DISCOV: A Neural Model of Colour Vision, with Applications to Image Processing and Classification

Suhas E. Chelian, Gail A. Carpenter
Department of Cognitive and Neural Systems
Boston University
677 Beacon Street
Boston, Massachusetts 02215 USA

[schelian, gail] @cns.bu.edu

http://cns.bu.edu/techlab
http://cns.bu.edu/celest

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Suhas E. Chelian and Gail A. Carpenter
Department of Cognitive and Neural Systems, Boston University
677 Beacon Street, Boston, Massachusetts 02215 (USA)
Corresponding author: S. Chelian (schelian@cns.bu.edu)

ABSTRACT

The DISCOV (DImensionless Shunting COlour Vision) system models a cascade of primate colour vision cells: retinal ganglion, thalamic single opponent, and two classes of cortical double opponents. A unified model formalism derived from psychophysical axioms produces transparent network dynamics and principled parameter settings. DISCOV fits an array of physiological data for each cell type, and makes testable experimental predictions. Properties of DISCOV model cells are compared with properties of corresponding components in the alternative Neural Fusion model. A benchmark testbed demonstrates the marginal computational utility of each model cell type on a recognition task derived from orthophoto imagery.

1. COLOUR VISION PHYSIOLOGY AND MODEL PREDICTIONS

Physiological recordings from retinal, single opponent, and two double opponent cell types (Figure 1) are summarized in Figure 2a. Square 4, for example, shows responses to a black spot surrounded by red. For this image input, a retinal red cell has a maximally negative center response (black); a red-green double opponent I cell has an intermediate negative center response (dark grey); and a red-green double opponent II cell has in intermediate positive center response (light grey). Center responses of the DISCOV model (Figure 2b) exactly match all those found in the literature, except for the double II responses in squares 9 and 10. For these two cases, model predictions reverse the reported intermediate positive and negative center responses. Note that this analysis shows that the Neural Fusion "double opponent" model (Figure 2c) is functionally a single opponent model.

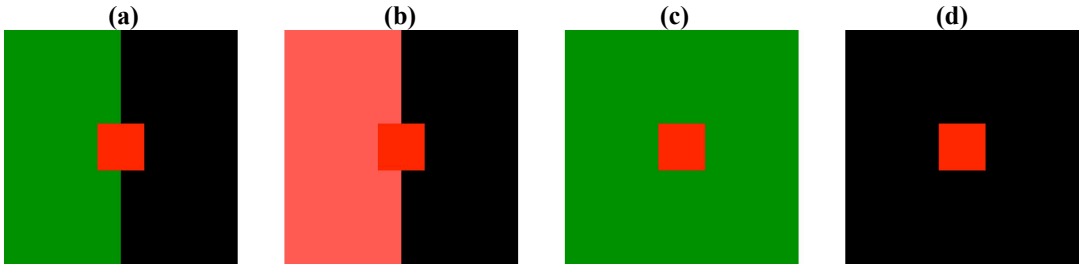

Figure 1: Receptive fields of (a) retinal, (b) thalamic single opponent, and (c, d) cortical double opponent colour cells, illustrated here for red/green image channels. (a) Retinal cells exhibit a center-surround spatial antagonism derived from their cone inputs. The ideal stimulus for a cell with excitatory red center and inhibitory red surround is a red center surrounded by anything but red.[1] (b) Thalamic single opponent cells exhibit a center-surround chromatic antagonism with red-green (or blue-yellow) colour pairs. The ideal stimulus for the excitatory red center / inhibitory green surround cell is a red center surrounded by anything but green.[2,3] Note that "red center" here means "any colour with a maximal red component," and "anything but green" means "any colour without a green component." Thus, for example, an excitatory white center / inhibitory black surround input would also be expected to produce a maximal center response, as would a solid red field. (c) Double opponent I cells, popularized by Livingstone and Hubel,[2] exhibit both center-surround spatial antagonism within each colour and chromatic antagonism between colours. The ideal stimulus for the illustrated red-ON, green-OFF excitatory center / red-OFF, green-ON inhibitory surround cell is a red center surrounded by green. (d) Double opponent II cells, reported by T'so and Gilbert,[4] exhibit chromatic antagonism within the center and surround of the cell, and the surround is also broad-band suppressive. The ideal stimulus for this cell is a red center surrounded by black.

