A Computational Model for Multiple Potential Actions for Inferred Movement Goals

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Abstract: Klaes et al. showed that multiple potential actions could be generated only single spatial cue according to task rule. Also they reported that population activities of the PPC neurons which represent two different motor goals might be biased. The motivation of this paper is to make a computational model which can reproduce Klaes's experimental results. We have proposed a decision making model which has the PFC layers encoding the rule informations and showed that the potential action for the inferred goal was observed in the PPC layer, and the balance of the potential actions in the PPC layer varied depending on the connection strength from PFC to PMd. These results suggest that the observed biased potential actions during the memory periods were the result of "trade-off" for achieving the balanced multiple potential actions while the spatial cue was presented.

Keywords: action choice, computational model, parietal cortex, potential actions, premotor cortex, rule selection task

1 INTRODUCTION

Recent studies have demonstrated that when animals are presented multiple action goals, they compute multiple potential goals (multiple potential actions) based on visual inputs simultaneously and choice an action from them [1][2][3]. These studies have also reported that frontparietal cortex, specifically PPC (Posterior Parietal Cortex), PMd (Premotor Dosal), and PFC (Prefrontal Cortex) relate to information processing on generating potential actions[1][3].

Cisek et al. [1] observed neural responses corresponding to potential actions in primate motor area. In this experiment, two reaching goals (spatial cues) were presented to monkeys and successive cue (color cue) indicated the correct goal which monkeys had to select. Although the spatial cues generated two potential actions in PMd, one of the potential actions was specified by color cue presentation. [1]. Cisek and his colleagues also demonstrated that a computational model composed of frontoparietal stream simulated the process of generation and selection of potential actions as short term memory of visual inputs [2].

On the other hand, Klaes et al. showed that multiple potential actions could be generated even when only

single spatial cue was visually presented. In this experiment, monkeys were trained to reach in the same or opposite direction to the presented spatial cue depending on the rule cue which are successively presented. Neurons in the primate PPC simultaneously represented two distinct potential actions corresponding to direct and opposite (inferred) movement goals[3]. This result means that the potential actions are not only the short term memory of the presented spatial cues, but the representation of the movement goals internally generated by the neural processes using information of the presented cues.

In the Klaes's rule-selection task, it is also reported that the population tuned activities of the PPC neurons which represent two different motor goals might be biased. Interestingly, trained monkeys showed a preference to reach the opposite direction of the spatial cue, and neural activities correspond to the inferred direction in the PPC become strong during the spatial cue period. This biased neural activity was balanced only if the probabilities of the rewards were adjusted to reinforce balanced choice behavior.

In this paper, we propose a computational model which generates multiple potential actions and decides appropriate one according to the task rules in the

Klaes's task. We also show that this model also exhibits the biased or balanced potential actions depending on parameter values and consider the mechanisms of the biased potential actions observed in the Klaes's task.

2 METHODS

2.1 Process of the Psychological Experiment

First, we show the potential motor-goal task[3] (Fig.1) which we simulate in this study. This paradigm is the fundamental framework of Klaes's experiments.
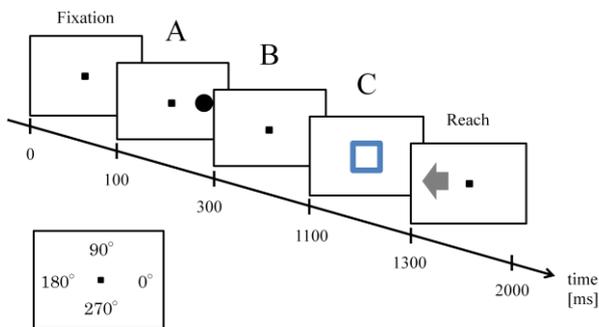
Fig. 1. Rule selection task. The inset shows directions of the spatial cue.

At stage A in Fig.1, a spatial cue (one of the four positions: 0, 90, 180, 270 degree) is provided for 200ms. Then, the subject should keep this memory at least for 800ms. At stage C, after the rule cue (direct or inferred rule) is provided, the subject is required to the same direction as the spatial cue (direct rule) or the opposite direction (inferred rule) alternatively. The direct (or the inferred) rule is instructed by a green (or blue) square on the fix point.

2.2 Framework of Model

In this study, we expand the Cisek's computational model to go through with the potential motor-goal task. Our model neurons, neural connections within layers and inter-layers, and the basic structure of the network are almost the same as Cisek's model. Two main differences are as follows: (1) We introduced two prefrontal layers that are responsive to direct and inferred rules

(PFC_D and PFC_I), (2) There are synaptic connections from PFC_D and PFC_I to corresponding neurons in the first PMd layer.

