A Generative Model of Decorrelating Color Sensitive Retinal Ganglion Cells

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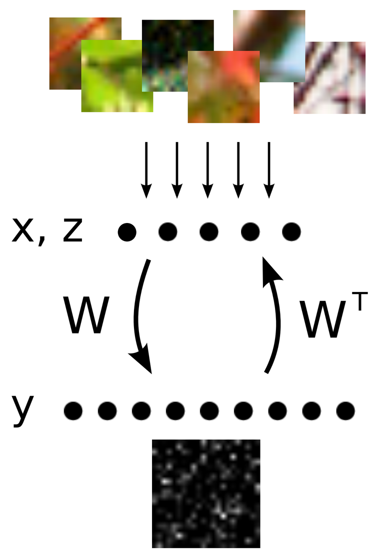
Introduction

Neuroanatomical studies have shown that the mammalian retina consists of many parallel, equally potent microcircuits [2] which in turn drive numerous different retinal ganglion cell (RGC) types, indicating the retina's functional role of pre-processing visual-information before reaching the visual cortex. Theoretical models suggest that the retina encodes information efficiently, using minimal resources whilst transmitting maximum information [3].

Generative Model

The effect of minimizing metabolic costs had been explored by [4] utilizing a simple generative model, equating connection weights to synaptic strengths and the network's output to neural firing rates. We extended the model, which processes gray scale images [4], to color images. Additionally the hidden layer neural activations were only allowed to be positive and the imposed weight constraint was simplified by removing one threshold parameter.



$$y = \max(0, W \cdot x) \quad (1)$$
$$z = W^T \cdot y \quad (2)$$
$$err = x - z \quad (3)$$
$$\Delta W = \eta * y \odot err \quad (4)$$
$$\Delta W_i = -k * \mathrm{sgn}(W_i) * \mathrm{abs}(W_i)^p \quad (5)$$

Model parameters are: **k** strength, **p** shape of the metabolic weight-constraint and η learning rate. ($\cdot$ inner, $\odot$ outer product)

- The algorithm for learning the connection weights **W** in the generative model takes five steps: For an input vector **x** and matrix **W**, the hidden activity (1) is computed. The input is reconstructed (2) and the reconstruction error (3) is used in the Hebbian learning rule (4), updating **W**. Afterwards the weight constraint (5) is applied to the receptive field (RF) of each hidden neuron i.
- Constraining the connection strengths in this model is crucial for the emergence of localized, difference of Gaussian (DOG) shaped receptive fields, resembling those of retinal ganglion cells (RGC).

Parametric Fitting

After the training process converged, the receptive fields were fitted with a spatio-chromatic elliptical DOG parametric model. The DOG model has a set of 13 parameters:

- the elliptical Gauss function has center μ_x μ_y, spread σ_x σ_y and rotation θ.

$$gauss(x, y) = e^{-a(x-\mu_x)^2 + 2b(x-\mu_x)(y-\mu_y) + c(y-\mu_y)^2} \quad (6)$$
$$a = \cos^2(\theta)/2/\sigma_x + \sin^2(\theta)/2/\sigma_y \quad (7)$$
$$b = -\sin 2(\theta)/4/\sigma_x + \sin 2(\theta)/4/\sigma_y \quad (8)$$
$$c = \sin^2(\theta)/2/\sigma_x + \cos^2(\theta)/2/\sigma_y \quad (9)$$

- the DOG function has ratio of center to surround γ and scale of the surround part relative to the center part k_s.

$$DOG(x, y) = gauss(x, y) - k_s \, \gamma \, gauss(x, y) \quad (10)$$

- the chromatic part of the model with additional parameters **bias** and **direction** for each color channel:

$$DOG_{rgb}(x, y) = [red, green, blue] \quad (11)$$
$$red = bias_r + direction_r \, DOG(x, y) \quad (12)$$
$$green = bias_g + direction_g \, DOG(x, y) \quad (13)$$
$$blue = bias_b + direction_b \, DOG(x, y) \quad (14)$$

In the fitting process each receptive field is compared with a reconstruction generated by the spatio-chromatic parametric model. A single run of the fitting algorithm emits a set of parameters which reconstruct the given receptive field with the smallest error. From a sequence of fitting attempts, the best fit, with the smallest reconstruction error, is chosen.

