex.

3 Preliminary Research

Kohonen's self organizing maps and their variants have been utilized to model poses found in varying speeds of human locomotion [3] and as the state input and action output of a reinforcement learning algorithm [4]. While such algorithms do ensure topological preservation of input and output data of a control system, such research do not focus on the visualization of such process and the replication of the aspect of overlap in movement representation.

Neurological modeling has had contributions from the field of machine learning using deep neural networks, and while models proposed in such field excel at accurately replicating the sensor input and motor output of biological systems and in turn obtaining an internal representation of the learned concepts, such representation lack clear signs of overlap and topological-preservation of motor outputs.

4 Approach

Cortical learning's two distinct features are topological-preservation of sensor input and motor output data and, in the case of motor cortices, overlap in representation of ethologically significant actions. With preliminary research experiments having analyzed neural signals using Kohonen's self organizing map (SOM) and strengthened our understanding of the cerebral cortex, we integrate such in our model to attempt to replicate the features of cortical learning. In addition, in order to represent trial-and-error learning, we utilize reinforcement learning as a framework in which we structure our model.

The policy consists of 3 components: Pose selector $Selector()$, pose representation SOM $SOM_{Pose}()$, and inverse kinematics $IK()$. The 3 components act as the policy for the reinforcement learning framework. We discretize the action space into poses. Based on the current state given by the environment, the pose selector outputs a selected pose and the inverse kinematics component outputs actions that lessens the distance between the selected pose.

$$\begin{aligned} pose\_index_t &= Selector(s_t) && (5)\\ pose_t &= SOM_{pose}(pose\_index_t) && (6)\\ a_t &= IK(w_{pose_t}) && (7) \end{aligned}$$

For the selector, we used a modified self organizing map, where the weights in each neuron are composed of a tuple of weight values representing the organized values of the state input and a tuple of q-values the size of the number of output poses Equation 8. The pose resection SOM selects the pose whose index in the q-vector is the highest, and the corresponding pose represented in the pose representation SOM is activated Equation 9. Finally, the inverse kinematics function outputs the appropriate action for the agent to reach the selected pose.

$$w_{Selector} = [state_t, q_0, q_1, ..., q_i, ..., q_{num(w_{Pose})}] \tag{8}$$

$$\begin{aligned} pose\_index_t &= Selector(s_t) && (9)\\ &= \arg\max_i q_{pose\_index} && (10) \end{aligned}$$

5 Experiment

We tested our approach and proposed model by training it on a 2-dimensional navigation task, where the agent has to navigate to 2 predetermined specific target locations within 1000 timesteps, using Q-learning with epsilon-greedy exploration. 4 instances of navigation tasks are generated by using a random number generator to specify the target locations for each task, and afterwards the corresponding selectors are generated and trained to execute such within 500 epochs. Additionally, the pose SOM is pre-trained on a uniform distribution between the range of 0 and 1 for both axis for 50,000 epochs.

The trained selectors were able to select a sequence of nodes in the pose SOM that resulted in reaching the two target locations in each task, with their return values nearing the optimal return values for their corresponding tasks Figure 1.

Most importantly, the nodes in the pose SOM utilized by the selectors show overlap in their distributions, replicating the aspect of overlap in movement representation in the motor cortex Figure 2.

