Neuronal Copying of Spike Pattern Generators

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Temporal Coding

There is a rapidly accumulating body of empirical evidence which demonstrates that spike timing patterns of sub-millisecond precision are reliably generated in the sensory cortices[1]

However, the task of investigating temporal coding is one of great empirical difficulty, requiring simultaneous recording from a large number of single neurons over extended time periods[2]

Several computational models, utilising spiking neural networks and spike-timing driven plasticity rules, have begun to examine methods for the supervised learning of temporally coded patterns

These have generally demonstrated that a single neuron can be trained to fire at some specific time in response to a specific spatiotemporal input pattern[3]

However, each of these models neglects axonal delays, and thus rely on afferent firing within the timescale of membrane integration

The supervised learning mechanisms employed are also frequently biologically infeasible[4]

Polychronous Groups and Synfire Chains

Polychronous groups (PCGs) and synfire chains are putative temporally coded cell assemblies that reliably reproduce specific spatiotemporal activity patterns with millisecond precision

The self-organisation of both PCGs and synfire chains has been demonstrated in neural network models that utilise spike-timing dependent plasticity (STDP)[5]

Temporally coded cell assemblies can be constructed that perform Boolean logic operations[6]

The capacity for PCGs / synfire chains within a network exceeds the number of synapses

However, the use of supervised learning to create PCGs / synfire chains that perform a specified spatiotemporal activity mapping has yet to be demonstrated

The Neuronal Replicator Hypothesis

We have previously proposed that a constrained natural selection algorithm operates within the brain at very rapid timescales in order to solve high-dimensional and rugged search problems[7]

The units of neuronal selection must be entities that replicate and exhibit hereditary variation

We have presented several hypothetical methods of neuronal replication, including the copying of neuronal topologies and bi-stable activity patterns[8]

Here, we investigate the phenotypic copying of temporally coded cell assemblies (i.e. PCGs) in a spiking neural network using a biologically inspired supervised learning algorithm

This forms a conceptual framework for the consideration of how neuronal replication may operate within and between cortical columns in order to replicate spatiotemporal activity mappings (i.e. PCGs) with heredity and mutation

1: van Rullen and Thorpe (2002); Izhikevich (2006)
2: Bowers (2009)
3: Ponulak and Kasinski (in press); Gutig and Sompolinsky (2006); Carnell (in press)
4: But see Ponulak and Kasinski (in press)
5: Doursat and Bienenstock (2006); Izhikevich (2006)
6: Gutig and Sompolinsky (2006); Izhikevich and Hoppensteadt (2009)
7: Sternberg and Davidson (1995); Fernando and Szathmáry (2009)
8: Fernando, Karishma and Szathmáry (2008); Fernando, Goldstein and Szathmáry (submitted)
9: Izhikevich (2004)
10: Bi and Poo (1998); Dudman, Tsay and Siegelbaum (2007)
11: Turrigiano and Nelson (2004)

The Network Model

Feed-forward architecture (corresponding to an abstract cortical column)

Simulated 'Izhikevich' neurons with randomly assigned axonal delays[9]

Sub-threshold synaptic weights (such that >2 afferent spikes are required to fire a neuron)

Spike- and Input- timing dependent plasticity (ITDP)[10]

Spatiotemporal activity patterns provided to input layer and laterally to train output layer

Synaptic scaling mechanism[11]

