Automatic Evolution of Multimodal Behavior with Multi-Brain HyperNEAT

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ABSTRACT

An important challenge in neuroevolution is to evolve multimodal behavior. Indirect network encodings can potentially answer this challenge. Yet in practice, indirect encodings do not yield effective multimodal controllers. This paper introduces novel multimodal extensions to HyperNEAT, a popular indirect encoding. A previous multimodal approach called situational policy geometry assumes that multiple brains benefit from being embedded within an explicit geometric space. However, this paper introduces HyperNEAT extensions for evolving many brains without assuming geometric relationships between them. The resulting Multi-Brain HyperNEAT can exploit human-specified task divisions, or can automatically discover when brains should be used, and how many to use. Experiments show that multi-brain approaches are more effective than HyperNEAT without multimodal extensions, and that brains without a geometric relation to each other are superior.

Keywords

Indirect Encoding; Modularity; Multimodal Behavior

1. INTRODUCTION

Success in many domains requires agents capable of complex multimodal behavior, i.e. agents able to switch between distinct policies based on environmental context. This paper uses HyperNEAT [4] to evolve neural network brains for agents. However, HyperNEAT is extended to produce Multi-Brain HyperNEAT (MB-HyperNEAT)\(^1\), which allows a single agent to have multiple brains.

2. BACKGROUND AND EXTENSIONS

HyperNEAT evolves Compositional Pattern Producing Networks (CPPNs) to specify connectivity patterns across indirectly-encoded substrate networks. The substrate must be embedded within a geometric space (Figure 1a). HyperNEAT can generate arbitrarily large networks, theoretically capable of generating multimodal behavior. However, an easier way to realize multimodal behavior is with several smaller networks, rather than with a single large one.

\(^1\)Download at southwestern.edu/~schrum2/re/mb-hyperneat.html

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Situational policy geometry [1] is an existing approach that generates multiple brains. Agents have distinct brains for different situations, but they share an underlying geometric relationship due to an additional situation input in the CPPN (Figure 1b). A human must decide which brain to use in each situation. These restrictions limit the applicability and effectiveness of the method.

This paper presents three main extensions to HyperNEAT to produce MB-HyperNEAT. Each idea is inspired by the direct-encoded Modular Multiobjective NEAT [3]: (1) The network structure from Multitask Learning is adapted to create multitask CPPNs (Figure 1c). In this case, a human must still specify when each policy is used. (2) Preference neurons [3] are added that allow evolution to discover when an agent should use each brain (Figure 1d). In this way, a different brain can be active on each time step, allowing evolution to autonomously discover an effective task division. (3) Module mutation operators [3], enable the automatic creation of new modules. Module mutation is a structural mutation operator that adds a new output module to a network. If brain substrates have preference neurons, then each application of module mutation to a CPPN creates a new brain substrate that the agent can arbitrate between using preference neurons.

3. EXPERIMENTS

Experiments are conducted in two previous multimodal domains (team patrol and dual task) and two new ones (lone patrol and two rooms). These domains all use simulated Khepera robots.

Team patrol was originally used to demonstrate the effectiveness of situational policy geometry [1]. A team of robots must advance into a maze, and then return to their starting point. The new lone patrol domain uses the same environment, but requires a single robot to explore each part of the maze instead of a team. Dual task [2] consists of two isolated tasks, hallway navigation and foraging, with no clear geometric relation between the behaviors required in these tasks. The new two rooms domain requires hallway navigation and foraging coningelled in a single environment: Two foraging rooms are separated by a convoluted hallway.

Standard HyperNEAT, which has only one module (1M), provided a performance baseline. Situational policy geometry (SPG) and multitask (MHT) approaches had multiple modules using a human-specified task division. Approaches not depending on such task divisions include CPPNs with two (2M) and three (3M) preference modules, and CPPNs using different forms of module mutation: \(\text{MM}(P)\), \(\text{MM}(R)\), or \(\text{MM}(D)\).

4. RESULTS

The results show that multimodal approaches discover better behavior faster than 1M, and that multitask and preference neuron ap-
5. CONCLUSION

This paper combines the HyperNEAT indirect encoding and the MM-NEAT approach to evolving modular networks, thereby realizing the strengths of both approaches. Results show that the resulting MB-HyperNEAT approach outperforms a previous attempt to merge HyperNEAT with multimodal extensions, and that it is possible to evolve modular ANNs when a human-specified task division is unavailable. The conclusion is that MB-HyperNEAT is a promising toolkit for evolving complex multimodal behavior that can reduce the need for specialized domain knowledge.

6. REFERENCES


