Design and preliminary results of a joint metamemory experiment for the evolution of co-representation

Yusuke Yamato[1], Reiji Suzuki[1] and Takaya Arita[1]

[1]Graduate School of Informatics, Nagoya University, yamato@alife.cs.i.nagoya-u.ac.jp

Introduction

The ability of humans to take joint action with others is essential for living in a society. This ability is based on sharing representations, predicting actions, and integrating predicted effects of one's own and other's actions (Sebanz et al., 2006). The ability to share representations, called co-representation, is essential to predict the actions of others and coordinate their own actions based on integrated predicted effects of their and other's actions. A constructive approach using evolutionary experiments is expected to provide detailed insights into cognitive process. Among such studies, Sangati and Hofmann (2020) defined co-representation minimally as an internal state of one agent that correlates with future action of the other agent and functionally contributes to the generation of coordinated joint performance. Their evolutionary experiments using the Joint Tracking task (Jordan and Knoblich, 2003) successfully evolved agents that could cooperate to track a target and showed statistical dependence between the internal state of one agent and the actions of the other agent.

We believe that showing the existence of a representation that functionally contributes to the generation of coordinated joint performance is important to prove co-representation. Our goal is to evolve neural networks that can acquire co-representations through direct interactions with the other agent. To this end, this paper proposes a new metacognitive task, the Joint DMTS (delayed matching to sample) task, in which the ability to represent metacognition of the other agent as co-representation is essential to solve the task. The current study is an extension of Yamato's evolutionary experiments with a metamemory task performed by an individual agent composed of neural networks with neuromodulation, focusing on the acquired structures and mechanisms of metamemory (Yamato et al., 2019a,b, 2020, 2022). We report on the results of the preliminary experiment towards the evolution of co-representation.

Joint DMTS Task

Fig. 1 shows an overview of the proposed task, an extension of the DMTS task with a decline option to detect metamemory in animals (Hampton, 2001) to a task that can be solved cooperatively by two agents. While the Joint DMTS task is a general framework, which can be used for various subjects (e.g., a pair of monkeys), we introduce the task using a case with a pair of neural networks. The task is composed of 4 phases. In the study phase, two agents receive and memorize the same target pattern composed of 5 binary digits. In the delay phase, both agents receive a pattern consisting of only 0 as a distractor pattern a predefined number of times. In the choice phase, they select to take or decline the trial while continuing to receive a signal meaning they are in that phase. If an agent selects to decline, it means the agent entrusts the other agent to take the test. Otherwise, the agent takes the test by herself. If both select to take the test, each agent is rewarded with the average of its own and the other's rewards multiplied by the conflict penalty of 0.667. Additionally, if both agents decline the test, they are rewarded with nothing (0.0). In the test phase, the agent that selects to take the test receives candidate patterns one by one in random order and selects one of them as the answer. If it matches the target pattern, the agent is rewarded with a large reward (1.0). The best strategy is to delegate to the other agent the response when the other's cognitive performance is greater than its own. To do this, it seems necessary for them to have some internal representation related to the other's cognitive performance as co-representation, and to achieve action coordination based on it.

Evolutionary Model

For the evolutionary experiment, we use a situation in which the above metacognitive ability is particularly adaptive. First, we use a clone of the focal agent as its partner when evaluating the fitness of each agent. The cognitive performance may differ due to the cognitive error rate described later. We assume a situation where a certain degree of homogeneity among agents has evolved, which is typically expected to be required for cooperative problem-solving. Our focus is to understand how dynamic role-sharing based on co-representation can occur between such homogeneous agents. Second, an error probability in cognition, termed cognitive error rate (cer), is independently assigned to each agent. cer represents the cognitive property of how incorrectly each agent recognizes the target pattern. Specifically, we assume agents will always fail the test at this rate regardless of their actual behavior. The reason we use cer is that experimenters can directly control the difference in the cognitive performance between agents, and thus the interactions between them can be examined efficiently by setting up an exhaustive set of two agents' cers.