Visual inputs include spatial cues and rule cues (Fig.2). The information of position of a spatial cue is provided to PPC, PFC_D and PFC_I neurons. In case of a rule cue, rule information is given to PFC_D or PFC_I alternatively. Each neuron in PPC, PMd, and M1 has directional preference to reach, and its neighboring neurons represent close directions. The arrow in Fig.2 shows the direction of each projection of synaptic connection. To generate two neural activities representing potential plans from a spatial cue, the PFC_I neuron should excite PMd layer neurons which represent the direction opposite from the spatial cue.

On the other hand, within each of the frontparietal layers except PFC, neurons with similar directional preferences excite each other, whereas neurons with different preference mutually inhibit each other.

Since some neurons are excited and others are suppressed in this competitive neural field, some groups of activated neurons usually appear. We regard the activated group represents a potential action (potential action plan). Neural activities generated in PPC, PFC_D, PFC_I layers are integrated in PMd1 layer.
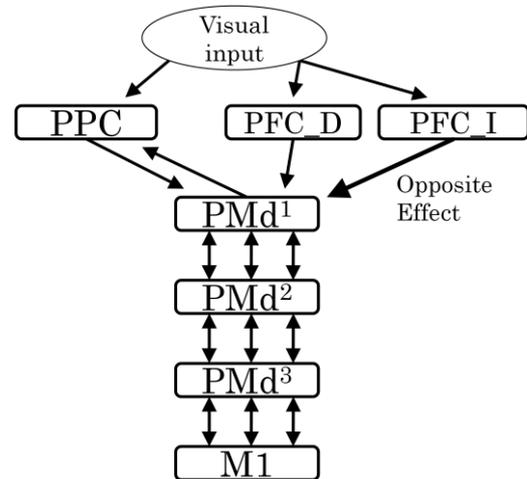
Fig. 2. Framework of this model [2]

2.3 Neuron Model

We use the "mean-rate leaky-integrator" neurons model. The mean firing rate of i th neuron at layer N

follows this differential equation [2]:

$$\frac{dX_i^N}{dt} = -\alpha X_i^N + (\beta - X_i^N) \cdot \gamma \cdot E_i^N - X_i^N \cdot I_i^N + \Theta, \quad (1)$$

where X_i^N is the activity of the i th neuron in layer N, E_i^N is the excitatory input to the neuron, I_i^N is the inhibitory input to the neuron, α is the decay rate, β is the neuron's maximum activity, and γ is the excitatory gain. Θ is a Gaussian noise. Each parameter value follows Cisek's numerical experiments[2].

2.4 Neural Connections between Layers

To excite two neurons in different layers each other if they insist similar directions, the synaptic weight from j th neuron in layer N to i th neuron in layer M depends on the difference of neuron index $(i-j)$ as follows:

$$\begin{cases} W_{ji}^{N \to M} = 0.4 - 0.2(i-j) & \text{if } i-j \geq 0 \\ W_{ji}^{N \to M} = 0.4 + 0.2(i-j) & \text{if } i-j < 0 \end{cases} \quad (2)$$

The synaptic weights from PFC_I to PMd1, however, should be relatively so strong that the neural activity representing direct direction supported by PPC and PFC_D competes with that of inferred direction by PFC_I only. Otherwise, the potential action in an inferred direction will be suppressed away. Thus we introduced an amplitude parameter κ to examine the effects of synaptic weights from PFC as follows:

$$\begin{cases} W_{ji}^{PFC \to PMd1} = \kappa \cdot \{0.15 - 0.015(i-j)\} & \text{if } d \geq 0 \\ W_{ji}^{PFC \to PMd1} = \kappa \cdot \{0.15 + 0.015(i-j)\} & \text{if } d < 0 \end{cases} \quad (3)$$

When we think of PFC_D (PFC_I), we regard κ as κ_D (κ_I).

3 RESULTS

3.1. Balanced Potential actions in Memory Period

Figure 3 shows activity of the model network at $\kappa_D = \kappa_I = 1.0$.

The cue direction neurons in the PFC_D and the inferred direction neurons in the PFC_I were activated by the visual input. During the cue period, neural populations encoding the cue direction in the PPC and PMd layers were strongly activated.

The potential actions in the PPC were balanced during the memory period (Fig.1 B) because the connection strength from the PFC_D and the PFC_I were same value. On the other hand, PPC neurons showed biased potential actions during the cue period because of the additional visual input to the PPC population tuning to the cue direction.
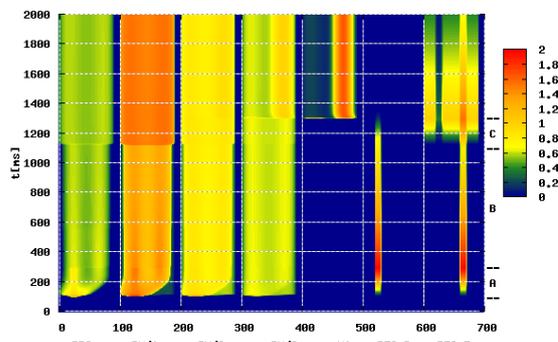
Fig. 3. Population result for the balanced data set (0 degree cue, Inferred rule, $\kappa_D = \kappa_I = 1.0$). A is the spatial cue period, B is the memory period, and C is the rule cue period.

