

Spiking Neural Network for Asset Allocation Implemented Using The TrueNorth System

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CECEP Architecture



- The CDO is the decision making engine within the CECEP architecture
- These very simple examples quickly become very complex in realistic systems
 - Billions of possible outcomes





Name	Specification
Raining	IF Implication.explanation = Raining THEN Implication.evidence.Ground.moisture = Wet AND Implication.evidence.Sky.visibility = Cloudy
Broken Pipe	IF Implication.explanation = BrokenPipe THEN Implication.evidence.Ground.moisture = Wet OR (Implication.evidence.Sky.visibility = Clear AND NOT Implication.evidence.Ground.moisture = Dry)
Dry Ground	IFF NOT (Implication.explanation = Raining OR Implication.explanation = BrokenPipe) THEN Implication.evidence.Ground.moisture = Dry
Wet Ground	IFF Implication.evidence.Ground.moisture = Wet THEN Implication.explanation = Raining OR Implication.explanation = BrokenPipe

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Spiking M by N

Network

dendrites

synaptic

ayons

neurons

3/20

- Optimized resource allocation is extremely computationally expensive
- We need low SWaP alternatives, large problems are currently prohibitively expensive to solve.
- This is done using a series of spiking neurons that fire according to the most logical vehicle assignment options
- This work covers a MATLAB implementation of the spiking neuron based algorithm









Objective

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- Optimized resource allocation is extremely computationally expensive
- We need low SWaP alternatives, large problems are currently prohibitively expensive to solve.
- This is done using a series of spiking neurons that fire according to the most logical vehicle assignment options
- This work covers a MATLAB implementation of the spiking neuron based algorithm



Allocation Problem Size	Number of Possible Solutions
2×2	9
4×4	625
6×6	117,649
8 × 8	43,046,721
10 imes 10	25,937,424,601



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Spiking M by N

Network

synaptic

axon

neurons

Outline



- CECEP Applications
 - ${\scriptstyle \bullet}$ M by N Asset Allocation in SNNs
 - Method
 - Algorithm
 - TrueNorth Implementation
 - Results in TrueNorth
 - Latest Implementation and Results on Loihi

Neuron Model

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- Single neuron holds connection between one vehicle and one target
 - Capable of allocating N vehicles for M separate targets using N×M neurons
- Weight Parameters
 - TTA: Time to the target
 - Priority: Necessity of reaching target
 - TOT: Hold time for vehicle once target is reached
 - Probability of Success: Likelihood that a target will be completed by a certain vehicle
 - TTC = TOT + TTA
- Control Parameters
 - CM: Connectivity matrix hold vehicle-target compatibility
 - τ: A vehicle can only be assigned to one target
 - β: Penalize (but do not stop) multiple vehicles from reaching a single target



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Algorithm Block Diagram



- Flow of inputs and outputs for the algorithm
 - Spike accumulation is proportional to a weighted sum of priority, success, and time
 - Spikes occur depending on compatibility, as well as vehicle and target status
 - a) Base Accumulation Rate
 - b) Control Variables
 - c) Neuron Grid
 - d) Allocation Result



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Simplified Algorithm Block Diagram



- Flow of inputs and outputs for the algorithm
 - Spike accumulation is proportional to a weighted sum of priority, success, and time
 - Spikes occur depending on compatibility, as well as vehicle and target status



Example Allocation



Connectivity Matrix Response



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Example Allocation



Vehicle Control Response



Example Allocation



Target Control Response



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TrueNorth Implementation



- Circuits display the 2 by 2 scenario
 - Simple example mainly for demonstration
- 9 Inputs
 - 1 Uniform Spiking
 - 4 Vehicle Control
 - 4 Task Control
- 12 Outputs
 - 4 Vehicle Control Send
 - 4 Task Control Send
 - 4 Final Outputs
 - 3 Duplications of the same circuit

Neuron Accumulation



Neuron Accumulation with Control Variables



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TrueNorth Allocation Results

- Allocation results show which neuron numbers are spiking at the end of an allocation execution
- 2 by 2
 - Neurons: 1 4
 - Result [1 2]
- 4 by 4
 - Neurons: 4 5 9 15
 - Result [4 1 1 3]





