Perceptual and physical dimensions are dissociated in brightness and lightness perception

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Abstract

A fundamental issue in psychology and neuroscience concerns the relationship between the dimensions of perception and the physical dimensions of the world. Standard theories of visual surface perception, for instance, postulate that brightness and lightness constitute perceptual dimensions corresponding to the physical dimensions of luminance and reflectance. Here we introduce an alternative theory in which brightness and lightness correspond to computationally defined modes, rather than dimensions, of perception. According to the theory, blackness and whiteness constitute the dimensions—putatively related to the neural ON and OFF channels of vision—underlying the perception of black, white and gray shades. The theory quantitatively unifies and generalizes many extant theoretical concepts and perceptual phenomena, and makes several testable predictions. This work provides the first detailed example in which perceptual dimensions are specified according to the computational properties of the brain rather than in terms of 'reified' physical dimensions.

Keywords: Brightness, lightness, dimension, physical, perceptual, computation, gamut relativity

A central problem in psychology and neuroscience is to identify the relationship between the mind, the brain and the outside world. Conventional approaches to understanding this relationship have historically identified, with few exceptions, the dimensions of perception with the physical dimensions of the world [1]. Standard theories of visual perception, for instance, posit that *brightness* and *lightness* constitute the perceptual counterparts to the physical dimensions of luminance (light intensity physically registered by the eye) and diffuse surface reflectance (ratio of physically incident and reflected light intensity) [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]. According to this view, brightness and lightness dimensions are defined with respect to fixed, or *absolute*, bright/white and dark/black poles [10]. It has been proposed, furthermore, that brightness and lightness constitute the dimensions underlying a two-dimensional (2D) perceptual space [15], with the former dimension providing information about illumination intensity and the latter dimension surface reflectance. A key finding that is typically taken as evidence supporting this theoretical position is that subjects instructed to match stimuli on the putative dimensions of brightness ('perceived luminance') or lightness ('perceived reflectance') tend to correctly match the luminance or reflectance values of stimuli, respectively [3, 5, 6, 16, 12, 13, 14].

The present study makes three key theoretical contributions that depart radically from the conventional theories outlined above. Firstly, an alternative computational solution to the problem of specifying the identity of the dimensions underlying the perception of black, white and gray shades, or *achromatic surface colors*, is presented. The theory abandons the conventional notion that the range, or *gamut*, of perceivable achromatic colors varies between absolute poles. The achromatic color gamut is instead defined relative to the visual system's characterization of spatial illumination and reflectance differences, giving rise to the name of the current theory: *Gamut relativity* [17]. Secondly, a new computational approach to the problem of computing achromatic surface colors independently of spatial variations in illumination (e.g. shadows) is introduced. Thirdly, a new computational interpretation of brightness and lightness is provided. This interpretation suggests that brightness and lightness are more correctly characterized as *modes*, rather than dimensions, of achromatic color perception. By this it is meant that brightness and lightness correspond to different representations of achromatic colors under the different 'assumptions'—represented by the visual system as the value of a single free parameter—of spatially uniform and variable illumination, respectively.

More generally, the theory unifies and generalizes key extant theoretical concepts—namely, local simultaneous contrast, anchoring and scission [2, 18, 19, 20, 3, 4, 5, 6, 21, 7, 8, 9, 11, 22, 23, 24, 25, 26]—within a simple geometrical framework that quantitatively explains several challenging psychophysical phenomena.

1. The theory of gamut relativity

We motivate the need for a new theory by considering the conventional approach to understanding the so-called Gelb effect [27, 8, 9]. The Gelb effect is typically observed using physical papers and a hidden spotlight [9]: A piece of paper that appears black in 'room illumination' appears white when illuminated by a hidden spotlight of high intensity in an otherwise darkened room. When a paper that appears a shade of gray in room illumination is now placed in the spotlight, the newly introduced paper looks white—but *whiter* than the white of the original 'black' paper—and the paper that previously appeared white now appears a shade of gray. The process is repeated with additional papers of progressively higher reflectance up to a paper that appears white in room illumination. Each new paper appears progressively whiter, and all papers that previously appeared white become progressively blacker. The effect can be simulated using a tissue placed in front of a computer monitor and presenting squares of progressively higher luminance against a black background (see Methods).

The conventional explanation of the Gelb effect is framed in terms of an *anchoring process* applied to the putative lightness dimension [8, 9]. According to this *lightness anchoring theory*, the region of highest luminance in a scene is always 'assigned' to the white pole of the lightness axis, with all other lightness values being assigned values closer to the black pole. This is computationally accomplished by calculating the logarithms of the luminance ratios (log luminance ratios) formed between the region of highest luminance in the scene and each individual region in the scene (e.g. $\log_{10}(100/10) = 1$, where the highest luminance value is the numerator and luminance is defined in units of cd/m^2). Lightness anchoring theory thereby interprets the 'null' log luminance ratio—formed by the highest luminance region with itself ($\log(100/100) = 0$)—as appearing white. Lightness anchoring theory does not, however, explain why each new white square appears whiter than previous white squares, nor does it easily explain other challenging psychophysical data [8, 9].

We propose that the Gelb effect instead provides evidence in favor of the postulate that 'blackness' and 'whiteness' form the dimensions underlying achromatic color perception (Fig. 1) [17]. Whereas the conventional brightness and lightness dimensions vary respectively from bright-to-dark and black-to-white, blackness and whiteness vary from *nothing*, or *zero*, to some arbitrary maximum value. The theory predicts [17] that these dimensions are related to the neural activity levels in the visual ON and OFF channels [28, 29], which vary from zero to some arbitrary maximum value. The theory postulates, furthermore, that all achromatic colors are composed of various proportions of blackness and whiteness—that is, as points in *blackness-whiteness space*—a proposal originally attributed to Hering but subsequently largely forgotten [30, 31, 32].

The application of the anchoring process [27, 8, 9] *in the context of the theory of gamut relativity* allows us to simulate a wide range of psychophysical data outside the scope the conventional lightness anchoring theory. To accomplish this goal, highest luminance anchoring is applied to the blackness dimension, ensuring that the region of highest luminance in a scene is assigned a blackness value of zero. The highest luminance value is called the *blackness anchor*. Unlike lightness anchoring theory, then, gamut relativity suggests that the 'null' log luminance ratio represents an absence of blackness, rather than a fixed white point (Fig. 1A). According to gamut

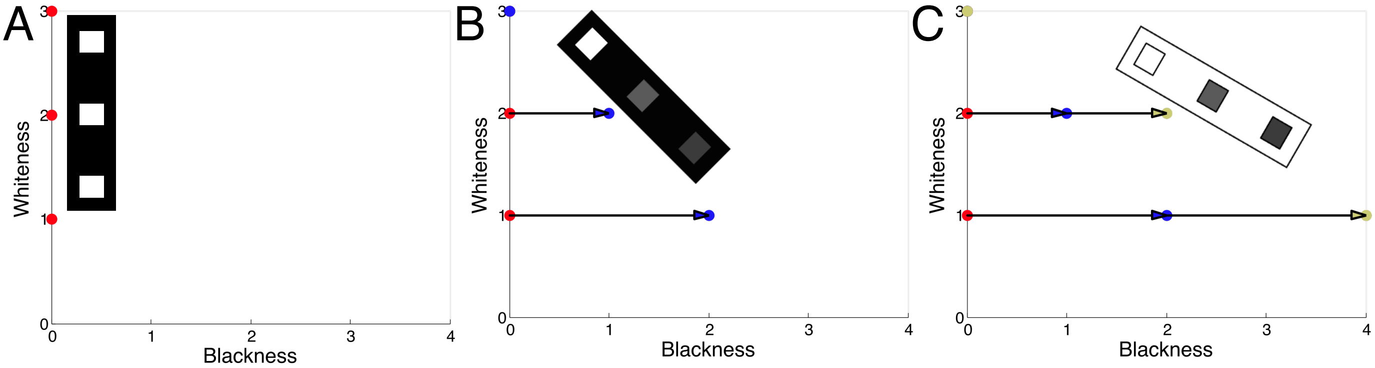

Figure 1: **The theory of gamut relativity illustrated in terms of the Gelb effect.** A piece of 'black' paper appears white when illuminated by a hidden spotlight of high intensity in an otherwise darkened room. When a 'gray' paper is now placed in the spotlight, the newly introduced paper looks *whiter* than the white of the original 'black' paper, which now appears gray. The process is repeated with additional papers, with each new paper appearing progressively whiter, and all other papers appearing progressively blacker. (A) **Whitening of 'new' papers**: Each square of increasing luminance is anchored to the whiteness axis: Each square, seen in isolation, thus increases in whiteness but not blackness (this increase cannot be depicted in the set of white squares shown together). (B) **Blackening of 'previous' papers**: Each 'previous' white square increases in blackness with the addition of each 'new' white square, as depicted by the vector shift. The whiteness of each 'previous' square nonetheless remains constant. The line joining all blue points defines the range of perceivable achromatic colors, or gamut, corresponding to the illumination level specified by the highest luminance value. (C) **Enhanced blackening of 'previous' papers**: Placing a background with luminance equal to the highest square around all the squares results in an additional blackness component, from local simultaneous contrast, being added to each 'previous' white square. This component is depicted as an additional vector shift added to the shift supplied by blackness anchoring. The net result is that the achromatic color gamut becomes more negatively sloped. All these properties contribute to the simulations of lightness matching data in the Gelb effect (Fig. 2).

relativity, the property of whiteness is instead associated with the whiteness dimension. Whiteness values are computed as the log luminance ratios formed by each region and a constant luminance value, termed the *whiteness anchor*, that is set arbitrarily low (e.g. $\log(100/0.1) = 3$, where the whiteness anchor is the denominator). Whiteness values, like blackness values, are therefore always non-negative.

According to gamut relativity, the fixed whiteness anchor ensures that each new square of increasing luminance in the Gelb effect is represented as a whiter shade of white (Fig. 1A), corresponding to points of increasing value along the whiteness axis (e.g. $\log(10/0.1) = 2$ becomes $\log(100/0.1) = 3$). Each old square, by comparison, is blackened slightly by the addition of each new square of higher luminance, due to blackness anchoring (e.g. $\log(10/10) = 0$ becomes $\log(100/10) = 1$, where the numerator is the blackness anchor). The point in the achromatic plane corresponding to the 'old' white square in the Gelb series thus shifts, for example, from $(blackness, whiteness)$ co-ordinates $(0, 1)$ to $(1, 1)$ (Fig. 1B). The point corresponding to the 'new' white square in the example above is given by the co-ordinates $(0, 2)$. In general, we can characterize co-ordinates in terms of the following simple rule: The region of highest luminance defines the intercept, on the whiteness axis, of a straight line with negative slope, and all points of lower luminance fall on this line (e.g. $slope = (1 - 2)/(1 - 0) = -1$ and $intercept = 2$, in the example above).

Any given line is termed an *achromatic color gamut*, defined perceptually as the range of achromatic colors that can be seen in a region by varying the luminance of that region between the values of the whiteness and blackness anchors, keeping all other variables fixed. This definition implies that the achromatic color gamut varies with changes in illumination intensity. As illumination intensity—and hence the highest luminance value in the scene—increases, the entire achromatic color gamut is rigidly translated up the whiteness axis. This proposal is consistent with recent psychophysical data showing that two co-ordinates are required to specify achromatic colors seen under different illumination intensities [15, 16]. Due to this illumination dependency, achromatic colors seen under different illuminants—that is, defined by different gamut lines—cannot be perfectly matched [15, 16].

Recent psychophysical measurements and computational analyses suggest that the achromatic color gamut also depends on the luminance values of the spatial background against which targets are seen [33, 17]. According to gamut relativity, this dependency is due to local simultaneous contrast [11], which contributes additional whiteness and blackness components to the achromatic colors specified by anchoring. Each component is proportional to the log luminance ratio of a region and its immediate background [22, 24], and is sensitive to edge polarity [25, 26]. Whiteness (blackness) is 'induced' into a region when the luminance of the region is higher (lower) than the background, forming a contrast *increment* (*decrement*). As with the anchoring component, only positive whiteness and blackness values are allowed. The influence of local simultaneous contrast is to increase (decrease) the slope of the achromatic color gamut associated with contrast increments (decrements) (Fig. 1C). Similar to the dependency of the achromatic color gamut on illumination intensity, this property of the theory ensures that achromatic colors seen against different backgrounds cannot generally be perfectly matched [17].

Another recent finding that plays a crucial role in the theory's explanations of the psychophysical phenomena discussed below is that blackness values are more strongly weighted by the visual system than whiteness values [17]: For equal physical changes in stimulus luminance, changes in blackness values are approximately 4 times greater than corresponding changes in whiteness values.

2. Simulation of lightness matching in the Gelb effect

The properties of the theory outlined above allow us to simulate psychophysical measurements of the Gelb effect obtained by instructing subjects to match the lightness of each square to a series of 'standard' Munsell chips (Fig. 2A) [27, 8, 9]. Munsell chips are typically arranged on a uniform white background illuminated by a light source of different intensity to the source illuminating the Gelb series. The proposed dependence of the achromatic color gamut

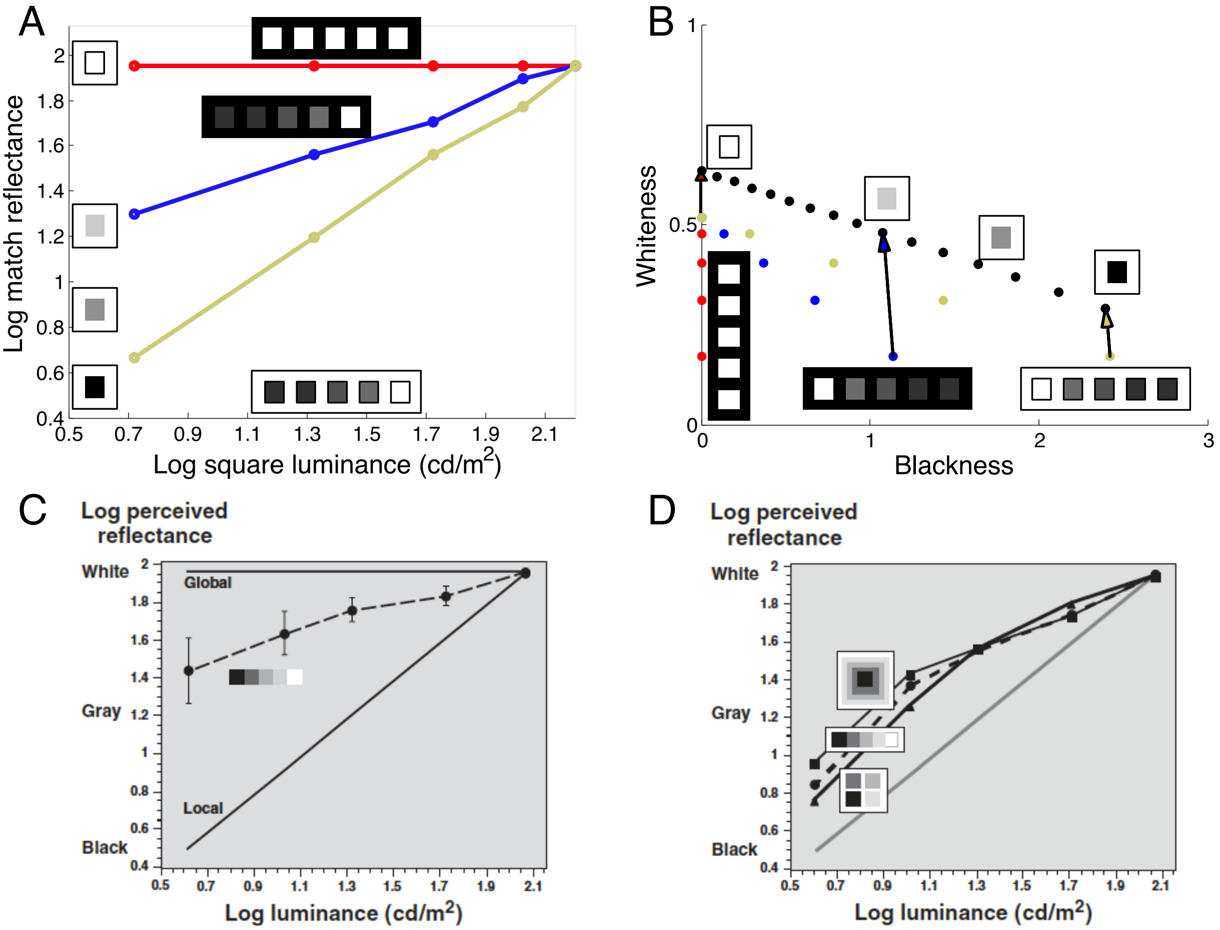

Figure 2: **Simulation of lightness matching in the Gelb effect.** (A) The simulation procedure selects the Munsell chip that minimizes the perceptual distance between any given square in the Gelb series and all chips on the Munsell scale. **Anchoring**: Each square, when first presented, appears a shade of white and is matched to the Munsell chip of highest reflectance (red points). **Gamut compression**: When presented together, the same squares appear compressed relative to the Munsell scale (blue points). **Insulation**: The introduction of a white background surrounding the Gelb series eliminates the compression effect (yellow points). (B) Corresponding points in blackness-whiteness space defined by blackness and whiteness dimensions. The black points represent colors in the Munsell series. **Anchoring**: The Munsell series lies in a different 'slice' of blackness-whiteness space due to the higher illumination intensity and the different background associated with the Munsell series relative to the Gelb series. Each highest luminance square is anchored to the whiteness axis, meaning that each square, when first presented, increases in whiteness but not blackness. As the point representing the highest reflectance Munsell chip is always closer to each shade of white than any other point in the Munsell series, the simulation procedure always selects this chip, despite the perceptual experience of escalating whiteness. **Gamut compression**: The final arrangement of squares is matched to the upper half of the Munsell scale. **Insulation**: The white background decompresses the Gelb series gamut due to the effect of local simultanenous contrast. (C) Data showing gamut compression and predictions of local and global anchoring processes in the lightness anchoring theory, reprinted from Fig. 11.8 of [9]. (D) Data showing insulation, reprinted from Fig. 11.7 of [9].

on illumination intensity means that gamuts corresponding to the Gelb series and Munsell series are shifted relative to one another along the whiteness axis (Fig. 2B). Despite this offset, subjects typically match the highest luminance Gelb square to the highest reflectance Munsell chip. The theory simulates this finding in terms of the hypothesis that subjects select the Munsell chip that best matches each progressive shade of white in the Gelb series (Fig. 2A,B) [15, 16, 33, 17]. This hypothesis is supported by recent studies [15, 16, 33, 17] showing that subjects instructed to perform brightness or lightness matches can generally only make approximate matches that minimize the perceptual difference between regions.

The theory simulates the puzzling observation that subjects choose Munsell chips ranging only from middle gray to white when required to match each square in the final arrangement of Gelb squares, despite the fact that the paper of lowest reflectance appears black in room illumination (Fig. 2B,C). This so-called 'gamut compression effect' is explained in terms of the greater weight applied by the visual system to blackness relative to whiteness [17]. The white background surrounding the Munsell series induces blackness into each chip by means of local simultaneous contrast, whereas the low luminance background surrounding the Gelb series induces whiteness into each square (this negligible influence was omitted from the simulation). This asymmetry means that points representing the Munsell series are stretched along the blackness axis relative to points corresponding to the Gelb series, ensuring that the Munsell chips that best match the Gelb squares are all of relatively high reflectance (Fig. 2B,C).

