# Co-occurrence of color and luminance edges in natural scenes

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**Abstract** Spatial resolution for color is poor, and reports that V1 simple cell respond to oriented achromatic stimuli have led to the view of two independent processing streams, a high-resolution achromatic form system and a low-resolution unoriented color surface system. Recent data have challenged this view, showing that V1 simple cells respond also to oriented chromatic stimuli [5, 7] and that color is processed both in the dorsal and ventral stream [2]. Here we analyze the statistical distribution of luminance and chromatic edges in natural scenes. We show that few edges are characterized exclusively by luminance or chromatic information alone. Instead, the vast majority of edges combine luminance and chromatic information, supporting recent physiological findings of the joint processing of chromatic and luminance information. While few edge are characterized by a pure chromatic contrast, these edge are important for particular ecologically relevant tasks such as the detection of ripe fruit against foliage. Overall, we suggest that chromatic information makes edge detection more robust and provides important additional information for the proper segmentation of objects.

The detection of edges is frequently one of the first processing steps both in artificial and natural systems. Traditionally, this process is conceptualized in neurophysiological theories and computationally realized in image processing systems as an *achromatic* process.

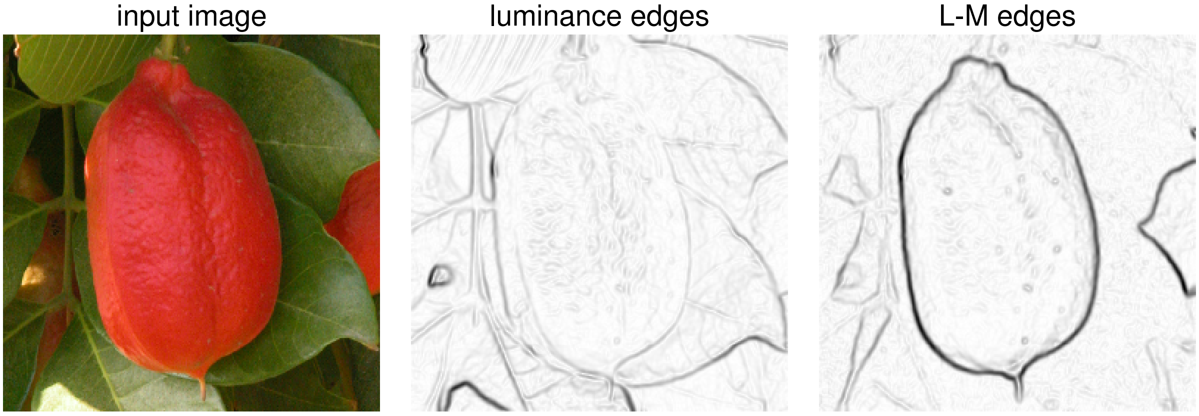

**Fig. 1:** Image of a fruit and the edges detected in the luminance plane and the L-M plane which signals reddish-greenish variations. While the object contour is faintly if at all represented by the luminance edges, a strong response occurs in the L-M plane which almost perfectly delineates the object. Chromatic information helps to separate objects from background.

However, important information about object boundaries is sometimes represented only in chromatic channels. Consider the image of a red fruit on green foliage (Fig. 1): In the luminance image, the edges of the fruit are hardly detectable, because the luminance of the fruit is almost the same as the luminance of the background foliage. Any image processing system which tries to detect objects based on luminance information alone would probably miss the fruit. Adding chromatic information changes the situation completely. In the L-M channel, which represents reddish-greenish signal variations, the object boundaries of the fruit is almost perfectly represented. An image processing system which can use this chromatic information will probably detect the fruit.

