# On the Behavior of Spatial Models of Color

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**ABSTRACT**

There is a growing family of algorithms that treat/modify/enhance color information in its visual context, also known as *Spatial Color* methods (e.g. Retinex or ACE). They produce results that, due to a changing spatial configuration, can have a non-unique relationship with the physical input. In authors' opinion judging their performance is a challenging task and is still an open problem. Two main variables affect the final result of these algorithms: their parameters and the visual characteristics of the image they process. The term visual characteristics refers not only to the image's digital pixel values, (e.g. calibration of pixel value, the measured dynamic range of the scene, the measured dynamic range of the digital image), but also to the spatial distribution of these digital pixel values in the image. This paper does not deal with tuning parameters, rather it discusses the visual configurations in which a Spatial Color methods show interesting, or critical behavior. A survey of the more significant *Spatial Color* configurations will be presented and discussed. These configurations include phenomena, such as color constancy and contrast. The discussion will present strengths and weaknesses of different algorithms, hopefully allowing a deeper understanding of their behavior and stimulating discussions about finding a common judging ground.

## 1. INTRODUCTION

Color sensation is not directly linked to the spectral characteristics of the perceived signal. With the same triplet of stimuli, almost any color sensation can be reproduced ("Yet, when we measure the amounts of light in the world around us, or when we create artificial worlds in the laboratory, we find that there is no predictable relationship between flux at various wavelengths and the color sensations associated with objects." [1]).

The term "*Spatial Color*" refers to a family of algorithms that recompute wavelength/energy arrays into calculated color appearance arrays, or preferred color enhancement arrays, according to the spatial distribution of pixel values in the scene. (See Table 1 - Definitions of terminology)

| Term | Definition | Example |
|---|---|---|
| Visual (spatial) image characteristics | Properties of a scene that affect the response of human vision | Simultaneous contrast target: grays on white and black |
| Digital value | Calibration of digit | Middle gray (18% maximum) e.g. digit 153 |
| Digital tone scale | Measured calibration curve relating scene radiance to pixel values in the digital image | Device profile |
| Scene dynamic range | Measured radiance range of the original scene | From 50 to 3000 cd/m$^2$ |
| Image dynamic range | Digital range of image expressed in number of bits | 8 or 16 bit per channel image |
| Spatial distribution | The spatial distribution of radiances, or digital values | Described by Fourier transform (with phase component) |

Table 1 Some important definitions used in the paper.

## 1.1. Tones Scale Rendering

Many of the readers, particular the older ones, have had the experience of printing black and white photographs with an enlarger in a dark room (The dark-room-deprived younger readers will have to visualize the following in terms of contrast adjustments in Photoshop). The negative in the enlarger was parallel to the table. A lamp above the negative had an on/off adjustable timer. The light from the lamp is collected by the enlarger lens and projected on the table top and the image is carefully focused. We placed a small piece of light-sensitive paper on the table and developed the test strip to check for exposure. With correct exposure we would make a test print of the entire image to evaluate the image. The next critical step in rending the negative-to-print was to evaluate the contrast. Print papers came in a variety of grades. If the image lacked contrast, we substituted a higher grade of paper (higher slope of print optical density/negative optical density), which uniformly increased the contrast of the print. If the image lacked details in the whites and the blacks, we substituted a lower grade of paper. Large volume automated photo processing required a one-paper-fits-all-scenes approach. A 40 year effort went into the optimization of a "Tone Scale" curve [2,3]. The work was led by Kenneth Mees from 1904 to 1958 as Director of Research of Kodak [4]. The standard compromise Tone Scale is S-shaped. Low slope for white and blacks, slope 1.0 for skin tones and slopes > 1.0 for midtones. When one compares the Tone Scale curve of positive/negative film with a digital camera image printed on an ink-jet printer, despite the span of fifty years in introduction of the media, the shape of the optimized tone scale functions are the same [5].

## 1.2. The Death of Tone Scale Functions and the Birth of Spatial Imaging.

For twenty years Edwin Land looked for the optimal Tone Scale for Polaroid instant film. Unlike conventional positive/negative prints, there is no opportunity to interpret the information in the high-dynamic range negative and optimize the low-dynamic-range print. The optimal Tone-Scale function had to be installed in the film in the factory. Land worked with photographers such as Ansel Adams, Clarence Kennedy, and many others, to find the best film response.

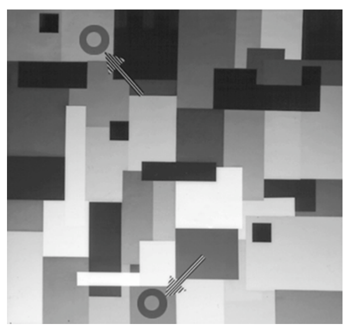

Fig. 1 - Land and McCann black and white Mondrian.

For Land the *Black and White Mondrian* marked the death of the Tone Scale as a viable approach to optimizing high dynamic range images [1]. The *Black and White Mondrian* experiment used an array of white, gray and black papers in non-uniform illumination from a single lamp. The position of the lamp was selected so that the luminance from a black paper near the lamp was equal to the luminance from a white paper at the top of the Mondrian. Despite the fact that the white at the top sent the same luminance to the eye as the black at the bottom, humans report that the white paper appears white and the black paper appears black. Appearances of white and of black correlate with the same luminance. Prints have a different property, namely that luminance controls the optical density of the paper. With one exposure, the white gray and black papers at the top can be accurately reproduced. This overexposed the papers at the bottom such that all papers are reproduced as white. It takes a much smaller exposure to reproduce the bottom white, gray, and black papers. That lower exposure causes the white, gray, and black papers at the top to be all black. When Land did this experiment (Fig. 1), he realized that that there can be no universal, optimal Tone Scale in photography. The only situation that allows a single Tone Scale function is perfectly uniform illumination.

Tone Scale manipulation can only accentuate the contrast of some partial range of luminances, at the expense of others. The range of reflectances in the print is fixed. If we start with a linear, slope 1, Tone Scale we can accurately reproduce uniformly illuminated scenes made up with the same range of reflectances. S-shaped tone scale curves, used in most imaging, increase the range of acceptable images by using low-slope responses for white and blacks. Nevertheless, such tone scales cannot satisfactorily handle the *Black and White Mondrian*. Here the illumination has the same range as reflectances; the combination is a squared range. We can use a low-slope tone scales placing the white in the high illumination at the highest value, and the black in the low illumination at the lowest. Such a print looks like seeing the Mondrian in a fog, nothing like the original experiment. All the edge ratios have be reduced by a factor of two to make the scene fit in the range of the print. On October 13, 2007, we will mark the 40th anniversary of Tone Scale's demise at Land's OSA Ives Medal Address [1]. That same lecture provided a demonstration of the first (analog) electronic *Spatial Color* image processing.