The theory also simulates the previously unexplained observation that the addition of a white surround around the Gelb series eliminates the gamut compression effect. The theory is able to simulate this 'insulation effect' because the addition of the white surround induces blackness into the Gelb series by means of local simultaneous contrast. This manipulation weakens the asymmetry between the Gelb series and the Munsell series, as both are now seen against white backgrounds, and therefore largely eliminates the gamut compression effect (Fig. 2D). The residual difference is explained by the fact that each square in the Gelb series is also affected by local simultaneous contrast from neighboring squares, reducing the total local simultaneous contrast signal relative to the chips in the Munsell series, each of which is completely surrounded by white (see Methods).

3. A new solution to the problem of achromatic color constancy

A key task of the visual system is determine whether two image regions with different luminance values have the same reflectance under different illuminants, or different reflectances under the same illuminant, or *some linear combination of these two extremes*. This is known as the problem of *achromatic color constancy* [2, 3, 4, 5, 6, 34, 9, 11, 22].

One approach to solving this problem concerns the distinction between local and global anchoring [8, 9]. This approach asserts that global anchoring is favored when a scene is uniformly illuminated, and local anchoring is favored when different regions of a scene are variably illuminated. Stated in terms of the conventional lightness anchoring theory, global anchoring means that the region of highest luminance in the entire scene anchors the lightness values of all other regions, and local anchoring means that the highest luminance value *within each illumination level* anchors all the lightness values in that level. A single free parameter, λ, controls the balance between local ($\lambda = 0$) and global ($\lambda = 1$) anchoring. Under the assumption of an identical spatial arrangement of surfaces viewed under different illuminants, local anchoring ensures that surfaces with the same reflectance values viewed under different illuminants have the same lightness values [8, 9]. Local anchoring thereby effectively discounts the illuminant, giving rise to lightness constancy. Local-global lightness anchoring has previously been invoked to explain gamut compression in the Gelb effect [8, 9] (Fig. 2C), though local-global blackness anchoring is not required to explain gamut compression in the theory of gamut relativity.

Here we generalize local-global anchoring in the context of gamut relativity. According to the theory, blackness values are computed either globally with respect to the highest luminance value in the entire

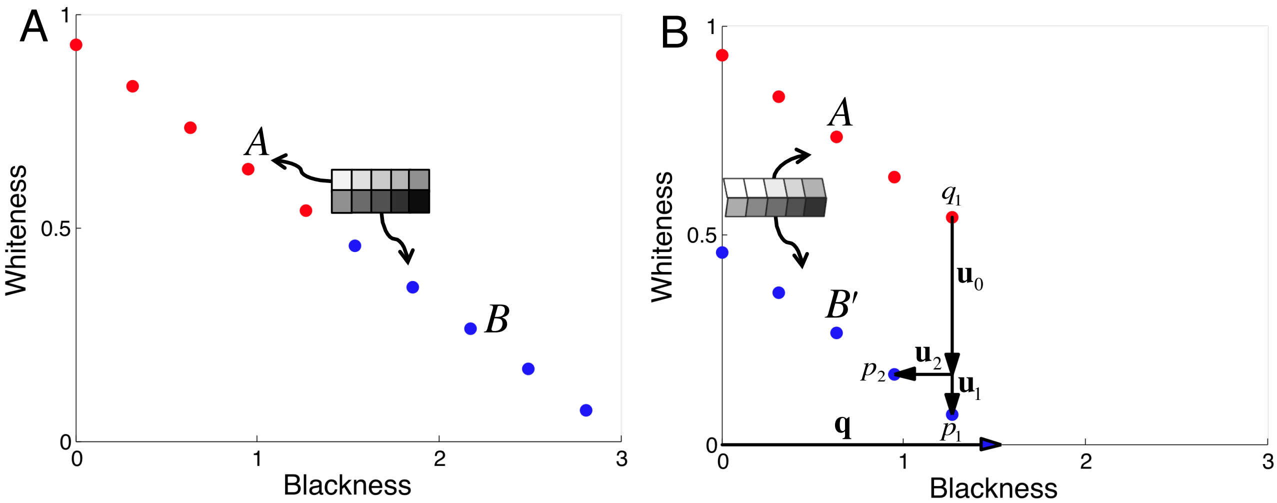

Figure 3: **A new solution to the problem of achromatic color constancy**. (A) **Global blackness anchoring**: A global blackness anchor is applied to all squares in the depicted arrangement; namely, achromatic surface colors with relatively high luminance, as in the set A (red dots), and relatively low luminance, as in the set B (blue dots). (B) **Local blackness anchoring**: This process translates the achromatic surface colors (B) with low luminance to an anchor point on the whiteness axis, giving rise to the surface colors represented by B'. In this example, local anchoring is induced by a change in the depth relationship between upper and lower squares, depicting differential illumination. It is conjectured that the surface colors represented by A are computationally treated as a 'standard' set of surface colors by the visual system against which the 'comparison' surface colors represented by B' are 'assigned' for the purposes of perceptual grouping into surface representations. According to this conjecture, termed the **correspondence principle**, under the assumptions of identically distributed reflectance values and local blackness anchoring, points representing the same reflectance values, such as q_1 and p_1, will always be closer to one another than points representing different reflectance values, such as q_1 and p_2. The vector, $\mathbf{q}$, lying on the blackness axis indicates the color of the shadow that is produced through local anchoring, which is a process equivalent to complete scission into surface and shadow colors (see Methods). Note that this point lies further away from the standard surface colors (upper red points) than do any of the comparison colors (lower blue points), indicating that in general the shadow color cannot become spuriously 'assigned' to any standard colors due to the correspondence principle. Note the different scales on the abscissa and ordinate.

image (Fig. 3A) or locally with respect to the highest luminance values under relatively low and high illumination levels, respectively (Fig. 3B). Whiteness values continue to be computed relative to a fixed luminance value. Local blackness anchoring defines different gamuts in high and low illumination (Fig. 3B). Local blackness anchoring ensures that surfaces with the same reflectance values viewed under different illuminants have the *same blackness values*, under the assumption of an identical spatial arrangement of surfaces viewed under different illuminants.

Due to the asymmetry in blackness-whiteness weights, coupled with an appropriate choice of metric, the following *correspondence principle* is guaranteed under local blackness anchoring (see Methods): Points corresponding to the *same* reflectance under different illumination levels lie *closer to one another in blackness-whiteness space* than all other points corresponding to *different* reflectances under different illumination levels (Fig. 3B). Approximate matches between surface colors under different illumination levels are conjectured to reflect this principle.

The theory posits, furthermore, that the transition from global to local anchoring is mathematically equivalent to a process of *scission* [2, 35, 18, 19, 20], or vector decomposition, in blackness-whiteness space (see Methods). This vector decomposition process splits otherwise unitary achromatic colors into pairs of distinct colors, which can be interpreted as surface and shadow colors. The parameter λ embodies the degree of shift from global to local anchoring; $\lambda = 0$ implies that no scission whatsoever occurs, whereas $\lambda = 1$ implies that scission is complete. As λ can take any value between these extremes, it is possible that scission is partial. The parameter λ may therefore be equally well termed the anchoring or scission parameter. This geometrical framework suggests that shadow colors can be represented as vectors falling directly on the blackness axis, meaning that shadows always appear a pure shade of black, with the blackness value itself depending on the difference in illumination between regions and the value of λ (Fig. 3B). The sum of the shadow vector and each decomposed surface color equals the corresponding globally anchored surface color appearing under the relatively higher illumination level specified by the global anchor (Fig. 3A). This observation predicts that a type of conservation principle governs the computation of surface colors by the visual system (see Discussion).

We conjecture that achromatic surface colors appearing under a relatively high illumination level act as 'standard' colors to which surfaces in shadow are perceptually 'assigned' by means of a putative grouping process, the details of which remain to be studied. Surfaces seen under relatively high illumination levels are thus predicted to appear in 'plain view'—without the appearance of an overlaying illumination color—consistent with available psychophysical data [20, 36]. As surfaces in high illumination are considered the standard to which surface colors under lower illumination levels are perceptually assigned, the theory suggests a reason for why achromatic color space is planar. In the plane, the scission process allows points representing shadows to be displaced further away from the standard colors than surface colors in low illumination (Fig. 3B). In one perceptual dimension, by contrast, no distinction could be made between standard and comparison surface colors, and points representing shadow and surface colors would generally lie ambiguously close to one another.

4. Brightness and lightness as perceptual modes

A key new idea of gamut relativity is that lightness and brightness are modes, rather than dimensions, of visual perception. These modes correspond to local anchoring (complete scission), on the one hand, and global anchoring (zero scission), on the other. This idea also implies that lightness and brightness are extremes of a continuum of perceptual modes determined by the value of the anchoring/scission parameter, λ, which varies continuously in the range, $0 < \lambda < 1$. The brightness mode corresponds to global anchoring or zero scission ($\lambda = 1$) and the lightness mode to local anchoring or complete scission ($\lambda = 0$). Intermediate perceptual modes represent a balance between the extreme modes of brightness and lightness: They represent the visual system's tendency to 'hedge bets' on whether different image regions are uniformly or variably illuminated.

Various factors are predicted to modulate the balance between brightness and lightness, such as cues to the classification of edges as changes in reflectance or illumination (edge classification) [7, 35, 23, 37], whether surface regions lie in the same depth plane (depth adjacency) [38, 37], the number of discriminable regions in a scene (scene articulation) [39, 3, 5, 6, 40, 41, 23, 12, 13, 42], and instructions influencing top-down cognitive biases (task instructions) [3, 4, 5, 6, 7, 12, 13, 25]. The theory suggests that edge classification, scene articulation and task instructions all contribute to determining the perceptual mode of a subject performing a psychophysical experiment. The lightness mode is favored by illumination-edge classification, depth stratification, high scene articulation, and lightness matching instructions. The brightness mode is favored by reflectance-edge classification, depth adjacency, low scene articulation, and brightness matching instructions.

To illustrate the new approach, we simulate a classic psychophysical experiment on the influence of task instructions and scene articulation on achromatic color matching behavior [3]. We first consider a brightness matching task using simple center-surround stimuli: The subject adjusts the luminance of a 'test' region, shown against a background with a certain luminance value, such that the brightness of the test region is approximately the same as that of a 'reference' region, shown against a background with a certain luminance value (technically, reflectance and illumination values were simulated on a computer monitor, under 9 illumination levels in the test region [3]). To simulate this task, we assumed that subjects performed the task in the brightness mode ($\lambda = 1$). The theory simulates the finding [3] that subjects instructed to match brightness adjusted the luminance of the test region to have roughly the same luminance as the reference region when this region was a contrast increment, but adjusted the test region to have considerably lower luminance than the reference region when this region was a contrast decrement (Fig. 4A-C).

The increment-decrement asymmetry can be understood by plotting the geometrical elements in blackness-whiteness space corresponding to stimuli in the experiment (Fig. 4B). The black lines indicate the 1D 'slices' of blackness-whiteness space corresponding to the gamut that the subject is able to perceive in the target region by varying the luminance of the test region from low to high. The achromatic color of the test region is thereby physically constrained to lie on these functions, allowing only approximate matches for test stimuli in which the background luminance differs between test and reference displays. Local simultaneous contrast, associated with differences in background luminance surrounding the test region, determines the slopes and offsets of these slices (in its absence, all lines would be identical): Regions with steep and shallow negative slopes correspond to contrast increments and decrements, respectively [17]. The inflection points for these functions depend on background luminance, which differs for each of the 9 illumination conditions. The large black dots denote the achromatic colors of the four reference regions used in the [3] study. Brightness matches made to incremental targets correspond to colored dots above the black dots, whereas matches to decremental targets correspond to colored dots positioned below the black dots. The discrepancy between the colored and black dots represents the influence of contrast that prevents perfect brightness matches from being made when targets lie on backgrounds of different luminance [17].

In the case of incremental targets, the simulation procedure sets the luminance of the test region roughly equal to that of the reference region. This occurs because the influence of local simultaneous contrast is minimal for increments, due to the small weight applied to the whiteness dimension. Luminance is therefore the primary factor determining incremental achromatic colors. In the case of decremental targets, the simulation procedure sets the luminance of the test region below that of the reference region. This is because the influence of local simultaneous contrast in the blackness dimension is substantial. The best approximate match therefore occurs at a substantially lower luminance value in the test region than that of the reference region.

To simulate the task of brightness matching in highly articulated Mondrian displays, we assumed that subjects performed the matching task in an intermediate mode ($\lambda = 0.5$). The theory simulates the finding that subjects instructed to match bright-

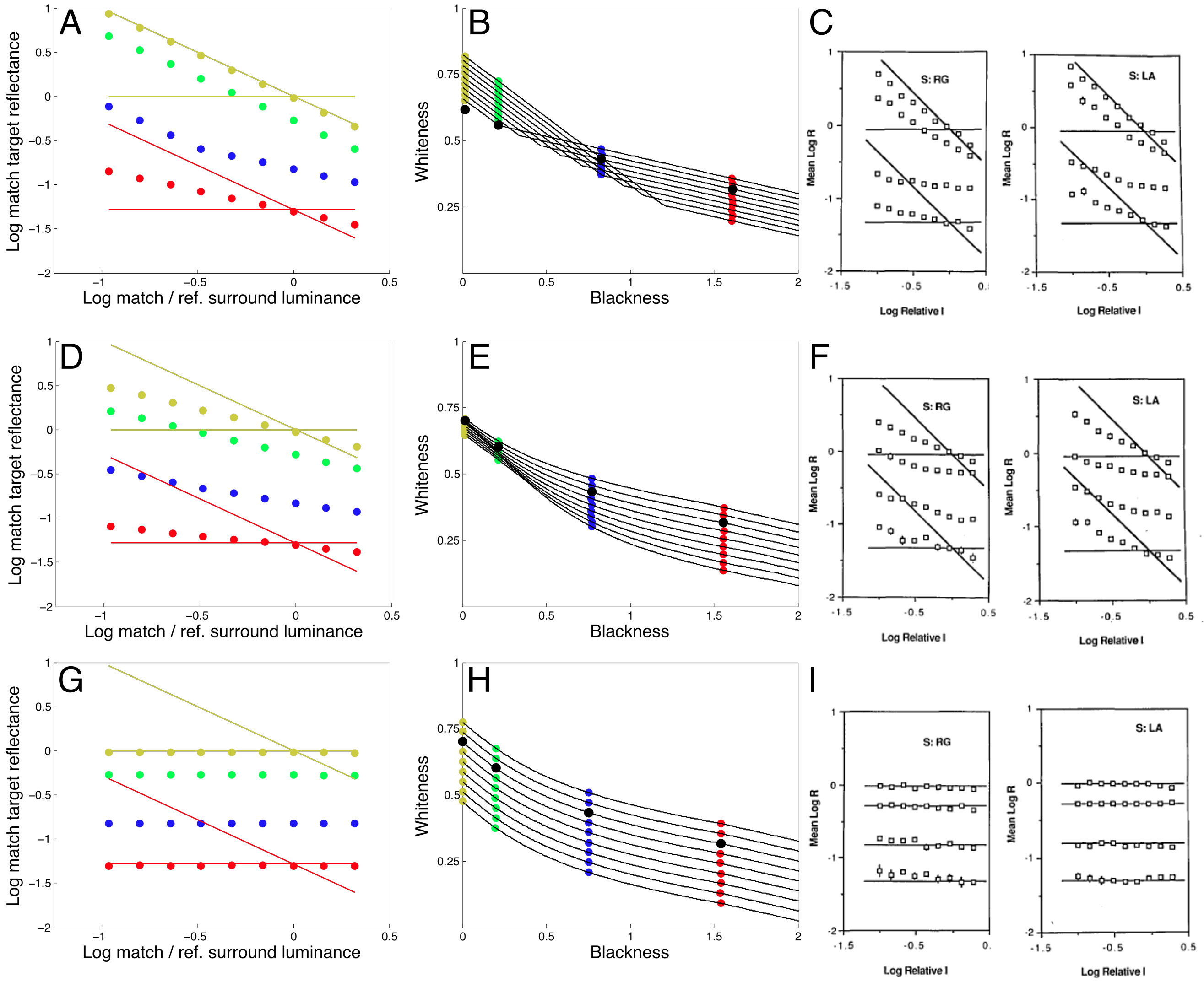

Figure 4: **Brightness and lightness as perceptual modes.** Simulation study of brightness and lightness matching in [3]. We calculated the minimum perceptual distances between reference and test colors under different assumptions concerning the value of the anchoring parameter, λ. This was done by discretely sampling potential test luminance settings within the range specified by the experimental stimuli. (A-C) **Brightness matching in simple center-surround displays** ($\lambda = 1$). (A) Luminance settings of the test region, plotted in terms of simulated reflectance values, plotted against the log ratio of reference to match surround luminance values. The theory proposes that surface colors seen under different illuminants correspond to different 1D 'slices' through blackness-whiteness space, with each slice containing its own unique set of black, gray and white shades. The color range specified by any given slice depends on both illumination intensity and the distribution of reflectance values within the image. Each black line shows the color range associated with the target test region as the luminance of the region is varied, and each colored dot represents a predicted luminance setting based on the color selection procedure. The large black points denote the achromatic colors of the four reference regions. The horizontal red and yellow lines denote perfect reflectance matching, and the negatively sloped red and yellow lines denote perfect luminance matching. (B) Corresponding points plotted in blackness-whiteness space. (C) Comparison data from [3]. The theory predicts the increment-decrement asymmetry very well: Matches for reference regions with higher reflectance (yellow, green) are closer to perfect luminance matches than regions with lower reflectance (red, blue), which are closer to perfect reflectance matches. (D-F) **Brightness matching in a (highly articulated) Mondrian display** ($\lambda = 0.5$). All matches are shifted towards the reflectance matching line, but the increment-decrement asymmetry remains intact. (G-I) **Lightness matching in a Mondrian display** ($\lambda = 0$). All matches fall approximately on the lines denoting perfect reflectance matching.

ness in Mondrian displays tended to set the luminance of the test region much lower than in simple center-surround displays. The asymmetry between contrast increments and decrements remains similar to that observed in simple center-surround displays, consistent with the data (Fig. 4D-F). The effect of local simultaneous contrast in the Mondrian display is to transform the linear 'slices' occurring with center-surround displays into curvilinear functions. This occurs because, as the luminance of the test region varies from low to high, the test region becomes an increment with respect to a progressively greater number of surround regions. The test region thus smoothly varies from a complete decrement (low luminance) to a complete increment (high luminance), resulting in the curvilinear functions. The achromatic color of the test region is again physically constrained to lie on these functions, generally allowing only approximate matches to be made.

We next simulated the lightness matching task in highly articulated Mondrian displays, assuming that subjects performed the task in the lightness mode ($\lambda = 0$). The theory simulates the finding that subjects instructed to match lightness performed nearly perfect reflectance matches (Fig. 4G-I). Lightness matching can be geometrically understood in terms of vertical lines extending from each reference color through all points of constant blackness. The points at which these lines intersect the curved lines representing each color range in Fig. 4H selects the unique set of achromatic colors corresponding to identical reflectance values across illuminants. Due to the greater weight applied to the blackness dimension, lightness matches based on minimization of perceptual distance correspond exactly to veridical reflectance values. We also simulated the task of lightness matching in center-surround displays (assuming $\lambda = 0$), obtaining results similar to those obtained with the Mondrian display [3].