It has been suggested that the ability to process chromatic information and red-green variation in particular has evolved for precisely this task, namely to detect ripe fruit against a background of green foliage [1,14]. More recently, it has been shown that the spectral sensitivities of photo pigments in primates are optimal for the detection of finding fruit or young tasty leaves among a background of mature leaves [16,17]. Here we investigate the more general hypothesis that the advantage of having access to chromatic information is not limited to the detection of fruits and leaves, but instead applies to any objects which have a different color than the background. By combining luminance information with chromatic information the detection of objects becomes easier and more robust. However, this would only make sense if many object borders are defined by a combination of luminance and chromatic contrast. A parsimonious system may still rely on luminance information alone, but taking chromatic information into account would make the detection more robust and reliable. In the following we focus on edge detection, since edge detection is one of the first processing step in object recognition, both in artificial and natural vision system.

In particular, we investigate the statistics of luminance and chromatic edges in natural scenes to asses the possible contributions of chromatic information to edge detection. In particular, one wants to know whether all information about edges is essentially contained in the achromatic version of the image, or, alternatively, if and what kind of information can only be obtained form the chromatic channels. The ideas is as follows: A full chromatic images is first separated into a pure luminance image plane and two chromatic images, one varying between reddish-greenish, the other between purple-chartreuse. In this step it is important that the achromatic images are *isoluminant*, i.e, that they contain no luminance differences. Clearly, a simple difference of RGB channels cannot achieve this property. Instead, one has to use a color space where luminance and chromatic information is properly separated. Here we use the DKL color space [3, 10] whose three cardinal axes (achromatic luminance; reddish-greenish or L-M; and purple-chartreuse or S-(L+M)) are derived from the peak sensitivities of neurons in the LGN, i.e, at the second major processing stage after the initial absorption by the three cone classes. After this transformation, edges are detected in each of the three images planes. Next, the edges within, say, the reddish-greenish image plane are compared to the edges in the achromatic images: for every images pixels we evaluate the strength of the edge in the achromatic image and strength of the corresponding pixel in the reddish-greenish plane. The joint histogram of the edge strength in two images is a formalization of this idea.

The joint histograms show that few edges are characterized exclusively by luminance or chromatic information alone. Instead, the vast majority of edges combine luminance and chromatic information. A joint processing of luminance and chromatic information, as supported by recent physiological findings, will thus result in more robust and reliable edge detection and object recognition. Chromatic signals provide a general advantage, which is not limited to special tasks such as the detection of ripe red fruits against green foliage. Chromatic information makes edge detection more robust and provides important additional information for the proper segmentation of objects.

# Results

The two joint histograms of luminance edges and edges detected in each of the two chromatic channels are depicted in Fig. 2.