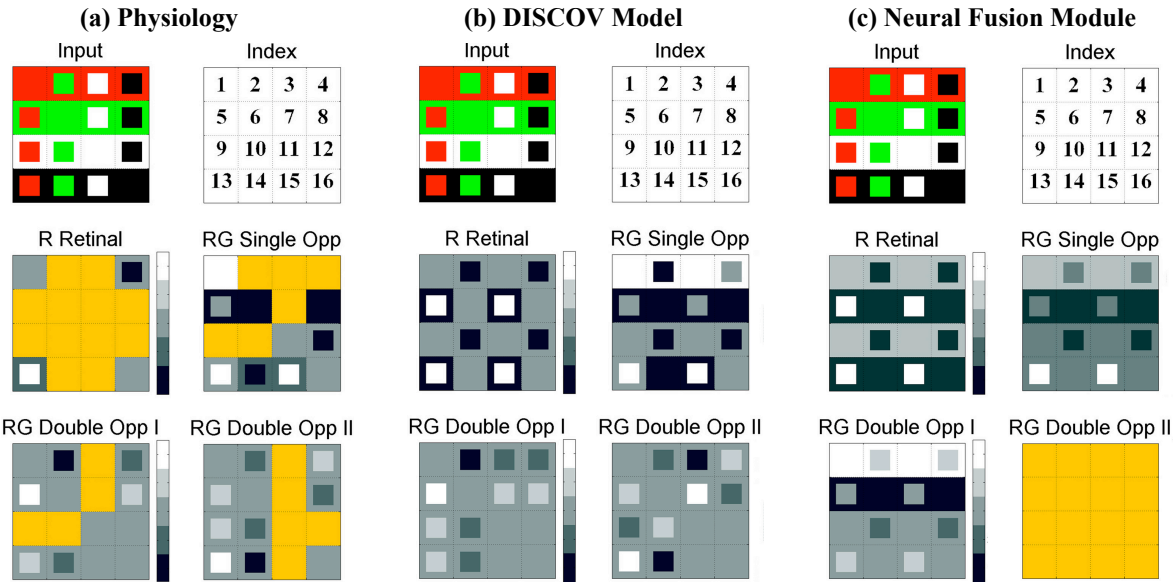

Figure 2: Response profiles of red/green cell types (retinal, single opponent, and double opponent I, II) from (a) physiology, (b) the DISCOV model, and (c) the Neural Fusion Module[5]. Elements of 4x4 arrays in the top row indicate the center and surround inputs for 16 experiments for each cell type. Response bins (white=high to black=low) represent strong positive, intermediate positive, baseline, intermediate negative, and strong negative responses, respectively. Orange squares represent outcomes that are unreported (a) or not modeled (c). White image inputs mix all colours maximally (R=G=1); black inputs have no colour components (R=G=0).

Gaps in reported data (orange squares in Figure 2a) correspond to DISCOV model predictions (Figure 2b). For example, DISCOV predicts that a white spot surrounded by green (square 7) will produce strong positive center responses from red retinal and red-green double opponent II cells, baseline center responses from red-green single opponent cells, and intermediate positive center responses from red-green double opponent I cells.

