The Spatial Properties of Contrast

John J. McCann and Alessandro Rizzi
McCann Imaging and Dipartimento di Tecnologia dell'Informazione
Università di Milano
Belmont MA, USA and Milano, Italy

Abstract

Contrast is the well-known observation in which a gray in a white surround appears darker than in a black one. An example is a 32 by 32 pixel gray area subtending 0.75 degrees visual angle on a black background - 256 pixels on a side. The gray appears darker when surrounded by a band of white - 12 pixels wide. The white band is made up of 2112 individual white pixels. If these white pixels are redistributed uniformly in the black background the gray appears much lighter. This paper measures the gray appearance as influenced by 2112 white pixels in a 27 different spatial configurations. The set of different spatial patterns of white pixels that generate the same matching lightness for gray are defined as equivalent backgrounds. The paper then analyzes the spatial properties of equivalent backgrounds. Gray appears darkest when the solid white surrounds the gray and is contiguous with it. In the case of the distributed white pixels, the gray appears lighter. This paper presents an analysis of the spatial properties of intermediate surrounds that give the gray center equal visual appearances.

Introduction

Spatial processing in human vision makes identical retinal stimuli appear different.[1-5] Different spatial configurations of surrounds can make substantial changes in appearance. The goal of this paper is to measure the appearances of a wide range of different spatial arrangements of an identical set of pixels. By comparing the results of observer matches, we can identify different patterns of surround that have the same effect of the human spatial processing mechanism, namely the observers pick the same match. Patterns that generate equal matches for a constant test patch are defined as equivalent backgrounds.

Sets of displays having equivalent backgrounds can be used for analyzing different spatial models of vision.[2,6-25] A model that mimics the human visual process will be able to correctly predict which spatial patterns are equivalent and will appear the same.

Experimental Procedure

Experiments have shown that distance from a white and enclosure by a white changes the appearance of grays as much as one third the range of white to black.[26,27] Size on the retina and spatial pattern can change similar patterns from observer reports of contrast to reports of assimilation.[28-29] This paper reports experiments using 27 different spatial patterns all composed of a central test patch (made up of 1024 light-gray pixels) on a background (made up of 2112 white pixels, 62,400 black pixels). These targets were computer generated and displayed on a CRT monitor which was viewed at a distance of 38 inches. The square gray center element subtended 0.75° and the entire 256 by 256 display subtended 5.9°. The rest of the monitor screen was covered with opaque material in a darkened room. Observer matches were made using a paper Munsell chart with samples every 0.25 Munsell Values. This matching target was placed in front of the observer in an opaque box, so that no light illuminating the standard papers fell on the computer monitor. The observer looked down to see the matching Munsell Value target and looked up to see the test display. The data described here show results for a minimum of four observations for one of the observers. The average deviation for this observer for all fifty displays including controls was 0.28 Munsell Value units; the maximum deviation was 0.55 units; the minimum deviation was 0.0 .

Controls

Figures 1 and 2 illustrate two control experiments. In this paper the only observer task was to find a match in the Munsell Value scale for the central gray square patch. The first control patch varied the pixel value of the gray patch in a white surround (pixel value 255). The second control experiment used pixel value 140 for the gray patch and varied the value of the uniform surround.

Obviously, when the experimenter decreased the digital value of the central patch the observer matched it to a

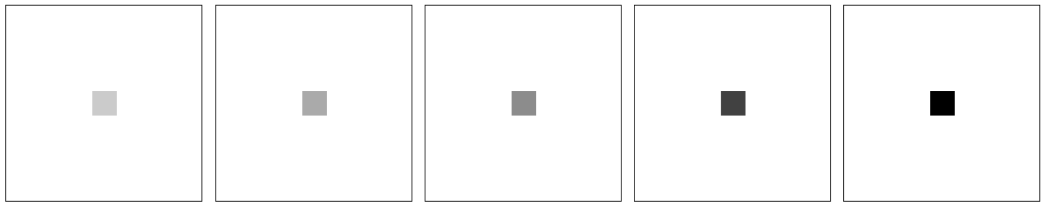

Figure 1 demonstrates the change in lightness with luminance of the central test square in a uniform white surround.