5. Discussion

The theory of gamut relativity explains a number of empirical observations that have not previously been explained by alternative theories of brightness or lightness [2, 18, 19, 20, 21, 7, 8, 9, 11, 22, 15, 16, 24, 25, 26]. The theory explains; (1) the seemingly paradoxical escalation of whiteness in the Gelb effect; (2) the accompanying gamut compression effect; (3) the insulation effect that counteracts gamut compression; (4) the observation that regions under relatively high illumination intensity are generally treated by the visual system as 'standard' surface colors; (5) the simultaneous sensitivity of the visual system to illumination level and surface reflectance; (6) how the visual system establishes the correspondence between achromatic surface colors under relatively high and low illumination levels; (7) the effects of task instructions on achromatic color matching behavior; (8) the asymmetry in brightness matching behavior accompanying contrast increment and decrements; (9) the effect of scene articulation on brightness matches. The theory also explains many additional phenomena that fall outside the scope of this article.

The theory predicts that the gamut compression effect in the Gelb effect can be eliminated by surrounding the Munsell series with a black background rather than a white background. The theory also predicts that varying the illumination level on the Munsell series will vary the perceptual distances between each white square in the Gelb and Munsell series in psychophysically measurable manner [15, 16, 33, 17]. The proposed computational equivalence of anchoring and scission implies, furthermore, that the visual system obeys a conservation principle in the computation of achromatic colors: Surface and illumination colors that have undergone local anchoring/scission must sum to produce a globally anchored color. Experiments manipulating the value of the anchoring/scission parameter, λ, may be helpful in testing this prediction.

According to the theory of gamut relativity, different achromatic color gamuts correspond to different 1D 'slices' through blackness-whiteness space, with each slice containing its own unique set of black, gray and white shades. Due to the anchoring/scission and local simultaneous contrast processes that mediate gamut relativity, the achromatic color gamut specified by any given slice depends on both illumination intensity and the distribution of reflectance values within the image. One is led inexorably to the conclusion that *no representation of physical reflectance is computed by the visual system*: Any given achromatic color gamuts bears no principled relation to physical reflectance values—as the Gelb effect directly illustrates—and only the relationships between gamuts are computationally meaningful for the purposes of achromatic color constancy. Our analyses thereby support the idea that the visual system is more concerned with the relationships between object surfaces under different illumination levels than with the estimation of absolute quantities corresponding to physical dimensions [34, 1]. Our work implies, in this sense, that the brain does not solve the 'inverse optics' problem of estimating absolute physical quantities [43, 44].

We suggest that conventional theories of perception in psychology and neuroscience have historically suffered from 'reification' of the physical dimensions of the world; that is, the tendency to make concrete identifications between perceptual and physical dimensions where only abstract relationships exist. Reification manifests itself in the fallacious conclusion, for instance, that subjects instructed to perform lightness matches *actually* compute physical reflectance, when in fact their behavior is more correctly explained in the following abstract fashion: Lightness matching corresponds to a perceptual mode that supports the computation of veridical correspondence relations between achromatic colors corresponding to identical reflectance values under different illuminants in a 2D perceptual space composed of blackness and whiteness dimensions. Gamut relativity thus provides an exemplary alternative to the naive reification that has historically plagued the study of the relationship between the mind, the brain and the outside world [1].

6. Methods

6.1. Mathematical basis of the theory

Let $i \in \{1, 2, ..., I\}$ index the individual regions of a Mondrian display, under the assumption that each region forms a partial border with all other regions. Let the vector, $\mathbf{r}$, represent a set of reflectance values viewed under illuminants indexed by $j \in \{1, 2, ..., J\}$, with corresponding intensity values ℓ_j. Multiplying the reflectance vector with each scalar illuminant value, we have luminance values, $\mathbf{x}_j = \ell_j \mathbf{r}$, where $x_{i,j}$ is the luminance value of the ith region under the jth illuminant, such that $\mathbf{x}_j = (x_{i=1,j}, x_{i=2,j}, ...x_{I,j})$.

Let $\hat{x}_{i,j} = \prod_{n=1}^{N} \min(x_{i,j}, x_{n,j})$ be the rectified product of all luminance values smaller than, or equal to, $x_{i,j}$. The whiteness value, ψ, of the ith region under illuminant ℓ_j is given by

$$\psi_{i,j} = (1-\alpha)\left((1-\beta_i)\log\frac{x_{i,j}^N}{\hat{x}_{i,j}} + \nu \log\frac{x_{i,j}}{k_{\psi_{i,j}}}\right) \quad (1)$$

where $k_{\psi_{i,j}} = \min(\min(\mathbf{x}_j), k_\psi)$ is the whiteness anchor for the ith region, k_ψ is the *default* whiteness anchor, $\alpha = 0.87$ is the *overall* weight of blackness relative to whiteness [33, 17], β_i ($0 \le \beta_i \le 1$) is the *length* of the decrement border relative to the increment border formed with region i [17], and $\nu = 1.81$ is the weight applied to the anchored luminance term.

Let $\bar{x}_{i,j} = \prod_{n=1}^{N} \max(x_{i,j}, x_{n,j})$ represent the rectified product of all luminance values equal to, or greater than, $x_{i,j}$. The blackness value, ϕ, of the ith region under illuminant ℓ_j is then given by

$$\phi_{i,j} = \alpha\left(\beta_i \log\frac{\bar{x}_{i,j}}{x_{i,j}^N} + \mu \log\frac{k_{\phi_{i,j}}}{x_{i,j}}\right) \quad (2)$$

where $k_{\phi_{i,j}} = \max(\mathbf{x}_j)$ is the blackness anchor for the ith region under illuminant ℓ_j, $\mu = 0.9$ is the weight applied to the anchored luminance term.

The free parameter, λ, modifies the anchor associated to ℓ_2 in the following way

$$k_{\phi_{i,2}} = \max(\mathbf{x}_1)^\lambda \max(\mathbf{x}_2)^{(1-\lambda)} \quad (3)$$

where $0 < \lambda < 1$. We propose that λ represents the weight applied by the visual system to the two extreme choices of anchor. The setting $\lambda = 1$ represents a global anchor for all regions indexed by i, whereas the setting $\lambda = 0$ represents local anchoring determined by the maximum luminance values in $\mathbf{x}_1$ and $\mathbf{x}_2$, respectively. For this reason, we term λ the *anchoring* parameter.

6.2. Procedure

We used the theoretical parameters estimated in [17], together with the stimulus information provided in [27], [3], and [36] to generate the simulation results. The simulation procedure involved calculating reference points in blackness-whiteness space to which test colors were matched. The best-matching luminance value corresponded to the value that minimized the Minkowski metric, $\Delta \mathbf{a}_{i,j,p,q} = [(\psi_{i,j} - \psi_{p,q})^n + (\phi_{i,j} - \phi_{p,q})^n]^{\frac{1}{n}}$, where $n = 1$ defines the Manhattan metric, and $n = 2$ defines the Euclidean metric. The choice of n had little bearing on the results. We present results obtained with the former for expositional simplicity. The software was written in MATLAB Version 7.9 (R2009b). For the simulations of the Gelb effect, the influence of local simultaneous contrast formed between each square and the farther background was omitted, as available psychophysical data indicates that local simultaneous contrast requires the target and inducer to lie approximately in the same depth plane [9].

The parameters, $k_{\psi_{i,j}}$ and $k_{\phi_{i,j}}$, perform the roles of anchoring in the theory. They determine the minimum and maximum luminance values at which the achromatic color, $\mathbf{a}_{i,j} = (\phi_{i,j}, \psi_{i,j})$, of region i under illuminant ℓ_j is perceived as a *pure* shade of black ($\psi_{i,j} = 0$, $\phi_{i,j} > 0$) and white ($\psi_{i,j} > 0$, $\phi_{i,j} = 0$), respectively. The anchor, $k_{\phi_{i,j}}$, was set equal to the highest luminance value defined by the vector, $\mathbf{x}_j$. This anchor determined the blackness value, $\phi_{i,j}$, of region i illuminant ℓ_j, excluding the influence of local simultaneous contrast. In this study, the anchor applied to the whiteness dimension was defined as $k_{\psi_{i,j}} = k_\psi$, where k_ψ was a constant for any given simulation. We set $k_\psi = 1 \frac{cd}{m^2}$ for most simulations, though the results do not depend significantly on the value of this parameter. We set $k_\psi = 0.1 \frac{cd}{m^2}$ for simulations of the [3] experiment, as this value simplified the presentation of the results. In our simulations of brightness matching, we assumed for simplicity that $k_\phi = 50 \frac{cd}{m^2}$ was a constant, as for all but two of the conditions in [3] the highest luminance value was constant. The simulation result is not significantly affected by this assumption, but the exposition is greatly simplified.

6.3. *Simulation of the Gelb effect on a computer monitor*

Consider a square of low luminance shown against a background of even lower luminance on a computer monitor (Supplementary PPT file). The square, having higher luminance than the background, is said to form a *contrast increment* with the background. The square appears a dark shade of gray on the monitor but appears a dull white when a piece of tissue paper is placed over the entire display. A new square, whose luminance value is slightly higher than that of the first square, is now added to the display. The new square now appears a shade whiter than the white of the original square when seen in isolation, and the original square now appears blacker than it did in isolation. The process can be repeated with additional squares. The square with the highest luminance always appears white, yet each new square in its turn appears whiter than the previous white square, and all previous squares appear blacker with the addition of each new square.

6.4. *Log-linearity of the achromatic color gamut*

Setting the whiteness and blackness anchors to 1 and 100, and varying target luminance in three equal log steps (1, 10 and 100), blackness and whiteness values vary as follows; Blackness: $\log(100/1) = 2$, $\log(100/10) = 1$, $\log(100/100) = 0$; Whiteness: $\log(1/1) = 0$, $\log(10/1) = 1$, $\log(100/1) = 2$. It is thus clear that blackness and whiteness values respectively decrease and increase linearly with equal log luminance steps, meaning that the achromatic color gamut is log-linear. For the local simultaneous contrast component, varying the luminance of a region from low to high (in equal log steps) on a background of low luminance, for example, whiteness varies as follows: $\log(1/1) = 0$, $\log(10/1) = 1$, $\log(100/1) = 2$. Similarly, for a background of high luminance, blackness varies as follows: $\log(1/1) = 0$, $\log(10/1) = 1$, $\log(100/1) = 2$. As the local simultaneous contrast component is log-linear, the sum of anchoring and local simultaneous contrast components must also be log-linear.

6.5. *Definition of local and global anchoring*

In the following, we assume $J = 2$, where $\ell_1 > \ell_2$, such that $x_{i,1} > x_{i,2}$ for all values of i. In the case of global anchoring, we set the anchor in the blackness dimension, $k_{\phi_{i,j}}$, to provide a global anchor for all regions indexed by i. This process ensured that blackness values, $\phi_{i,j}$, were computed with respect to the highest luminance value, $k_{\phi_{i,j}} = \max(\mathbf{x}_1)$, in the entire image. If the lowest luminance value in the image was greater than the default anchor in the whiteness dimension, $\min(\mathbf{x}_2) > k_\psi$, then all image regions were assigned the default anchor, $k_{\psi_{i,j}} = k_\psi$, otherwise a new anchor was applied, corresponding to the lowest luminance value in the image, such that $k_{\psi_{i,j}} = \min(\mathbf{x}_1)$.

In the case of local anchoring, we set $k_{\psi_{i,1}} = \max(\mathbf{x}_1)$ and $k_{\psi_{i,2}} = \max(\mathbf{x}_2)$, to regions under illuminants ℓ_1 and ℓ_2. Local anchoring applied to blackness ensured that, given the assumption of a common reflectance vector $\mathbf{r}$ viewed under separate illuminants ℓ_1 and ℓ_2, the blackness values indexed by i must be equal, $\phi_{i,1} = \phi_{i,2}$. Blackness values thereby remained invariant with respect to illumination, whereas whiteness values $\psi_{i,j}$ remained unaffected by anchoring. Local anchors in the whiteness dimension were assigned to regions under different illumination only for the special case of the region i indexing the lowest luminance value, $\min(\mathbf{x}_1)$, under high illumination ℓ_1.

6.6. *Anchoring as a scission process*

Anchoring can be interpreted as a process of perceptual scission, as follows: Let $\hat{\phi}_{i,2} = \phi_{i,2}(k_{\phi_{i,2}})$ represent the blackness value of the region of highest luminance, and hence lowest blackness, under dark illumination ℓ_2. We can now reinterpret anchoring as a transformation of the achromatic colors, $\mathbf{a}'_{i,2} = \{\psi_{i,2}, \phi_{i,2}\} \neq \mathbf{a}_{i,2} = \{\psi_{i,2}, \phi'_{i,2}\}$, which behaves according to

$$\phi'_{i,2} = \phi_{i,2} - \lambda\hat{\phi}_{i,2} \tag{4}$$

where λ is the anchoring parameter. By the above transformation, the blackness values of regions under illuminants ℓ_1 and ℓ_2 are made equal, $\phi'_{i,2} = \phi_{i,1}$, with $\lambda > 0$. The vector difference between transformed and untransformed achromatic colors, $\mathbf{a}''_{i,2} = \mathbf{a}_{i,2} - \mathbf{a}'_{i,2}$, is interpreted as the achromatic color of the shadow overlaying the surface color, $\mathbf{a}'_{i,2}$.

6.7. *The correspondence principle*

Letting the sets of points A and B' be represented by linear functions, f_A and $f_{B'}$, respectively, if the gradients, $\dot{f}_A = \dot{f}_{B'}$, of these functions satisfy the constraint, $-1 < \dot{f}_A = \dot{f}_{B'} < 0$, then application of a Manhattan metric guarantees perfect invariance to differential illumination, as shown by the inequality $\mathbf{u}_0+\mathbf{u}_1 < \mathbf{u}_0+\mathbf{u}_2$ pertaining to Fig. 3B. Under conditions of intermediate anchoring ($\lambda < 1$) the function, $f_{B'}$ will only be partially translated along the blackness axis, and so perfect invariance is not guaranteed. Perfect invariance is also not guaranteed when non-identically distributed reflectance values are viewed under different illuminants, due to the effect of local simultaneous contrast.

6.8. *The effect of local simultaneous contrast*

The theory explains the asymmetry in the processing of increments and decrements in terms of constraints imposed by illumination invariance and color discriminability: Local simultaneous contrast plays a modulatory role in brightness and lightness perception by enhancing achromatic color discriminability. The curvilinear functions in Fig. 4, for instance, increase the perceptual distances between points representing achromatic colors under individual illuminants relative to the case of anchoring alone. This enhanced discriminability either facilitates or weakens the dependence of achromatic color on illumination level, by either increasing or decreasing the gradient, $\dot{f}_j$, of each curvilinear function, f_j. In the case of contrast increments, local simultaneous contrast increases this gradient, thereby enhancing the tendency to match luminance in brightness matching tasks. In the case of contrast decrements, local simultaneous contrast decreases the gradient, thereby enhancing the tendency to match reflectance. Contrast decrements therefore manifest better invariance to illumination changes than contrast increments. In the case of contrast increments, the enhanced discriminability engendered by local simultaneous contrast is limited by the potential to undermine the correspondence principle by increasing $\dot{f}_j$. In the case of contrast decrements, we assume that the limited coding range of neurons imposes a key constraint that prevents $\dot{f}_j$ from approaching zero.

7. References

[1] J. J. Gibson, *The ecological approach to visual perception* (Lawrence Erlbaum, Boston, 1979).

[2] E. H. Adelson, *The New Cognitive Neurosciences*, M. Gazzaniga, ed. (MIT Press, Cambridge, MA, 2000), pp. 339–352.

[3] L. E. Arend, R. Goldstein, *J Opt Soc Am A* **4**, 2281 (1987).

[4] L. E. Arend, R. Goldstein, *J Opt Soc Am A* **7**, 1929 (1990).
[5] L. E. Arend, B. Spehar, *Percept Psychophys* **54**, 446 (1993).
[6] L. E. Arend, B. Spehar, *Percept Psychophys* **54**, 457 (1993).
[7] B. Blakeslee, D. Reetz, M. E. McCourt, *J Vis* **8**, 1 (2008).
[8] A. Gilchrist, *et al.*, *Psychol Rev* **106**, 795 (1999).
[9] A. L. Gilchrist, *Seeing black and white* (Oxford University Press, New York, NY, 2006).
[10] A. L. Gilchrist, *Curr Biol* **17**, R267 (2007).
[11] D. Jameson, L. Hurvich, *The perception of brightness and darkness* (Allyn & Bacon, Boston, MA, 1967).
[12] J. A. Schirillo, *J Opt Soc Am A* **16**, 793 (1999).
[13] J. A. Schirillo, *J Opt Soc Am A* **16**, 804 (1999).
[14] J. Schirillo, A. Reeves, L. E. Arend, *Percept Psychophys* **48**, 82 (1990).
[15] A. D. Logvinenko, L. T. Maloney, *Percept Psychophys* **68**, 76 (2006).
[16] A. D. Logvinenko, R. Tokunaga, *Atten Percept Psychophys* **73**, 1886 (2011).
[17] T. Vladusich, Simultaneous contrast and gamut relativity in achromatic color perception.
[18] B. L. Anderson, *Psychol Rev* **110**, 785 (2003).
[19] B. L. Anderson, J. Winawer, *Nature* **434**, 79 (2005).
[20] B. L. Anderson, J. Winawer, *J Vis* **8**, 1 (2008).
[21] B. Blakeslee, M. E. McCourt, *Vis Res* **44**, 2483 (2004).
[22] E. H. Land, J. J. McCann, *J Opt Soc Am* **61**, 1 (1971).
[23] A. D. Logvinenko, *Neurosci Lett* **334**, 5 (2002).
[24] M. E. Rudd, K. F. Arrington, *Vis Res* **41**, 3649 (2001).
[25] M. E. Rudd, *J Vis* **10**, 1 (2010).
[26] T. Vladusich, M. P. Lucassen, F. W. Cornelissen, *J Vis* **6**, 1126 (2006).
[27] J. Cataliotti, A. L. Gilchrist, *Percept Psychophys* **57**, 125 (1995).
[28] S. W. Kuffler, *J Neurophysiol* **16**, 37 (1953).
[29] P. H. Schiller, *Trends Neurosci* **15**, 86 (1992).
[30] P. Heggelund, *Vis Res* **14**, 1071 (1974).
[31] P. Heggelund, *Vis Res* **14**, 1081 (1974).
[32] P. Heggelund, *Vis Res* **32**, 2107 (1992).
[33] T. Vladusich, M. P. Lucassen, F. W. Cornelissen, *PLoS Comput Biol* **3**, e179 (2007).
[34] D. H. Foster, S. M. Nascimento, *Proc Biol Sci* **257**, 115 (1994).
[35] A. L. Gilchrist, S. Delman, A. Jacobsen, *Percept Psychophys* **33**, 425 (1983).
[36] S. Zdravković, E. Economou, A. Gilchrist, *Perception* **35**, 1185 (2006).
[37] A. Radonjić, D. Todorović, A. Gilchrist, *J Vis* **10**, 12 (2010).
[38] A. L. Gilchrist, *Science* **195**, 185 (1977).
[39] M. K. Albert, *Perception* **35**, 433 (2006).
[40] A. L. Gilchrist, V. Annan, *Perception* **31**, 141 (2002).
[41] K. J. Linnell, D. H. Foster, *Perception* **31**, 151 (2002).
[42] J. A. Schirillo, S. K. Shevell, *Perception* **31**, 161 (2002).
[43] D. Marr, *Vision: A computational investigation into the human representation and processing of visual information* (The MIT Press, 1982).
[44] T. Poggio, V. Torre, C. Koch, *Nature* **317**, 314 (1985).