2. DISCOV MODEL COMPUTATIONS

DISCOV model simulations compute steady-state activations z of a dimensionless shunting equation:

$$\frac{d}{dt}z = -Bz + (1-z)Cx - (1+zD)y \tag{1}$$

where x is the average (excitatory) signal to a small center square; y is the average (inhibitory) signal to a large surrounding square; A is the ratio of the area of the large square to the area of the small square; B is the passive decay rate; C is the ratio of the strength of the excitatory input (center square) to the strength of the inhibitory input (whole square); and D is the ratio of the excitatory potential to the inhibitory potential. Note that large signals x to the center drive z toward its maximum value, 1; and large signals y to the surround drive z toward its minimum value, -1/D.

When inputs x=y=0, z converges to the baseline value 0. Otherwise, with B assumed to be small relative to x or y, the steady-state activation is:

$$z = \frac{Cx - y}{Cx + Dy} \tag{2}$$

DISCOV model retinal, single opponent, and double-opponent I and II cells share a common set of parameter values. Simulation results summarized in Figure 2b are valid with parameter constraints:

$$2 < A, \qquad 1 < D, \qquad 1 < C < (3+D)/2 \tag{3}$$

Typical parameters meeting these constraints are A=25 (as shown in Figure 1), C=1.1, and D=2.

Dimensionless image component colour band values range from 0 to 1. For the red-green examples in this paper, 0≤R,G≤1. When the red ON-channel component equals R, the model OFF-

channel input equals its complement, 1-R. In the DISCOV model, retinal and single opponent cells use only ON-channel components, while double opponent I and II cells use both ON- and OFF-channel components. The notation [*x*/*y*]= [X/Y] designates a channel input X averaged across the center and a channel input Y averaged across the surround. For example, [*x*/*y*]=[R/G] denotes *x* as the input R of the red ON-channel averaged across the small center square and *y* as the input G of the green ON-channel averaged across the large surrounding square.

Table 1: DISCOV model center/surround input components. $[\ldots]^+$ denotes rectification.

Cell type	**DISCOV model**
Retinal (R)	[R / R]
Single opponent (RG)	[R / G]
Double opponent I (RG)	{ [R / R]$^+$ + [1-G / 1-G]$^+$ }-{ [G / G]$^+$ + [1-R / 1-R]$^+$ }
Double opponent II (RG)	{ K [R / R]$^+$ - [1-G / 1-G]$^+$ }-{ K [G / G]$^+$ - [1-R / 1-R]$^+$ }

Table 1 defines DISCOV model cell computations. For example, the maximum response of a retinal red model cell [R/R] occurs when R=1 in the image center and R=0 elsewhere (Figure 2, squares 5,7,13,15). In Equation (2), x=1, y=A^{-1}, and $z = \left(C - A^{-1}\right) \Big/ \left(C + DA^{-1}\right) \equiv E$, a maximal response which is close to 1 when A is large. With a uniform red input (Figure 2, square 1), x=y=1 and $z = (C-1)/(C+D) \equiv \varepsilon$, a baseline response which is small when C is close to 1. Double opponent models combine rectified retinal cell outputs from both ON- and OFF- channels. The maximum response of a double opponent I model cell occurs with R=1 and G=0 in the center and R=0 and G=1 in the surround (Figure 2, square 5). With these inputs, [R/R] = [1-G/1-G] = E and [G/G] = [1-R/1-R] = -1/D, producing a cell response of 2E. This same input produces the response $\{KE - E\}$ in a double opponent II model cell, which is intermediate positive compared to that cell's maximal response of $\{KE - \varepsilon\}$. The double opponent II parameter K is constrained to lie between 1 and E/ε.

Table 2: Car (center) pixel accuracy as a function of model cell type combinations. Single Opp = single opponent, DO I = double opponent I, and DO II = double opponent II. Percent correct is listed in the following order: overall car accuracy, then red, green, white, and black car accuracy.