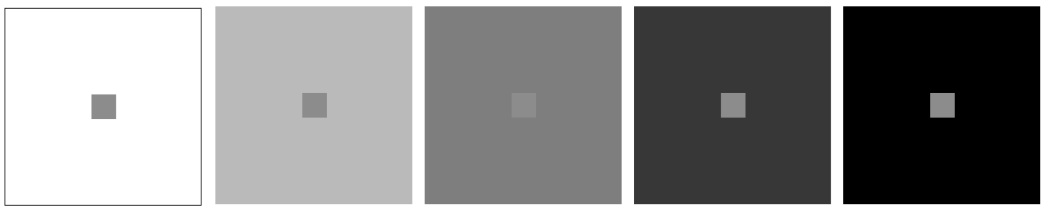

Figure 2 demonstrates the change in lightness with luminance of the surround around a constant test square.

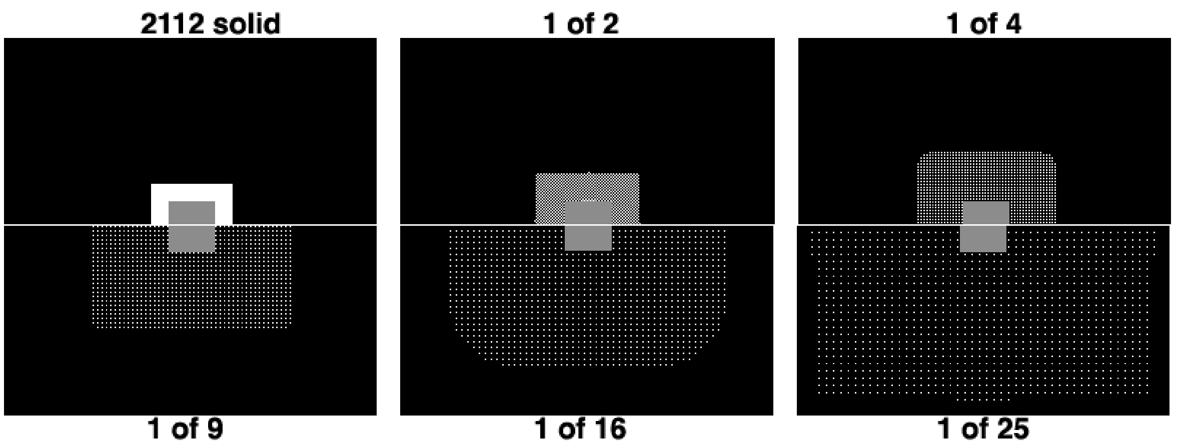

Figure 3a shows a series of 6" Snow" displays made of the same pixel elements. Each display has been enlarged to see the one pixel whites. Only half is shown here to conseve space. There all have a central patch that is 32 by 32 pixels with a constant pixel value of 140. They all have a black background of 62,400 pixels (value 0). They all have a white surround of 2112 pixels (value 255). Top: The first display on the left has 12 rectangular bands of white adjacent to the gray test patch. The zone surrounding the test patch has a 1/1 white pixel fraction. In the second display the adjacent zone has a 1/2 white pixel fraction. The zone is a checkerboard of black and white pixels. In the third display, the adjacent zone has a 1/4 white pixel fraction. Bottom: In the fourth display, the adjacent zone has a 1/9 white pixel fraction. In the fifth and sixth displays, the adjacent zone has 1/16 and 1/25 white pixel fractions.

darker Munsell Value. The experimenters choses the constant gray central patch stimulus (digital value 140) for the surround experiment. With a white surround (digital value 255), the observer match was 5.19±0.44. With darker surrounds the observer matched lighter Munsell Values. Below digit 100 matches reached an asymptote of Munsell Value 8.0. The surround can influence the observer choice of match over one-third of the range from white to black.

Dispersion of White ("Snow")

Figure 3 shows the beginning of the series of constant average displays. The target on the left has a 32 by 32 pixel central gray patch (digit value 140). It is surrounded by a 12 pixel band of white. The rest of the target is black. The observer match was 6.50±0.39. The second target rearranges the 2112 white pixels into a checkerboard pattern; every other pixel is white or black. The

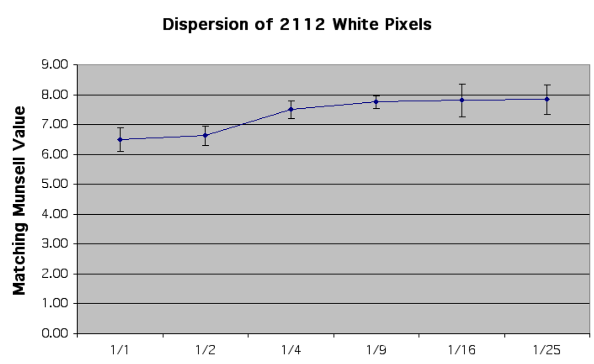

Figure 3b plots matching Munsell Values for patches in Figure 3a. The solid white adjacent to the gray test patch is matched by 6.50±0.39, while the 1/25 white pixel fraction was matched by 7.85±0.49. All displays have identical global average or "GrayWorld" value.