Brightness and Darkness as Perceptual Dimensions

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A common-sense assumption concerning visual perception states that brightness and darkness cannot coexist at a given spatial location. One corollary of this assumption is that achromatic colors, or perceived grey shades, are contained in a one-dimensional (1-D) space varying from bright to dark. The results of many previous psychophysical studies suggest, by contrast, that achromatic colors are represented as points in a color space composed of two or more perceptual dimensions. The nature of these perceptual dimensions, however, presently remains unclear. Here we provide direct evidence that brightness and darkness form the dimensions of a two-dimensional (2-D) achromatic color space. This color space may play a role in the representation of object surfaces viewed against natural backgrounds, which simultaneously induce both brightness and darkness signals. Our 2-D model generalizes to the chromatic dimensions of color perception, indicating that redness and greenness (blueness and yellowness) also form perceptual dimensions. Collectively, these findings suggest that human color space is composed of six dimensions, rather than the conventional three.

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Introduction

It is well-known that our perception of achromatic colors, or grey shades, depends on the contrast between adjacent surfaces [1]. A nearby surface induces either brightness or darkness into the target depending on the polarity of the inducing contrast (Figure 1). Brightness is perceived if the target region has higher luminance than the background (increment), whereas darkness is perceived if the target has lower luminance (decrement). It is also known that brightness or darkness is proportional to the contrast magnitude at the inducing luminance edge [1]. In more complex or naturalistic displays, both brightness and darkness may be simultaneously induced on a single surface. Some computational models of achromatic color perception [2–5] posit that brightness and darkness subtract to determine the perceived grey shade. This is equivalent to stating that bright and dark constitute the endpoints of a one-dimensional (1-D) achromatic color space containing all possible grey shades.

The 1-D computational model is contradicted by the findings of several psychophysical studies in which subjects attempt to match achromatic colors associated with different image regions (reviewed in [6]). In a typical achromatic color-matching experiment, subjects adjust the luminance of a matching surface such that the appearance of the surface matches the appearance of a reference surface. Many researchers have observed that, when such matches are completed, residual differences in the color appearance of reference and matching surfaces often persist. Such residual unmatched differences are consistent with a computational model in which achromatic color space is composed of two or more dimensions [6–8]. According to one such model [6,7], the achromatic color space is composed of one dimension corresponding to surface reflectance and the other dimension corresponding to illumination intensity. One key problem with this model is that it assumes that subjects can independently estimate reflectance and illumination, even though the eye receives only a mixture of these two information sources—a difficult, though not insurmountable, problem known as color constancy [9,10]. More immediately, it remains unclear how such a model can explain any difficulty subjects may have in matching achromatic colors in flat, computer-generated displays. As computer screens only emit light, it becomes difficult or impossible to meaningfully parse the visual display into reflectance and illumination components (just as, for example, the impression of depth is critically impoverished in the absence of binocular disparity).

The present work represents an alternative approach to identifying the dimensions of achromatic color space. Our approach is motivated by the possibility, foreshadowed above, that brightness and darkness may themselves constitute perceptual dimensions [8]. As detailed in the Discussion section, this approach offers certain advantages over the reflectance–illumination theory of achromatic color representation [6,7], including neural plausibility. Indeed, attempts have previously been made [8,11,12] to link perceived brightness and darkness to the respective properties of the parallel bright (ON) and dark (OFF) visual pathways. Although the ON and OFF pathways run in parallel from

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Author Summary

Vision scientists have long adhered to the classic opponent-coding theory of vision, which states that bright–dark, red–green, and blue–yellow form mutually exclusive color pairs. According to this theory, it is not possible to see both brightness and darkness at a single spatial location, or an extended set of locations, such as a uniform surface. One corollary of this statement is that all perceivable grey shades vary along a continuum from bright to dark. At first glance, the notion that brightness and darkness cannot coexist on a single surface accords with our common-sense notion that a given grey shade cannot be simultaneously both brighter and darker than any other grey shade. The results presented here suggest that this common-sense notion is not supported by experimental data. Our results imply that a given grey shade can indeed be simultaneously brighter and darker than another grey shade. This seemingly paradoxical conclusion arises naturally if one assumes that brightness and darkness constitute the dimensions of a two-dimensional perceptual space in which points represent grey shades. Our results may encourage scientists working in related fields to question the assumption that perceptual variables, rather than sensory variables, are encoded in opponent pairs.

the primate retina to the second processing area (V2) of visual cortex [13], direct evidence linking them to brightness and darkness perception is lacking [14].

Here we endeavor to directly test the hypothesis that brightness and darkness form the perceptual dimensions of achromatic color space. We devise some simple visual displays in order to demonstrate that brightness and darkness signals remain separated at the highest levels of processing, rather than interacting by subtraction. In one such display, for example, a grey reference ring is bordered by a black disk and a white background (Figure 2A). The inner edge between ring and disk, and the outer edge between ring and background, have equal contrast ratios but opposite polarities. The black disk thereby induces brightness into the ring, whereas the white background induces darkness. In a second display, the grey reference ring is bordered by a white disk and a black background (Figure 2B), with the complementary consequences in terms of induction.

We model the grey shade associated with the reference ring as a point in a 2-D "grey space" formed by the induced brightness and darkness signals. Likewise, we model the grey shade associated with a matching ring—which differs from the reference ring in terms of either luminance, contrast, or both—as a point in grey space. In two psychophysical experiments, we quantify the perceptual differences between many pairs of reference and matching rings. We find that grey shades are identical only if the ring, disk, and background all possess the same luminance values in both reference and test displays (the displays are identical). The residual perceptual differences between non-identical display pairs are well-predicted by our 2-D model, even when the details of the experimental design differ markedly.

Results

Experiment One: Simultaneous Presentation, Variable Edge Contrast

The rationale of Experiment One is perhaps best illustrated through an example: consider the above-mentioned

Figure 1. Brightness and Darkness Induction

Viewed from left to right, the grey disks appear to vary from dark to bright, even though they share the same luminance value. This *induction effect* arises because the background luminance varies along a gradient, leading to a change in the polarity and magnitude of contrasts formed against the disks. Brightness refers to the perceived luminance, or grey shade, of the disk when the luminance of the disk is greater than that of the background. Conversely, darkness is defined as the perceived luminance of the disk when the luminance of the disk is less than that of the background. The conventional way of thinking about this perceptual effect is that darkness is simply the negative of brightness, meaning that all the grey shades above are contained in a 1-D continuum, like real numbers along a number line.

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stimulus in which a black disk induces brightness and a white background induces darkness into a reference ring (Figure 2A). The subject attempts to adjust the luminance of the matching ring to make it appear the same grey shade as the reference ring. Now suppose that the magnitude of brightness and darkness induced into the matching ring is much less than that induced into the reference ring (Figure 2A). In other words, the matching background is light grey (rather than white) and the matching disk is dark grey (rather than black). Assuming that brightness and darkness constitute perceptual dimensions, the subject can never adjust the luminance of the matching ring to make the reference and matching rings appear exactly the same grey shade. To match the brightness dimension, for example, the subject must increase the contrast of the brightness-inducing edge in the matching display to equal the high contrast of the brightness-inducing edge in the reference display. Conversely, the subject must increase the contrast of the darkness-inducing edge in the matching display to equal the high contrast of the darkness-inducing edge in the reference display. These two options are mutually incompatible, as *increasing* the contrast of the brightness-inducing edge must necessarily *decrease* the contrast of the darkness-inducing edge, and vice versa. Thus, in attempting to decrease the mismatch in the brightness dimension, the subject inadvertently increases the mismatch in the darkness dimension, and vice versa.

The above reasoning implies that only partial color matches are possible in such a display. It further implies that the ease with which subjects can make matches will increase as the contrast difference between reference and matching displays decreases. To estimate the quality of achromatic color matches in experiment one, we had subjects rate the "possibility of making a perfect match" on a 1–10 scale, after they had completed each setting (10 = perfect match; 1 = no possible match; intermediate values = partial matches of variable quality).

The results of Experiment One indicate that the possibility of making achromatic color matches declines with the contrast difference between the reference and matching rings (Figure 3). When the reference ring was bordered by a dark disk and bright background, subjects set the luminance of the matching ring closer to the luminance of the bright background. This implies that subjects placed more weight on

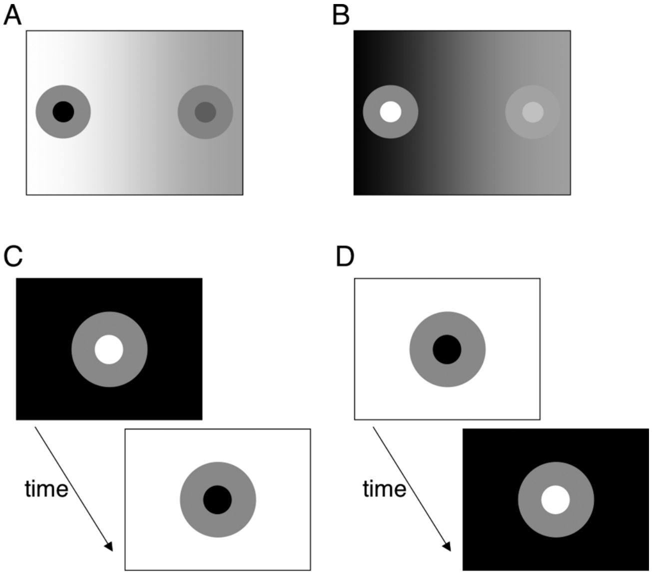

Figure 2. Stimuli Used in the Experiments

We are interested in the question of how to describe, for example, the achromatic color percept of a ring surrounded by a dark disk inducing brightness and a white background inducing darkness. Previous work, summarized in the main text, suggests that achromatic color space is composed of two or more dimensions. Here we argue that the achromatic colors of the above rings are described by separate brightness and darkness dimensions.

(A) Experiment One. Stimuli composed of a background brighter than both the reference (left side) and matching (right side) rings. A horizontal luminance gradient was rendered along the midline of the background such that the contrast formed by disk and background was different on the two sides (the gradient did not extend to the rings). Note that the contrast formed by the ring and disk on the reference side was of the opposite polarity to the contrast formed by the ring and background.

(B) Similar to (A) except that the background was darker than the rings, whereas the disks were brighter than the ring. In each stimulus, the background and central disk induced brightness or darkness into the rings by means of simultaneous contrast.

(C,D) Experiment Two. The polarity relationships reversed between successive presentations of reference and matching displays. See text for details of the experiments.

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matching darkness (induced by the brighter background) rather than brightness (induced by the darker disk). When the contrast of the darkness-inducing edge was low on the reference side of the display, for example, subjects set the luminance of the matching ring close to the luminance of the matching background in order to match this low contrast. More generally, we can say that the luminance settings fell close to theoretical predictions based on an assumption of perfect darkness matching: subjects *attempted to match the contrast of the darkness-inducing edge* across reference and matching rings, largely ignoring the contrast of the brightness-inducing edge. The results were rather different when the reference ring was bordered by a bright disk and dark background. In this case, subjects always set the luminance of the matching ring close to the luminance of the reference ring. This implies that subjects placed roughly equal weight on matching brightness and darkness in these conditions. Nonetheless, subjects rated the task of setting perfect color matches as progressively less possible as the contrast difference between match and reference displays increased, independently of the type of background.

To better understand the nature of achromatic colors, we modeled grey shades as points in a 2-D achromatic color space consisting of brightness and darkness dimensions. According to this model, subjects can perfectly match either brightness or darkness in our displays, but generally cannot match both simultaneously. We estimated the weights associated with brightness and darkness for each stimulus display by fitting the model to the luminance settings made by subjects (Materials and Methods). These fits were extremely accurate, explaining more than 96% of the variance in subjects' settings. The weights were allowed to vary with background and disk luminance to simulate gain control [4,5]: the influence of gain control was, however, quite small ($\sim$5% of the mean weight values) and did not affect our results greatly. We then attempted to predict the possibility ratings made by subjects based on these fitted weights. Within the 2-D perceptual space, we constructed a simple dissimilarity metric based on a modified version of the city-block method (Materials and Methods). These predictions agree remarkably well with subjects' possibility ratings (Figure 3).

We next plotted grey shades associated with matching rings as points in a 2-D grey space (Figure 4). We explain the impossibility of setting perfect matches by noting that subjects could only set grey values in the reference ring along the dotted colored lines (or directly along the horizontal and vertical axes, assuming that both edges share the same polarity) indicated in Figure 4. This is because adjusting the luminance of the matching ring to increase brightness (darkness) involves a simultaneous decrease in the amount of darkness (brightness). Subjects could therefore only adjust achromatic color of the reference ring along a single dimension—corresponding to luminance—within the 2-D grey space. Subjects were simply unable to tap into the rich gamut of achromatic colors available in the entire 2-D space.

The values of fitted brightness and darkness weights in our model reveal that darkness is about four times stronger than brightness in displays containing bright backgrounds (Figure 4). Why did subjects place more weight on matching the darkness dimension with bright backgrounds? We explain this behavior in terms of the well-known observation that darkness is inherently stronger than brightness [11,15,16], combined with the unequal circumferences of inner and outer ring edges. With bright backgrounds, the circumference of the outer darkness-inducing edge was three times the circumference of the inner brightness-inducing edge. Darkness was therefore weighted more heavily than its inherent value. With dark backgrounds, however, the circumference of the inner darkness-inducing edge was one-third of the circumference of the brightness-inducing edge. In this case, brightness and darkness weights were roughly equal. From these considerations, we calculate that edge weights are related to circumference by a power function with exponent $\sim$0.63 and that darkness is inherently about twice as strong as brightness (see Materials and Methods). This estimate is consistent with available data [11,15].

The dominance of darkness induction with bright backgrounds also indicates that possibility ratings were not based on the computation of Euclidian vectors in the 2-D space. Unlike the case with dark backgrounds (Figure 4)—where brightness and darkness weights were equally balanced—subjects did not minimize the vector between reference and matching rings. We instead found that the city-block metric

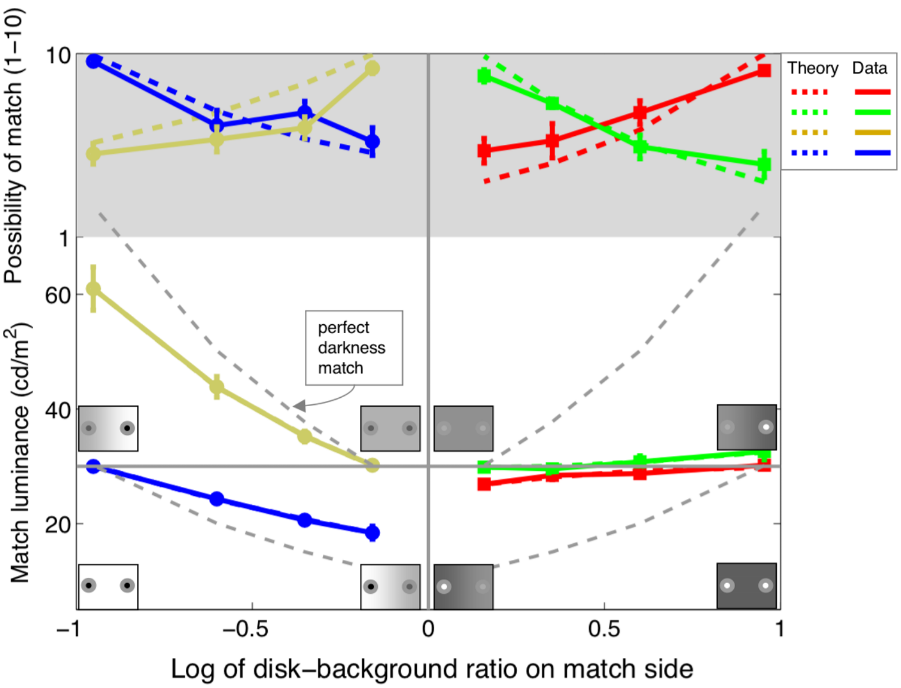

Figure 3. Possibility of Match Plotted against the Contrast Difference between Reference and Matching Displays

Average data from six subjects (error bars indicate standard errors of the mean). With bright backgrounds (left side), subjects adjusted the luminance of the matching ring to be either much higher (yellow data points in white region) or much lower (blue data points in white region) than the luminance of the reference ring (always at 30 cd/m^2). The dotted grey lines denote perfect darkness matches, indicating that subjects weighted darkness more heavily than brightness in this situation. With dark backgrounds (right side), subjects set the matching luminance close to the reference luminance (red and green data points in white region). In both cases, however, subjects rated matches as progressively less possible as the contrast difference between reference and matching sides of the displays increased (data points joined by continuous lines in grey region). This implies that brightness and darkness constitute dimensions of achromatic color space. We modeled this 2-D space by estimating brightness and darkness weighting factors from the luminance data (model fits are the continuous lines in the white region) and then predicting the possibility ratings from the fitted weights (dotted lines in the grey region). The model predictions agree reasonably well with the data. Symbols representing the stimuli are included to assist understanding of the data and should not be considered as realistic representations.

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[6]—in which residual color mismatches in the brightness and darkness dimensions are summed—is far more suitable for modeling the rating data (Materials and Methods). This result further implies that brightness and darkness pathways remain physically separated even at the highest processing levels (see Discussion).

Experiment Two: Successive Presentation, Variable Edge Polarity

In Experiment Two, we presented two grey rings in rapid succession, rather than simultaneously (Materials and Methods). Subjects first viewed the reference display (one second duration), followed immediately by the matching display (also one second duration). We employed a *similarity rating procedure* in which subjects rated how well the grey shade of the matching ring matched the grey shade of the reference ring (10 = perfect match; 1 = as different as black and white; intermediate values = partial matches of variable quality). We kept the overall contrast the same between the reference and matching displays but varied the relationship between edge polarities. In one condition (Figure 2C), the reference ring was bordered by a black background and a white disk. The subsequent matching ring was bordered by a white background and a black disk. A second condition was composed of the complementary set of polarity relationships (Figure 2D). In two control conditions, the polarity relationships of the reference and matching displays (disks and backgrounds) remained the same over the interval. In each trial, we varied the luminance of the reference ring between the maximum and minimum luminance values associated with the disk and background (see Materials and methods). The luminance of the matching ring remained constant throughout. The aim of the experiment was to determine the luminance value of the reference ring that produces the best color match with the matching ring. Note that subjects did not actually adjust any variables in the experiment, so the terms "reference" and "matching" are used in the heuristic sense in the context of the present experiment.