3.2 Biased Potential actions in Memory Period

Figure 4 shows activity of the model network at $\kappa_D = 1.0$, $\kappa_I = 5.3$. In the situation of larger KI, the projections from PFC_I to PMd excites the neural population to encode opposite goal more than direct goal in PPC. Simulated biased potential actions during the memory periods require at least a condition that $\kappa_D < \kappa_I$. This means that the connections from the PFC_I to the PMd is stronger than that from the PFC_D.

In the PPC layer, neural population encoding the direct cue direction was strongly activated during the spatial cue period. In contrast, neural population encoding the opposite cue direction was strongly activated during the memory period. The cause of inversion in active groups is due to the disappearance of the spatial cue during the memory period. Therefore, "direct" population became weaker, and "inferred" population became stronger relatively.

However, despite biased activities in PPC, this model chose appropriate an action according to the displayed rule, on the rule cue period. As a result, under the conform to the biased data set and choose the action

comfortable to rule cue which are consistent with the experimental data[3].
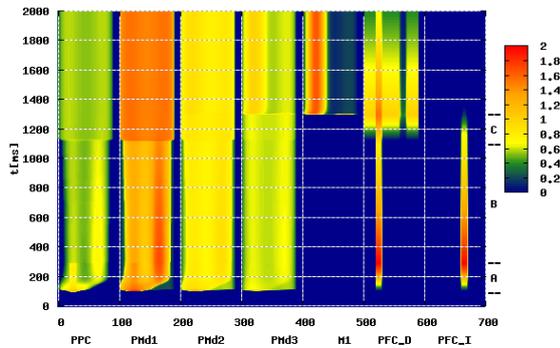
Fig. 4. Population result for the biased data set (0 degree cue, Direct rule, κ_D =1.0, κ_I =5.3).

3.3 Mechanism for bias of potential actions

Klaes et al. reported that, for the well trained monkeys, the potential actions in the PPC were biased during the memory periods. Two types of the rule cue (indicating the direct motor goal and the inferred motor goal) were equally presented in their experiment. So the biases of the potential actions may not be reasonable.

Figure 5 shows a population activities when the spatial cue was presented for a prolonged time (κ_D =1.0, κ_I =5.3). In this situation, the potential actions during the prolonged cue period seemed balanced. The time lag of the potential actions for the direct and the inferred goal is caused by the parameters β and γ which are different between PFC and PPC neurons. This time lag was responsible for the switching of the potential actions in the PPC for the short-lasting cue presentation (200-400 ms in Fig.4).

This result implied that the balance of the cue period may make it inevitable that the potential actions during the memory periods become biased. That is, although the bias of the potential actions (and the behavioral performance) of the trained monkeys is apparently unreasonable, this bias can be reasonably interpreted as the "trade-off" for the balanced activities of the potential actions when the spatial cue is continuously presented. We also insist that this hypothesis will be confirmable

by the physiological experiment that the cue stimulus will be continuously presented to the monkeys while this hypothesis is a matter of speculation at the current moment.
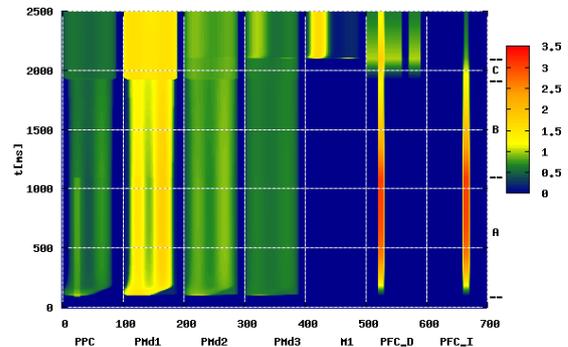
Fig. 5. Population result with longer spatial cue (0 degree cue, Direct rule, κ_D =1.0, κ_I =5.3).

4 CONCLUSION

In this paper, we proposed a decision making model with PFC layers which encodes the rule information of the task. This model generates the multiple potential actions which correspond to the candidates of the movement goals even when the single spatial cue was presented in the task.

We also demonstrated that the proposed model shows both the biased and balanced potential actions. This result suggests that the observed biased potential actions (and biased behaviors) during the memory periods were the results of "trade-off"s for achieving the balanced multiple potential actions while the spatial cue was presented.

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