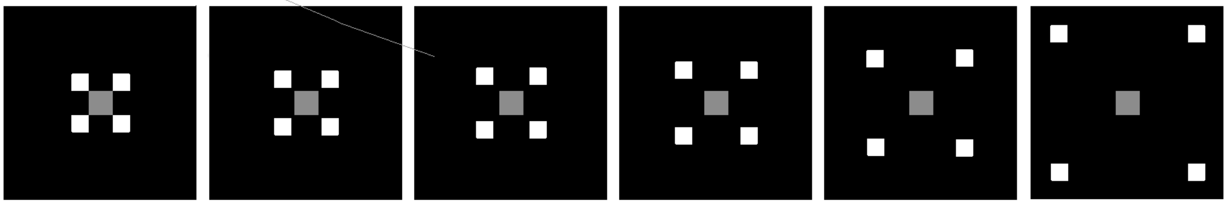

Figure 4a shows effects of relocating the 2112 white pixels on the diagonals of the display. Here the white pixels are shaped into four squares.

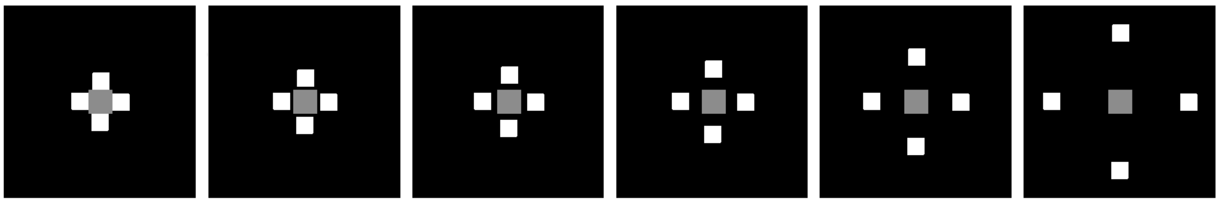

Figure 4b shows effects of relocating the 2112 white pixels in squares on the sides of the gray test patch.

third target has 1 white pixel and three black pixels; the fourth has one white pixel and 8 black pixels; the fifth has one white pixel and 15 black pixels; the sixth has one white pixel and 24 black pixels. The series began with a solid band of white and progressively diffused the white pixels. The effect on matches was to make them lighter. Figure 3b plots the Munsell Value for the targets in Figure 3a.

Corners and Sides

Figure 4 continues the series of constant average displays. The target on the left has the same 32 by 32 pixel central gray patch (digit value 140). In Figure 4a the 2112 white pixels form four squares on the diagonal of the target, while in Figure 4b the squares are adjacent to the sides of the gray. In the first target the white is adjacent to the gray. In the second through fifth the white is separated by 4, 8, 16, 32, and 64 pixels. The effect of separating the white squares from the gray patch was that matches were lighter.

Figure 4c plots the Munsell Value for the targets in Figure 4a and 4b. The sides have greater influence than the corners for the same separation from 0 to 8 pixels, namely the observer matches are darker. At a separation of 16 pixels the match for side and corner are identical. At greater separations the sides have darker matches.

Lines

Figure 5 continues the series of constant average displays. The target on the left has the same 32 by 32 pixel central gray patch (digit value 140). In Figure 5a the 2112 white pixels form lines parallel to the sides of the gray square. In the first target, the white is a solid band as in figure 3.

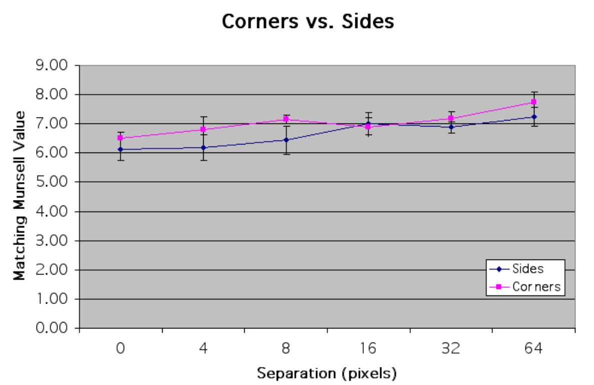

Figure 4c plots the matching Munsell Value for the test patches in Figure 4a and 4b. When the solid white squares are adjacent to the corners of gray test patch, it was matched by 6.50±0.20. When separated by 64 pixels it was matched by 7.75±0.35. All displays have identical global average value. When the solid white squares are adjacent to the sides of gray test patch, it was matched by 6.13±0.43. When separated by 64 pixels it was matched by 7.25±0.46. All displays have identical global averages.

