Synthetic Connectomics

Analyzing Evolved Neural Networks for Simple Reaching with a Tool

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Abstract

Connectomics is proving to be an effective new tool in neuroscience. However, the ultimate goal of collecting all synaptic connections in a brain is far from our reach. Furthermore, even if we have a complete connectome, due to the lack of functional and behavioral data, and lack of analysis tools, it is unclear ifwe can make sense of it. In this abstract, we propose a synthetic connectomics approach, where neural circuits evolved in a computer simulation is presented as a temporary alternative to the full biological connectome, to facilitate the development of analysis techniques. The synthetic brain is evolved using a neuroevolution algorithm called NeuroEvolution of Augmenting Topologies (NEAT) that allows evolution of complex topologies, as well as connection weights and polarity. The main advantage of this approach is that experimenters can have full access to connectivity, polarity, synaptic strength, neural activity, and also behavior. In this abstract, we present our work on applying NEAT to a reaching task for a jointed, articulated limb that can also pick up and use a tool. It turns out that it is non-trivial to analyze a tiny network of 15 simulated neurons that evolved to solve the task, even with full information from the simulated behavior. We combined (1) graph analysis where we showed that evolved circuits with more cycles (loops) in their network topology show higher performance, (2) activity time series clustering where we discovered four main clusters, and (3) aligning behavioral events and neural activity. Our work shows the complexity of connectomic analysis even with tiny (synthetic) neural networks where the full structural and functional data are known, and at the same time the potential utility of a synthetic approach to connectomics.

Michael Freitag (University of Passau, Germany) and Han Wang (Texas A&M University) contributed to new results not reported in the original SfN abstract (Freitag and Choe 2016; Wang et al. 2016). Also see Li et al. (2015).

Why Synthetic Connectomics?

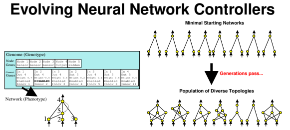
- Do we have the tools to analyze evolved neural circuits, given full access to the connectivity and function?
- Natural connectome lacks the following:
  - Sign: excitatory/inhibitory (positive/negative)
  - Weight: synaptic strength
  - Delay: both conduction delay and integration time
- We may need activity and behavioral data as well.

Cf. Jonas and Kording (2016); Triesch and Hilgetag (2016).

Approach

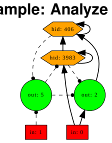
- Evolve growing neural networks in simple sensorimotor tasks.
- Analyze property of evolved circuit.
- We have full access to the circuit function.
  - However, we do not know how it works.

Evolving Neural Network Controllers



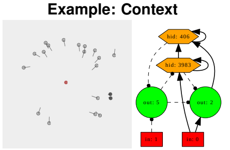
- We used NeuroEvolution of Augmenting Topologies (NEAT) algorithm by Stanley and Miikkulainen (2002).
- Networks of arbitrarily complex topologies can be evolved, leading to increasingly complex behavior.

Example: Analyze This!



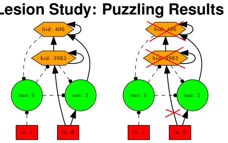
- Simple circuit evolved using Neuroevolution (NEAT).
  - Hard to know what it does without sensorimotor linkage: Brain in a vat.

Example: Context



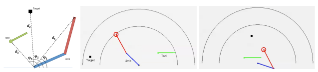
- Task: Navigation to goal.
- Input: fixed input (bias) and angle to goal.
- Output: thrust and angle adjust.

Lesion Study: Puzzling Results



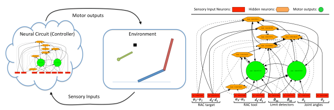
- Observe behavior after eliminating connections or neurons.
- Result: works well with almost everything gone!
  - Need to study behavior in a social context to fully

Example 2: Reaching Task



- Sensors: Joint angles/limits, angle/distance to target/tool.
- Motor: Control joint angle to reach target or tool (stick).
- Targets could be within/beyond reach.
- Reaching tool extends limb (automatic).