Decorrelation of Input

Subsequently the resulting parametric fits were then clustered via k-means into 7 clusters. The resulting receptive fields decorrelate the input into several distinct channels each spanning the entire simulated visual field, resembling parallel pathways [1] found in the primate retina. As a consequence of the weight constraint and the rectification in Eq. (1), receptive fields not contributing to reconstructing the presented images slowly die off.
An efficient code [3] emerges that uses a small number of RGC neurons and small weights to encode the presented input. However, slightly different model parameters, or training images with different overall statistics, tend to result in vastly different distributions of RGCs.

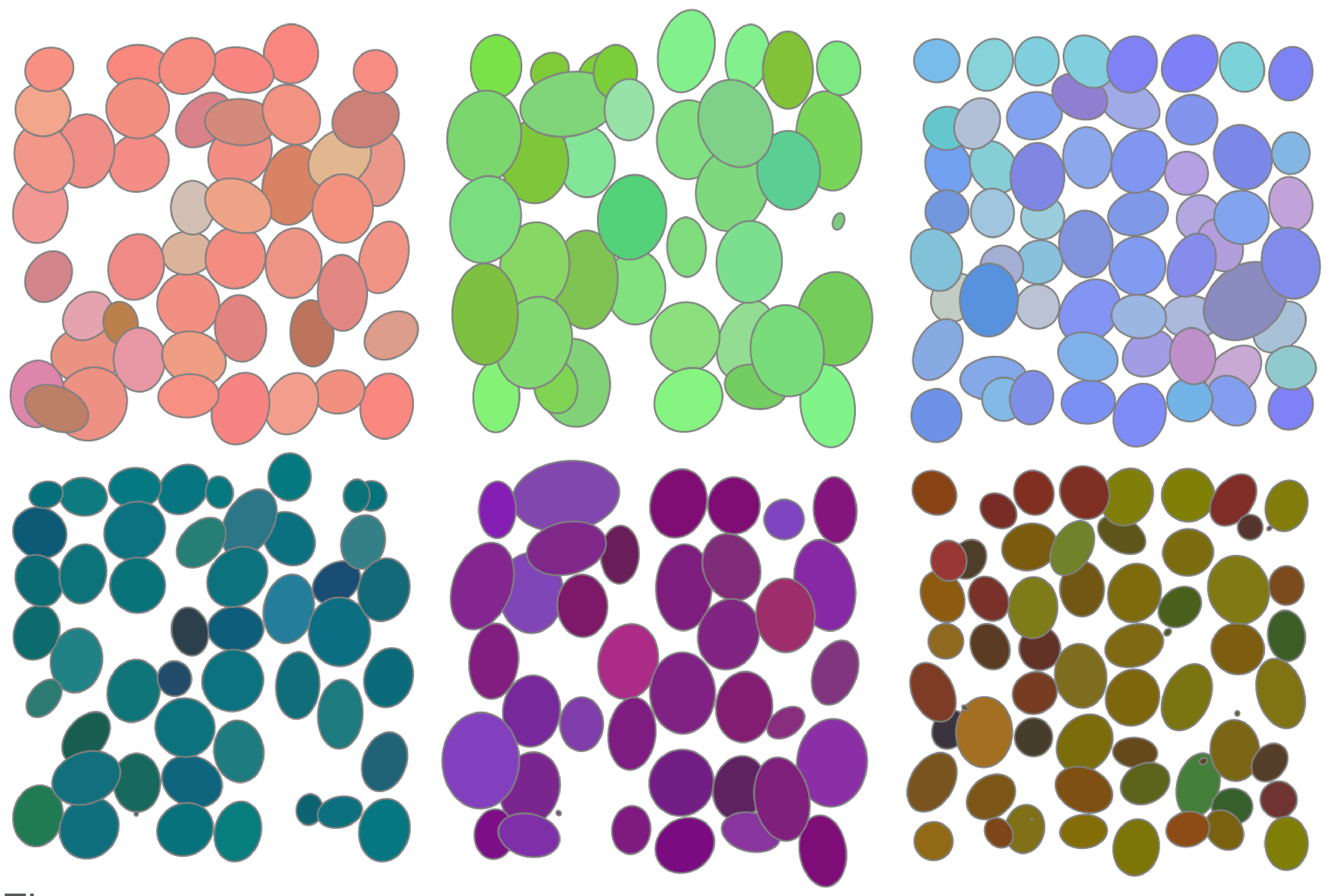


Figure : The figure shows parametric fits of the resulting receptive fields for 6 of the 7 clusters. Ellipses are drawn in the color of the strongest weight for each RGC. As the model has been trained from RGB images, the color of these center weights is mostly close to the RGB color space cube's edges. (Top row: red, green, blue. Bottom row: cyan (red-off), magenta (green-off), yellow (blue-off).) The 7th cluster contains non-local, non-DOG shaped receptive fields. The numbers of RGCs in each channel are: red (47), green (38), blue (60), cyan (48), magenta (38), yellow (63). Not shown: non-DOG (26), zero (256). Total (576).