### 1.3. Goals of *Spatial Color* Models

Since this very first proposal of spatial processing, several models have been developed so far [6-15, 34-37] (bibliography reports only a partial list). They all share the idea of recomputing color of each pixel through the spatial distribution of values in the image, but a lot of differences arise according to their purpose. From this point of view, *Spatial Color Algorithms (**SCA**)* can be led by mainly three different goals:

1. Accurately model the human vision system (HVS) predicting color appearance, ***[SCA-HVS Model]***
2. Aim to enhance images in the direction of human visual appearance, ***[SCA-Rendering]***
3. Attempt to calculate the actual reflectance of an object from the radiance (reflectance*illumination). ***[SCA-Reflectance]***

Since SCAs can have three distinct goals, three different kind of outcomes are expected, and three different measures of performance are required.

*SCA-Reflectance* has the goal of estimating the physical reflectance of objects in different illuminants. The measurement of error is simply the difference in optical density at each wavelength between the actual measured surface reflectance and the *SCA-Reflectance* estimate. In most of the cases, this measurement reports on the accuracy of the objects reflectance and ignores the effect of the objects surface. These algorithms attempt to find an engineering solution to the ill-posed problem of solving for reflectance from the color signal (reflectance*illumination) [18,31,32]. We want to recall that human vision does not do this; it calculates appearances that are close to reflectance, but show significant departures from reflectance. These departures serve as important signatures of the underlying visual mechanisms [19-22]. Since the problem of estimating reflectance from the color signal is ill-posed, these algorithms need constraints or assumptions on the scene content, illumination or geometry and rarely rely on spatial computation. For these reasons the details of SCA-Reflectance have not been treated in this paper.

*SCA-HVS Models* attempt to mimic the response of human vision. There are a number of important examples in which human appearance does not correlate with reflectance. The simplest example is Simultaneous Contrast: humans and *SCA- HVS Models* both report different grays on white and black surrounds, while *SCA- Reflectance* has to report these different grays as identical. The human visual response to low-spatial frequencies is another example of a departure of appearance from physical reflectances of the input image. With luminance gradients, human appearance does not correlate with rates of change of luminance on the retina [47-52]. Quantitative measurements of how accurately SCA-Models are able to predict the HVS visual response is the metric for these algorithms.

*SCA-HVS Model* and *SCA-Render* can be seen as two similar families with qualitatively common but quantitatively different results. However, any model of vision has strict requirements concerning calibration of input information. At each retinal receptor, or model pixel the physical description of the radiometric stimulus must be exactly calibrated and unique. Everything about the pixel must be defined: radiances, angular subtends, and even temporal durations. One cannot capture random images off the web and calculate *SCA-HVS Model* responses that have any meaning. Alternatively, one can use *SCA-Render* algorithms to process such a random image and find that it significantly improves the images appearance (see Sect. 3). One can alter contrast, improve the visibility of dark areas in HDR images, and provide an important service to improve images that capture radiances in a scene. The contrast of images can be controlled to meet observer preferences rather than observer matches. Since the filtering process is not calibrated and the goal is to render a preferred image, judgment of results rely on subjective parameters and cannot be absolute.

A good example of difference in goals of *SCA-HVS Model and SCA-Render* is the use of slide duplicating film in alternative to the more common slide film. In the first case (log output / log input slope = 1.0 for duplication film) the image digital values are linearly mapped to the film density values in order to preserve their original ratios. The digital

values are proportional to log scene radiances. In the second case, standard slide film, density values are rearranged to get a more pleasant image. Here, the film has a slope 1.6 (optical densities) over much of the scene. Experiments measuring observer preferences show that higher contrast and colorfulness images are preferred to accurate reproduction. [16,17].
In a similar way, applications of spatial processing that aim to model human vision requires the output to follow quantitatively the (non linear) response of the HVS. A different application is to process the scene to render the image qualitatively, but not quantitatively, in accord with the HVS response to the scene, in this way pleasing observer preferences. However, regarding spatial color, in both cases the mechanisms at the base of each model are inspired by the HVS.

In this paper we are not going to present new data or experiments; it aims to be just an ordered presentation of previous works, together with some examples, to show to the reader some interesting particularities of spatial color algorithms, modeling or inspired by human vision.

## 2. BASIC CHARACTERISTICS OF SPATIAL COLOR ALGORITHMS

The spatial comparison mechanism is one of the basic tools through which the HVS performs normalizations, e.g. color constancy. HVS sees visual information according to the mutual relationship of the lightness/chromatic values of the scene content [23]. Changes in the overall radiance have the same effect on both parts of spatial comparison (i.e. ratio of adjacent pixels). Thus, spatial ratios of radiances do not change with overall illumination changes and can be used to model human constancy perception. This can happen at a global and/or local level.

If the goal is image enhancement (*SCA –Rendering*), this can be an interesting and useful property that links to the relativity of the exposure principle in photography. On the contrary if the goal is modeling HVS (*SCA -HVS Model*), we have to consider that HVS always can estimate the absolute intensity of the maximum light level in the scene. An example from everyday life is when in a dark room we perceive a small amount of light entering the room from some small aperture. Without looking outside, we are able to have a rough idea of the kind of weather or which hour in the morning we are waking up. This phenomenon is well described by the Hipparchus line in experiments that measure the appearance of objects in complex images [24].

A second important characteristic at the base of human perception is locality. Some point-wise levels of radiance can originate a completely different visual response (digital value in digital images) according to the image visual (spatial) characteristics. This mechanism is also at the base of several visual illusions and more than one experiment has shown it [9,10,12].

Spatial filtering in its broader sense includes classic methods like convolution filtering and other forms of signal processing. The main difference of spatial color compared with these methods is that spatial methods are always image dependent [33]. This reason is at the base of their higher computational cost, but also the base of their local and global behavior.

### 2.1. Levels of appearance

When dealing with a rich and extremely complex "machine" as the HVS is, agreement on some important terms is required. The committee on Colorimetry of the Optical Society of America in "The Science of Color" [53] reported the following definitions:

- **Sensation**: "mode of mental functioning that is directly associated with stimulation of the organism";
- **Perception**: "mode of mental functioning that include the combination of different sensations and the utilization of past experience in recognizing the objects and facts from which the present stimulation arises".

