Opponent Color Space Motivated by Retinal Processing

Silvio Borer[1)] and Sabine Süsstrunk[2)]
1) Laboratory of Computational Neuroscience
2) Laboratory for Audiovisual Communications
Swiss Federal Institute of Technology (EPFL), Lausanne, Switzerland

Abstract

We introduce a new opponent color space, which aims to mimic the color processing in the primate retina. Recent data from physiology and morphology are used to determine the model and its parameters. The input signal in LMS representation is first nonlinearly transformed by a response saturation stage. Then a linear, spatially extended transformation computes the opponent representation. In contrast to other opponent color spaces, our model does not have a luminance component. Our three components are blue-yellow, red-green, and green-red. It is the spatial extension that allows us to distinguish between the last two. Furthermore, we show that we can reverse the transformation and obtain a LMS representation from the opponent encoding.

Introduction

There are different motivations for the definition of a color space. One can use a XYZ representation, in which it is possible to match every visible color with a linear combination of the primaries with positive coefficients. The LMS encoding is motivated by the fact that it represents the cone responses in the retina. One can define an opponent color space that is suitable for compression, e.g. YC_RC_B. But they are all based on the idea of color encoding of a point-light source, and they view a digital image as a collection of light spots. In our coding model, we use the topological structure of an image to encode color. How this coding is done is motivated by the color processing in the primate retina.

Color Coding in the Retina

An image presented to the retina is sampled by cone photoreceptors maximally sensitive to long (L cones), middle (M cones), or short (S cones) wavelengths. Because of response saturation, cones respond nonlinearly to flashes of light of increasing intensity. The peak response r of a cone to a flash of light, relative to its maximal value r_{max}, is given by

$$r/r_{max}=1-exp(-ki) \quad (1)$$

where i is the flash intensity and k is a constant characteristic to each cell.[8] There are adaptation mechanisms in cones, which we don't include in our model. Then the signal is processed through bipolar cells and ganglion cells, which are the output cells of the retina. Furthermore, there are two layers of lateral connections, the horizontal cell and the amacrine cell layer. With the current knowledge of physiology and morphology one distinguishes three populations of ganglion cells[5]: the *midget*, the *parasol*, and the *small bistratified* ganglion cells. Midget ganglion cells receive indirect input from L and M cones, but they lack significant S cone input. They have a center surround organization. In the parafoveal region the center receives input from a single cone, and there midget ganglion cells show color opponency, whereas in the periphery they are non opponent.[4] In the parafovea there are four types of midget cells, ON and OFF cells, and both types have either a red or a green center.

The small bistratified are the blue-ON ganglion cells.[6] They have spatially overlapping ON and OFF receptive fields and are color opponent, with input from 2-11 S cones to the ON field.[3] The OFF part has input from L and M cones and has about the same size as the blue-ON field.[5]

Parasol ganglion cells have a center-surround organisation but are non opponent. They receive mixed input from L and M cones in their center and surround. They have a different dynamical behaviour than the other two types[2] and project to the magnocellular layer in the lateral geniculate nucleus. Because the magnocellular layer is generally linked with the analysis of motion, we exclude this cell type from our color space model.

Opponent Color Space

In a digital image each pixel is represented by its RGB values. With the cone sensitivity functions[10,9] we can calculate the cone excitation at each location. Let us denote by L(x), M(x) respectively S(x) the cone excitation at point x. To get to our opponent representation we first compute a pointwise nonlinear transformation like (1)

$$\begin{aligned} L_s&=1-exp(kL) \\ M_s&=1-exp(kM) \\ S_s&=1-exp(kS) \end{aligned} \quad (2)$$

where k is a constant. The value of k depends on the choice of the range of the input values, so we arbitrarily fix k=1. Then we compute a red-green (R_G) and a green-

red (G_R) opponent signal, which corresponds to the midget ganglion cell with either a red or a green center and an opposite surround. Further, there is a blue-yellow (B_Y) signal corresponding to the small bistratified ganglion cell. We take the center size of B_Y to be just one pixel so that we get an invertible mapping. More precisely

$$R_G = L_s - p * M_s$$

$$G_R = M_s - p * L_s \quad (3)$$

$$B_Y = S_s - p*(L_s+M_s)$$

where p and q are lowpass filters. We use regularly spaced samples of a cubic B-spline for the discrete filters p and q. Different surround sizes for the midget ganglion cells are reported in the literature. In Ref. 7 the surround is about 2-3 times bigger than the center, in Ref. 1, 6-14 times, so different values for p are possible. A reasonable size for the B_Y surround filter q is 20 samples.[5] We use a weighting of the surround of 4/5 in relation to the center, as in Ref. 7, i.e. we normalized the filters to sum to 4/5.