By systematically manipulating edge polarity across reference and matching displays—but keeping the overall contrast the same—we sought to take advantage of the finding in Experiment One that brightness and darkness induction depend on relative edge circumference. All else being equal, the ring-background edge of a given display induced stronger brightness or darkness than the ring-disk edge. This implies that *the achromatic color of the ring changes when edge polarity reverses* across reference and matching displays. Critically, we used the *same ratio of edge circumferences* in Experiments One and Two (Materials and Methods). This allowed us to make a set of theoretical predictions—based on the estimated brightness and darkness weights obtained in Experiment One—to test against the data from Experiment Two. For each of the four conditions of Experiment Two, we inserted the brightness and darkness weights derived from Experiment

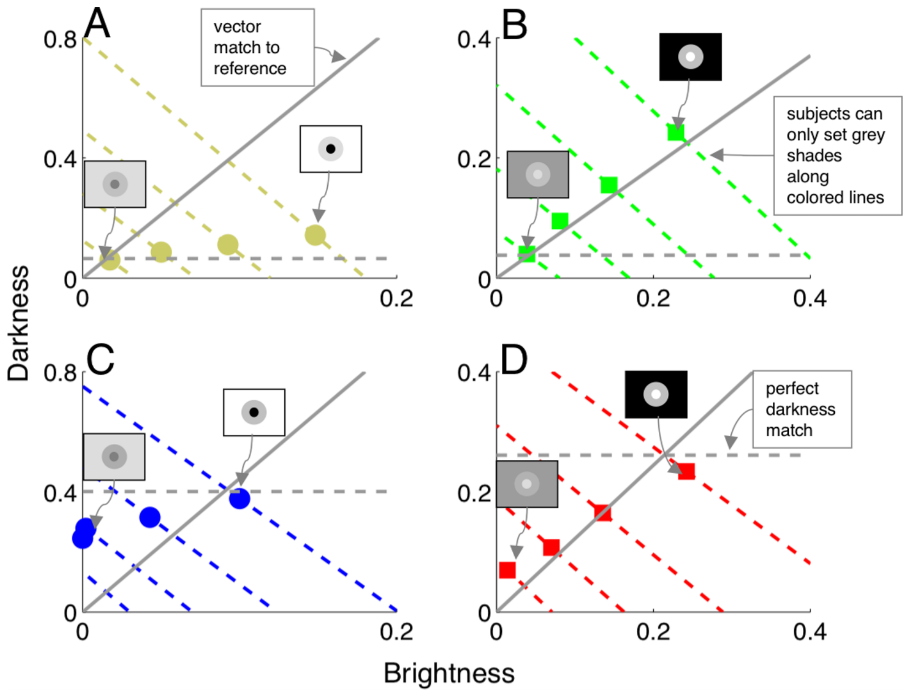

Figure 4. Brightness and Darkness as Perceptual Dimensions

(A–D) Achromatic color space consisting of brightness and darkness dimensions. For each luminance value of the matching ring, we plot the corresponding grey shade as a point in the 2-D grey space. Horizontal dotted lines denote perfect darkness matches. Dotted colored lines represent the gamut of grey shades available in the single dimension of luminance space along which subjects can physically adjust the matching ring. Solid grey lines are the approximate vector projections of the grey shade associated with the reference ring onto all matching displays. The intersections of these projection lines with the lines-of-adjustment roughly indicate the grey shades that subjects would set if they were minimizing the vector between reference and matching rings. Subjects did not appear, however, to minimize this vector. This is particularly evident with brighter backgrounds (A,C), where subjects placed far more weight on matching the darkness component than the brightness component. The different scales for brightness and darkness in (A) and (C) provide further evidence that subjects weighted darkness more heavily than brightness.

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One into the equations governing the 2-D grey space (Figure 5).

To understand the resultant predictions, consider first a control condition in which the disk and background luminance values are identical for reference and matching displays (Figure 5A). It is clear that the best match (similarity rating = 10) occurs when the reference and matching rings share identical luminance values. In terms of Figure 5A, the black square representing the matching ring coincides exactly with the middle green disk. As the reference- to matching-ring luminance ratio varies in either direction, however, we expect systematic and symmetric deviations from the perfect match. In other words, we expect only partial matches for the remaining green disks in Figure 5A.

A different scenario arises when the polarity relationships between reference and matching rings are reversed. Consider, for example, the black square representing the matching ring in Figure 5B. It is clear that none of the red disks corresponding to the reference rings coincide with the position of the black square. This implies that subjects cannot choose a luminance value of the reference ring to ensure an exact match with the matching ring. The closest possible match, in this case, coincides not with the middle red disk but with one of the disks nearer the bottom of the line of red disks. This observation implies that, in addition to rating the resultant similarity as less than perfect, subjects should choose a luminance value for the reference ring that deviates systematically from the luminance value of the matching ring. The model predicts, in other words, a skewed relationship between similarity ratings and the reference- to matching-ring luminance ratio.

The mean ratings of six subjects are plotted in Figure 6 along with the model predictions. To a first approximation, the model accurately predicts many aspects of the data. In particular, the model correctly predicts the roughly symmetric rating profiles in the control conditions (Figure 6A and 6C). The model also correctly predicts the skewed nature of the data curves in the reversed-polarity conditions (Figure 6B and 6D). The model does fall down somewhat, however, in predicting the magnitude of the deviation from perfect matches in these conditions. More specifically, the model predicts close to perfect similarity ratings for certain luminance ratios in the condition corresponding to the white reference background and black disk (Figure 6D). The data curve does not support this prediction but rather appears to peak at a level comparable to the peak associated with the curve associated with the black reference background and white disk (see Discussion). In summary, the 2-D model does a reasonable job of quantitatively predicting the results of an experiment differing in several details from the original experiment from which the model was derived.

Discussion

In Experiment One, we showed that as the contrast difference between reference and matching displays increased, subjects were progressively less able to produce perfect achromatic color matches. Subsequent modeling of

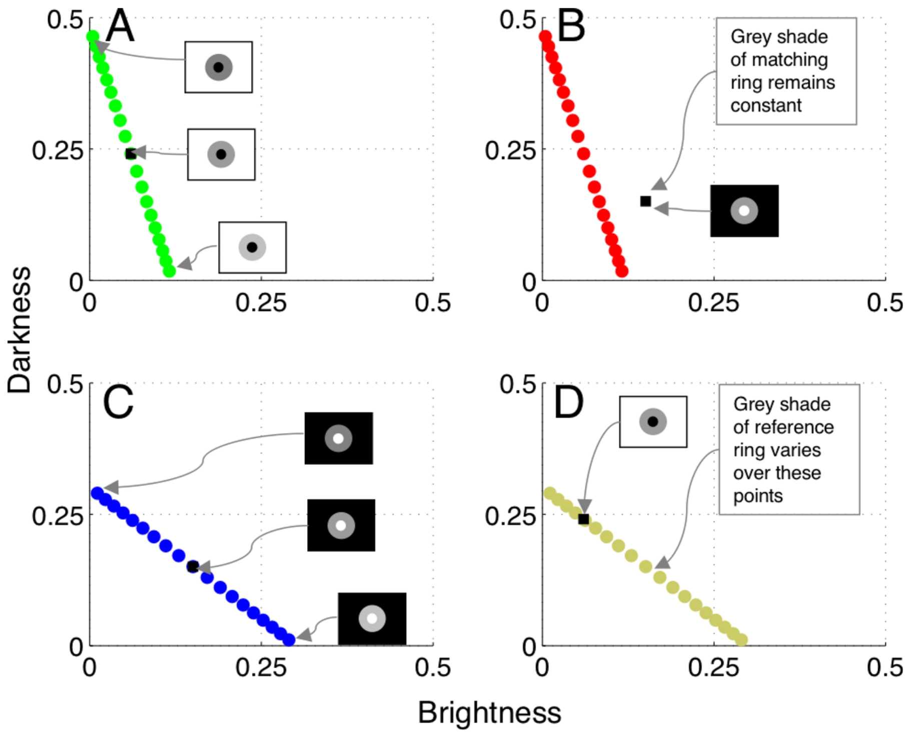

Figure 5. Model Predictions for the Reversed-Polarity Experiment (Experiment Two)

The model predicts that subjects will rate ring pairs as identical only when the grey shades associated with reference (colored disks) and matching (black squares) coincide in grey space (A,C). Otherwise, the model predicts that perfect matches will not be possible (B,D). The black square in (D) does not coincide exactly with the position of a yellow disk, although it is very close.

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these data supported the conclusion that brightness and darkness form perceptual dimensions, with darkness being weighted twice as strongly as brightness. One problem with this interpretation, however, was that decreasing the ring contrast led to a "foggy" appearance resembling transparency [17,18]. Could this fogginess have caused the reported difficulty in making perfect matches? In Experiment Two, we generated stimuli in which overall contrast was high in both reference and match displays. Thus, we reasoned, any difficulty in matching achromatic colors could not be attributable to differences in overall contrast. The similarity ratings of subjects were reasonably consistent with the quantitative predictions of our 2-D model. Perhaps the most important discrepancy was that the model predicted perfect color matches in cases where subjects actually perceived residual color differences. This discrepancy may result from gain control acting on edge signals [4,5,19–21]—which would act to curve nominally straight lines in achromatic color space [6,8]—thereby distorting our estimates of points in grey space. Although we found a small effect of gain control in Experiment One, we chose to omit this factor in our predictions for Experiment Two in order to cap the degrees of freedom of our model. Alternatively, it may be that achromatic color space is composed of even more than two dimensions, with luminance offering a possible candidate for the extra dimension [22,23]. Further experiments are clearly required to resolve this issue.

What might be the functional advantage of the 2-D grey space introduced here? Relative to a 1-D space, the range of achromatic colors available in a 2-D space is enormous. Whereas a 1-D space encodes (n) grey shades (just noticeable differences), a 2-D space contains $\left(\frac{n}{2}\right)^2$ grey shades. Compared to a 1-D space with n = 1,000, for example, the number of discriminable grey shades in a 2-D space equals 250,000. Such a 2-D representation may play a key role in the encoding of achromatic colors in natural environments, where object surfaces form both increments and decrements with respect to variegated backgrounds [24]. The preservation of brightness and darkness information in a 2-D space ensures that the visual system is sensitive to the variance and skewness of luminance pixels bordering an object, rather than just the mean. Such sensitivity may facilitate object detection at low contrasts and play a role in texture discrimination [25–30].

Our framework is consistent with the recent finding that the visual system uses skewness as an image cue to classify bright and dark image regions into "object" and "light" properties [29]. The computation of object and light properties is not, however, required to explain our data. A perceptual space composed of brightness and darkness dimensions explains most of our findings in a parsimonious and quantitative manner. Indeed, our results provide a challenge to anchoring theories of achromatic color perception [10,31] and to the proposal that the dimensions of achromatic color space correspond to object and light properties [6,7]. Several studies have shown that subjects often need to be explicitly instructed to interpret flat, computer-generated displays in terms of object and light properties [21,32,33]. In the present study, subjects were explicitly instructed to match grey shades they saw, rather than putative object or light properties. Importantly, some recent psychophysical findings suggest that judgments of object and light properties may be based on spatial

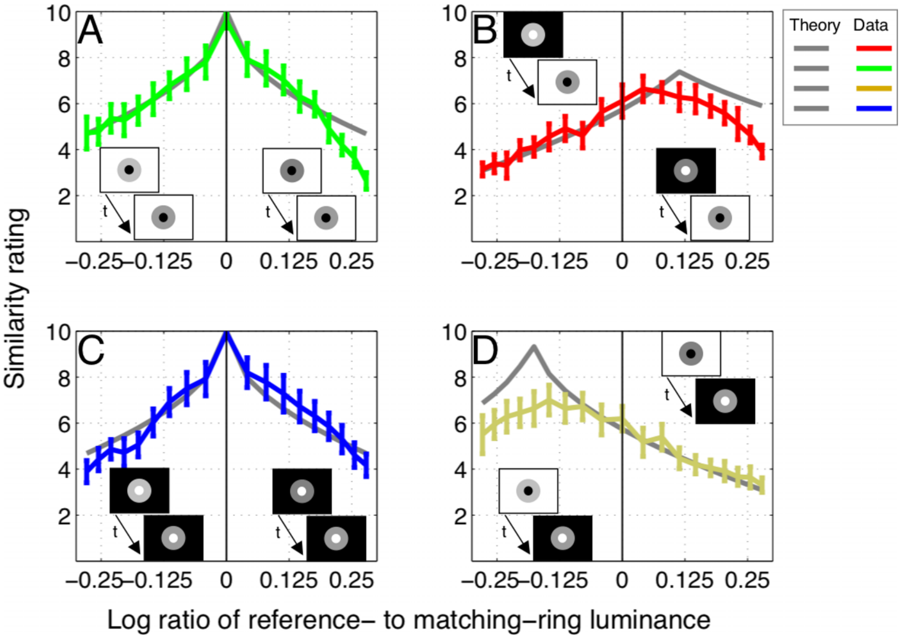

Figure 6. Results of the Reversed-Polarity Experiment (Experiment Two)

Average data from six subjects (error bars indicate standard errors of the mean). The model correctly predicts the data curves associated with the two control conditions (A,C). The data curves for the reversed-polarity conditions are consistent with the predicted skewness (B,D), and to a lesser degree with the amount of mismatch.

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comparisons of surface brightness (and, by extension here, darkness) across different regions of a 3-D scene [34,35]. In our displays, it remains problematic to describe how object and light properties might vary with the difference in contrast magnitude (Experiment One) or polarity (Experiment Two) between reference and matching displays. How, for instance, should one interpret a change in edge polarity between displays? The polarity reversal would not itself seem to carry conflicting information about object and light properties, as both local contrast magnitude and luminance remain the same.

It is well-known that the edges directly bordering a target surface (local edges) and edges distant from the target surface (remote edges) both contribute to achromatic color [3–5,20,21]. The present study helps to clarify the results of our previous study [5] in which we found that subjects had greater difficulty making achromatic color matches with opposite-polarity (relative to same-polarity) combinations of local and remote edges. This puzzle is clarified by noting that opposite-polarity edge combinations simultaneously induce both brightness and darkness into a surface. As in the present study—in which we simultaneously induced brightness and darkness at different local borders—this would lead to a situation in which only partial color matches are possible. Consider, for example, a disk-ring reference configuration in which the local edge induces brightness into the *disk*, whereas the remote edge induces darkness into the disk. In our previous experiment, subjects adjusted a matching disk on a uniform background to appear the same grey shade as the reference disk. This means that the polarity of the disk relative to the background could be either an increment or a decrement. Subjects could therefore match either brightness or darkness, but not both.

It is perhaps illuminating to speculate on the phenomenological aspects of simultaneously perceiving brightness and darkness. Anstis [36] studied the "metallic" or "lustrous" appearance of a surface region composed of both brightness and darkness, generated either through monocular or binocular fusion. The binocular effect is generated by fusion of a dark disk (decrement) presented to one eye with a bright disk (increment) presented to the other eye. The monocular version is obtained by rapidly modulating (in time) the polarity of a disk with respect to a steady background [11]. A third (monocular) version of the effect is generated by embedding a grey disk in a black Ehrenstein pattern on a white background [37]. In all cases, edges of opposite contrast polarity combine to give the overall impression of lustre to the surface. Anstis [36] argued that lustrous surfaces often shimmer, leading him to conclude that lustre is associated with competition between local bright (ON) and dark (OFF) channels [12]. Our results suggest precisely the opposite conclusion. We claim that ON and OFF channels remain separate at the highest levels of processing, giving rise to percepts of simultaneous brightness and darkness, which can be interpreted as appearing lustrous. A weak impression of lustre may be seen in Figure 2A and Figure 2B, where the higher-contrast rings appear "sharper" or more "metallic" than the "softer-appearing" low-contrast rings. This conclusion implies that lustre can be dissociated from shimmer.

How much evidence is there to link the properties of ON and OFF pathways with brightness and darkness perception [11,12]? A recent neurophysiological report reveals that gain control operating in early ON and OFF pathways is sensitive to the variance, but not the skewness and kurtosis, of background pixels [19]. Demonstrations of perceptual sensitivity to skewness [29] thus further highlight the mismatch between the properties of early ON and OFF pathways and achromatic color perception [12,14]. As indicated previously,

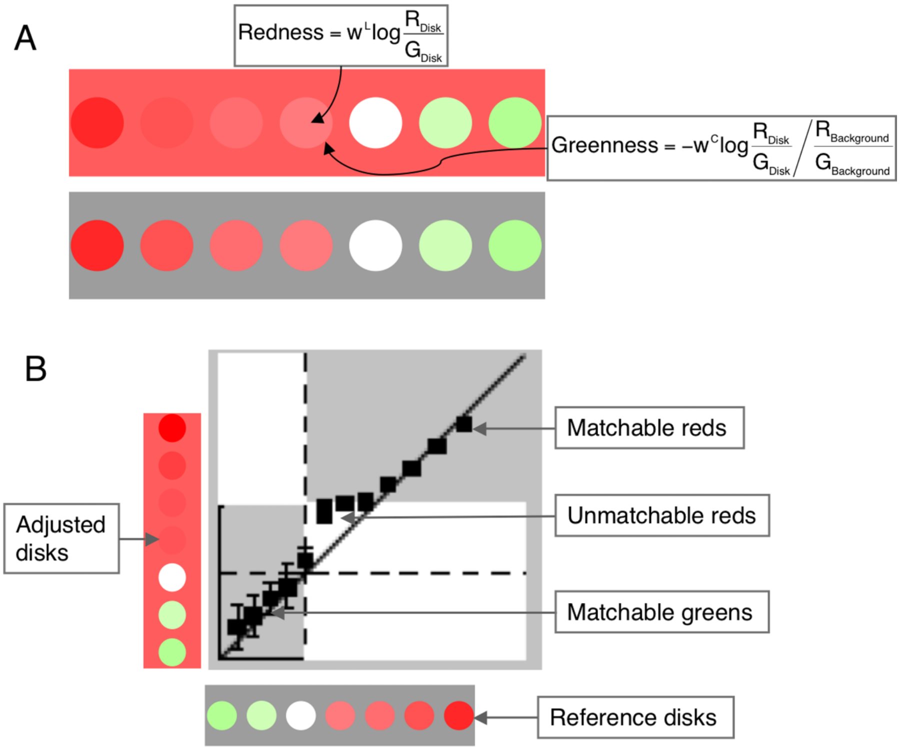

Figure 7. Redness and Greenness as Perceptual Dimensions

(A) Stimulus conditions giving rise to mixed color percepts composed of complementary local and edge-induced colors.

(B) The *x*- and *y*-axes correspond to the CIE-designated redness and greenness of the reference and matching displays, respectively. The matching (or adjustable) disk is matchable to the reference disk when the reference disk is green (the red matching background adding greenness to the matching disk) or more red than the matching background (the red matching background subtracting redness from the matching disk). No match can be made, however, when the disk is *less red* than the matching background. We claim that this is because the matching background adds greenness to the matching disk, which remains separate from the local redness. As there is no corresponding color induced from the grey reference background into the reference disk, only a partial color match is possible. Data adapted from [18].

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separate ON and OFF pathways are maintained even at the level of V2 in monkey visual cortex [13]. Researchers have claimed that some neurons in V1 and V2 encode achromatic colors [38–41]. These claims have, however, been disputed [42–44]. To correlate with achromatic color perception in our displays, a visual area would need to combine local edge information into a global surface representation [4,5,21]. The computational nature of this brain area remains to be elucidated.

As a final twist, we propose that redness and greenness—as well as blueness and yellowness—may form perceptual dimensions [18], rather than canceling [45–47]. Ekroll et al. [18] have shown that subjects can only match certain combinations of local and remotely induced colors (Figure 7). Subjects can, for example, adjust a matching disk on a red background to appear the same hue and saturation as a green reference disk on a grey background. Subjects can also make a suitable match when the *reference disk is a more saturated shade of red than the matching background*. Subjects cannot, however, perform suitable matches when the *reference disk is a shade of red less saturated than the matching background*. Ekroll et al. described similar results for blueness and yellowness perception.