Consequently, let us use the terms Stimulus, Sensation and Perception with the above definitions.
To this aim let us use the following example: according to the question posed to a person who observes the swimming float shown in Fig. 2, different answers can arise. If the question is about the quality of radiance coming from the two visible sides of the float the answer can be very different (see Fig. 2 top right). If the question is "which paint should a painter use to depict an image of the float ?", the answer will be slightly different (see Fig. 2 bottom right). Finally if the answer is "the float is painted with the same paint ?", the answer will be yes.


Fig. 2 – New Hampshire swimming float

The stimulus level regards the signal that reaches the eye, while the sensation regards the visual appearance without any attempt to recognize objects, shadows or scene and lighting geometries. This paper deals with sensation and how Spatial Color mechanisms transform the stimulus into sensation. Further, it does not attempt to predict the observers' answers to questions about an objects surface. A single model should not be asked to give multiple answers.

### 2.2. SCA common structure

SCAs share a common structure of two phases. In the first phase each pixel is recomputed from scratch according to the spatial distribution of the other pixels in the image (all, or some of them, as prescribed by each implementation). To form the output image, the matrix of reciprocal a-dimensional values, spatially recomputed in the first phase, is scaled in the second phase onto the available output dynamic range according to global anchoring principles and to the model goal. In this second phase LUT and/or gamma non-linear adjustment can be added according to the SCA goal. Two possible global anchoring principles are White Patch (independent channel maximization to the white) and Gray World (independent channel averaging on the middle dynamic range value). This second phase is a final global scaling that does not affect the local properties of the algorithms, and can be used to obtain particular image enhancement properties.

## 3. SPATIAL ALGORITHMS BEHAVIOR

In this section we discuss some properties of *Spatial Color Algorithms* through examples.
All the spatial color filtering examples in this paper, are computed with one of these algorithms. These are Retinex in some of its various implementations [1,7,8,9,10,11,13,34-37], and ACE also in its implementation and speeded up versions [12,14,25,26]. Since the aim of the paper is not their comparisons and for the sake of brevity, it will not be specified for each example which algorithm (and parameters) has been used to obtain the presented results. Discussion will regard the overall behavior and not the single output value. If interested in details, the reader can refer to the bibliography.

### 3.1. Color constancy

The image processing community studies two different kinds of color constancy: human and machine color constancy. The difference between the two is substantial. Perceived signal is always a spectral mix between the light and the reflectance within the scene. The goal of machine vision, the second approach, is to totally discount the illuminant in order to estimate the objects' reflectance. Its term of evaluation is the estimate precision and, since it is using only pointwise signal information, the problem is ill-posed. Consequently, this kind of method needs some constraints on the illumination, or on the scene geometry, or the spectral components or the number of illuminants. Biological systems had to face the same problem. Since animals cannot impose constraints on the scene, evolution chose a different approach.
The first type of color constancy refers to human vision in which the goal is to perceive stable colors within changes in illumination. Although human constancy is impressive, it is never perfect. Human color matching experiments show specific departures from perfect constancy. These departures correlate with spectral crosstalk of cone receptors [1]. Cone crosstalk occurs only as a result of independent L, M and S spatial comparisons [20]. Spatial comparisons stabilize the color of objects for humans, but cone crosstalk leaves small traces of imperfect constancy in colored

objects that can provide useful information about the illuminant. Here we use the term color constancy referring to the human one.

Figure 3 (upper row) shows a plastic toy skate under different illuminants. These images are taken from an image DataBase especially devised for testing color constancy algorithms [29]. These input images are photographs taken with a Canon Powershot A50 in 5 illuminants; respectively PHILIPS Neon Natural Daylight 6500°K, PHILIPS Neon Fluotone 4100°K, OSRAM Concentra Green R80, OSRAM Concentra Blu R80 and OSRAM Bellalux Insecta. The second row shows enlargements of the red skate tip in all 5 input images to show the difference of appearance in and out of the scene context.

Results of spatial color constancy follow HVS in its departure from perfection [30], as it can be noticed from the skate images in the third row, enlarged in the fourth row. In fact, SCA output produces similar and constant neutral gray digital values, but colors that vary according to the original color cast. This is the important signature of biological color constancy. This property is a direct result of spatial comparisons. It cannot be modeled with single pixel computations. [38]

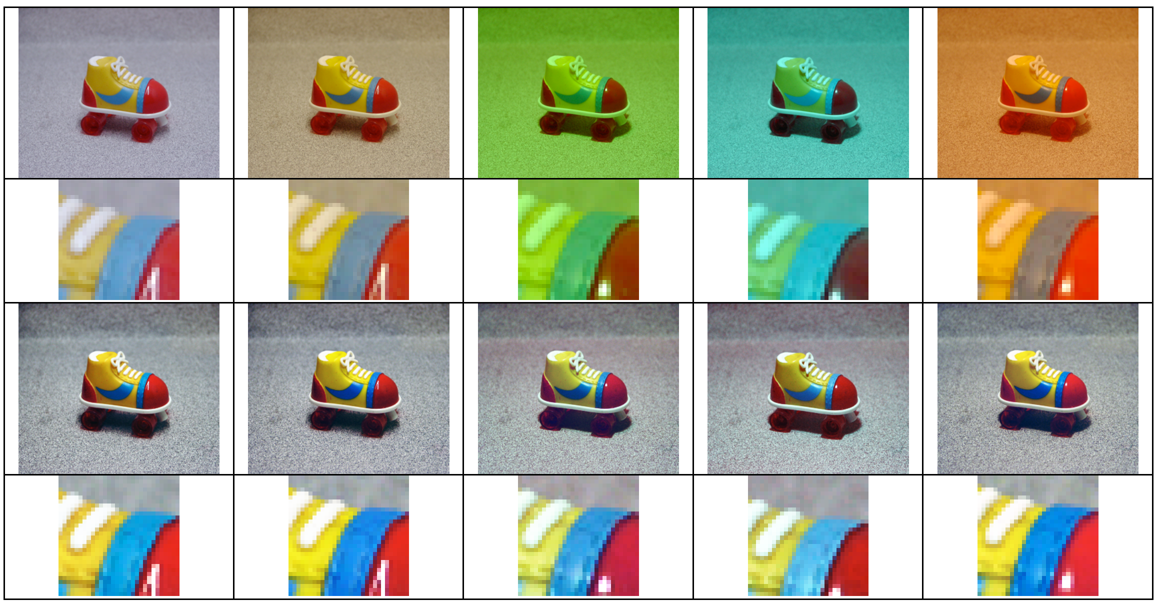

Fig. 3 – Object under different illuminants [29] and a SCA output. Note the similarities of the whites and grays in the bottom row. Also note, the small shifts in the colors of the yellows, reds and blues.