Task: Reaching Close/Far Targets



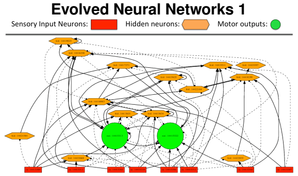
- Sensors: Joint angles/limits, angle/distance to target/tool.
- Motor: Control joint angle to reach target or tool (stick).

Fitness Evaluation

- D: final distance to target
- S: number of steps to reach target
- T: number of times tool picked up
- R: number of times target reached
- P: number of times tool picked up when needed
- ... : DS, DT, DST, etc. (multiplied combination)

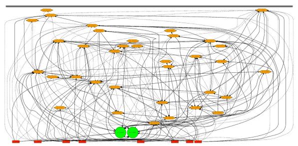
Task: 50% within reach, 50% beyond reach targets

Evolved Neural Networks 1



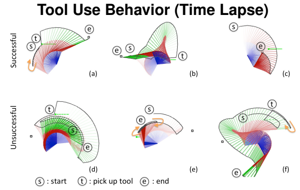
Fitness = S^2T

Evolved Neural Networks 2



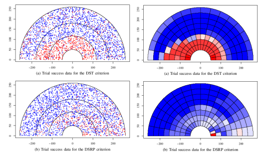
Fitness = DS

Tool Use Behavior (Time Lapse)



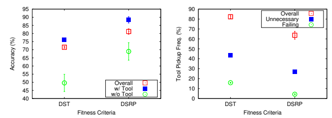
- Top: success, Bottom: failure

Failure Modes (T vs. RP)



- Blue: success, Red: failure.
- Criterion RP more successful with close targets.

Target Reaching Performance (2/2)

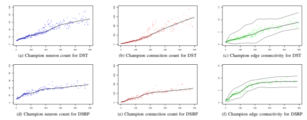


- Criterion T vs Criterion RP: Higher performance, less unnecessary tool use, and fewer failures with criterion RP.

How to Understand the Evolved Networks?

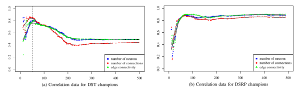
- Analyze basic statistics (neurons, connections, etc.)
- Analyze recurrent loops (cycles in the connectivity).
- Clustering of activation dynamics.
- Correlated behavior and activation dynamics.

Network Structure Trend



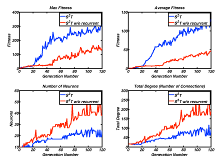
- DST and DSRP show different trends: neurons, connections, and edge connectivity (minimum number of connections to remove before paths from input to output neurons get disconnected).

Network Structure vs. Perf. Trend



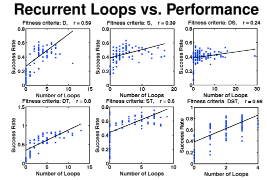
- DST peaks and levels off low, while DSRP continuously improves.

Importance of Recurrent Connections



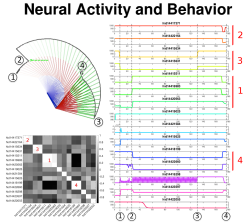
- Faster evolution (top), more compact networks (bottom).

Recurrent Loops vs. Performance



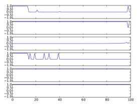
- Number of loops positively correlated with performance.

Neural Activity and Behavior



Periodic Behavior and Chaos

Type	Number of trials	Percentage
Period-2 orbit	1693	88.55%
Period-4 orbit	102	5.33%
Period-6 orbit	23	1.20%
Period-8 orbit	11	0.58%
Period-12 orbit	23	1.20%
Period-16 orbit	14	0.73%
Other	46	2.41%
Total	1912	100.00%



- Periodic behavior and chaos in failed cases.
- Period-2 orbit dominates (rapid oscillation).

Conclusion

- Synthetically evolved neural circuits in a simple control task
  - Full anatomical, functional, and behavioral data.
  - Small but still very challenging to analyze.
- Synthetic connectomics can help us:
  - Identify the kind of data needed.
  - Develop analysis tools.

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