Cell types used for training and testing	***DISCOV* % correct overall:** red, green, white, black	***Neural Fusion* % correct overall:** red, green, white, black
Retinal, Single Opp, DO I	**87.0**: 98.8, 74.1, 77.1, 97.9	**61.3**: 47.4, 50.4, 71.9, 75.4
Retinal, Single Opp, DO II	**72.2**: 58.1, 61.3, 75.0, 94.5	(not modeled)
Retinal removed (from line 1)	**78.9**: 96.7, 56.1, 62.8, 100.0	**42.7**: 49.1, 34.6, 22.7, 64.3
Single Opp removed (from line 1)	**82.3**: 99.4, 73.4, 73.3, 83.0	**64.8**: 55.6, 54.4, 72.7, 76.4
DO I or DO II removed	**58.8**: 17.3, 49.0, 74.6, 94.2	**58.9**: 39.7, 46.3, 71.7, 77.7

Table 3: Marginal utility of model cell types. An up arrow represents a positive effect on recognition accuracy, a down arrow represents a negative effect, and a dash represents a negligible effect (<2%).

Model cell type	***DISCOV*: Effect on % correct**	***Neural Fusion*: Effect on % correct**
Retinal	↑ **8.1**: ↑ 2.1, ↑ 18.0, ↑ 14.3, ↓ -2.1	↑ **18.6**: – -1.7, ↑ 15.8, ↑ 49.2, ↑ 11.1
Single Opp	↑ **4.7**: – -0.6, – 0.7, ↑ 3.8, ↑ 14.9	↓ **-3.5**: ↓ -8.2, ↓ -4.0, – -0.8, – -1.0
DO I	↑ **28.2**: ↑ 81.5, ↑ 25.1, ↑ 2.5, ↑ 3.7	↑ **2.4**: ↑ 7.7, ↑ 4.1, – 0.2, ↓ -2.3
DO II	↑ **13.4**: ↑ 40.8, ↑ 12.3, – 0.4, – 0.3	(not modeled)

3. ASSESSING THE MARGINAL COMPUTATIONAL UTILITY OF MODEL CELL TYPES ON A BENCHMARK RECOGNITION PROBLEM

The benchmark recognition task described in this section assesses the marginal utility of each colour vision model cell type. Image pixel values are derived from a MassGIS 0.5*m* resolution orthophoto image (http://www.mass.gov/mgis). Background pixels are samples of red dirt, green grass, white sand, and black road, and center pixels are portions of red, green, white, and black cars. The resulting images are similar to the inputs in Figure 2. The task is to identify car (center) colours in different background (surround) contexts.

Each composed image was processed by DISCOV and Neural Fusion model red retinal, red-green single opponent, and red-green double opponent I cells, as well as by DISCOV model red-green double opponent II cells. Exemplars included three spatial scales, with 1, 9, and 25 center pixels, each with the surround-to-center area ratio A=25. Learning and recognition were carried out by a default ARTMAP[6] neural network with five voters, with results averaged across 50 random training orders.

Classification was first performed with three model cell types, and then with one cell type removed (Table 2). If recognition accuracy for a given class declined, the deleted cell type was rated as helping to identify that class (up arrow in Table 3). For example, using retinal, single opponent, and double opponent I cell types, DISCOV correctly labeled 98.8% of red car pixels (Table 2, line 1). With the double opponent I model component removed, red car recognition accuracy dropped to 17.3% (Table 2, line 5). The DISCOV double opponent I model cell was thus deemed to assist red car recognition by 81.5% (Table 3, line 3).

Table 3 shows that each DISCOV model cell type makes a positive contribution to overall car pixel classification. In contrast, the Neural Fusion single opponent model component has an overall negative effect on car pixel classification. As shown in Figure 2, computational properties of the Neural Fusion double opponent I cells are similar to those of that model's single opponent cells. Correspondingly, the marginal contribution of DISCOV double opponent I cells is dramatically greater than that of the Neural Fusion cells on the benchmark recognition task.

The development of DISCOV colour cell models is being carried out in the context of a large-scale research program that is integrating cognitive and neural systems derived from analyses of vision and recognition to produce both biological models and technological applications.[7]

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