We explain these paradoxical results in terms of the assumption that redness and greenness (blueness and yellowness) form perceptual dimensions. Following Brenner et al. [48], we propose that local color signals (within a surface region) and remote color signals (induced at edges) combine to give rise to the color percept. If the local color signal is red, for example, and the induced color signal is green, then the resultant percept will be composed of both redness and greenness. In the above example, the matching disk *can* be adjusted to match the reference disk *when the reference disk is green*. To understand why, consider a subject attempting to match only the local green color. Matching the local green component alone will not be sufficient because the red matching background also adds greenness to the matching disk. In order to make a perfect match, the subject therefore dials down the physical greenness of the matching disk by an appropriate amount. Similarly, subjects *can* perfectly match the reference disks whose *red shades are more red than the matching background*. Again consider a subject setting a match for the local redness alone. This match will not be perfect because the red matching background subtracts redness from the matching disk. A perfect match thus requires dialing the physical redness of the matching disk up by a certain amount. No match can be made, however, when the reference disk is *less red than the matching background*. Consider a subject matching only the local redness. This requires setting the matching disk as a physical shade of red slightly less saturated than the red of the matching background. The key point here is that the red matching background induces greenness into the match disk. The 2-D model advocated here implies that this induced greenness does not subtract from the local redness. As there is no corresponding greenness induced from the grey reference background into the reference disk, matching only the local redness will *not* give rise to a perfect color match. In such cases, subjects display a wide range of behavioral strategies in a vain attempt to solve an insoluble problem [18].

Materials and Methods

Experiment One. Monitor calibration and experimental methods/procedures were similar to those documented elsewhere [5]. The stimuli consisted of a reference ring of constant luminance (30 cd/m^2). The starting value of the matching ring varied randomly between 10 and 90 cd/m^2. The reference disk and background adopted luminance values of either 10 and 90 cd/m^2 (high contrast) or 25 and 36 cd/m^2 (low contrast). The matching disk and background adopted luminance values of either 10 and 90, 15 and 60, 20 and 45, or 25 and 36 cd/m^2. In total, 16 reference-match combinations of these luminance values were used. The diameters of the inner and outer ring edges were respectively 2° and 6°, and the centers of matching and reference disks were 14.4° apart. The gradient in background luminance was restricted to be within 6.2° about the midline of the monitor. Order of stimulus presentation was pseudo-randomized.

Computational model. We seek to characterize the residual perceptual difference between reference and matching rings, as follows. Let R, B, D correspond to the luminance values of the ring (R), the bright (B) contiguous surface, and the dark (D) contiguous surface (either disk or background). Following our previous approach [5], we define the respective brightness and darkness signals associated with the ring as $x_B = w_B[\log\frac{R}{D}]^+$ and $x_D = w_D[\log\frac{B}{R}]^+$. The parameters w_B and w_D represent the weights applied to the increment and decrement signals computed in the ON and OFF pathways of early visual processing [11,12]. The operator $[\ ]^+ = \max\left(\log\frac{a}{b}, 0\right)$ represents half-wave rectification, implying that only non-negative brightness and darkness values are possible. By writing separate equations for matching and reference displays with appropriate scripting (superscripts m and r for match and reference), we define the matching task as the task of setting $x_B^m = x_B^r$ and $x_D^m = x_D^r$. We solve these equalities separately for $\log R^m$, giving $\log R_B^m = \log\frac{R^r D^m}{D^r}$ and $\log R_D^m = \log\frac{R^r B^m}{B^r}$. We then assume that subjects weight the two estimates of $\log R^m$, giving the generic solution for the log of the matching ring luminance as $\log R^m = \widehat{w}_B^j \log\frac{R^r D^m}{D^r} + \widehat{w}_D^j \log\frac{R^r B^m}{B^r}$, with the superscript $j = 1,2$ representing the inner and outer edges. We estimated the weights using a nonlinear least-squares optimization routine. Note that we identify the values of the estimated weights with the *theoretical weights* associated with brightness and darkness dimensions, $\widehat{w}_B^j = w_B^j$ and $\widehat{w}_D^j = w_D^j$. We adopt this interpretation even though the theoretical weights cancel during calculation of the separate brightness and darkness solutions, $\log R_B^m$ and $\log R_D^m$. The argument is that subjects attempt to compromise between perfect darkness and brightness matches by setting $\log R^m$ between the values $\log R_D^m$ and $\log R_B^m$, meaning that we can estimate the *relative brightness and darkness weights*, such that $w_B^j + w_D^j = 1$.

We then separately calculated absolute differences between reference and matching rings in the brightness and darkness dimensions of achromatic color space:

$$\Delta x_B^j = w_B^j \left| \left[\log\frac{R^r}{D^r}\right]^+ - \left[\log\frac{R^m}{D^m}\right]^+ \right| \text{ and}$$
$$\Delta x_D^j = w_D^j \left| \left[\log\frac{B^r}{R^r}\right]^+ - \left[\log\frac{B^m}{R^m}\right]^+ \right|.$$

Note that a perfect match is only possible for "identity matches" ($B^m = B^r$ and $D^m = D^r$). Match possibility was computed using a modified city-block metric suitable for bounded data, $mp_{CB}^j = 10(1 - \mathrm{asin}((\Delta x_B^j + \Delta x_D^j)^{0.5}))$. We also constructed a measure based on the Euclidian metric, $mp_E^j = 10(1 - (\Delta x_B^{j^2} + \Delta x_D^{j^2})^{0.5})$. This measure did not, however, correspond closely with the data, a conclusion consistent with previous results [6]. In practice, we allowed weights to vary linearly with the luminance of the matching background and disk. This factor simulated gain control of edge signals [4,5]. The ensuing model had eight free parameters, two for each of the colored curves in Figure 3. We also tested a model in which the weights remained constant with contrast, giving a total of four free parameters. This model performed only marginally worse. In other words, edge weights did not vary greatly with edge contrast. The results shown in Figure 3 were derived using the more complex model. We assumed throughout the modeling that subjects obeyed one of the constraints, $B^m > R^m > D^m$ or $B^m < R^m < D^m$, depending on the stimulus. This was true for all but the leftmost data point in Figure 4C. All computations were performed in Matlab (version 7.0.4, The MathWorks) using standard and customized functions.

Experiment Two. The design of Experiment Two was the same as that of Experiment One, except for the changes below, which were tailored to counter specific criticisms of the reviewers. The changes were as follows: (1) the reference and matching rings were presented in rapid sequence, rather than simultaneously, in order to minimize the role of eye movements and adaptation (simultaneous presentation would also have required a very steep, therefore noticeable, luminance gradient across the screen); (2) the subjects' task was to *judge the similarity in grey shades* of the successive rings, thereby minimizing the use of elaborate strategies during a matching task. Even though there was no matching task, we adopt the nomenclature of calling the first display the reference and the second the matching display; (3) the polarity of the reference and matching disks and backgrounds either stayed the same or flipped in polarity, whereas the total contrast, $\log\frac{D^r B^m}{B^r D^m}$, remained constant throughout; (4) in each trial, the luminance of the reference ring had one of 19 luminance values, defined as constant steps in log space between the minimum and maximum values of the disk and background (15 and 60 cd/m^2). The value of the matching ring always remained constant at 30 cd/m^2. The experiment had four conditions, with trials being randomized across conditions. In the two control conditions, the polarity of the disks and backgrounds stayed the same ($D^r = D^m = 60$, $B^r = B^m = 15$, $D^r = D^m = 15$, $B^r = B^m = 60$). In the other two conditions, the polarity of the disks and backgrounds flipped ($D^r = B^m = 60$, $B^r = D^m = 15$, $B^r = D^m = 15$, $D^r = B^m = 60$). Subjects performed one entire run of the experiment in order to generate an internal scale for the similarity ratings. The ratio of diameters of the inner and outer ring edges was the same as in Experiment One (1:3). The rings were, however, much larger than in Experiment One, with the ring and disk subtending approximately 3.5° and 10.5°, respectively.

Proof: 1-D space implies perfect achromatic color matching. Letting $x_B = w_B[\log\frac{R}{D}]^+$ and $x_D = w_D\ [\log\frac{B}{R}]^+$ again, assume that the early brightness and darkness signals subtract at a cortical processing stage [13], then *net* brightness and darkness signals are computed as $\Psi_B = [X_B - X_D]^+$ and $\Psi_D = [X_D - X_B]^+$. Since Ψ_B and Ψ_D cannot be simultaneously positive, all possible grey shades can only contain either brightness or darkness, but not both at the same time. Thus, all grey shades can be specified by a single number, as seen most easily by removing the half-wave rectification constraint on Ψ_B and Ψ_D, implying that $\Psi_B = -\Psi_D$ and $-\Psi_B = \Psi_D$. Thus the corollary of the subtraction assumption is that all possible grey shades are contained within a single dimension. To see how a 1-D space implies perfect matching, let Ψ_r and Ψ_m equal either the net brightness or darkness associated with the reference and matching rings, respectively. Letting $\Psi_m = \Psi_r$, we derive $\log R^m = \left(\widehat{w}_B^j \log\frac{R^r D^m}{D^r} + \widehat{w}_D^j \log\frac{R^r B^m}{B^r}\right)(\widehat{w}_B^j + \widehat{w}_D^j)^{-1}$. The existence of this solution shows that the luminance of the matching ring can always be set to achieve a perfect match. We have confirmed this result using a 1-D model of the data presented here.

Calculation of darkness–brightness weight ratio. Let the *true* darkness–brightness weight ratio be represented by $\frac{w_D}{w_B}$. We know the two circumference-biased estimates, $\frac{\widehat{w}_D^{IN}}{\widehat{w}_B^{OUT}} = \frac{w_D}{w_B}\left(\frac{3C^{IN}}{C^{IN}}\right)^n$ and $\frac{\widehat{w}_D^{IN}}{\widehat{w}_B^{OUT}} = \frac{w_D}{w_B}\left(\frac{C^{IN}}{3C^{IN}}\right)^n$. Thus, $\frac{w_D}{w_B} = \frac{\widehat{w}_D^{OUT}}{3^n \widehat{w}_B^{IN}} = \frac{3^n \widehat{w}_D^{IN}}{\widehat{w}_D^{OUT}}$. We solve, $n = \log\sqrt{\frac{\widehat{w}_D^{OUT}}{\widehat{w}_D^{IN}}\frac{\widehat{w}_B^{OUT}}{\widehat{w}_B^{IN}}}\,/\log(3) \approx \log\sqrt{\frac{0.8}{0.2}\frac{0.5}{0.5}}\,/\log(3) \approx 0.63$, giving $\frac{w_D}{w_B} \approx \frac{0.8}{3^{0.63}0.2} = \frac{3^{0.63}0.5}{0.5} \approx 2$.

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References

1. Wallach H (1948) Brightness constancy and the nature of achromatic colors. J Exp Psych 38: 310–324.
2. Grossberg S, Todorovic D (1988) Neural dynamics of 1-D and 2-D brightness perception: A unified model of classical and recent phenomena. Percept Psychophys 43: 241–277.
3. Arrington KF (1996) Directional filling-in. Neural Comput 8: 300–318.
4. Rudd ME, Zemach IK (2004) Quantitative properties of achromatic color induction: An edge integration analysis. Vision Res 44: 971–981.
5. Vladusich T, Lucassen MP, Cornelissen FW (2006) Edge integration and the perception of brightness and darkness. J Vis 6: 1126–1147.
6. Logvinenko AD, Maloney LT (2006) The proximity structure of achromatic surface colors and the impossibility of asymmetric lightness matching. Percept Psychophys 68: 76–83.
7. Heggelund P (1992) A bidimensional theory of achromatic color vision. Vision Res 32: 2107–2119.
8. Izmailov CA, Sokolov EN (1991) Spherical model of color and brightness discrimination. Psychol Sci 249–259.
9. Foster DH (2003) Does colour constancy exist? Trends Cogn Sci 7: 439–443.
10. Gilchrist A, Kossyfidis C, Bonato F, Agostini T, Cataliotti J, et al. (1999) An anchoring theory of lightness perception. Psychol Rev 106: 795–834.
11. Magnussen S, Glad A (1975) Brightness and darkness enhancement during flicker: Perceptual correlates of neuronal B- and D-systems in human vision. Exp Brain Res 22: 399–413.
12. Schiller PH (1992) The ON and OFF channels of the visual system. Trends Neurosci 15: 86–92.
13. Wang Y, Xiao Y, Felleman DJ (2007) V2 thin stripes contain spatially organized representations of achromatic luminance change. Cereb Cortex 17: 116–129.
14. Rossi AF, Paradiso MA (1999) Neural correlates of perceived brightness in the retina, lateral geniculate nucleus, and striate cortex. J Neurosci 19: 6145–6156.
15. Hamada J (1985) Asymmetric lightness cancellation in Craik-O'Brien patterns of negative and positive contrast. Biol Cybern 52: 117–122.
16. De Weert CM, Spillmann L (1995) Assimilation: Asymmetry between brightness and darkness? Vision Res 35: 1413–1419.
17. Anderson BL, Winawer J (2005) Image segmentation and lightness perception. Nature 434: 79–83.
18. Ekroll V, Faul F, Niederee R (2004) The peculiar nature of simultaneous colour contrast in uniform surrounds. Vision Res 44: 1765–1786.
19. Bonin V, Mante V, Carandini M (2006) The statistical computation underlying contrast gain control. J Neurosci 26: 6346–6353.
20. Rudd ME, Arrington KF (2001) Darkness filling-in: A neural model of darkness induction. Vision Res 41: 3649–3662.
21. Rudd ME, Zemach IK (2005) The highest luminance anchoring rule in achromatic color perception: Some counterexamples and an alternative theory. J Vis 5: 983–1003.
22. Shapiro AG, D'Antona AD, Charles JP, Belano LA, Smith JB, et al. (2004) Induced contrast asynchronies. J Vis 4: 459–468.
23. Shapiro AG, Charles JP, Shear-Heyman M (2005) Visual illusions based on single-field contrast asynchronies. J Vis 5: 764–782.
24. Frazor RA, Geisler WS (2006) Local luminance and contrast in natural images. Vision Res 46: 1585–1598.
25. Arend LE, Spehar B (2004) Mechanisms of contrast induction in heterogeneous displays. Vision Res 44: 1601–1613.
26. Brown RO, MacLeod DI (1997) Color appearance depends on the variance of surround colors. Curr Biol 7: 844–849.
27. Chubb C, Nam J (2000) Variance of high contrast textures is sensed using negative half-wave rectification. Vision Res 40: 1695–1709.
28. De Bonet JS, Zaidi Q (1997) Comparison between spatial interactions in perceived contrast and perceived brightness. Vision Res 37: 1141–1155.
29. Motoyoshi I, Nishida S, Sharan L, Adelson EH (2007) Image statistics and the perception of surface qualities. Nature 447: 206–209.
30. Spehar B, Debonet JS, Zaidi Q (1996) Brightness induction from uniform and complex surrounds: A general model. Vision Res 36: 1893–1906.
31. Bressan P (2006) The place of white in a world of grays: A double-anchoring theory of lightness perception. Psychol Rev 113: 526–553.
32. Arend LE, Spehar B (1993) Lightness, brightness, and brightness contrast: 1. Illuminance variation. Percept Psychophys 54: 446–456.
33. Arend LE, Spehar B (1993) Lightness, brightness, and brightness contrast: 2. Reflectance variation. Percept Psychophys 54: 457–468.
34. Robilotto R, Zaidi Q (2004) Limits of lightness identification for real objects under natural viewing conditions. J Vis 4: 779–797.
35. Robilotto R, Zaidi Q (2006) Lightness identification of patterned three-dimensional, real objects. J Vis 6: 18–36.
36. Pinna B, Spillmann L, Ehrenstein WH (2002) Scintillating lustre and brightness induced by radial lines. Perception 31: 5–16.
37. Anstis SM (2000) Monocular lustre from flicker. Vision Res 40: 2551–2556.
38. Kinoshita M, Komatsu H (2001) Neural representation of the luminance and brightness of a uniform surface in the macaque primary visual cortex. J Neurophysiol 86: 2559–2570.
39. Roe AW, Lu HD, Hung CP (2005) Cortical processing of a brightness illusion. Proc Natl Acad Sci U S A 102: 3869–3874.
40. Rossi AF, Rittenhouse CD, Paradiso MA (1996) The representation of brightness in primary visual cortex. Science 273: 1104–1107.
41. Boyaci H, Fang F, Murray SO, Kersten D (2007) Responses to lightness variations in early human visual cortex. Curr Biol 17: 989–993.
42. Cornelissen FW, Vladusich T (2006) What gets filled-in during filling-in? Nat Rev Neurosci 7. doi:10.1038/nrn1869-c1
43. Cornelissen FW, Wade AR, Vladusich T, Dougherty RF, Wandell BA (2006) No functional magnetic resonance imaging evidence for brightness and color filling-in in early human visual cortex. J Neurosci 26: 3634–3641.
44. Vladusich T, Lucassen MP, Cornelissen FW (2006) Do cortical neurons process luminance or contrast to encode surface properties? J Neurophysiol 95: 2638–2649.
45. Hsieh PJ, Tse PU (2006) Illusory color mixing upon perceptual fading and filling-in does not result in "forbidden colors." Vision Res 46: 2251–2258.
46. Hurvich LM, Jameson D (1974) Opponent processes as a model of neural organization. Am Psychol 29: 88–102.
47. Miyahara E, Smith VC, Pokorny J (2001) The consequences of opponent rectification: The effect of surround size and luminance on color appearance. Vision Res 41: 859–871.
48. Brenner E, Granzier JJ, Smeets JB (2007) Combining local and global contributions to perceived colour: An analysis of the variability in symmetric and asymmetric colour matching. Vision Res 47: 114–125.

Simultaneous contrast and gamut relativity in achromatic color perception

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Abstract

Simultaneous contrast refers to the respective brightening (darkening) of physically identical image regions surrounded by regions of low (high) luminance. A common method of measuring the strength of simultaneous contrast is achromatic color matching, in which subjects adjust the luminance of a target region to achieve an achromatic color match with another region. Here we present psychophysical data questioning the assumption, built into many models of achromatic color perception, that achromatic colors are represented as points in a one-dimensional (1D) color space or gamut. We present an alternative model in which achromatic colors are computed as the vector sum of local luminance and contrast vectors in a two-dimensional (2D) perceptual space composed of brightness and darkness dimensions. Achromatic color matches are shown to reflect the relative perceptual distances between points lying on lines defining different reference frames, each dependent on surround luminance, in brightness-darkness space. We term this concept *gamut relativity*. The model thereby suggests a novel geometrical approach to the computational analysis of simultaneous contrast.

Keywords: Achromatic, color, brightness, darkness, contrast, luminance, gamut, relativity

1. Introduction

One of the best known illusions in vision research is *simultaneous color contrast*. In the context of *achromatic color perception*—the perception of gray shades—simultaneous contrast manifests itself in the respective *brightening* and *darkening* of physically identical image regions, such as a series of disks of constant luminance, viewed against surrounding image regions of variable luminance, such as a series of rings varying in luminance from low to high (Fig. 1).

Figure 1: Simultaneous contrast. The disks all have the same luminance values, yet one tends to perceive disks surrounded by rings with luminance higher (lower) than the background as relatively dark (bright). The color bar below represents the one dimensional (1D) space, or gamut, of achromatic colors, as conventionally conceived.