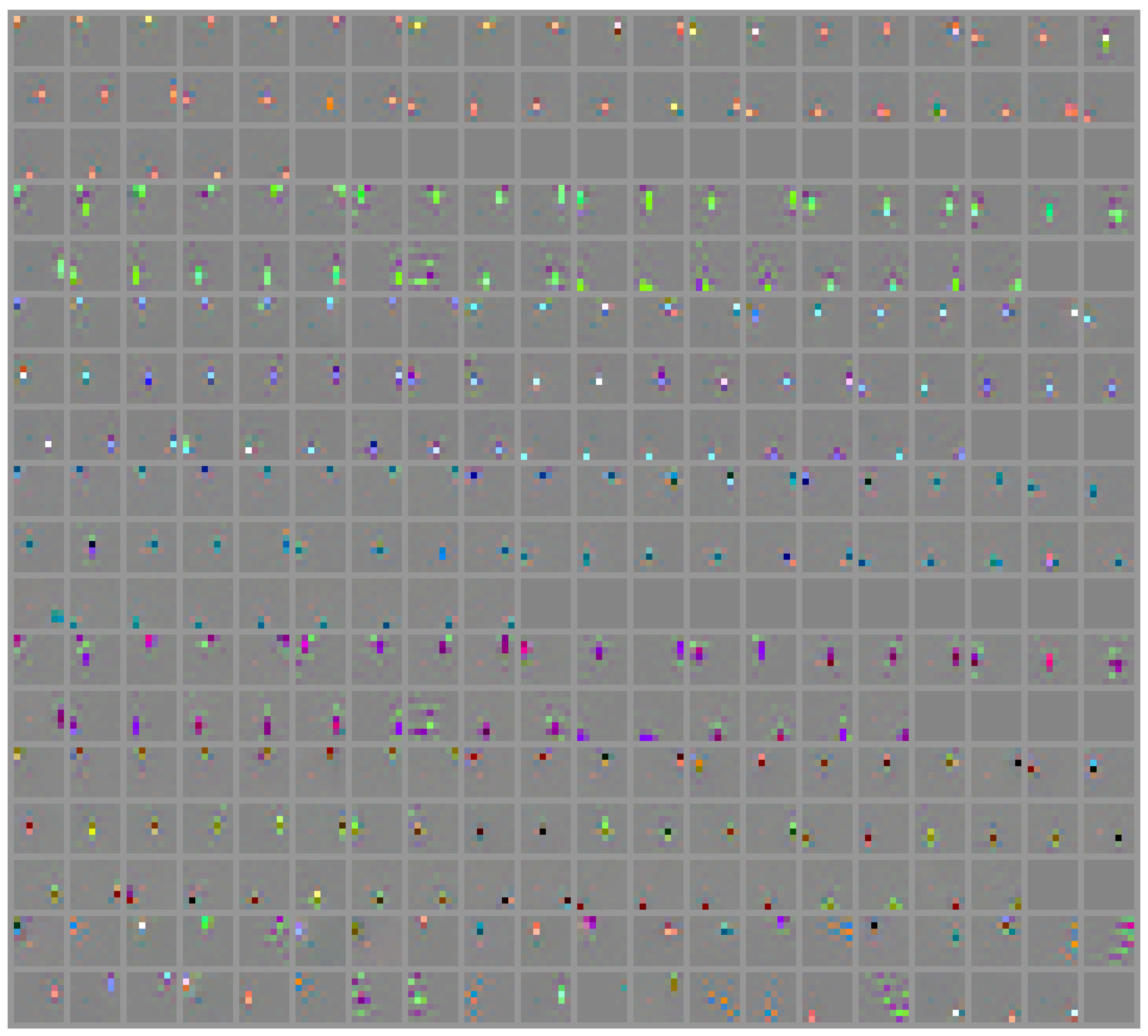


Figure : A trained map **W** with 8×8 RGB input and a hidden layer of 24×24 units. About 44 % of the receptive fields have died off (their weights have decayed to zero). The last two rows contain non-DOG RFs, some zero-weight RFs are not shown for space reasons.

