Modeling the Evolution of Retina Neural Network

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ABSTRACT

Vital to primary visual processing, retinal circuitry shows many similar structures across a very broad array of species, both vertebrate and non-vertebrate, especially functional components such as lateral inhibition. This surprisingly conservative pattern raises a question of how evolution leads to it, and whether there is any alternative that can also prompt helpful preprocessing. Here we design a method using genetic algorithm that, with many degrees of freedom, leads to architectures whose functions are similar to biological retina, as well as effective alternatives that are different in structures and functions. We compare this model to natural evolution and discuss how our framework can inspire neuroevolution.

CCS CONCEPTS

• Computing methodologies → Genetic algorithms; *Neural networks*; Modeling methodologies;

KEYWORDS

genetic algorithm, retina, neural network, evolution

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1 INTRODUCTION

Retina serves as the first visual processing unit in animals' visual systems. The neural circuitry is very similar across species [5] with respect to topology, such as lateral inhibition, in which a group of cells suppresses the activities of their surrounding cells so as to enhance sharpness and modify color discrepancy [3, 6, 7]. Is this similarity due to a general optimization principle? Though cannot answer the question directly, we use genetic algorithm to simulate the evolutionary process and analyze the resulting structures with high fitness in order to gain a better understanding of the evolutionary process.

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Figure 1: A diagram of retina process. Only 2 types of interneurons are shown to save space.

2 METHOD

2.1 Retina Model

In this work we assume radial symmetry in retina and thus use only 1-D recurrent neural networks. Photoreceptors (PRs, input layer) and retina ganglion cells (RGCs, output layer) have the same and fixed amount of neurons for all networks at any generation, since the algorithm would otherwise maximize the numbers of PRs and RGCs to enhance visual acuity, and "ignore" effective processing.

During simulation, the PRs receive constant, slightly perturbed edge inputs, while modulated by the recurrent inputs from interneurons (Fig. 1). The only spiking neurons in the retina, RGCs also receive input from the interneurons. The exponential integrationand-fire model is used to simulate the spiking activities of RGCs. The neuronal dynamics, in general, can be described by:

$$\tau^{(j)} \frac{\mathrm{d}}{\mathrm{d}t} V^{(j)}(t) = -(V^{(j)} - V_{rest}) + \sum_{i} V^{(i)^{T}} W_{ij}$$
(1)

where $V^{(j)}$ is the vector of membrane potentials of type¹ *j*, limited within [0, 1] for physiological plausibility. Each type receives from some other types *i*. τ , time constant; V_{rest} , the resting potential. The mean firing rates of RGCs are the input to the trainable perceptron that perform regression on the edge locations (Fig. 1).

2.2 Genome

We use genetic algorithm as an imitation of natural evolution. The number of interneuron types in each retina is initialized to 0. In the following generations, the individuals may gain or lose interneuron

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¹ "Type" is the same as "layer". However, to downplay the notion of spatial order, since forward and backward skip connections do happen, the term "layer" is circumvented.

types through mutation and crossover. Each neuronal type, *i*, except for the PR and RGC, has variable number of cells. Moreover, each type possesses a time constant τ , shape parameters, and binary encoding of pre- and postsynaptic features, all of which are mutable. Specifically, the shape parameters determine the projection and reception ranges, and the overlap between the projection range of the presynaptic type and reception range of the postsynaptic type determines the weight magnitudes. In our simulation, we take the advantage of Beta distribution PDF to control the projection and reception range. The polarity of weights from type *i* to *j* is the product of the presynaptic feature encoding of *i* and postsynaptic feature encoding of *j*. For simplicity, encoding is either +1 or -1. Finally, all types but RGC have a variable set *C* containing the indices of the postsynaptic types that this type projects to.

2.3 Selection, Crossover, and Mutation

We use the binary tournament selection algorithm [4]. For each of the parents, 2 rivals are drawn from the population without replacement. The rival with better fitness evaluation has higher chance to be the parent. During crossover, the values associated with one type of neurons are passed together to the offspring and do not mix with those of other types. Each mutation phase after crossover contains (1) changes in the values of the variables and (2) deletion and duplication of a neuron type.

2.4 Fitness Evaluation

We postulate that the major selective pressure is based on retina performance and not directly on architectural features. It is thus evaluated with a perceptron representing early simple cognitive processing. The evaluation measures how well a retina can emphasize edges, while not restricting a retina's topology or dynamics; comparably, in nature, visual animals need to infer the locations of objects' boundaries.

At each generation, every retina receives a the same set of perturbed 1-D edges with different edge locations. Each retina is associated with a perceptron initialized at every generation and trained to map from the RGC firing rates to edge locations (Fig. 1). The sample size, learning rate, and training epochs are set such that they are insufficient for the perceptron to be well-trained, so the retina should preprocess the raw inputs to some degree that makes the training easier. Each retina's output on the fixed testing set is used to test its trained perceptron. The R^2 score of a perceptron determines the main component of the associated retina's fitness.

We also penalize, with small weight, complexity that contributes trivially to the effectiveness, for the number of synapses affects energy consumption and light absorbance [2]. Structures where interneurons are connected to more types will have smaller gains:

$$g = \begin{cases} 0 & C^{(0)} = \emptyset \text{ or } n_t = 0\\ \sum_{i=1}^{n_t} \frac{1 - |\operatorname{length}(C^{(i)}) - 1|}{n_t} & \operatorname{otherwise} \end{cases}$$
(2)

Finally, a retina's fitness equals $0.85R^2 + 0.15g$ where the weights are set according to preliminary experiments.

3 RESULTS AND DISCUSSION

Multiple trials of 400 generations have been run. In each generation, 10 of 150 individuals survive. Across all trials, the survival gain,



Figure 2: An example of the fitness scores (different colors) of survivors over generations.

defined as the difference between the minima of the survivors at the first and last generations, is significantly greater than 0 (left-tailed p test, $p = 9.3 \times 10^{-44} < 10^{-3}$). This together with the non-decreasing fitness scores demonstrates the efficacy of our algorithmic design that it optimizes retina topology and dynamics. The simulated evolution does not happen in every generation, but manifests several breakthrough points, between which the intervals vary (Fig. 2), agreeing with the Darwinian theory punctuated equilibrium [1].

Case studies of the connection matrices and tuning curves of the survivors at the final generations from different trials report that all survivors' RGCs have well-separated spatial tuning curves. Some also contain the center-surround receptive field resembling that of biological retina. This is reasonable because well-separated spatial tuning makes RGC firing more informative, while center-surround tuning, a subset of it, may further boost the informativeness.

Nature contains more variables and non-survival-driven evolution. Unlike our simulation, in nature a new species may not always have higher "fitness scores" than their antecedents; factors such as genetic drift may give rise to a more complex, non-monotonic relation between changes and survival. These factors may explain the non-existance of spatial tunings not fallen into the center-surround class, but are well-separated and have high fitness in our simulation.

Finally, our framework may inspire neuroevolution. The topology and dynamics of a neural network can be optimized with evolutionary algorithms, by keeping finding better networks that ease the computation and enhance the performance of another model, instead of by designing loss functions directly. This approach may free the optimization from human bias and empiricism.

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