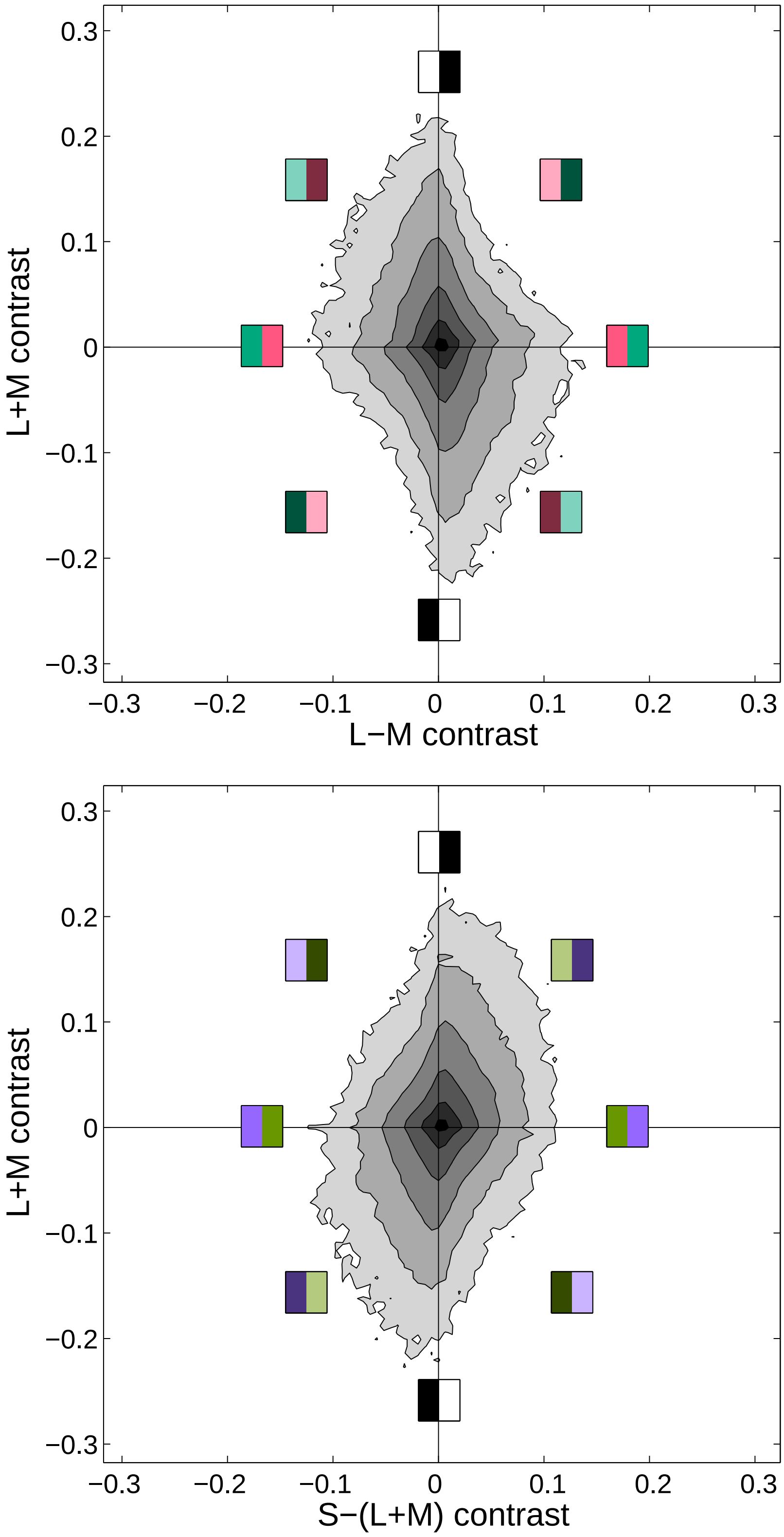

**Fig. 2:** Joint edge histogram of the luminance channel (L+M) with the L-M channel (reddish-greenish signal variations) and the S-(L+M) channel (purple-chartreuse signal variations).

The joint histogram of luminance and L-M edges has a high excursion along the luminance axis and also strong isoluminant L-M edges. Isoluminant edges are not rare, but occur with equal strengths as other edges. However, the large majority of edges do not fall on either axes but is combines luminance and chromatic contrast. The distribution is not symmetrical but has a higher excursion along the second diagonal, which results from many edges between bright green and dark reddish objects, such as leaves in full sunlight against soil or shadow.

A similar joint histogram occurs for the luminance and S-(L+M) edges, with less pronounced isoluminant edges. Again, the distribution is not symmetrical but has a higher excursion along the main diagonal. Again, bright greenish objects cause this higher excursion, this time leading to stronger edges between bright greenish and dark bluish objects than between dark greenish and bright bluish objects.

Inspection of edge maps in individual images reveals that some prominent object boundaries are weak or missing in the luminance edge map but are clearly delineated in the L-M plane. For example, red fruits or flowers against green foliage, that are hardly visible in the luminance plane, give rise to strong object boundaries in the L-M plane (cf. Fig. 1).

Having evaluated the joint occurrence of chromatic and luminance edges, we have also investigated the co-occurrence of edges in the two chromatic channels. The joint histogram for chromatic L-M and S-(L+M) edges is almost circular (Fig. 3).

