A Recurrent Neural Network Model of Rule-guided Delayed Tasks

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Abstract

We developed a recurrent neural network model of rule-guided behavior to simulate neural activity in rule-guided tasks. Our model was constructed using neural system identification (Zipser, 1992) and a fully recurrent neural network model was optimized to perform a rule-guided delayed task. The response properties of the hidden units were compared to those of neurons to examine the degree to which the model accounts for the experimental data (White and Wise, 1999). The temporal patterns of the hidden units were consistent with the physiological results. The close similarity between the behavior of the model units and biological neurons shows that the brain uses mechanisms like those of the model, and that ample mutual connections in the prefrontal cortex are the basis for promoting flexible learning.

Key words: Rule-guided behavior, Recurrent network, Prefrontal cortex, Working memory

1 Introduction

The prefrontal (PF) cortex has long been suspected to play an important role in cognitive control [1]. Several studies have examined the role of the PF cortex in processing information about stimuli, rewards, errors, and so on. Recently, much attention has been directed to 'rules' that guide goal-directed behavior. The flexibility of our behavior is caused mainly by our ability to abstract such rules from a circumstance and apply them to other situations. White and Wise (1999) studied single-neuron activities in the PF cortex while

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a monkey performed a rule-guided task according to two different rules: the 'conditional rule' and the 'spatial rule' [2]. The task required the monkey to maintain fixation of the target location, which consisted of four light spots. For the conditional rule, the shape of the visual cue indicated the correct target. For the spatial rule, the location of the visual cue indicated the correct target. The rule to be applied in each trial was indicated by the color of a fixation spot that was presented before the visual cue (Fig. 1). Between one-third and one-half of the PF neurons showed activity differences that could be attributed to the rule. There was no significant regional segregation. These data support the hypothesis that the PF cortex plays a role in guiding behavior according to previously learned rules. Other studies have yielded similar results [3–5].

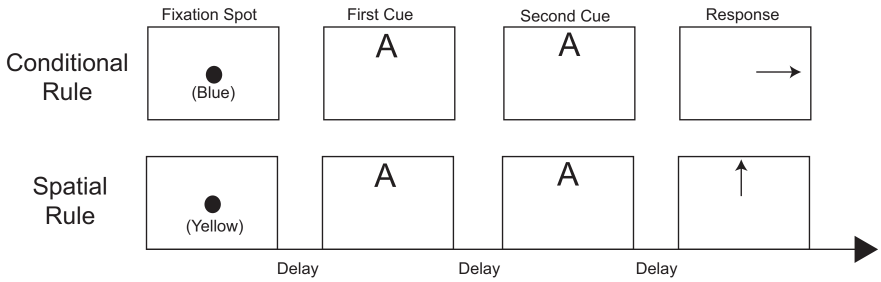


Fig. 1. An example of the behavioral tasks (White and Wise, 1999).

We have already proposed a neural network model of rule-guided behavior and simulated other physiological results [6]. However, the interpretation of the simulation results was limited, because the percentage of rule-selective units was small, which was inconsistent with the physiological results. Moreover, the temporal patterns of the rule-selective units differed slightly from those of biological neurons, especially for the patterns of buildup activities.

In this study, we developed a neural network model of rule-guided behavior that could accommodate the results of other physiological studies. In addition, we also compared the model units with neurons selective for information other than rules. Our model was constructed using neural system identification [7] and a fully recurrent neural network model was optimized to perform a rule-guided delayed task.

2 Modeling Methods

The PF cortex is connected with virtually all sensory neocortical and motor systems. Physiological results indicate that there is little difference in the distribution of neurons preferring different types of information in the PF area. Therefore, we assumed that the PF area is a single uniform layer. Our model contains three layers: input, hidden, and output layers. The input layer has three input modules: the first represents 'what' information (object module),

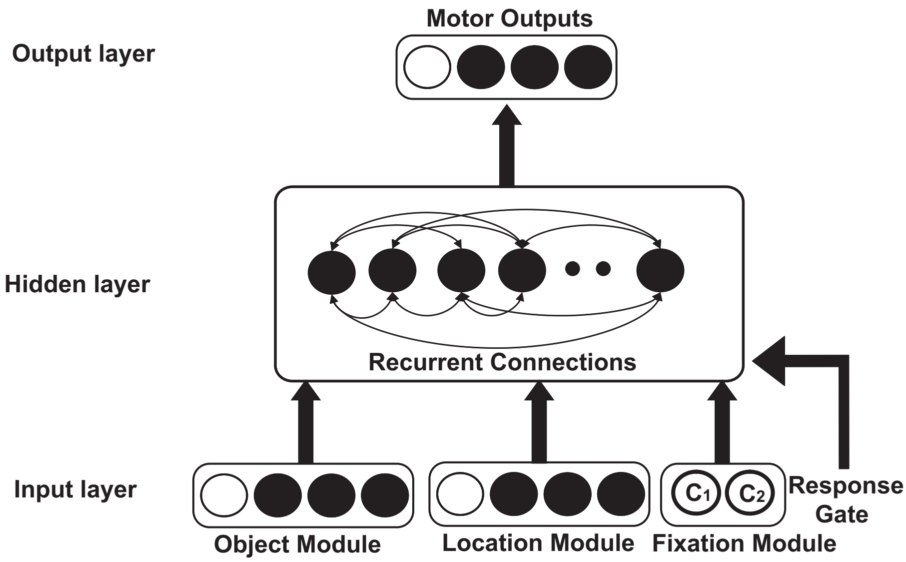


Fig. 2. The neural network architecture includes input, hidden, and output layers. The input layer consists of an object module, a location module, a fixation module, and a response gate. The hidden layer consists of recurrently connected sigmoidal units. The output layer represents the direction of fixation.

