Cartesian Genetic Programming encoded Artificial Neural Networks: A Comparison using Three Benchmarks

Andy Turner & Julian Miller
at568@york.ac.uk & Julian.miller@york.ac.uk
Cartesian Genetic Programming

First Implemented by J. F. Miller & P. Thomson, 2000
Web page: http://www.cartesiangp.co.uk/

Key Points
• Form of Genetic Programming
• Cyclic and acyclic graphs
• Any data type e.g. ints, floats, images, videos ...
• Any function e.g. XOR, sigmoidal, sin ...
• Inbuilt neutrality and genetic drift (Miller et al, 2006)
• Natural resilience to bloat (Miller, 2001)
• Typically uses a (1+4)-ES
• Mutation only (no crossover)
• Not just for circuits

Andy Turner
at568@york.ac.uk
CGP Structure

Genotype

One row, four columns

Phenotype

Andy Turner

at568@york.ac.uk
First published by Maryam. M. Khan et al, 2010

**Minor changes to CGP to encode Neural Networks**
- **F** Function i.e. sigmoid, radial basis...
- **C** Unchanged
- **W** Connection Weight
- Inputs Unchanged
- Outputs Unchanged

**CGPANN Features**
- Evolves Weights
- Evolves Number of Neuron
- Evolves Topology
- Evolves Arity of Neurons (indirectly)
- Evolves Functions
- All of the advantages of CGP
Weight Evolution
• Does not require differentiable neuron functions
• Does not require a precise fitness function
• Does not struggle to train deep topologies
• Searches weight space

Topology Evolution
• Does not require a suitable topology to be known in advance
• Produces topologies which would not usually be considered
• Searches topology space

Node Transfer Evolution
• Does not require suitable node functions to be known in advance
• Can easily use a mix of node functions
• Searches function space
Inactive Nodes

Genotype

- Inactive Nodes
- Active Nodes

Phenotype

Andy Turner
at568@york.ac.uk
Example ANN

Andy Turner
at568@york.ac.uk
Multiple Connections between two nodes

Allow Multiple Connections

Only use first Connection

Average Connections

Cap Connection

Andy Turner

at568@york.ac.uk
Benchmarks

- Double Pole Balancing
- Ball Throwing
- Proben1: Cancer1

Parameters

- (1+4)-ES
- Uniform Mutation
- No Crossover
- Only Bipolar or Unipolar Sigmoid
- Allowed multiple connections between nodes

Comparison

- Can only use averages
- Data not available for statistical significance tests
Double Pole Balancing

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<thead>
<tr>
<th>Method</th>
<th>Evaluations</th>
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<tbody>
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<td>DirE</td>
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Andy Turner

at568@york.ac.uk
Ball Throwing

Method | Evaluations
--- | ---
CGPANN | 6069
Compressed CoSyNE | 8220
CoSyNE | 10224

**Diagram**

Arm Angle → Arm Torque

Arm Velocity → Neural Network → Release Ball
9 Tumor Descriptors → Neural Network → Classification

Data from University of Wisconsin Hospital (O. Mangasarian et al, 1990)

Following the Proben1 Document (L. Prechelt, 1994)

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Proben1: Cancer1

Andy Turner

at568@york.ac.uk
Overall:
CGPANN is a highly competitive NeuroEvolutionary strategy which assumes very little about the structure of the neural network to be evolved.

Take Home Message:
CGPANN directly evolves the weights, number of nodes, topology, and nodes function of artificial neural networks. CGPANN also indirectly evolves the arity of each node. Additionally CGPANN has all of the benefits of CGP; natural resilience to bloat and neutrality in the genotype aiding evolution through genetic drift.
Questions