TrueNorth Allocation Results

- Allocation results show which neuron numbers are spiking at the end of an allocation execution
- 6 by 6
 - Result [2 4 1 5 3 3]
- 8 by 8
 - Result [1 3 4 3 5 8 5 7]









Algorithm Comparison



	Exhaustive Search Using K80 GPU			TrueNorth Spiking System			
Allocation Size	Baseline CDO Reward	Baseline CDO Result	Effective Reward	Allocation Result	Answer Rank	Answer Percentile	
3×3	18.8703	[2 1 1]	18.4807	[2 1 2]	2 of 64	98.44%	
4×4	11.377	[4 1 1 3]	11.377	[4 1 1 3]	1 of 625	100%	
5×5	22.6219	[1 5 2 4 1]	22.6203	[1 5 2 3 1]	2 of 7776	99.99%	
6×6	31.2628	[2 4 1 5 3 3]	31.2628	[2 4 1 5 3 3]	1 of 117649	100%	
7×7	48.448	[4 2 2 6 5 6 7]	40.6019	[4 6 4 2 5 5 7]	6847 of 2.09M	99.67%	
8×8	40.8782	[1 3 4 7 5 3 6 8]	39.1283	[1 3 4 3 5 8 5 7]	111 of 43.0M	~100%	

- The best allocation for each case was determined using a GPU exhaustive search
- The table compares this result to the approximate result obtained from the Loihi spiking system

Timing Comparison



• Runtime comparison between the exhaustive search and spiking system

Allocation Size	CDO Search Time (GPU)	TrueNorth Execution Time	TrueNorth System Speedup
3×3	224 ms	47 ms	4.76×
4×4	231 ms	53 ms	4.36×
5×5	233 ms	52 ms	$4.48 \times$
6×6	234 ms	43 ms	$5.44 \times$
7×7	269 ms	56 ms	$4.80 \times$
8×8	955 ms	40 ms	23.88×

- Solution space on an asset allocation problem grows with problem size
 - Neuron utilization grows at a much smaller rate

Allocation Problem	Number of	Number of Acc.
Size	Possible Solutions	Neurons
2 imes 2	9	4
4×4	625	16
6 × 6	117,649	36
8×8	$43,\!046,\!721$	64
10 imes 10	$25,\!937,\!424,\!601$	100

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- Loihi implementation of the same algorithm
- Loihi photo shows portable USB stick
 This work was performed via remote login





Control Variable Spiking Layer



Spiking System Comparison



- Loihi demonstrates significant speedup of TrueNorth
 - Mainly due to shorter cycle time and non uniform intervals

Allocation Size	CDO Search Time (GPU)	Loihi Execution Time	Loihi System Speedup	TrueNorth Execution Time	TrueNorth System Speedup
3×3	224 ms	0.312 ms	717×	47 ms	4.76×
4×4	231 ms	0.384 ms	601×	53 ms	4.36×
5×5	233 ms	0.319 ms	730×	52 ms	4.48 imes
6×6	234 ms	0.414 ms	565×	43 ms	$5.44 \times$
7×7	269 ms	0.428 ms	629×	56 ms	$4.80 \times$
8×8	955 ms	0.737 ms	1296×	40 ms	23.88×

SWaP Comparison

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- General System Comparison
 - Exhaustive/Traditional vs. Embedded/Approximate
 - Approximate solution leads to dramatic increase in efficiency
 - In general, this result shows how the proposed algorithm enables portability of inference algorithms

	Trad. CPU / GPU System	Spiking Systems	Ratio
Size	2240 in^3	24 in^3	93×
Weight	20 lb	$0.5 \ \mathrm{lb}$	40×
Power	500 W	< 70 mW	$7142 \times$
Accuracy	100%	99%	-

Next Steps

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- Asset Allocation
 - More complete algorithm comparison
 - Study of maximum scalability
 - Comparison of methods for large scale allocation problems

- Loihi
 - Energy Benchmark
 - Maximum Scalability