the second 'where' information (location module), and the third the color of the fixation spot (fixation module). The object and location modules consist of four neurons each, one of which is activated. That is, 16 object-location combinations can be encoded in the input layer. The fixation module has two neurons, which represent two colors: blue or yellow. Moreover, the model has an additional input, the response gate, which indicates the timing of the output. The output layer consists of four neurons representing four saccade directions. The output units receive input from all of the hidden units, but do not feed back to them. The hidden layer consists of recurrently connected sigmoidal units.

The output of the ith model unit in the hidden layer on time cycle $t + 1$ is given by

$$h_i(t+1) = f(\sum_j hw_{ij} h_j(t) + \sum_k v_{ik} z_k(t) - b_i) \tag{1}$$

where hw_{ij} represents recurrent connections from every hidden unit and v_{ik} represents weighted connections from every input unit z_k. Each unit has a bias, b_i. $f(x)$ is the sigmoid function.

Each motor output on time cycle $t + 2$ is defined as

$$o_m(t+2) = f(\sum_i ow_{mi} h_i(t+1) - b_m) \tag{2}$$

where ow_{mi} represents the weighted connections from the hidden units. Each unit has a bias, b_m.

Our previous models always used randomized sequences of inputs while training. That is, the model didn't know when the cues were input and which cues were input. In this study, we adopted sessional learning: the same patterns of sequences were provided at variable intervals, which is similar to the paradigm of the physiological experiments. The connections were optimized through a gradient descent using real-time recurrent learning (RTRL) [8]. We used this algorithm to train the network to perform the required behavior, with no intention of claiming that the algorithm is similar to the learning mechanisms in the brain. Models were generated by training networks for roughly 10^7 network time steps. Training ceased when the mean square error was less than .03.

3 Results

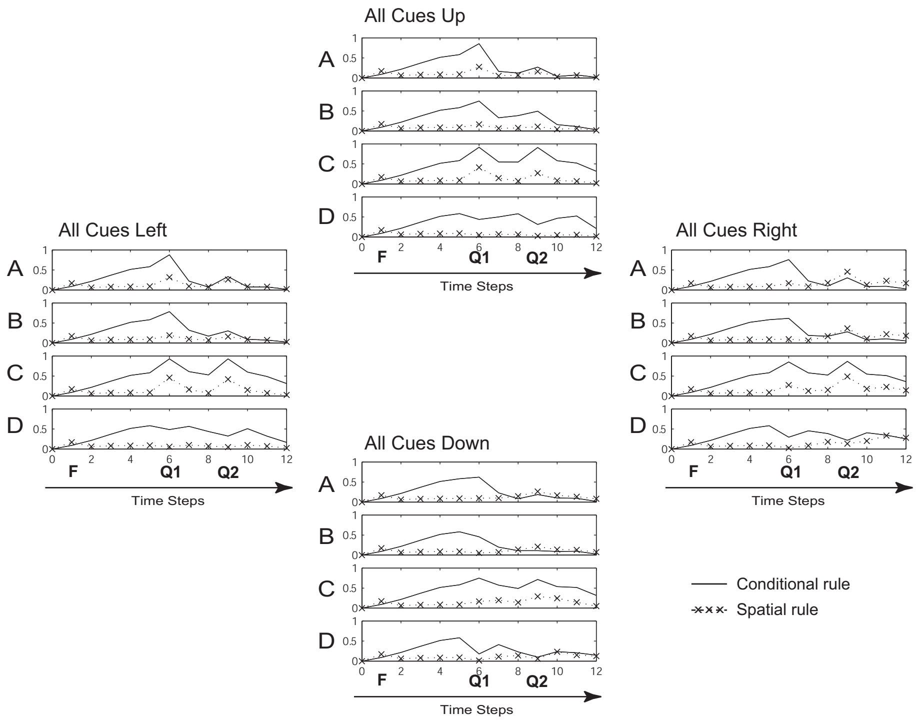
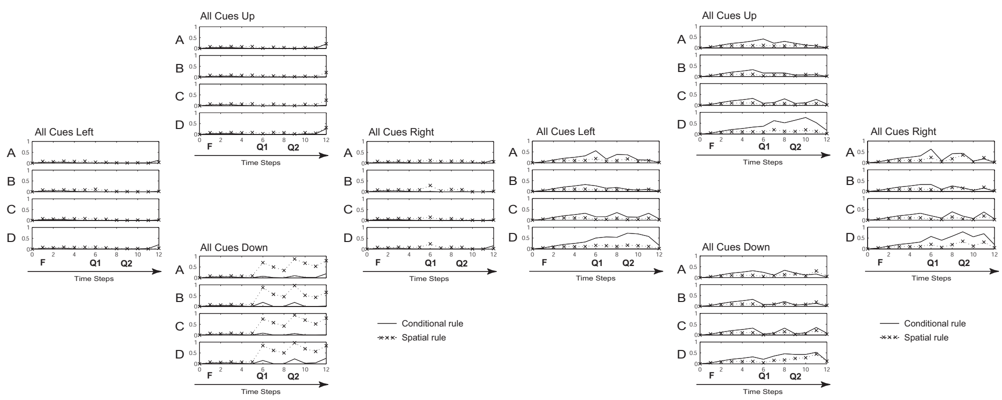