In the second through fourth targets the white lines are separated by 1, 3, 7 black pixel lines (2,4,8 pixels per cycle). The effect of separating the white lines was that matches were lighter. Figure 5b plots the Munsell Value for the targets in Figure 5a. In addition, data from two other targets is plotted. The fifth display took the 8 pixel per cycle pattern and moved it 8 pixels from the gray. The sixth target used a vertical 8 pixels per cycle and an horizontal 2 pixels per cycle pattern.

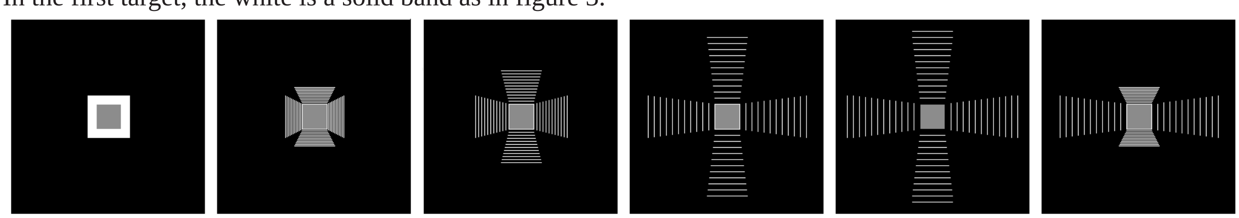

Figure 5a shows the effects of relocating the 2112 white pixels into parallel stripes with variable spacing.

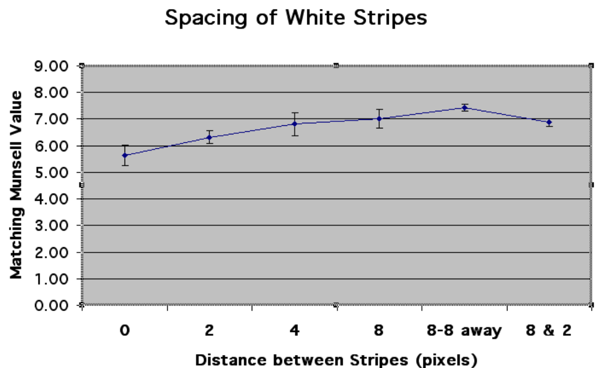

Figure 5b plots the Matching Munsell Value for the test patches in Figure 5a. When the solid white surround was adjacent to the gray test patch, it was matched by 5.64±0.39. When the white was broken up into alternating black and white stripes with 2, 4 and 8 pixels per cycle, the matches were 6.31±0.24, 6.81±0,43, and 7.00±0.35. When the 8 pixel per cycle pattern was moved 8 pixels away from the gray test patch, the match increased to 7.44±0.13. When the display was 2 pixels per cycle vertically and 8 pixels per cycle horizontally the match was 6.88±0.14. All displays have identical global average value.

Equivalent Background

The range of observer matches for the 27 patterns with identical white gray and black pixel counts is from 7.85 to 5.19. This is 2.6 lightness units on a scale in which white is 9.6 and black is 1.5. Hence the surround with identical average statistics can manipulate the matching lightness one-third of the range between white and black.

One of the goals of this paper is to understand the underlying mechanisms of the large changes in appearance. Obviously, the spatial pattern of the white pixels is controlling the appearance. The mechanism, however, is not at all obvious. Figure 6a displays the set of different surrounds that generated Munsell matches of 7.0. In the control experiments, the digital value 199 (84%max luminance) in a white surround matches Munsell 7.0. With the gray set to 140, the surround digital value of 173 (76%max luminance) generates Munsell 7.0.