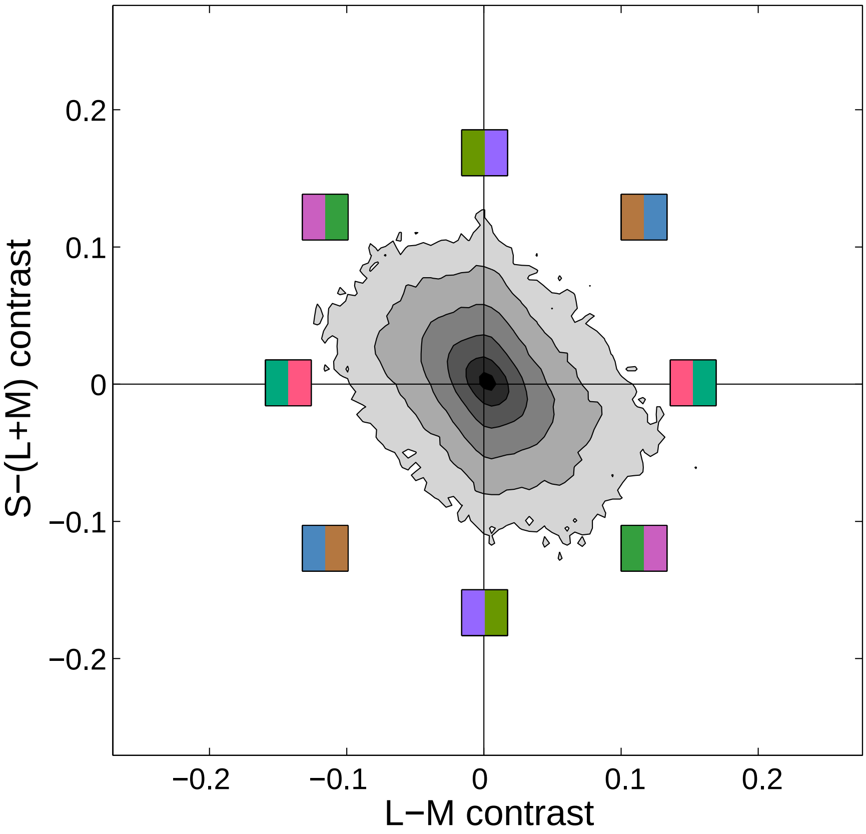

**Fig. 3:** Joint edge histogram of the two chromatic channels.

The largest edge contrast occurs near the second diagonal between green and magenta. Edge contrast along the main diagonal which roughly corresponds to edges between yellow and blue objects is smallest. The reason for that is unclear but may reflect particular properties of natural scenes, where few highly saturated blue objects on yellow background (or vice versa) are to be found, while highly saturated reddish-magenta objects on highly saturated green background (such as a flower or fruit among leaves) are more frequent.

For comparison to the joint edge histograms, we have also determined the joint histograms between individual cone excitations [15]. The data show that the cone excitations are highly correlated, because changes in light intensity will results in similar changes of cone excitations. Also, the correlation is highest between L and M cones because of their highly overlapping spectrum.