Regarding the amount of color correction, SCAs have an interesting property. They are unsupervised; they detect and correct automatically a possible color cast, tuning automatically their effect according to the characteristic of the cast.
Spatial comparison probably originated to compensate the poor signal acquired by the retina. Fig. 4 shows a colored scene acquired with two different spectral sensitivities, shown on the right side. The first is a typical film response (digital camera one is similar) with a very limited overlap, while the second is that of human cones (including pre-retinal absorptions), with a considerable overlap. From a signal detection point of view, the result of this big crosstalk is an image with poorly saturated colors. Using human spectral sensitivities the maximum red/green ratio possible is 2, not enough to fill the expected color dynamic range of a standard 8 bit per channel image range. These pale colors contradict our everyday perception experience: the colors we perceive are not this pale. A possible explanation is a post-acquisition mechanism of spatial dynamic range expansion and value dequantization. These two properties of SCA are presented in the following sections.

In 1889 Frederick Ives tried to combine Maxwell's invention of color photography with Maxwell's color matching functions [41]. He proposed that color separations, used to make color reproductions, would have the most "natural color" if the separations had the same spectral sensitivities as humans. He published a book [39] and filed a US patent

[40]. Despite a significant investment in the idea of using broad sensitivity functions, Ives abandoned the idea and used narrow-band filters in his 1895 commercial Kromstop color cameras.

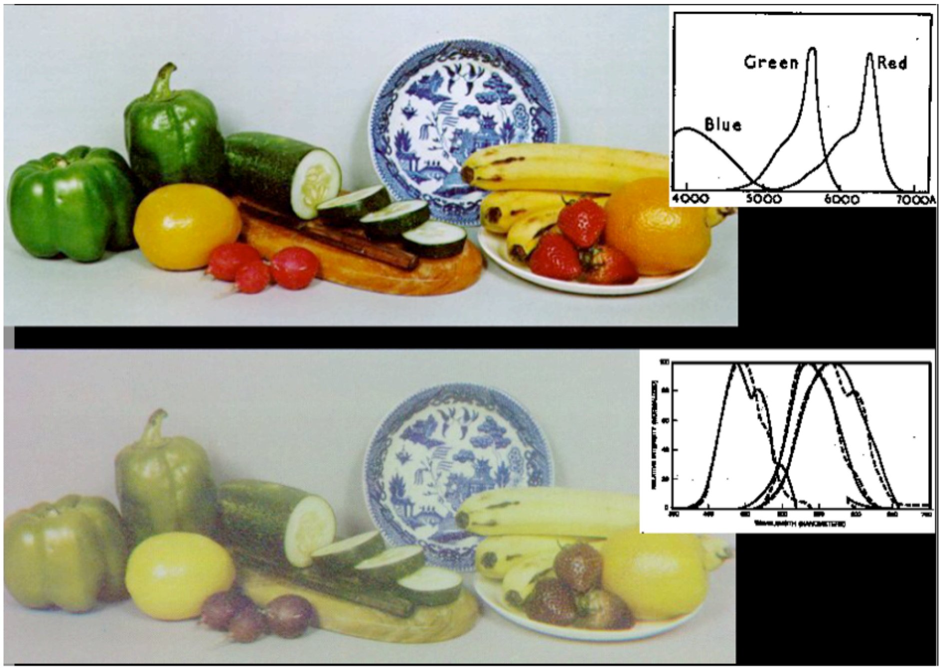


Fig. 4 – Color scene acquired through film (up) and human (bottom) spectral sensitivities

### 3.2. Global and local effect

SCAs realize an adjustment to image content through spatial comparisons. Their behavior is highly image dependent [33]. It mimics the spatial signature of human vision. Low-dynamic range images with many white areas and well-distributed tonal range need no spatial adjustment. High-dynamic-range images with many dark and unbalanced areas require strong spatial adjustment.

Fixed spatial filters can be shown to be effective for some images [45-47], but cannot mimic HVS on the full range of possible images, from a foggy day to sun plus shade.

HVS realizes this property in a variable way, according to the spatial information and to the spatial-frequency content of the scene.

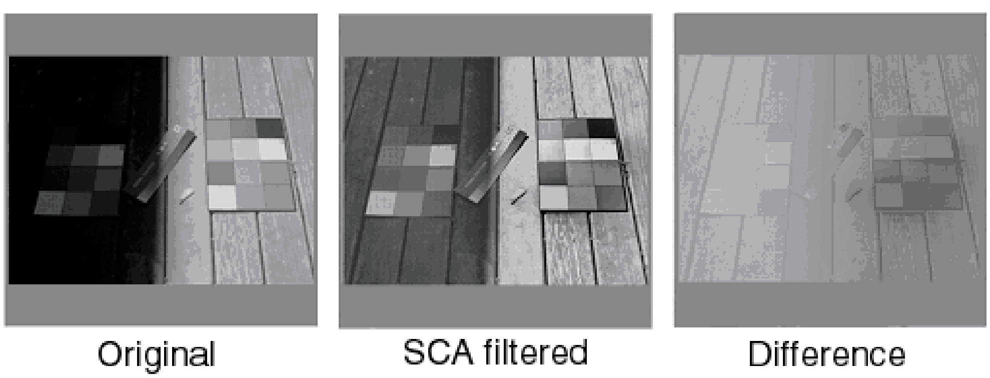


Fig. 5 – Test targets in sun and shade

Local filtering effect can be easily seen from the above example. Fig.5 shows images of a pair of Jobo test targets in sun and shade. The original image is rendered so that digits are proportional to log luminance and the black square in the sun (top row-right in the test target) is the same digit as the white square in the shade (second row-right in the test target), namely digit 80. In the SCA processed image black in the sun is rendered to an output digit of 27, while the white in the shade is rendered as an output digit of 169. The difference image shows the different local spatial filtering.

### 3.3. Gradients and shadows

Our human vision system tends to discount smooth radiance variation and to preserve or amplify edges and sharp variations. For professional photographers this is a well-known phenomenon. In setting the lighting for a still life picture, the ability of a good photographer is to estimate in advance how shadows will be reproduced on the film (or CCD), since HVS perceives them strongly reduced. Which frequencies are reduced and which amplified again depends on the visual (spatial) image characteristics [33,47-52].

SCAs exhibit a similar behavior. They are edge-preserving filters, but on gradients and shadows, their tendency is to reduce them. As the major part of their characteristics, the magnitude of gradient reduction is parameter dependent. It derives from the local effects of SCA.

