Learning the receptive field properties of complex cells in V1

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Abstract

A defining feature of complex cells is their spatial phase invariance, namely that they respond strongly to oriented sinusoidal grating stimuli with a preferred orientation but with a wide range of phases.

Recent work [2] has shown that complex cells have a great diversity and only a subset can be characterized by the classical energy model.

We propose a biologically plausible learning model for complex cells that:

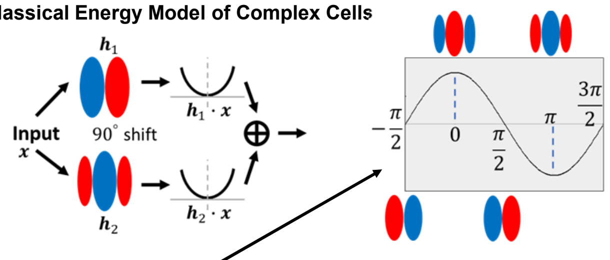
- Pools inputs from simple cells [3]
- Learns connections between simple and complex cells from natural image input
- Learning uses a modified version of the Bienenstock, Cooper, and Munro (BCM) rule [4,5]

Our results indicate that the learning rule can describe a diversity of individual complex cells, similar to that observed experimentally.

This study provides a plausible explanation for how complex cells can be learned using biologically plausible mechanisms.

Model

Classical Energy Model of Complex Cells



- θ: orientation
- ϕ: phase (0 to 2π)
- (x_0, y_0): centre
- f_0: spatial frequency
- σ_x, σ_y: standard deviations that determine width and length of the Gabor function
- A: amplitude

Features:

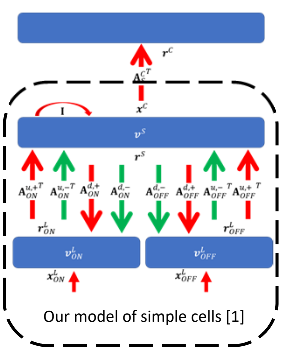
- Orientation selective
- Localized
- Invariant to phase

Questions:

- How does learning occur?
- How to account for observed diversity of complex cells?

Our Model of Complex Cells

- Response of complex cells: $\mathbf{r}^C = \mathbf{A}_S^{C\,T}\mathbf{x}^C$
- Normalized response of a complex cell *j*: $$r_{j,N}^C = \frac{\beta r_j^C}{\alpha + \sqrt{\sum_k (r_k^C)^2}}$$



- Input to complex cells: $\mathbf{x}^C = \langle \mathbf{r}^S \rangle$; the average of simple cell responses for a number of visual stimuli with temporal information.

Learning rule

- Modified **BCM rule** (Bienenstock et al., 1982):
$$\Delta a_{i,j} = \eta_a \left(x_i^C r_j^C (r_j^C - \theta_j) - \gamma_a a_{i,j}\right)$$
$$\Delta \theta_j = \eta_\theta \left((r_j^C)^2 - \theta_j\right)$$
- Modified **normalized-BCM** rule (Willmore et al., 2012):
$$\Delta a_{i,j} = \eta_a \left(x_i^C r_{j,N}^C (r_{j,N}^C - \theta_j) - \gamma_a a_{i,j}\right)$$
$$\Delta \theta_j = \eta_\theta \left((r_{j,N}^C)^2 - \theta_j\right)$$
- Connections are excitatory and bounded.

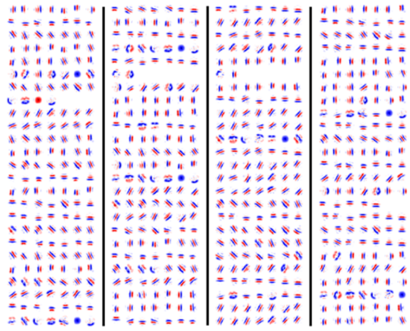
New experimental data [2]:

There is a wide range of complex cells, from less phase-invariant to energy-model-like cells [2].

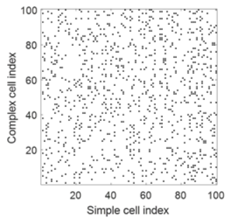
Phase: a subset of $[0\ 2\pi]$ vs a complete set of: $[0\ 2\pi]$

Results

Modified **normalized**-BCM learn different complex cells

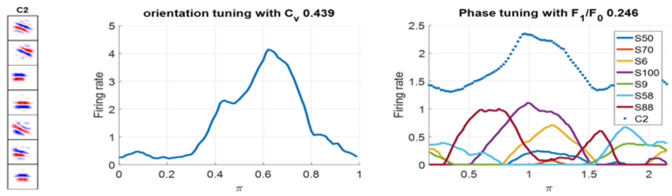


- Simple cells with significant weights
- Different subspaces
- More random pattern in simple-complex cell connection



Normalization brings competition [5]

Example: complex cell C2



Model complex cells compared with cat data: population statistics

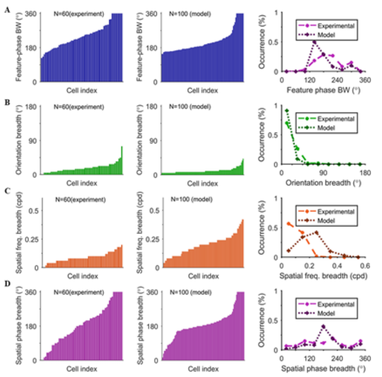
Compared to complex cell data in cat V1 [2]

Using the same methods of analysing this data:

- Feature phase bandwidth
- Orientation breadth
- Spatial frequency breadth
- Spatial phase breadth

Model can account for diversity

Close match between model and experimental data



Conclusions

Summary of complex cell model

Experimental phenomenon

- Range of phase invariance
- Orientation selectivity
- Diversity of complex RFs in cat V1 in a recent experimental study
- Population statistics

Biologically plausible model

- Build upon a biologically plausible model of simple cells
- Non-negative neural responses
- Local learning rule
- Dale's law

This study provides a learning model of complex cells in which simple cells are pooled and that accounts for the diversity of experimentally observed receptive field properties.

References:

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