In the constant average statistic targets the following targets have Munsell matches of 7.0:

A single white square of 2112 white pixels (1 side)
A dispersion fraction of 1/2
A corner square with 16 pixel separation
A side square pattern with 16 pixel separation
A line pattern of 8 pixels per cycle
A line pattern of 8 vert. and 2 horiz. pixels per cycle

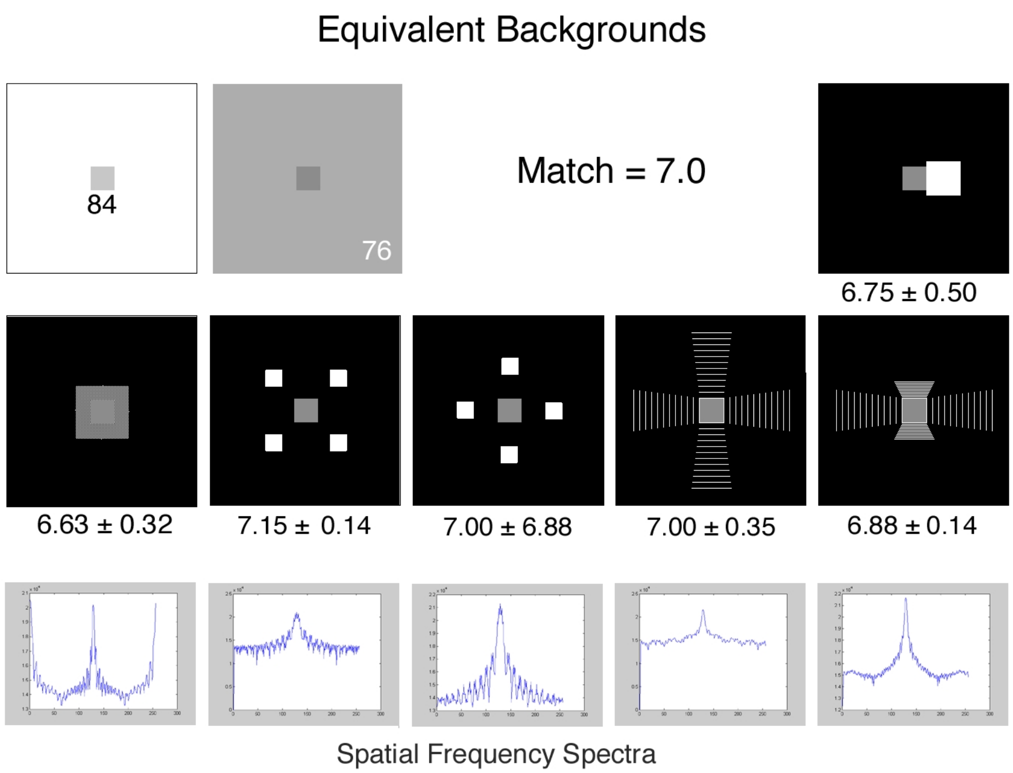

Figure 6a shows eight different displays with Matching Munsell Value = 7.0. The top left shows that in a white surround the central test patch that matched by 7.0 had a digital value of 199 (84%max luminance). In all other displays the gray test patch had a digital value of 140 with 2112 white pixels on 62,400 black pixel background. The asymmetrical square of white, the 1/2 dispersion fraction, the 16 pixel corners and sides separations, the 8 pixel cycle of stripes and the 8 vertical and 2 horizontal stripe patterns all acted as equivalent surrounds. They all made the 140 pixel value gray central patch match 7.0 Munsell Value. In an all white surround the gray central test area (digital value 140) was matched by a lightness of 4.94±0.43, while in an all black surround it was matched by 7.59±0.60. The bottom row plots of the spatial frequency spectra of the five displays in the middle row of Figure 6a.

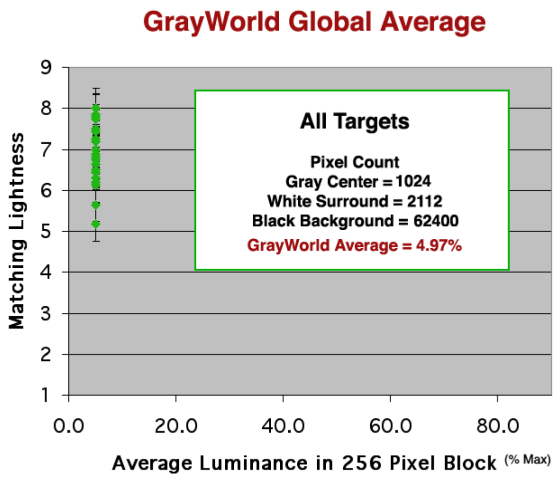

Figure 7 plots the "GrayWorld" global average for all displays vs. Matching Munsell Lightness. Here the digital values have been converted to average luminance. All displays have the same pixel composition and global average value. Observer matches vary for a high of 7.85 to a low of 5.19. Global average is not a good predictor of matching lightness.

Equivalent background patterns provide a challenge to spatial models of vision. Namely, models that are designed to calculate the appearance of lightness need to generate identical predictions for the central gray patch from these diverse spatial input targets.