In the evaluation process of each agent with a pair of cers, the agent performs 25 repetitions of a DMTS task without declining, receiving the results (1: correct, -1: incorrect) of its own and the other's previous test as inputs during the current study phase. The agent then performs 10 repetitions of the Joint DMTS task without any feedback of the test results, which requires correct inference of their cognitive abilities (i.e., cers) for better performance. This procedure is repeated over all combinations of its own and the other's cers. The total obtained score is used as their fitness.

Fig. 2 shows the overview of the neural network model. There are 10 input neurons, 2 output neurons, and a hidden layer containing an evolutionarily variable number of standard and modulatory neurons (Soltoggio et al., 2008). The topology of the network evolves without an upper limit on the number of neurons and connections through NEAT (Stanley and Miikkulainen, 2002). Each input value in all phases is slightly modified by adding a predefined amount of Gaussian noise ($\mu = 0.0$, $\sigma = 0.01$), promoting memory forgetting in the network.

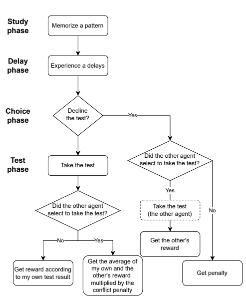

Figure 1: The flowchart of the joint DMTS task.

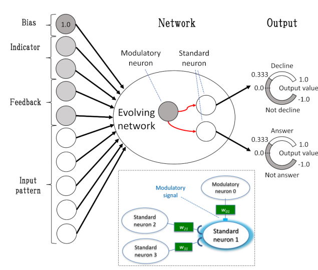

Figure 2: The overview of the neural network and the neuromodulation.

Result

We performed 10 experimental trials using the settings: the number of iteration times of generation $G = 1000$, population size $N = 1000$, and the number of task executions across all combinations of its own and the other's cers $T = 560$. We successfully found the agents that could properly solve the Joint DMTS task on all trials. In other words, they can delegate to the other the response appropriately according to the relative relationship between their own and the other's cers. We analyzed the networks of the best agents in some trials (Fig. 3) as representative agents. We first found that the evolved networks have a memory part, which is formed by mapping the value of each bit in the target pattern to the sign of a specific connection weight. During the test phase, it determines if a received pattern is a memorized pattern by examining the representation of the memory. We also found that these networks internally represent information about the relationship between its own and the other's cers by accumulating received results of its own and the other's previous test, independent of the memory part. Furthermore, we found that this representation mechanism of the pick-up agents is only realized either by learning the connection weight through neuromodulation (Fig. 3(a)) or retaining the neuron's activity using a single recurrent connection (Fig. 3(b)). Based on these representations, the networks decided to delegate the test to the other. These representations might be regarded as co-representations as they are represented through interactions with the other and can be used to coordinate actions.

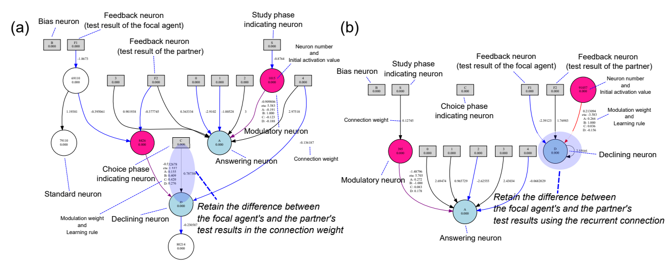

Figure 3: The representative evolved networks.

Conclusion

This paper proposed the Joint DMTS task, which might be used to evolve neural networks with the ability to have a representation of the cognitive performance of the other agents as a co-representation. We then reported on the results of the evolutionary experiment. We succeeded in evolving the neural networks that can be regarded as they have co-representation based on two mechanisms in the sense that they are represented through interactions with the other and can be used to coordinate actions.

Our experimental layout allows the task to be separable into a memory task and a task comparing feedback frequencies. If the same network implementation evolved in this experiment evolves when both of these tasks are used independently, it may allow room for a different interpretation of the results of this experiment. We are currently considering the design of a co-representation experiment that would provide clarification on this point.

Acknowledgements

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