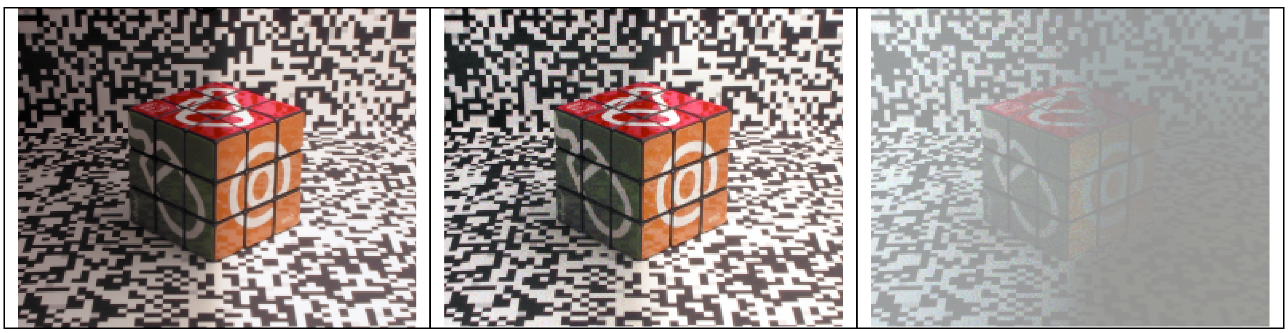

Fig. 6 – Object with shadow. Left the original, center the SCA filtered, right the difference image between the two [29].

Figure 6 (left) shows a colored cube with a shadow cast in the middle. The shadow appearance of the SCA output (center) is strongly reduced, as HVS does. On the right the difference image shows how spatial local effect worked for the shadow intensity reduction.

### 3.4. Dequantization

In SCAs, each pixel is recomputed according to the spatial distribution of the rest (or part) of the image. This local SCA property realizes an image-driven dequantization. Figure 7 shows the channel histograms of the original 8 bit color image (left) and two SCA filtered. The first output (center) has been filtered with an algorithm with a White Patch behavior, all the recomputed values lie on the right (lighter) side of the histogram, while the second (right) uses both White Patch and Gray World behaviors, recomputed values lay on both sides according to the image spatial pixel distribution. Visual appearance of each case is visible on top of Fig. 7.

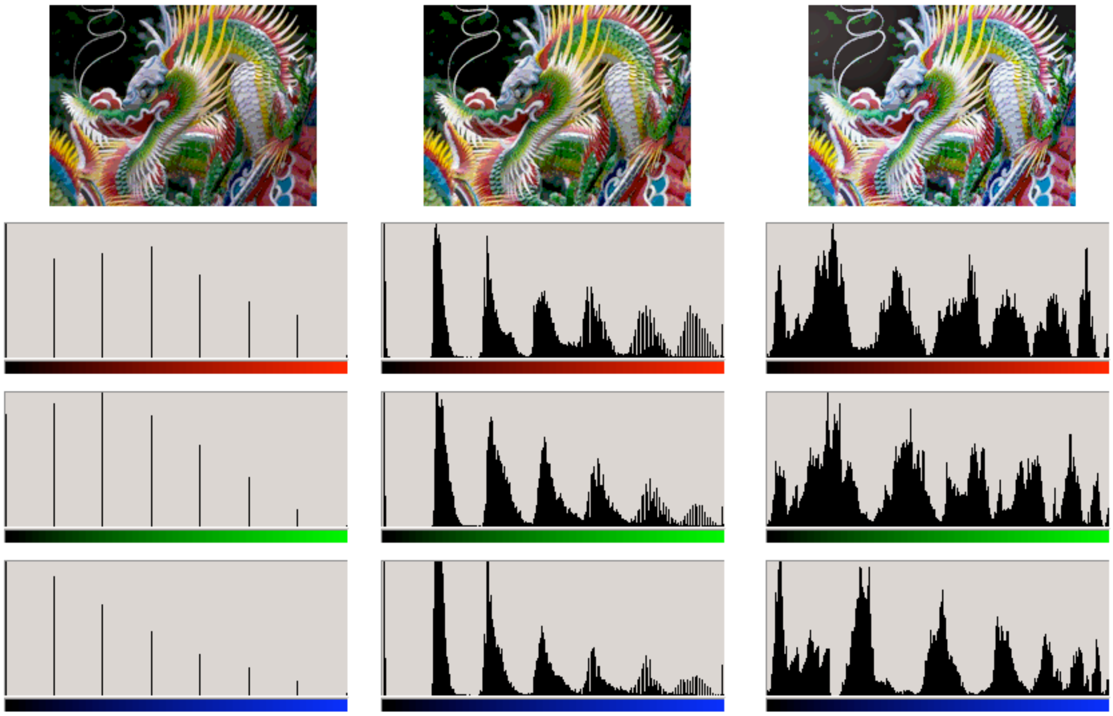

Fig. 7 –SCA spatial dequantization effect. Original (left), with WP behavior (center), with WP and GW behavior (right)

This particular property derives from the local properties of SCAs and from the fact that each pixel is recomputed from scratch. In fact, only a spatial approach can result in an image driven dequantization.

### 3.5. Low dynamic range images

Regarding dynamic range, there is a big difference between real world and digital imaging. Real world ranges from few candelas/$m^2$ of a romantic dinner (4cd/m2 from a white napkin) to six thousands candelas /$m^2$ of a sunny beach at noon. Imaging devices capture as best as they can this highly variable dynamic range with their limited range.

In Fig. 8, images with three different dynamic ranges are presented with their L histograms. The first image has a range limited to the center of the digit range, the second contains a wide range of tones, but most of the pixels are in a low dynamic range near the black. The third image is heavily underexposed. All of them have low contrast in the details. The bottom half of Fig 8 shows the SCA processed images and histograms.

On these images the *SCA-HVS Model* cannot be of great help because of a lack of calibration. However, *SCA-Render* can use spatial comparisons to redistribute pixel values to improve the image. If one considers the different goals for *SCA-HVS Model* and *SCA-Render* when processing a woodland scene in fog, the HVS versions reproduces what an observer would see, while SCA-Render enhances the spatial differences to fill the range of the output device.

SCA results in a local spatial re-computation of the pixels color and, according to the SCA goal and parameters, increases or lowers the output range expanding or decreasing the dynamic range up to the device limits.