The computational model candidates are:

Frameworks with depth planes and illuminants
GrayWorld
Spatial frequency filter models using single MTF
Multichannel spatial frequency models
Pyramid processing

It is difficult to calculate meaningful cognitive frameworks for either illumination or depth planes for these displays. The ideal model is one that only requires the array of pixel data, without additional interpretation of image segments. It is difficult to imagine the framework that controls variable lightness from the concentration of Snow. It is easy to see that global models would be unable to correctly predict the results of these experiments, e.g., GrayWorld - using the average of all luminances (Figure 7), or global maximum - normalizing by the single maximum value pixel in the entire image.

Further, a simple model employing a single filtration of spatial frequency energy distributions will not account for observer data. The bottom row in Figure 6 shows spatial frequency spectra of the middle row of targets. It is not obvious how a single filter will transform these inputs to equal outputs.

Results

Figure 8 shows the average values computed using very simple boxcar averages of the average local luminance Instead of ÒGrayWorldÓ we looked to ÒGraySuburbÓ av-

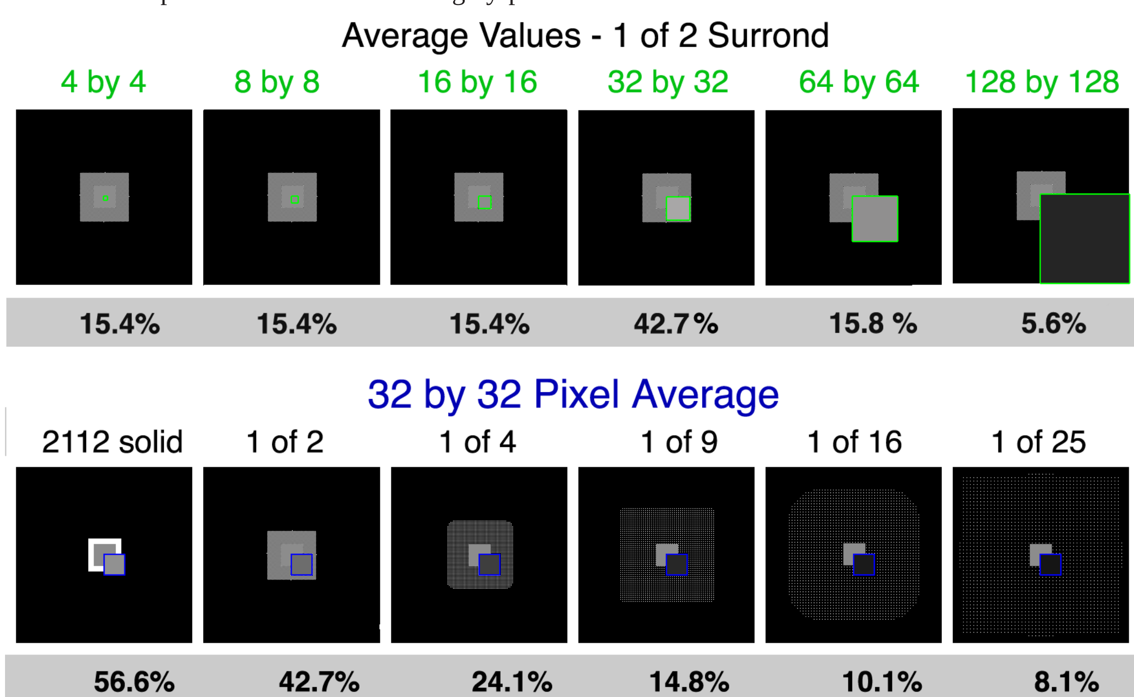

Figure 8 shows the results of different partial spatial averages. The first row reports different size averages for the 1 of 2 checkerboard surrounds. All averages included one of the four center gray pixels. The left box shows that the 4 x4 pixel average is 15.4% maximum luminance, followed by 8x8 average is 15.4%; 16x16 is 15.4%; 32 x 32 = 42.7% 64x64 = 15.8% and 128x128 = 5.6%. The second row reports different displays using only the 32x32 pixel average. All averages included one of the four center gray pixels. The left box shows that the 2112 solid display average = 56.6%; 1 of 2 display = 42.7%; 1 of 4 = 24.1%; 1 of 9=14.8% 1 of 16 = 10.1% and 1 of 25 = 8.1%.