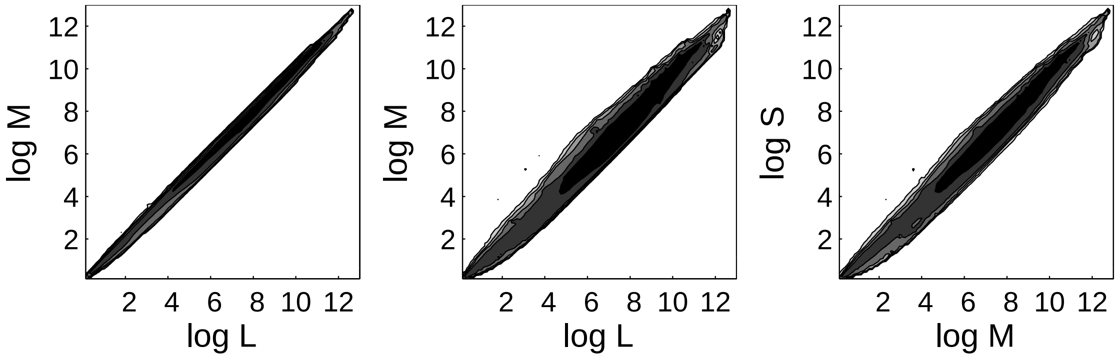

**Fig. 4:** Joint histograms of cone responses are highly correlated.

# Discussion

> Colors are only symbols. Reality is to be found in luminance alone.
> When I run out of blue, I use red.
>
> Picasso

In an anecdotal report, when asked about the meaning of his pink and blue periods, Picasso made the above statement. This statement perfectly reflects the traditional view which used to be common among scientists both in computer vision and physiology.

In physiology, the process of edge extraction was thought to be essentially achromatic. In this traditional, simplistic view, edges are processed by orientation-selective neurons driven by a pure luminance pathway, whereas the processing of color was thought to be limited to unoriented neurons [11]. Recent neurophysiological recordings have shown that this strict dichotomy is inadequate: orientation-selective neurons sensitive to a combination of color and luminance exists in the primary and secondary visual cortex [7–9]. In a recent study the sensitivity of neurons both in primary visual cortex (V1) and secondary visual cortex (V2) to color and orientation has been measured [5]. Color and orientation selectivity was quantified by an index ranging between 0 and 1. If orientation selective cells were basically color-blind, and color selective cells were not selective for orientation, both indices would show a strong negative correlation. However, a continuous, uncorrelated distribution of color and orientation selectivity was found (Fig. 5).

In computer vision, edge detection algorithms were mostly designed for the processing of achromatic images. However, despite tremendous effort, the multi-purpose edge detector