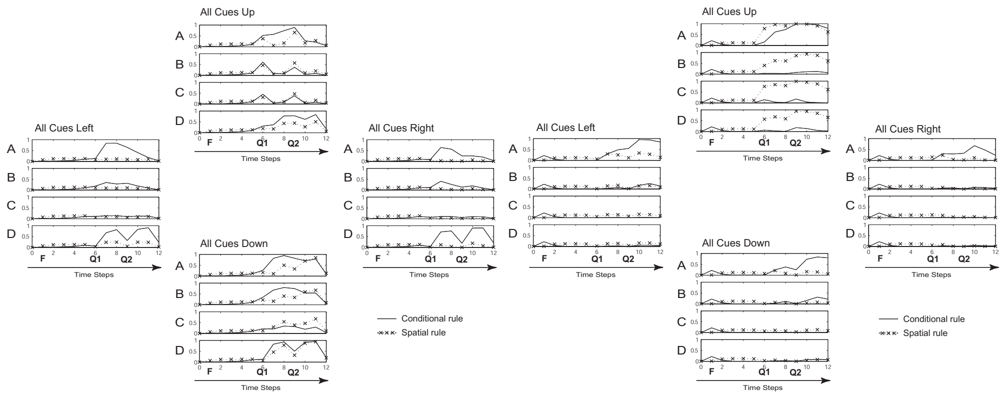
Fig. 3. An example of one hidden unit showing rule-selectivity with a preference for a conditional rule. **F** indicates the onset of fixation; **Q1** and **Q2** are the first and second cue onsets, respectively.

In a typical simulated behavioral trial, the fixation color was input in the first step. After a delay period (six steps), object and location information were input. After a second delay (three steps), object and location information were input again. After an additional delay (three steps), the response gate was loaded and motor output was produced (See Fig. 1). The network was successful in learning the rule-guided task. The response properties of the hidden units were compared with those of biological neurons to examine the degree to which the model accounts for the experimental data. Many units showed selectivity for the rule; i.e., the units had stronger activity when one rule was applied than when the other was applied (Fig. 3). In a typical model network consisting of 20 hidden units, rule selectivity was found in 40-50% of the population. This observation was confirmed in 10 model networks, trained using random weights. As for the temporal patterns, the activity gradually increased after onset of the fixation spot. After onset of the visual cues, this activity decayed. These temporal patterns are consistent with the physiological data. This buildup activity was thought to be an anticipatory effect, which shows that the model acquired the context of the experiment. Moreover, we could also simulate neuronal activity with location selectivity (Fig. 4(a)), object selectivity (Fig. 4(b)), a complex combination of location and object selectivity (Fig. 5(a)), or without a rule effect (Fig. 5(b)), as in the physiological results [2].



(a) (b)

Fig. 4. Graph (a) shows a hidden unit showing location selectivity (Down) with a preference for a spatial rule and (b) shows a hidden unit showing object selectivity (D) with a preference for a conditional rule. **F** indicates the onset of fixation; **Q1** and **Q2** are the first and second cue onsets, respectively.



(a) (b)

Fig. 5. Graph (a) shows a hidden unit with a complex combination of location and object selectivity as well as a preference for a conditional rule, and (b) shows a hidden unit without rule selectivity, but showing target selectivity. **F** indicates the onset of fixation; **Q1** and **Q2** are the first and second cue onsets, respectively.

4 Discussion

We simulated the results of a physiology experiment [2] using a recurrent network model with a simple input-and-output relation for executing a rule-guided task. Our model could explain the function of the PF cortex under the assumption that the object module corresponds to the inferior temporal cortex, the location module to the posterior parietal cortex, and the output layer to the motor-related area. Of course, it is difficult to directly connect RTRL with the learning mechanisms of the cerebral cortex. However, the close similarity between the behavior of the model units and biological neurons suggests that the brain uses mechanisms like those of the model, and our results suggest that ample mutual connections in the PF cortex are the basis for promoting flexible behavior, such as rule learning.

Moreover, the fact that our model simulated several physiological experiments well demonstrates the validity of our model. The architecture of our model is very simple, but our model has an advantage over other models for rule-learning [9] in that the prefrontal representations are not hand-coded.

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