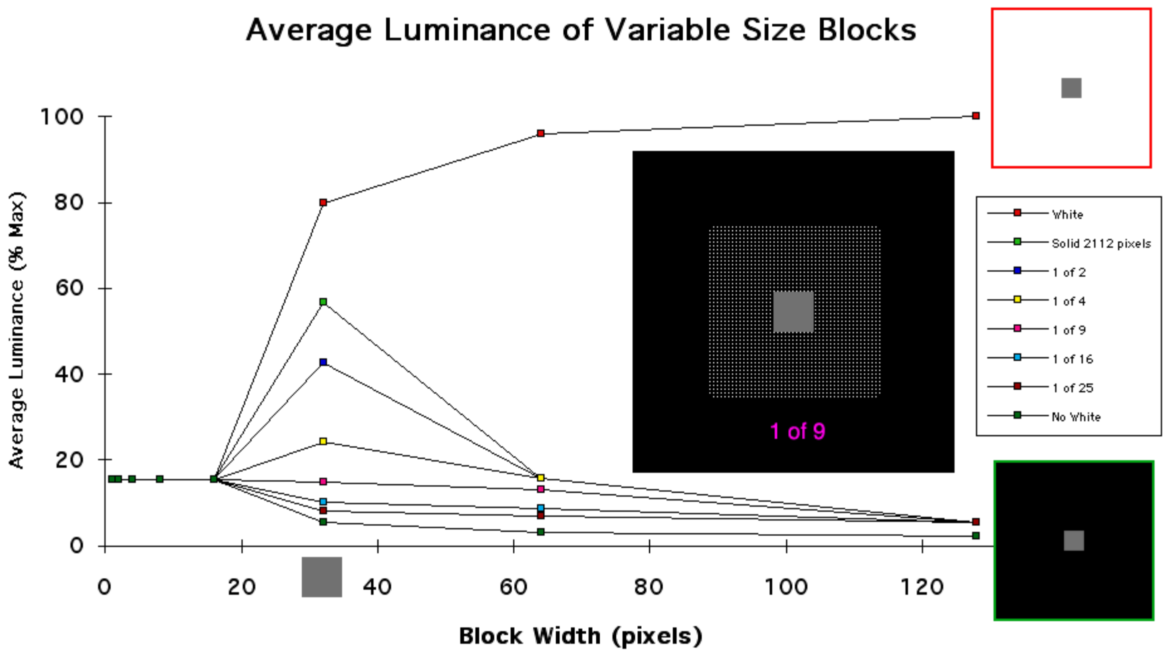

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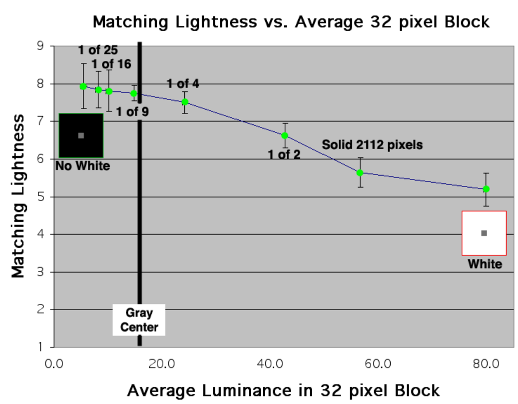
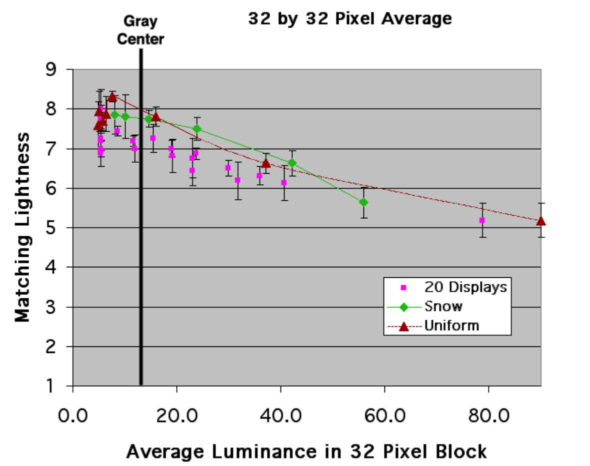
Figure 8b plots all sizes of local average for all "Snow" displays . This plot shows that the biggest differences in local averages are found in the 32 by 32 sample. The average value from smaller sizes is dominated by the central gray. The





average value of the larger sizes is dominated by the large black background.

Figure 9a plots the 32x32 pixel average vs. matching lightness for the Snow targets, along with the "all white" and "all black" backgrounds. The black vertical line shows the 15.4% average luminance of the gray center. When the average value is greater than 15.4% the matching lightness falls quickly with 32x32 average luminances. Below 15.4% a lower slope is observed.