Now we want to reconstruct the LMS color encoding from our R_G, G_R, B_Y representation. Let A be the linear operator p*. From equations (3) we get

$$L_s = R_G + A\,G_R + A^2 R_G + A^3 G_R + \ldots \quad (4)$$

We see that there are two geometric series and we get

$$L_s = (1-A^2)^{-1} R_G + A(1-A^2)^{-1} G_R \quad (5)$$

Analogous

$$M_s = G_R + A\,R_G + A^2 G_R + A^3 R_G + \ldots \quad (6)$$
$$= (1-A^2)^{-1} G_R + A(1-A^2)^{-1} R_G$$

From these results we can easily calculate L, M and S. Denotes F the Fourier transform, which maps p to its Fourier transform F(p), then we have

$$F((1-A^2)^{-1}) = 1/(1-F(p)^2) \quad (7)$$

Of course it's possible to calculate first the Fourier transform of equations (3) and then solve it, but we like to have the series expansion (4), which allows us to compute approximations without computing the Fourier transform.

Analysis of the Color Space

The above described opponent color space, although a bit more complex than just a linear transform of the three color values at each location, has the following advantages. It reinforces intensity edges, so that more importance is given to them. We can see this when we look at the series expansion (4) e.g. the L_s signal is decomposed into the R_G component and more and more blurred components, which carry mean signals. The edges are strongly represented in the R_G part. This is illustrated in the following example: Figure 1 shows the red component of an image. We computed the opponent representation, and figure 2 shows the R_G component. It is easily seen that edges are strengthened, whereas slowly varying shadows (low frequency information) are weakened.

Figure 1. The red component of an example image.

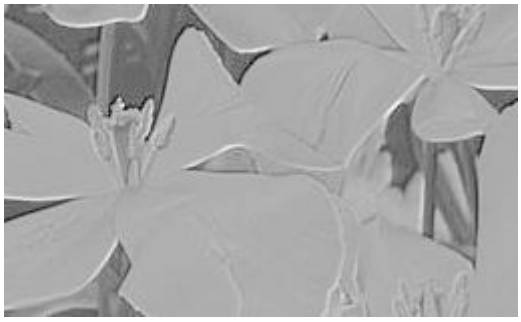

Figure 2. The opponent R_G component of the image in figure1.

Figure 3. The reconstruction using only the first two terms of equation (2).

In figure 3, we used equation (4) respectively (6) to reconstruct the original image from the opponent representation. Thereby we used only the first and the second term. We can see that already the second term adds some shadows to the image. By using the first five terms, we achieve a reconstruction with less than 5% mean squared error.

Another advantage of the opponent representation is that it depends less on the absolute intensity, because it computes differences between intensity values.

Of course, the properties of our color space depend on the sizes of the filters p and q. For very large sizes the filtered image is nearly constant. In equation (3), we subtract nearly constant values from the result of (2). So the encoding in the opponent color space is nearly constant with respect to the non-linear saturation correction. On the other hand, if one chooses p and q to have the size of just one sample, the color space computes a pixelwise encoding.

Conclusion

We showed how to code the color information in an image in a way similar to the one in the primate retina. Furthermore, we showed how to decode it and discussed the properties of this retinal encoding. A future direction of research is to analyze the statistical properties of natural color images encoded in our opponent color space.

References

1. Benardete, E. A. and Kaplan E., The Receptive Field of the Primate P Retinal Ganglion Cell, I: Linear Dynamics. *Visual Neuroscience* 14 (1997)
2. Benardete, E. A. and Kaplan E., The Dynamics of Primate M Retinal Ganglion Cells. *Visual Neuroscience* 16 (1999)
3. Chichlinsky, E.J. and Baylor D.A., Receptive-Field Microstructure of Blue-Yellow Ganglion Cell in Primate Retina. *Nature Neuroscience* 2 (1999)
4. Dacey, D.M., Primate Retina: Cell Types, Circuits and Color Opponency. *Progress in Retinal Research* 18 (1999)
5. Dacey, D.M., Parallel Pathways for Spectral Coding in Primate Retina, *Annual Review of Neuroscience* 23 (2000)
6. Dacey, D.M. and Lee, B.B., The "Blue-On" Opponent Pathway in Primate Retina Originates from a Distinct Bistratified Ganglion Cell Type, *Nature* 367 (1994)
7. Lee, B.B., Kremers, J., and Yeh, T., Receptive Fields of Primate Retinal Ganglion Cells Studied with a Novel Technique, *Visual Neuroscience* 15 (1998)
8. Schnapf, J.L., Nunn, B.J., Meister, M. and Baylor, D.A., Visual Transduction in Cones of the Monkey Macaca Fascicularis, *Journal of Physiology* 427 (1990)
9. Stockman, A. and Sharpe, L.T., Spectral Sensitivities of the Middle- an Long-Wavelength Sensitive Cones Derived from Measurements in Observers of Known Genotype, *Vision Research* 40 (2000)
10. Stockman, A., Sharpe, L.T., and Fach, C.C., The Spectral Sensitivity of the Human Short-Wavelength Cones, *Vision Research* 39 (1999)

Biography

Silvio Borer received his diploma in Mathematics from the University of Zurich in 1999. Since then he is a Ph.D. student in the Lab of Computational Neuroscience at the Swiss Federal Institute of Technology (EPFL), Lausanne, Switzerland.