Distribution in RGB colorspace

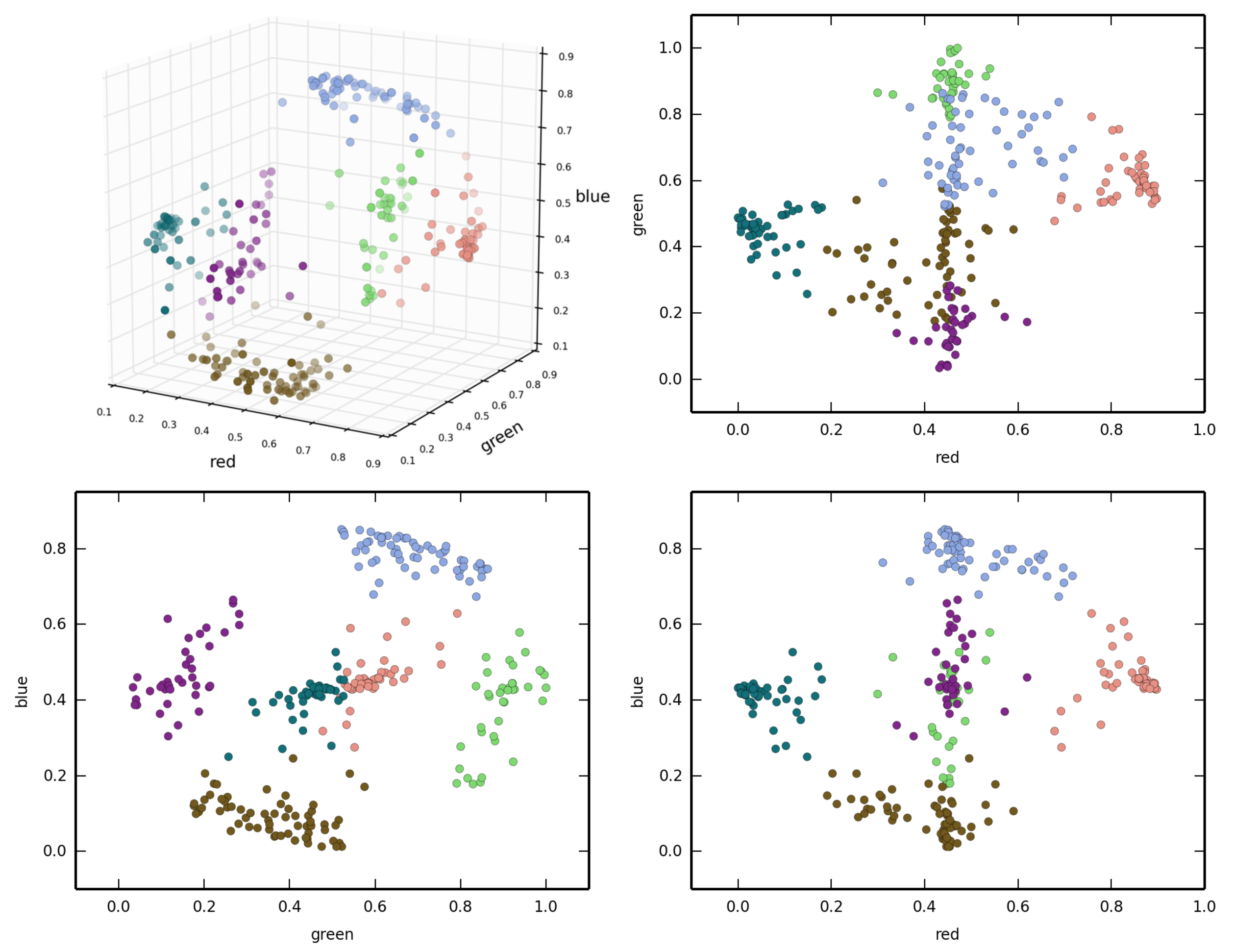


Figure : The plot shows the distribution of each RGC's strongest weights in the RGB color space. The weights of the 7th cluster (non-local, non-DOG RGC) have been omitted for clarity.