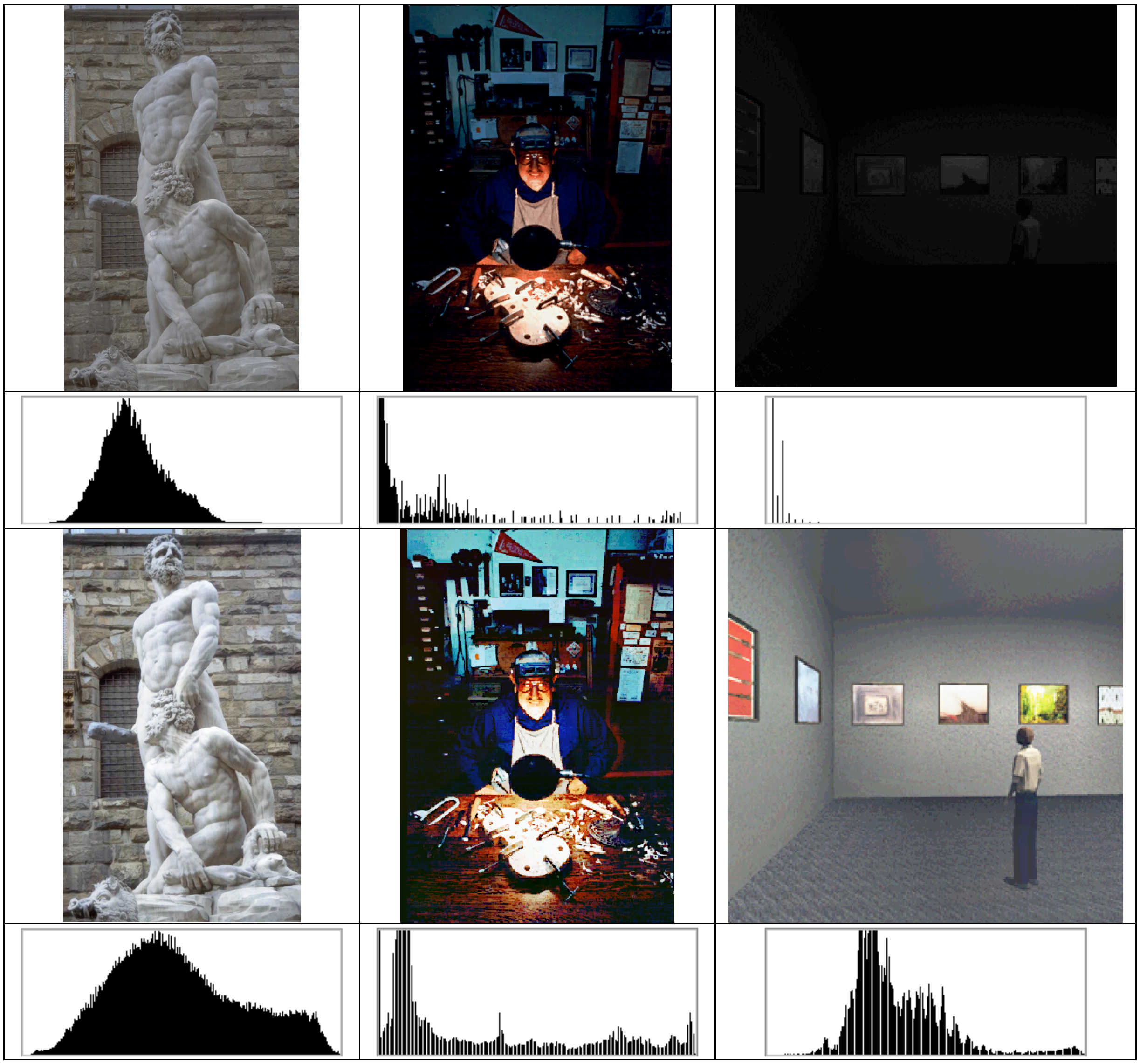

Fig. 8 –Images with their L histograms, before (up) and after SCA filtering.

### 3.6. SCA and image processing

A local spatial redistribution of the tone scale in the direction of HVS that is enhancement of visual features can result in an increment of efficacy of computer vision algorithm [42].

In the first row of Fig. 9 is visible an image before SCA filtering (left) and after SCA filtering (right). In the second row a classic second order edge detection algorithm has been applied on the images of the first row and in the third row an enlargement is shown. As it can be noticed SCA local contrast enhancement increased the visual content of the image and consequently the output accuracy of the computer vision algorithm.

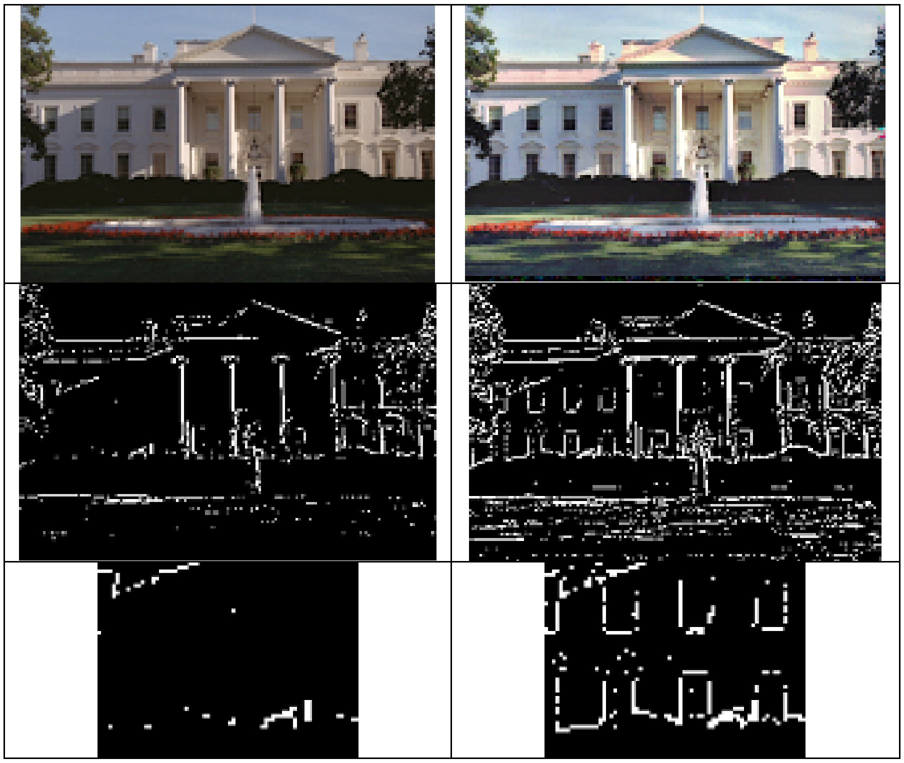

Fig. 9 – Effect of SCA filtering on edge detection.