References

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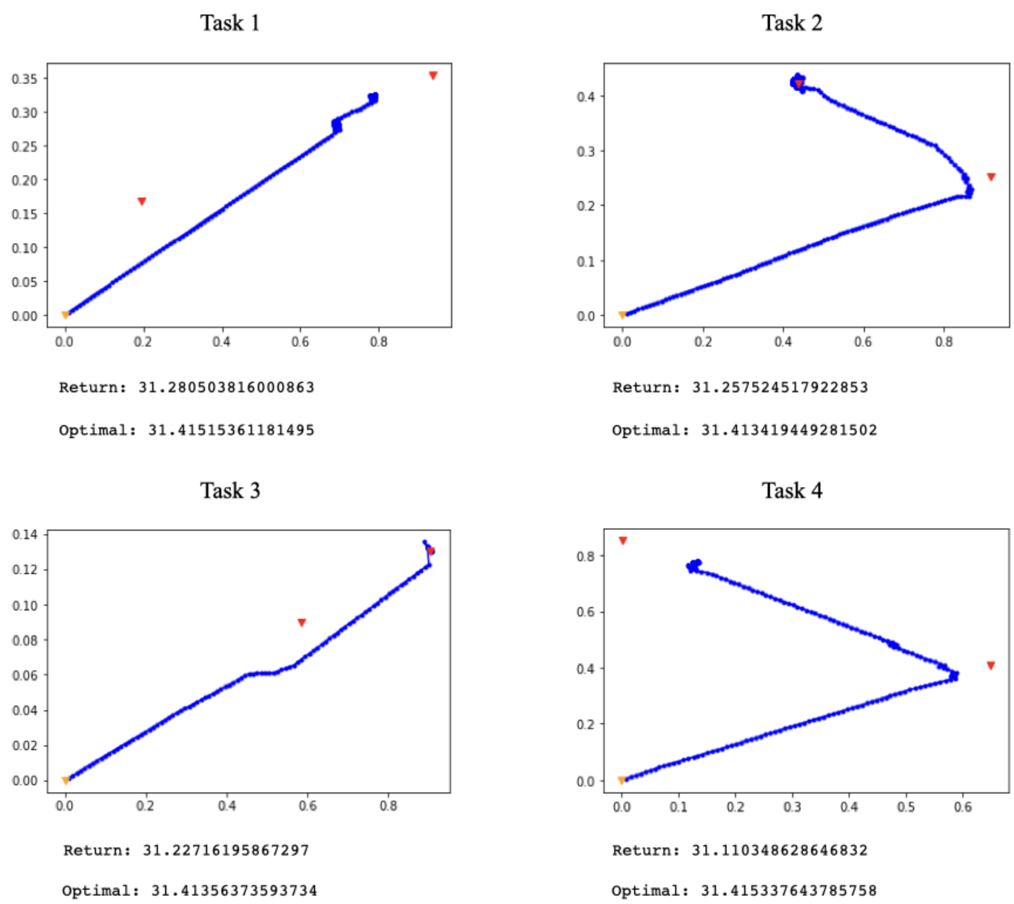

Figure 1: Trajectories of the selectors on their respective tasks, where the orange marker indicates the origin and the two red markers indicate the two target locations

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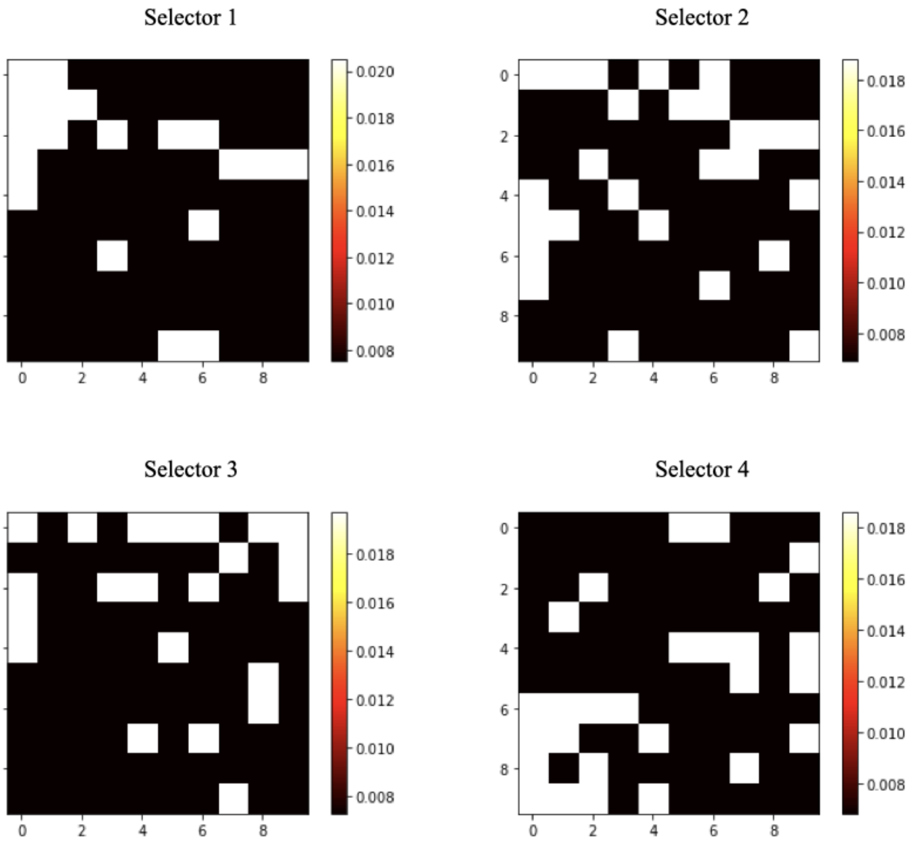

Figure 2: Heatmap of each selector's usage of the nodes in pose SOM, where the white cells depict utilization of its corresponding node by the selector, while the black cells depict otherwise