Convolution with Prototype RFs

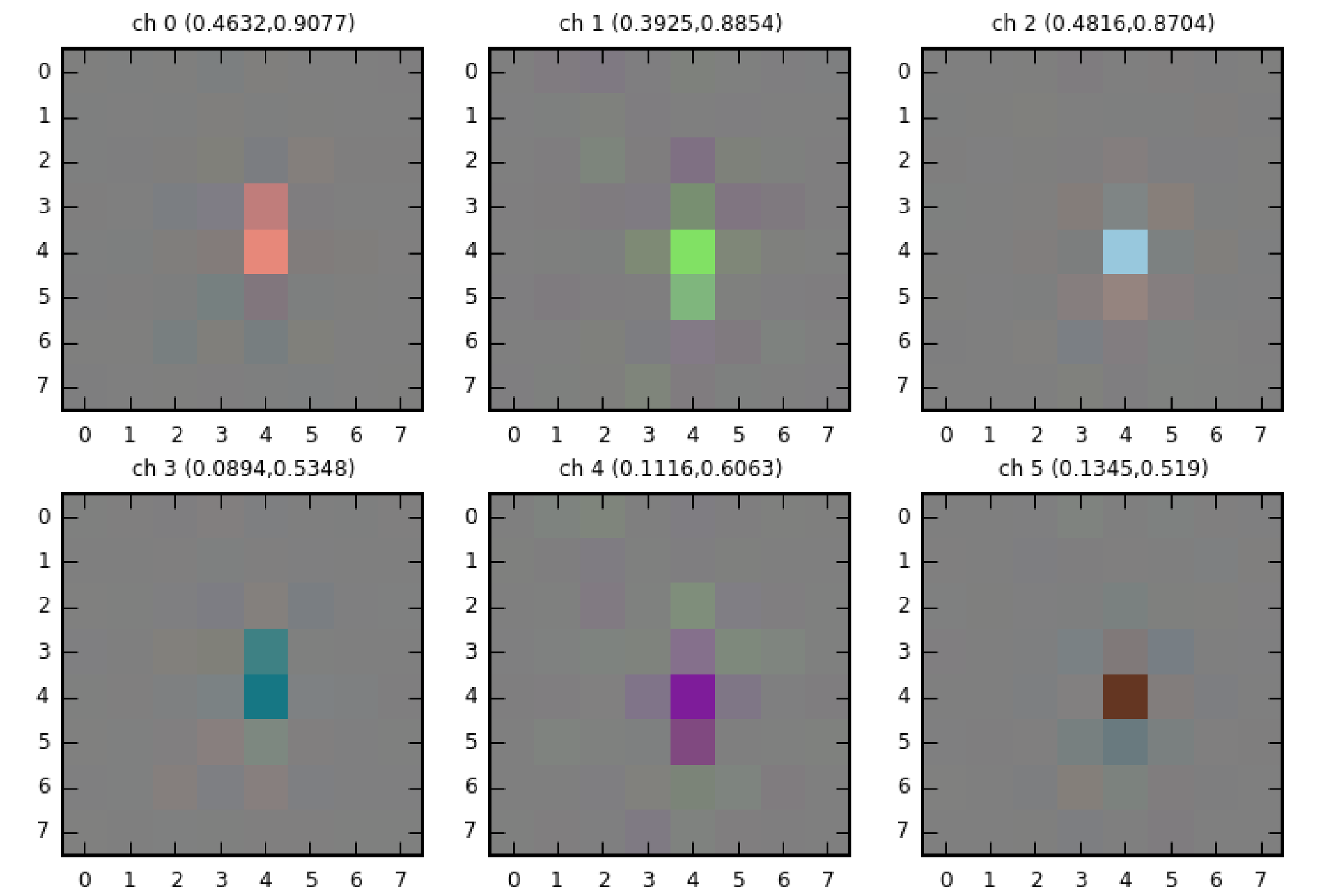


Figure : Prototype receptive fields (RF) for each channel: red, green, blue (1st row), cyan, magenta, yellow (2nd row). For each channel a RF near the visual fields center with a small reconstruction error has been chosen.

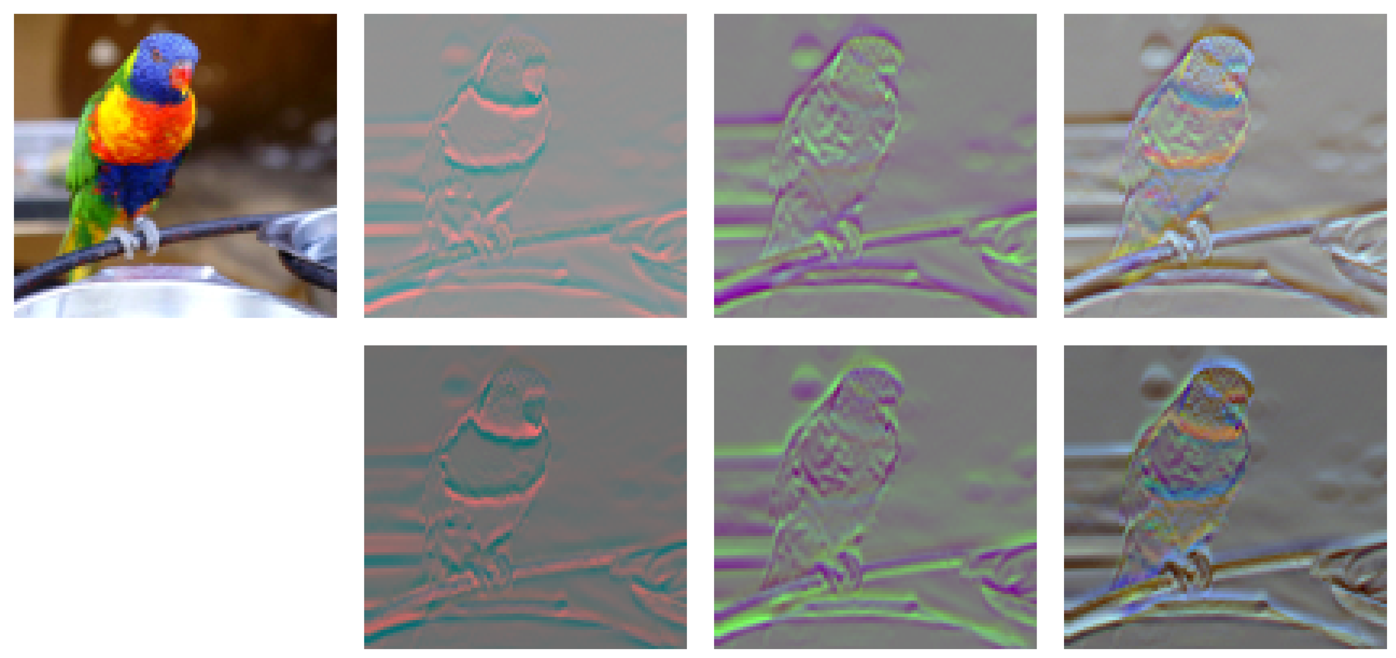


Figure : An image of size 100x94 pixels and its resulting images after filtering with a prototype RF of red-on, green-on and blue-on (1st row), red-off, green-off and blue-off (2nd row).

References

[1] G. D. Field and E. J. Chichilnisky. Information Processing in the Primate Retina: Circuitry and Coding. *Annual Review of Neuroscience*, 2007.
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[4] Benjamin T. Vincent and Roland J. Baddeley. Synaptic energy efficiency in retinal processing. *Vision Research*, 43, 2003.

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