1.1. Psychophysical background and aims

Simultaneous contrast and related effects in achromatic color perception are often modeled under the assumption that all achromatic colors can be specified within a one-dimensional (1D) space, or 1D achromatic color gamut; that is, by means of a *scalar* variable (Arrington, 1996; Blakeslee and McCourt, 1997, 1999, 2004; Cohen and Grossberg, 1984; Dakin and Bex, 2003; Grossberg and Todorović, 1988; Hamada, 1985; Heinemann and Chase, 1995; Land and McCann, 1971; Moulden and Kingdom, 1990; Pessoa et al., 1995; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Rudd, 2010; Spehar et al., 1996; Vladusich et al., 2006b; Wallach, 1948; Whittle, 1986, 1992). According to edge integration models, for instance, the achromatic colors of the disks shown in Fig. 1 are computed as the weighted sum of log luminance ratios determined at local (disk-ring) and remote (ring-background) edges (Land and McCann, 1971; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Rudd, 2010; Vladusich et al., 2006b). In cases where local and remote edges have opposite contrast polarity, as in Fig. 1, these models posit that brightness and darkness signals respectively induced from contrast increments and decrements cancel to produce net achromatic color values. When the net achromatic color is positive, brightness is perceived, and when the net achromatic color is negative, darkness is perceived. The computational convention of treating darkness as the negative of brightness is thereby effectively a statement concerning the 1D nature of the space encoding achromatic colors.

According to conventional 1D models of achromatic color representation, it should be possible to establish exact color matches between pairs of disks shown in Fig. 1. This is because subjects should always be able to adjust the physically 1D variable of disk luminance to establish a match within the perceptually 1D space of achromatic colors, modulo the effects of internal noise (Vladusich et al., 2007). We call such putatively exact matches *absolute* color matches to distinguish them from the concept of *relative* color matches introduced below.

Many vision researchers have, however, noted that subjects are often unable to make absolute color matches between pairs of targets viewed against backgrounds of different luminance or hue (Ekroll et al., 2002, 2004; Whittle, 1992; Logvinenko and Maloney, 2006; Vladusich et al., 2006b, 2007). The difficulty in setting color matches is illustrated in Fig. 2, where physically identical disks are embedded in low-luminance 'match' and high-luminance 'reference' surrounds, respectively. The disks viewed against the low-luminance background are contrast increments, whereas the disks viewed against the high-luminance background are contrast decrements. The task, then, is to choose an increment in the match series that best corresponds to a specific decrement in the reference series. In this example, the author has chosen, as a best match, a decrement in the match series that corresponds to a disk of slightly lower luminance than the target increment in the reference series. The match does not, however, appear to be an absolute one. We argue in this article that the difficulty in establishing absolute color matches can be traced back to the issue of correctly defining the dimensions of achromatic color space.

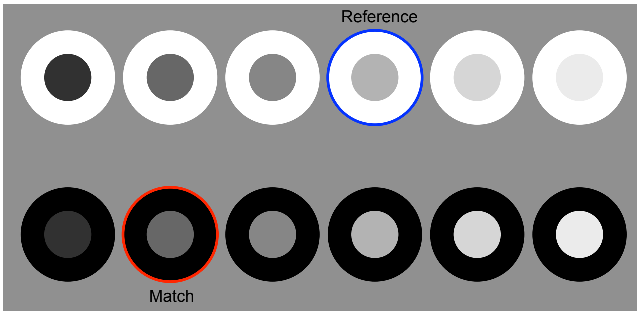

Figure 2: Due to simultaneous contrast, disks surrounded by white rings all appear darker than disks surrounded by black rings. The rings with the red and blue borders indicate the 'reference' and 'match' disks, respectively. The author has chosen, as an *approximate* match, an achromatic color in the match series that corresponds to a disk of lower luminance than the luminance of the reference disk. The color match appears unsatisfactory to the author, an observation consistent with a range of informal observations and psychophysical data (Ekroll et al., 2002, 2004; Whittle, 1992; Logvinenko and Maloney, 2006; Vladusich et al., 2006b, 2007).

To formally investigate the problem of establishing absolute color matches between targets viewed against different surrounds, we designed a psychophysical experiment using stimuli similar to those shown in Fig. 2. The experiment had two components (Fig. 3). In **Step 1**, subjects adjusted the luminance, x_j, of a target disk, j, viewed against a ring, q, that had one of 6 luminance values across different trials, to establish "brightness" matches with a background region, k, with constant luminance, x_k, against which the entire disk-ring configuration was viewed. (The quotation marks are used throughout to distinguish this instructional usage of the term, brightness, from the more technical usage associated

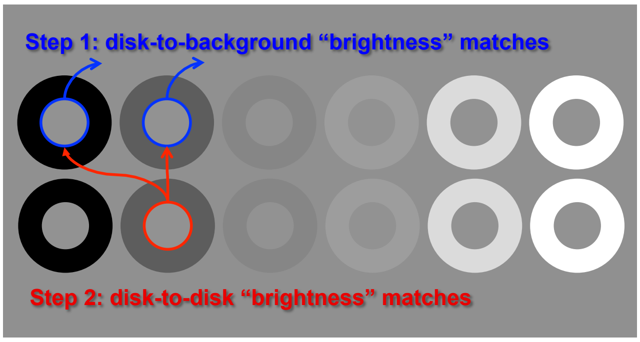

Figure 3: Design of the psychophysical experiment. In **Step 1**, subjects adjusted the luminance, x_j, of the disk, j, surrounded by ring, q, to match the "brightness" of a background region, k, with constant luminance, x_k. In **Step 2**, subjects adjusted the luminance, x_i, of disk, i, surrounded by ring, p, to match the "brightness" of disk, j, which was now equal to the mean disk luminance setting across trials, $\bar{x}_j$, associated with each ring luminance, x_q, in **Step 1**. This design allowed us to test key predictions of 1D models of the achromatic color gamut, as discussed in the text.

with the model.) In **Step 2**, subjects were shown the mean disk luminance setting across trials, $\bar{x}_j$, associated with each ring luminance, x_q, in **Step 1**. Their task was to adjust the luminance of disk, i, surrounded by a ring, p, that also had one of 6 luminance values across different trials, to match the "brightness" of disk, j. Subjects rated the *quality* of their matches in all trials and conditions.

The goal of the experiment was to test two key predictions of 1D models of the achromatic color gamut: Namely, that all color matches exhibit the properties of *equivalence* and *transitivity*.

Equivalence Subjects should be able to establish absolute color matches between any given disk and the background in **Step 1** and between pairs of disks in **Step 2**. This should manifest itself in very high ratings of match quality in all cases.

Transitivity Subjects should adjust the luminance values of any given disk in **Step 2** to be the same as the luminance settings made with the corresponding rings in **Step 2**, as these are the luminance settings whereby all disk colors are equal to the background, and hence one another, in **Step 1**.

As shown in the Results section, subjects' luminance settings and quality ratings provide strong evidence against the general existence of absolute achromatic color matches and hence of a 1D achromatic color gamut. To quantitatively model these data, we extended an extant model of achromatic color perception based on the hypothesis that brightness and darkness constitute the dimensions of a two-dimensional (2D) achromatic color space (Vladusich et al., 2007).

1.2. Modeling background and aims

Vladusich et al. (2007) investigated the source of achromatic color matching difficulties in displays in which brightness and darkness were both simultaneously induced into a single target region by means of local contrast increments and decrements, respectively (Fig. 4). These authors sought, more specifically, to test the assumption that brightness and darkness simultaneously induced into a single region would cancel out—an assumption, as discussed above, that is equivalent to stating that all achromatic colors constitute points in a 1D perceptual space—as predicted by standard models of achromatic color perception (Cohen and Grossberg, 1984; Grossberg and Todorović, 1988; Land and McCann, 1971; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Rudd, 2010; Vladusich et al., 2006b).

Vladusich et al. (2007) provided evidence that cancelation of brightness and darkness does not generally occur. Subjects adjusted the luminance of one member of a pair of gray rings that appeared against background-disk combinations differing in overall contrast, such as a very-low luminance background and very-high luminance disk on one side of the display, and a moderately-low luminance background and moderately-high luminance disk on the other. Subjects also rated the possibility of making satisfactory color matches between the rings (Vladusich et al., 2006b). The authors found that subjects' luminance settings were well fit by a model in which brightness and darkness contrast information contributed independently to the achromatic color of the rings

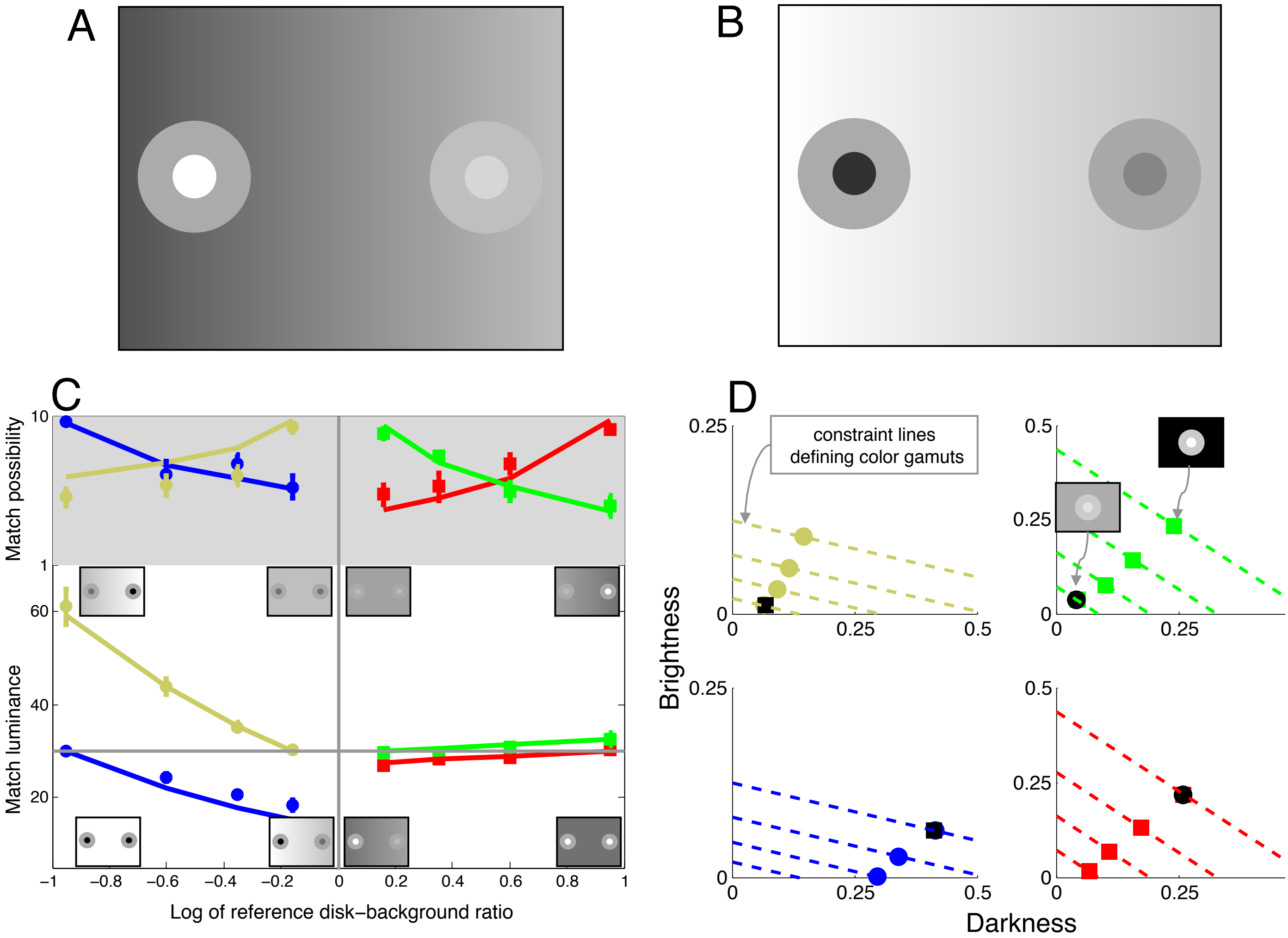

Figure 4: Mixed-polarity simultaneous contrast and relative color matching (Vladusich et al., 2007). (A) The two rings have the same luminance, and the same polarity relations with respect to the disks and backgrounds, but differ in overall contrast. (The background gradient was restricted to the central region of the display in the actual experimental stimuli.) The disks and backgrounds therefore induce both brightness and darkness into the rings. Subjects were required to adjust the luminance of one ring (the match ring) to match the achromatic color of the other ring (the reference ring). (B) Identical to (A) except for the reversal of contrast polarity. (C) Luminance settings (lower data points), ratings of match possibility (upper data points) and model fits (lines). Ratings of match possibility decreased as a function of the overall contrast difference between reference and match sides. Subjects could not establish absolute color matches between such ring pairs, calling into question the assumption of a 1D achromatic color gamut. The data were instead found to be consistent with a model in which brightness and darkness form the perceptual dimensions of a 2D achromatic color space. (D) Based on model fits to the luminance settings, Vladusich et al. (2007) plotted the ring colors in brightness-darkness space. Subjects set ring luminance to approximately minimize the perceptual distance between reference and match colors, denoted here by black and colored symbols, respectively. Note the different scales on the abscissa and ordinate in the blue and yellow subplots. Only achromatic colors defined by points falling on the dotted lines were 'available' to subjects during the matching task. These constraint lines define a family of color gamuts, each corresponding uniquely to specific combinations of disk and background luminance values. We term this concept *gamut relativity*. As the brightness and darkness signals in the model were based on contrast information alone, the geometry of the stimulus ensured that, when an edge with a given polarity had high contrast, the edge of opposite polarity had low contrast. Such a push-pull system thereby generates the negatively sloped linear gamut functions seen in the figure.

(Fig. 4). The model contained a free parameter controlling the weight of the brightness contrast signal relative to the darkness contrast signal, which was found to be approximately 2:1 in favor of darkness. Subjects' ratings indicated that the possibility of making satisfactory color matches decreased with the overall contrast difference between reference and match configurations. These ratings were well explained by a perceptual-distance metric computed from weighted brightness and darkness contrast signals obtained by fitting the subjects' *luminance settings*.

On the basis of these and other results, Vladusich et al. (2007) proposed that brightness and darkness constituted the perceptual dimensions of a 2D achromatic color space. This *brightness-darkness model* suggested that subjects cannot *absolutely* match the colors of regions bordered by edges of opposite contrast polarity because the color gamuts associated to regions differing in overall contrast are arranged as *parallel lines* in 2D achromatic color space (Fig. 4). Rather than performing absolute color matches, then, as expected on the basis of 1D models of the achromatic color gamut, subjects could only set *relative* color matches that *minimized the perceptual distance* between points in brightness-darkness space representing match and reference colors.

We introduce the term *gamut relativity* to describe the family of linear functions that 'slice up' 2D achromatic color space in different ways, depending on the 'reference frame' supplied by the luminance values of surrounding regions.

An outstanding computational issue is whether the model introduced by Vladusich et al. (2007) can be generalized to the conventional simultaneous contrast display, where the local edge formed between disk and ring is either an increment or decrement (Fig. 1), while preserving the useful explanatory properties established in Vladusich et al. (2007). As the extant version of the model includes only contrast information, it leads to the *incorrect prediction* that absolute color matches are possible by matching contrast information alone (Fig. 5). If both contrast and *local luminance* information were to contribute to disk color, however, luminance information would 'pull' against contrast information to give a net *compromise* match that may be consistent with data (Fig. 5).

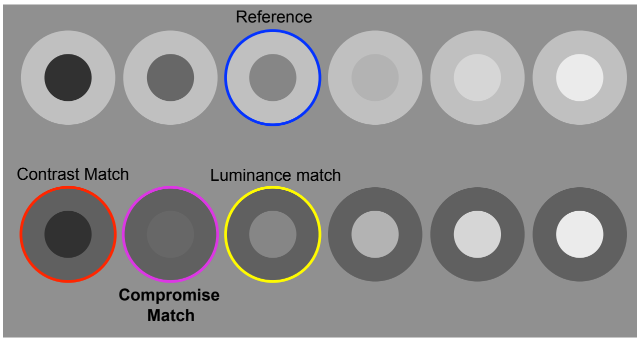

Figure 5: As the extant brightness-darkness model includes only contrast information, it incorrectly predicts that subjects can make absolute color matches between disks viewed against different backgrounds. To solve the problem, luminance information can be incorporated into the model, thereby ensuring that any color match between disks is a compromise between contrast and luminance information.

The present modeling work builds upon the existing brightness-darkness model by introducing an augmentation that allows local luminance and contrast information to combine in the computation of brightness and darkness. The specific instantiation of luminance representation advocated here involves a push-pull mechanism. All else being equal, when the luminance of a region is high, the contribution of the luminance signal to the brightness (darkness) of the region is high (low). In the limiting case in which all points in the visual field have a single luminance value (Barlow and Verrillo, 1976)—a *Ganzfeld*—the achromatic color of any point in the field is determined by local luminance information alone.

The augmented model predicts that subjects *cannot* increase or decrease the luminance of any given disk in Fig. 5 to establish absolute color matches between disk pairs, independently of the ring color. This is because, in a brightness-darkness space incorporating both contrast and luminance information, all increments (decrements) contain brightness (darkness) from contrast information, and *all increments (decrements) contain darkness (brightness)* from local luminance information. As subjects cannot generally match both contrast and luminance information simultaneously, the model predicts that *both brightness and darkness cannot simultaneously be matched*; that is, the model predicts that color matches are *relative*, rather than absolute. The modeling component of the article aims to quantitatively assess this prediction of relative color matching in terms of the data obtained from the psychophysical experiment outlined above.

2. Methods

2.1. Equipment and software

Stimuli were presented on a linearized 21 inch Sony GDM 520 computer monitor (40 × 30 cm, 1280 × 960 pixels, 85 Hz) using an ATI Radeon 8-bit color resolution graphics card. The maximum luminance producible on the monitor was 92.7 $\frac{cd}{m^2}$. Viewing distance was 80 cm. A reduction tunnel was used, and the inside of the tunnel covered by black cloth. Room lights were turned off and no dark adaptation period was used. The experiment was programmed in visual C^{++}. All luminance settings were made using arrow keys on a keyboard.

2.2. Subjects

Six (6) subjects participated in the experiment. Four subjects were experienced psychophysical observers. Only one subject was aware of the purpose of the experiment.

2.3. Stimuli and Procedure

Step 1: The stimuli consisted of disks subtending 1.57° visual angle surrounded by rings subtending 4.47°. For each of 6 ring luminance values, $x_q \in (5, 20, 40, 50, 70, 85)$ $\frac{cd}{m^2}$, subjects set the luminance of the disk, j, embedded in ring, q, such that the disk appeared the same "brightness" as a large background, k, of constant luminance, $x_k = 45$ $\frac{cd}{m^2}$. Subjects also rated the quality of the best possible match on a scale from 0 (no match possible) to 5 (perfect match). There were 12 repetitions for each setting. The order of presentation was randomized. Two identical disk-ring configurations were presented simultaneously, one on the right of screen and one on the left of screen. The disk luminance values were yoked, and the subject used the arrow keys on the keyboard to adjust the luminance values of both disks simultaneously. The starting luminance value of the disks was always 0 $\frac{cd}{m^2}$.