### 3.7. HDR

Here we discuss cases, in which the real world dynamic range is bigger than the imaging device one. It happens quite often, e.g. almost all the backlight situations.

There is a growing interest in HDR images as a way to encode a greater radiance range. Unfortunately at the final stage the HDR image has to be displayed on a lower dynamic (commercially available) device that shrinks or re-maps the digital values. This can happen quite often for two reasons: the number of HDR display devices is still limited and in any case their dynamic range is much lower than the available coding range of the majority of HDR image formats [43].

We want to recall that even if recent multiple-exposure HDR algorithms claim to correctly capture scenes with very high luminance ranges, image devices, as well as human eye, are severely limited by ocular and camera veiling glare [27,28]. Nevertheless, the resulting images are considerably better than conventional images with limited range.

Since HDR imaging works so well, there must be reasons, other than accurate luminance, that explains the improved images. The multiple exposure technique does significantly improve digital quantization. The improved digital quantization and improved range allows displays to present more spatial information to humans. When human vision looks at high-dynamic range displays, it processes them as it does real life scenes.Even if humans have more veiling glare than cameras, human spatial mechanisms are not adversely affected by departures from accurate radiance images on their retinas. Human vision spatial computation allows us to see more details in the shadows because of preserved local spatial information [28]. For these reasons, SCA can replace tone mapping operators (TMO) in fitting higher dynamic ranges into lower ones keeping the appearance of the areas in the scene by its properties of local spatial recomputation.

### 3.8. Unwanted color removal

There are cases in which the color cast is an important part of the image. In these cases, the spatial color should keep the “flavor” of the cast. In Fig. 10 are visible three examples in which a color cast gives to the image a particular visual effect.

In these cases the goal of the SCA and consequently its parameter tuning can make the difference. If the goal is modeling human vision, they should tend to increase the chroma, while if the goal is image enhancement, they can have a stronger effect on the dominant.

Fig. 10 – Cases of unwanted color removal.

However, as it can be noticed from the results in Fig. 10, SCA cast removal is local and never complete, thus the "flavor" of the original image is not completely lost. Parameters tuning or a conservative final scaling can allow the user to control this effect.

## 4. CONCLUSIONS

In this paper we have presented a survey on the characteristics of *Spatial Color Algorithms* (SCA) family.
They share a common property of calculating a new image from an array of radiometric digits. For this reason, they cannot be described using convolution filters and since their behavior changes according to the image content, their impulsive response is not fixed.
We have presented and discussed the various SCA characteristics (color normalization, shadow partial removal, contrast local enhancement, image driven tone rescaling and dequantization) and goals (mainly *SCA-HVS Model* and *SCA-Render*). According to them, different outcomes are expected, and different measures of performance required.

## REFERENCES


1. E. Land, J.J. McCann , "Lightness and Retinex Theory", J. Opt.SocAm., **61**, pp. 1-11, 1971.
2. C. E. K. Mees, The Fundamentals of Photography,1st Ed, 1920.
3. C. E. K. Mees and T. H. James, Eds., "The Theory of the Photographic Process", 1967, 1st Ed, 1920.
4. C. E. K. Mees, An Address to the Senior Staff of the Kodak Research Laboratories, Kodak Research Laboratory, Rochester, 1956.
5. J. J. McCann, "Color Imaging Systems and Collor Theory: Past, Present and Future", In Proc. SPIE **3299**, Human Vision and Electronic Imaging III; B, E. Rogowitz, T. N. Pappas; Eds., San Jose, p. 9-16, 1998.
6. E. Land, "The Retinex Theory of Color Vision", Scientific American, 237, 3, 2-17 (1977)
7. E. Land, "Recent Advances in Retinex Theory and Some Implications for Cortical Computations: Color Vision and the Natural image", Proc. Natl. Acad. Sci. USA, Vol. 80, 5163-5169 (1983)