Figure 9b plots the 32x32 pixel average vs. matching lightness for all the other targets. Diamonds plot the "Snow" displays; triangles plot the constant gray center with uniform gray surround (see Figure 2); circles plot all of the remaining constant global average displays. The vertical error bars plot one standard deviation of the mean of observer matches. There is no significant difference between the plots of "Snow" and uniform gray surround. Although the observer saw all the individual white pixels, the match for the gray center was the same as a uniform gray with the same 32 x32 spatial average. The remaining data(circles) are very similar, but slightly darker than the diamonds and triangles. This suggests that 32x32 pixel averages can be used to account for most, but not all of the other data. Clearly these displays have different values in the 64x64 pixel averages.

erages. Figure 8a shows the average local luminance when varying the size of average for a single display (top) and varying the same size of average on various displays (bottom). The average values show considerable variability despite the uniformity of the global statistic. Figure 8b shows that marked differneces in spatial averages are found only in same sizes of averages.

Figure 9 plots the local average for all displays and all sizes of average. The largest variability is in the 32x32 pixel averages. In other words, the snow displays have the most differentiable signal in the averages that are the same size as the central square. Smaller averages are dominated by the gray scale itself, while larger ones are dominated by the very large black surround.

Plots of matching lightness vs. average 32x32 luminance show a characteristic curve (Figure 9a). Of special interest is the fact that the plot of uniform grays fall on that same curve (Figure 9b). Furthermore, plots of all the other displays fall just below the Snow and uniform background data. This indicates that the 32x32 average shows high, but not perfect correlation with observer matches. These corners, lines and sides displays have different average signatures in the 64x64 displays and this may correlate with the darker matches.

Discussion

The design of these experiments was the collection of data for future use in designing models. The intent was to extend our understanding of how white pixels influence appearance. Whites have been assigned many different roles by frameworks, global normalization, determinants of illuminants, etc. These experiments go a long way to indicate that spatial average in the same spatial frequency range as the region of interest have an important role in computational models of lightness. They also show that Snow and uniform backgrounds have an indistinguishable effect on the lightness of a 32x32 gray area. Despite the visibility of the discrete single white pixels in the snow, the observer makes the match that correlates with the 32x32 pixel average. Figure 9 also shows that although the other figures have many different characteristics (lines, corners, sides), they have almost the same spatial signature in the 32x32 pixel averages.

These experiments are not intended to describe a model. Rather, they identify the underlying spatial information that is important to the human visual system. The results indicate that pyramid processing in which spatial comparisons are made first within levels and then between levels can work well to model this data. Alternatively, spatial frequency models that perform spatial comparisons within frequency channels, then combine channels can also work well.

Future plans include using this technique for analysis of multichannel influences on lightness matches. For this we need to find equivalent backgrounds using displays with spatial energy distributions in more than one spatial average domain. The really interesting question is how channels combine and interact. The plan is to use equivalent spatial backgrounds to understand pyramid level and frequency channel interactions.

Summary

This paper introduces the idea of equivalent background for testing spatial models of human spatial vision. It describes 50 different test targets of which 27 have identical pixel image statistics. It identifies sets of targets with equivalent backgrounds and analyses the result in light of different approaches to modeling spatial vision.

The results showed that despite a wide range of pattern types (Snow, Corners, Sides Lines and asymmetry) the observer matches showed very high correlation with very simple spatial averages. Uniform gray surround with the 32x32 spatial average were indistinguishable from those of Snow. Despite the clear visibility of the single white pixels, their influence as a surround was as the same as an equivalent uniform gray. There was no effect on matching lightness from the clearly visible white Snow.

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Biography

John McCann received his B.A. degree in Biology from Harvard University in 1964. He did research and managed the Vision Research Laboratory at Polaroid from 1961 to 1996. His work concentrated on research in human color vision, large format instant photography and the reproduction of fine art. He is a Fellow of the IS&T. He is a past President of IS&T and the Artists Foundation, Boston. In 2003, he recieved the IS&T /OSA Edwin Land Medal. He is currently consulting and continuing his research on color vision.

Alessandro Rizzi took the degree in Computer Science at University of Milano and received a PhD in Information Engineering at University of Brescia (Italy). He taught Information Systems and Computer Graphics at University of Brescia and at Politecnico di Milano. Now he is assistant professor at University of Milano teaching Multimedia and Human-Computer Interaction. Since 1990 he has been doing research in the fields of digital imaging and vision. His main research topic is the use of color information with particular attention to color adaptation mechanisms.