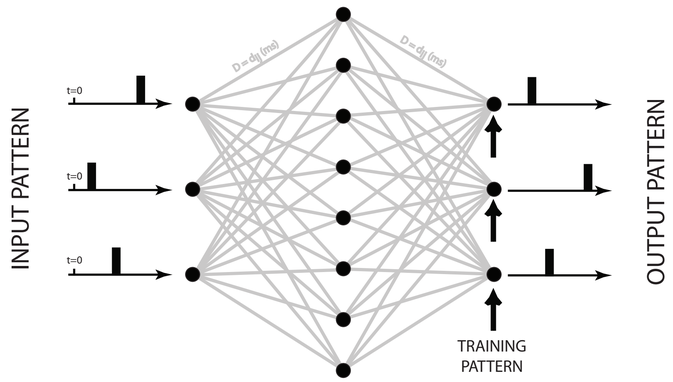

Figure 1: The Network Model

Input-timing Dependent Plasticity

Recent observations of Input-timing dependent plasticity (ITDP) in the hippocampus have demonstrated that afferent input to distal synapses - although relatively ineffective at driving post-synaptic firing - modulates the induction of LTP at proximal synapses within a certain temporal window (Figure 2). Here, we propose that similar mechanisms in the cortex could provide a biological correlate for the supervised learning of spatio-temporal mappings.

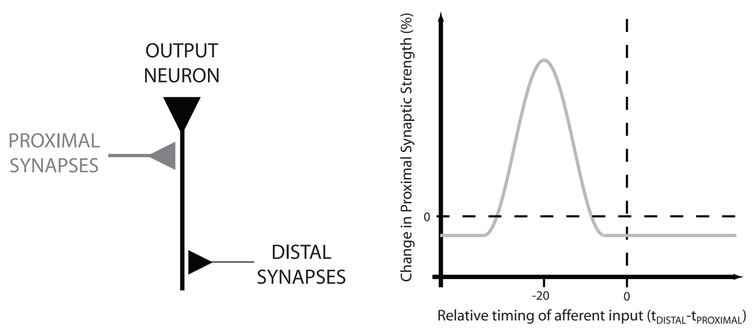

Figure 2: Input-timing dependent plasticity

Supervised Learning of Spatiotemporal Mappings

During supervised learning, neurons in the middle layer with input delays that correspond to the temporal latency of input firing are selectively activated

Potentiation of connections between the middle and output layers depends on the timing of afferent firing (STDP) and is modulated by ITDP

Scaling is required to prevent excess synaptic input to output neurons (causing latency reduction)

Following supervised learning, the network selectively performs the desired spatiotemporal activity mapping only when the latency of firing in input neurons matches the learned input pattern

The internal structure of different networks that are trained to perform this spatiotemporal activity mapping varies significantly - this is a phenotypic copying process

The fidelity of copying depends on the repertoire of inter- and intra- layer connections and their axonal delays, and is thus noisy and stochastic

These properties could correspond to heredity and mutation during replication?

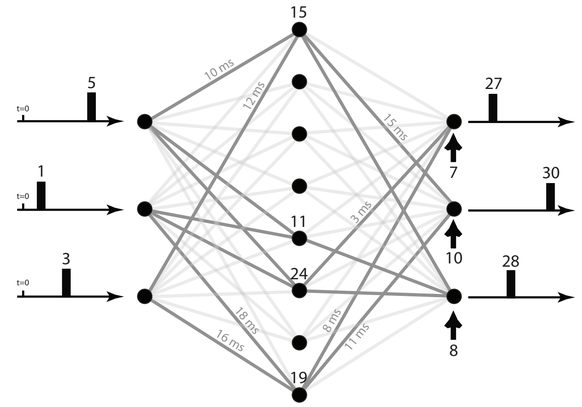

Figure 3: Learning spatiotemporal activity mappings with STDP and ITDP

Discussion

We have introduced a novel, biologically inspired methodology for the supervised learning of spatiotemporal activity mappings (i.e. PCGs) in feed-forward networks

This model can be generalised to include multiple intermediate layers, each of which is trained to selectively produce specific spatiotemporal activity patterns in response to specific temporal input correlations

This provides a conceptual framework for the consideration of temporally-coded, phenotypic neuronal replication in the human cortex

Hypothetically, by lateral transmission of input and output signals, multiple cortical columns can be trained to produce the same spatiotemporal activity mapping with heredity and mutation

Analysis of the emergent properties and wider implications of this model are currently underway