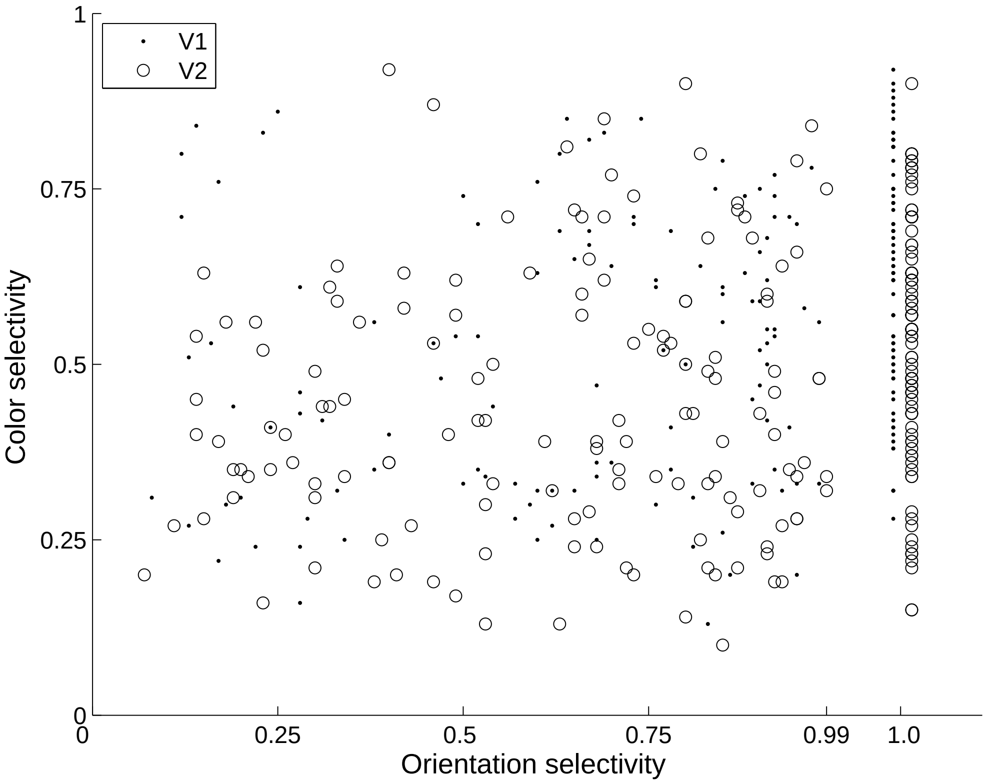

**Fig. 5:** Neurons in V1 and V2 are sensitive for color and orientation. Color and orientation are not correlated, but define independent dimensions.

which faithfully detects the relevant edges in an image has not been found yet. This failure may point to the importance of other visual modalities apart from luminance that play an important role in edge detection. Our results suggest that color is one modality which makes edge detection more robust.

We have presented further evidence for the joint processing of luminance and color from the statistical analysis of the distribution of chromatic and luminance edges in natural scenes. Object boundaries are not always characterized by pure luminance variations. Instead, most edges are characterized by a co-occurrence of chromatic and luminance contrast. Further, some prominent object boundaries are signaled robustly only in the chromatic L-M plane. Chromatic edges are also robust against luminance variations caused by +cast shadows. Overall, this suggests an important role for color in the detection of object boundaries. The neural networks in early visual areas seems to be perfectly adapted to the joint occurrence of luminance and chromatic edges in natural scenes.

# Methods

The analysis is based on 764 images from a publically available data base of calibrated color images [12]. The calibrated images are first transformed into LMS cone space, modeling responses of the L, M and S cones of a human observer. Next, LMS responses are transformed into a color-opponent space, with three axes sensitive to luminance (black-white), L-M (“reddish-greenish” or “cherry-teal”) and S-(L+M) (“purple-chartreuse”), resembling the chromatic preferences of retinal ganglion cells and LGN cells.

Formally, the following transformations of the $L$, $M$ and $S$ cone excitations are used [6,13]

$$
\begin{aligned}
Lum &= L + M + \varepsilon && (1)\\
LM &= (L - M)./Lum && (2)\\
SmLM &= (S - Lum)./(S + Lum) \ . && (3)
\end{aligned}
$$

The parameter $\varepsilon = 2^{-52}$ is a small constant which is added to avoid division by zero in the computation of $LM$ and $SmLM$.

Edges are detected in these three color-opponent planes using the Sobel operator, after normalizing each plane to the range [0, 1]. Finally, the joint histogram of edges strengths is computed for each image, and the joint histograms of all images are averaged. In a joint histogram, the value at position i, j is the number of pixels with value i in one channel and value j at the same location in the other channel. The joint histogram is an approximation of the joint probability density of pairs of edge pixels at same locations in different color planes.

For comparison to the joint edge histograms, we have also computed the joint histograms of the LMS cone excitations which provide the input to the further processing. Following an earlier study [15], the joint histograms are computed from a logarithmic transformation of the cone excitations. More precisely, each of the three cone excitations $L$, $M$, and $S$ is converted to a logarithmic signal (base 10), and the mean is subtracted:

$$
\begin{aligned}
L_{\log} &= \log L - \operatorname{mean}(\log L) && (4)\\
M_{\log} &= \log M - \operatorname{mean}(\log M) && (5)\\
S_{\log} &= \log S - \operatorname{mean}(\log S) && (6)
\end{aligned}
$$

The rationale for this transformation is as follows. The logarithmic transformation compensates for the large variations in the cone excitations, which, without the logarithmic transformation, leads to squeezing of many data points at the origin and a long-tailed extension at higher values. Further, the classical Weber-Fechner law states that same logarithmic changes in stimulus intensity are equally detectable [4,18]. Subtracting the mean, responses are independent of the overall illumination level. The transformation of individual cone responses is analogous to von Kries scaling, where individual cone classes are normalized independently.

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