8. D.J. Jobson, Z. Rahman, G.A. Woodel, "Properties and Performance of a Center/Surround Retinex", IEEE Transaction on Image Processing, March 1997.
9. J. J. McCann, "Lessons Learned from Mondrian Applied to Real Images and Color Gamuts", Proceedings of the IS&T/SID Seventh Color Imaging Conference, pp 1--8, 1999.
10. Marini D., Rizzi A., "A Computational Approach to Color Adaptation Effects", Image and Vision Computing, 18, 13 (2000) pp. 1005-1014.
11. A. Rizzi, D. Marini, and L. D. Carli, "Multilevel brownian retinex colour correction" Machine Graphics and Vision 11 (2/3), 2002.
12. Rizzi, C. Gatta, D. Marini, "A New Algorithm for Unsupervised Global and Local Color Correction", *Pattern Recognition Letters*, Vol 24 (11), pp. 1663-1677, July 2003.
13. Funt, B., Ciurea, F., McCann, J. "Retinex in Matlab", Journal of the Electronic Imaging, pp 48-57, Jan. 2004
14. Rizzi, C. Gatta, D. Marini, "From Retinex to Automatic Color Equalization: issues in developing a new algorithm for unsupervised color equalization", *Journal of Electronic Imaging*, Vol. 13, No. 1, January 2004, pp. 75-84.
15. D. Marini, A. Rizzi, M. Rossi, "Post-Filtering for Color Appearance in Synthetic Images Visualization", *Journal of Electronic Imaging*, Vol. 13, No. 1, January 2004.
16. H. de Ridder, F.J.J. Blommaert, E.A. Fedorovskaya, "Naturalness and image quality: chroma and hue variation in color images of natural scenes", Proceedings of SPIE -- Volume 2411, Human Vision, Visual Processing, and Digital Display VI, April 1995, pp 51-61.
17. H. de Ridder, "Image processing and the problem of quantifying image quality", IEEE International Conference on Image Processing 2001, Thessaloniki (Grece), vol. 2, pp 3-6.
18. B. Funt, K. Barnard, L. Martin, "Is Machine Colour Constancy Good Enough?", Proc. of ECCV98, pp,445.
19. J. J. McCann, "Mechanism of Color Constancy", Proc. IS&T/SID Color Imaging Conference, IS&T/SID, Scottsdale, Arizona, 12, 29- 36, 2004.
20. J. J. McCann, "Do humans discount the illuminant?", In Proc. SPIE **5666**, Human Vision and Electronic Imaging X; B, E. Rogowitz, T. N. Pappas, Scott J. Daly; Eds., San Jose, p. 9-16, 2005.
21. J. J. McCann, "Measuring Constancy of Contrast Targets in Different Luminances in Complex Scenes", Proc. IS&T/SID Color Imaging Conference, IS&T/SID, Scottsdale, Arizona, **14**, 297-303, 2006.
22. J. J. McCann, "Aperture and object mode appearances in images", In Proc. SPIE **6492**, Human Vision and Electronic Imaging X; B, E. Rogowitz, T. N. Pappas, Scott J. Daly; Eds., San Jose, 2007
23. J. J. McCann, "Do humans discount the illuminant?", In Proc. SPIE **5666**, Human Vision and Electronic Imaging X; B, E. Rogowitz, T. N. Pappas, Scott J. Daly; Eds., San Jose, p. 9-16, 2005.
24. J. J. McCann, "Measuring Constancy of Contrast Targets in Different Luminances in Complex Scenes", Proc. IS&T/SID Color Imaging Conference, IS&T/SID, Scottsdale, Arizona, **14**, 297-303, 2006.
25. C. Gatta, A. Rizzi, D. Marini, "Local Linear LUT Method for Spatial Color Correction Algorithm Speed-up", *IEE Proc. Vision, Image & Signal Processing*, June 2006, Vol. 153, Issue 3, pp. 357-363.
26. A. Artusi, C. Gatta, D. Marini, W. Purgathofer, A. Rizzi, "Speed-up Technique for a Local Automatic Color Equalization Model" Computer Graphics Forum, Volume 25 (2006), number 1 pp. 5–14.
27. J. J. McCann and A. Rizzi, "Optical veiling glare limitations to in-camera scene radiance measurements", in ECVP 2006 Abstracts, Perception, **35,** Supplement, p. 51, 2006.
28. J. J. McCann and A. Rizzi, "Spatial Comparisons: The Antidote to Veiling Glare Limitations in HDR Images", Proc ADEAC (SID/VESA) Atlanta, p. 155-158, 2006.
29. A. Rizzi, C. Gatta, D. Marini, "YACCD: Yet Another Color Constancy Database", SPIE&IS/T Electronic Imaging 2003, 21-24/01/03, S. Clara, California (USA).
30. A. Rizzi, L. Rovati, D. Marini, F. Docchio, " Unsupervised Corrections of Unknown Chromatic Dominants using a Brownian Paths Based Retinex Algorithm", Journal of Electronic Imaging, Vol 12(3), July 2003.
31. B. Funt, , "", Proc. IS&T/SID Color Imaging Conference, IS&T/SID, Scottsdale, Arizona, **14**, , 2006.
32. G. Finlayson, S. Hordley, P.Hubel, "Color by Correlation: A Simple, Unifying Framework for Color Constancy", *IEEE Trans. On Pattern Analysis Machine Intelligence*, Vol. 23, No 11, pp1209-1221, Nov. 2001.
33. J. J. McCann, "High-dynamic-range scene compression in humans", In Proc. SPIE **6057 -** 605707, pp.1-11, Human Vision and Electronic Imaging XI; B, E. Rogowitz, T. N. Pappas, Scott J. Daly; Eds., San Jose, 2006.
34. E. H. Land and J. J. McCann, "Method and system for reproduction based on significant visual boundaries of original subject", *U.S. Patent* 3,553,360, June 5, 1971

35. E. H. Land, L. A. Ferrari, S. Kagen and J. J. McCann, "Image Processing system which detects subject by sensing intensity ratios", U.S. Patent 3,651,252, Mar. 21, 1972.
36. J. Frankle and J. J. McCann "Method and apparatus of lightness imaging", *U. S Patent* 4384336, May 17, 1983.
37. K. C. Kiesel and W. R. Wray, "Reconstitution of images", U.S. Patent 4,649,568, Mar. 10, 1987.
38. J. J. McCann, "The history of spectral sensitivity functions for humans and imagers: 1861 to 2004", In Proc. SPIE **5667**, Color Imaging X, R. Eschbach, G. Marcu, Eds., San Jose, p. 1-9, 2005.
39. F. E. Ives, *A New Principle in Heliochromy*, Printed by the author, Philadelphia.1889.
40. F. E. Ives, US Patent, 432,530, 1890.
41. J. S. Friedman, *History of Color Photography*, The American Photographic Publishing Company, Boston, 13, 1945.
42. C. Gatta, A. Rizzi, D. Marini, " ACE: equalizzazione cromatica per algoritmi di computer vision", AI*IA 2002, Siena, september 2002.
43. Reinhard, E., G. Ward, S. Pattanaik, P. Debevec, *High Dynamic Range Imaging Acquisition, display and Image-Based Lighting*, Elsevier, Morgan Kaufmann, Amsterdam, chap 4, 2006.
44. T. P. Stockham, "Image Processing in the Context of a Visual Model", *Proc. IEEE,* 60, 828-284, 1972.
45. H. R. Wilson and J. R. Bergen, "A four mechanism models for threshold spatial vision", Vision Res., **26**, 19-32, 1979.
46. M.D. Fairchild and G.M. Johnson, "The iCAM framework for image appearance, image differences, and image quality," Journal of Electronic Imaging, **13**,126-138, 2004
47. J. J. McCann, R. L. Savoy, J. A. Hall and J. J. Scarpetti, "Visibility of Continuous Luminance Gradients", Vis. Research, **14**, 917-927, 1974.
48. R. L. Savoy and J.J. McCann, "Visibility of low spatial-frequency sine-wave targets: dependence on number of cycles", J. opt. Soc. Am., **65**, No. 3, 343-350, 1975.
49. J.J. McCann and J. A. Hall, Jr., "Effects of average-luminance surrounds on the visibility of sine-wave gratings", J. opt. Soc. Am., **70**, 212-219, 1980.
50. J. J. McCann, R. L. Savoy and J. A. Hall, Jr., "Visibility of Low Frequency Sine-Wave Targets, Dependence on Number of Cycles and Surround Parameters", Vis. Research, **18**, 891-894, 1978.
51. J.J. McCann, "Visibility of gradients and low-spatial frequency sinusoids: Evidence for a distance constancy mechanism", J. Photogr. Sci.Eng., **22**, 64-68, (1978).
52. R. L. Savoy, "Low Spatial Frequencies and Low Number of Cycles at Low Luminances" J. Photogr. Sci. Eng., **22**, 76-79, 1978.
53. Optical Society of America, Committee on Colorimetry, "The Science of Color", pp. 58-59, Crowell, New York, 1953.