Step 2: Each subject adjusted the luminance, x_i, of disk, i, surrounded by ring, p, to match the "brightness" of disk, j, whose luminance corresponded to the mean disk setting, $\bar{x}_j$, associated with each ring luminance value, x_q, in **Step 1**. The luminance values, $x_p \in (5, 20, 40, 50, 70, 85)$ $\frac{cd}{m^2}$, associated with ring, p, were the same as those used in **Step 1**. Subjects viewed the full crossing of ring pairings, giving 36 different stimuli. Subjects repeated each color match 6 times (in randomized order, with the match disk on the right or left of screen on 3 trials) and rated the quality of the best possible match on a scale between 0 and 5.

2.4. Model equations

Let x_i be the physical luminance value of a target region, i, forming borders with regions, $\bar{p}$ and $\hat{p}$, with respective luminance values, $x_{\bar{p}} > x_i$ and $x_{\hat{p}} < x_i$. Let us then define target darkness as

$$\phi_i = \alpha \left(\beta_i \log \left[\frac{x_{\bar{p}}}{x_i} \right] + \mu \log \left[\frac{k_d}{x_i} \right] \right) \tag{1}$$

where k_d, α and μ are constants, β_i is the *relative length* of the decrement border, and $[x] = \max(x, 1)$ is a half-wave rectification operator.

Target brightness is defined as

$$\psi_i = (1 - \alpha) \left((1 - \beta_i) \log \left[\frac{x_i}{x_{\hat{p}}} \right] + \nu \log \left[\frac{x_i}{k_b} \right] \right) \tag{2}$$

where k_b and ν are constants. The achromatic color of region, i, can be written as the vector sum of contrast and luminance vectors

$$\mathbf{a}_i = \mathbf{l}_i + \mathbf{c}_i \tag{3}$$

where the luminance vector is defined as

$$\mathbf{l}_i = \left\{ \alpha\mu \log \left[\frac{k_d}{x_i} \right], (1 - \alpha)\nu \log \left[\frac{x_i}{k_b} \right] \right\} \tag{4}$$

and the contrast vector

$$\mathbf{c}_i = \left\{ \alpha\beta_i \log\left[\frac{x_{\bar{p}}}{x_i}\right], (1-\alpha)(1-\beta_i)\log\left[\frac{x_i}{x_{\hat{p}}}\right] \right\} \tag{5}$$

2.5. General solutions for color matching tasks

Let region, i, with luminance, x_i, be the 'match' target region, and region, j, with luminance, x_j, be the 'reference' target region. Region, i, is surrounded by regions, $\bar{p}$ and $\hat{p}$, whereas region, j, is surrounded by regions, $\bar{q}$ and $\hat{q}$. We assume the luminance relations, $x_{\bar{p}} > x_i$ and $x_{\hat{p}} < x_i$, and $x_{\bar{q}} > x_j$ and $x_{\hat{q}} < x_j$. We further assume that darkness and brightness values are matched separately via the equalities, $\phi_i = \phi_j$ and $\psi_i = \psi_j$. Letting $x_{\bar{i}}$ and $x_{\hat{i}}$ denote the darkness and brightness solutions, respectively, we have

$$log(x_{\bar{i}}) = \frac{\log x_j^{\mu} x_{\bar{p}}^{\beta_i} + \log\left[\frac{x_{\bar{q}}}{x_j}\right]^{\beta_j}}{\beta_i + \mu} \tag{6}$$

and

$$log(x_{\hat{i}}) = \frac{\log x_j^{\nu} x_{\hat{p}}^{(1-\beta_i)} + \log\left[\frac{x_j}{x_{\hat{q}}}\right]^{(1-\beta_j)}}{1 - \beta_i + \nu} \tag{7}$$

The final luminance setting is then given by the weighted darkness and brightness solutions

$$log(x_i) = \alpha \log x_{\bar{i}} + (1-\alpha)\log x_{\hat{i}} \tag{8}$$

Note that, as k_d and k_b appear on both sides of the color matching equations, they cancel during the calculation of the above solution, meaning that x_i is independent of these parameters.

2.6. Model parameters

The parameter α, where $0 \leq \alpha \leq 1$, represents the *overall* weight of darkness *relative* to brightness (Vladusich et al., 2007). For any given color matching task, this parameter cancels during the calculation of the *individual* solutions to the brightness and darkness equations. As subjects cannot generally adjust the luminance of the match disk to simultaneously satisfy the solutions to both the brightness and the darkness equations, and since subjects are in principle free to place more weight on one solution than the other, α must be incorporated into the final estimate of the luminance setting in order to correctly weight the relative contributions of brightness and darkness to the total achromatic color.

The parameter β_z, where $0 \leq \beta_z \leq 1$, represents the weight of darkness contrast *relative* to brightness contrast for a generically indexed region, z. We assume that β_z is determined solely by the relative lengths of the incremental and decremental portions of a border. This includes cases where border polarity varies along the length of a single border demarcating a simply-connected target region, and cases in which the target region contains holes, such that the inside and outside borders of the region have unequal length. In the Vladusich et al. (2007) experiments using target rings defined by opposite-polarity contrasts on inside and outside borders, for example, $\beta_z = \frac{3}{4}$ for the outside border. In the case in which the border polarity is unitary, as in the experiment described here, $\beta_z = 1$ for increment matches and $\beta_z = 0$ for decrement matches.

The parameters μ and ν represent the weights applied to the luminance components of darkness and brightness, respectively. The values of these parameters are assumed to be non-negative. The parameters k_d and k_b determine the luminance at which achromatic colors appear purely bright and dark, respectively. The units of k_d and k_b are $\frac{cd}{m^2}$. As the remaining model parameters are dimensionless, the brightness and darkness values are dimensionless.

2.7. Estimation of match-quality ratings

In order to fit subjects' match-quality ratings, we employed a measure of perceptual distance, $d_{i,j}$, between two target colors, $\mathbf{a}_i$ and $\mathbf{a}_j$, namely,

$$d_{i,j} = 1 - e^{-r\Delta\mathbf{a}_{i,j}} \tag{9}$$

where $\Delta\mathbf{a}_{i,j} = (|\phi_i - \phi_j|^2 + |\psi_i - \psi_j|^2)^{\frac{1}{2}}$ is the Euclidean metric. The parameter, r, was varied by hand to approximately fit subjects' match-quality ratings. The use of this function is motivated by psychophysical experiments involving perceptual discrimination of shape and color (Nosofsky and Kantner, 2006). As $\Delta\mathbf{a}_{i,j}$ increases, $d_{i,j}$ asymptotically approaches a value of one. At $\Delta\mathbf{a}_{i,j} = 0$, two target colors are considered identical, as $d_{i,j} = 0$.

3. Results

3.1. Psychophysical results

The results of the experiment are shown in Fig. 6. The blue lines indicate data from **Step 1**, in which subjects matched disks to the background, and red lines denote data from **Step 2**, in which subjects matched pairs of disks. The upper (lower) parts of each subplot represent match-quality ratings (luminance settings). Each of the 6 subplots corresponds to a specific value of ring luminance: In **Step 1** (**Step 2**), the ring surrounded the disk that was adjusted to match the color of the background (another disk). The upper (lower) row of icons in each subplot corresponds to the adjustable disk-ring configurations in **Step 2** (**Step 1**).

As expected on the basis of simultaneous contrast, subjects in **Step 1** set disk luminance lower (higher) than the background when ring luminance was lower (higher) than the background. These data therefore indicate that subjects perceived a significant brightening (darkening) of disks surrounded by rings of low (high) luminance, and attempted to compensate by decreasing (increasing) disk luminance. Subjects' ratings of match quality were, moreover, relatively high and approximately constant as a function of ring luminance, suggesting that subjects were generally able to make satisfactory color matches for both incremental and decremental disk-ring contrasts.

Also as expected on the basis of simultaneous contrast, subjects in **Step 2** set match-disk luminance lower or higher than match-ring luminance, depending on the polarity of the disk-ring edge on the reference side. When the reference ring had lower luminance than the background, subjects matched contrast increments to increments for values of match-ring luminance lower than the background (left side of all panels in the upper row). Subjects matched decrements to increments, however, for all values of match-ring luminance higher than the background (right side of all panels in the upper row). A similar pattern of results was obtained in the case where the reference ring had higher luminance than the background (lower row of panels). Subjects therefore routinely matched opposite contrast polarities in **Step 2** of the experiment (see Discussion).

Subjects' luminance settings in **Step 2** deviated systematically from those in **Step 1**, with the absolute differences between luminance settings obtained in **Step 1** and **Step 2** statistically different from zero ($p < 10^{-7}$, $t_{35} = 7.42$). The disparity between luminance settings obtained in the two steps is *inconsistent* with the *transitivity* relations predicted by 1D models of the achromatic color gamut. Match-quality ratings were also significantly more variable in **Step 2** than in **Step 1** ($p < 0.001$, $F_{5,35} = 0.03$), *inconsistent* with the prediction that all achromatic color matches are *equivalent*. We conclude that achromatic color matches are neither equivalent nor transitive.

3.2. Model fits

We fit the brightness-darkness model to subjects' luminance settings in **Step 1** and **Step 2** of the experiment separately (Fig. 7). In the case of **Step 1**, the fit provided an excellent description of the luminance settings ($R^2 = 99.5\%$). Due to the limited number of data points, the error bounds on the parameter estimates were several orders of magnitude greater than the values of the parameters themselves. The estimated parameter values were as follows; Relative overall brightness weight: $\alpha = 0.15\pm > 10^5$ (the darkness weight is given by $1-\alpha$); Luminance weights corresponding to brightness and darkness, respectively: $\nu = 2.65\pm > 10^5$ and $\mu = 1.2\pm > 10^6$.

Based on the parameter values estimated from these fits, we calculated predicted values of the match-quality ratings, with the caveat that we adjusted the exponent value, r, of the perceptual distance metric to achieve an approximate fit to the rating data. The largest deviation from the predicted values of the match-quality ratings

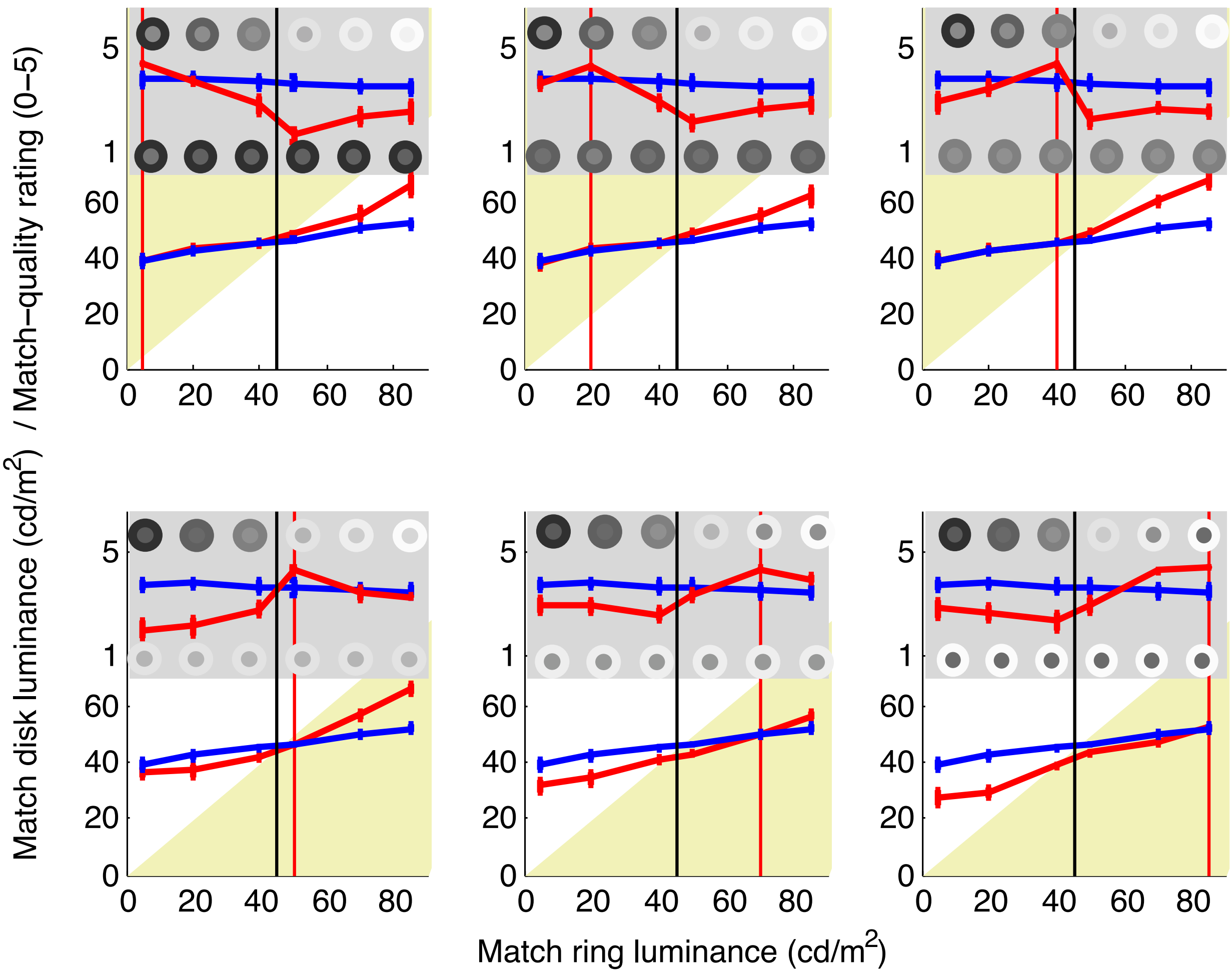

Figure 6: Psychophysical results. Blue lines indicate the data from **Step 1** (disk-to-background matching) and red lines denote the data from **Step 2** (disk-to-disk matching). The upper lines are the ratings of match quality, and the lower lines are the luminance settings. The vertical red line indicates the luminance of ring, p. The vertical black line indicates the increment-decrement transition (increments to the left, decrements to the right). The upper and lower disk-ring mnemonics indicate the match and reference configurations from **Step 2**, respectively. Data averaged over 6 subjects.

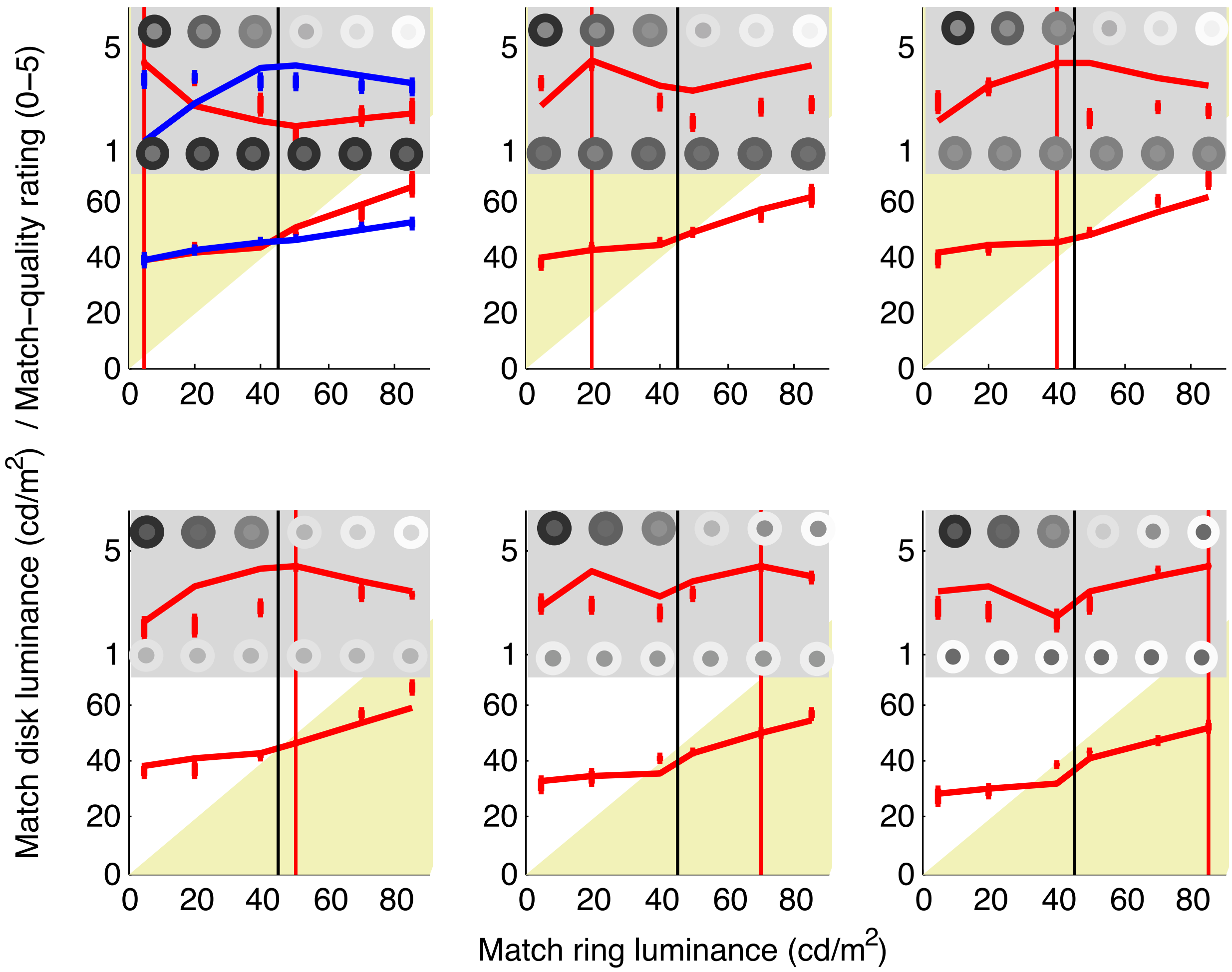

Figure 7: Modeling of the psychophysical data. Vertical blue and red error bars denote data points corresponding to disk-to-background matches (**Step 1**) and disk-to-disk matches (**Step 2**), respectively. The model was fit to luminance settings from each step separately, with the respective fits represented by blue and red lines. The model generally fit these data very well. The model parameters were then used to estimate the match-quality ratings, with the exponent parameter, r, in the calculation of perceptual distance, being adjusted by hand to achieve an approximate fit to the rating data. The exponent value, $r = 7$, was set the same for both steps. The largest discrepancy between model and data occurs for incremental match-quality ratings in **Step 1**, where the model incorrectly predicts low ratings, and for opposite-polarity match settings in **Step 2**, where the model incorrectly predicts higher match-quality ratings than observed in the data.

occurred for incremental disk-to-background contrasts.

The model also fit the luminance settings in **Step 2** of the experiment very well ($R^2 = 92\%$), though the predictions of match quality varied across conditions (Fig. 7). For the incremental reference configurations (top row of Fig. 7), for instance, the predictions deviated systematically from the data for many values of the disk-ring reference contrast. The predictions were, however, relatively good in the case of the decremental reference configurations (bottom row of Fig. 7). The estimated parameter values were as follows; Relative overall brightness weight: $\alpha = 0.13 \pm 0.16$; Luminance weights corresponding to brightness and darkness, respectively: $\nu = 1.81 \pm 2.2$ and $\mu = 0.88 \pm 0.23$. The error bounds on these parameters were therefore relatively acceptable. We also estimated the model parameters by fitting to the match-quality ratings and then predicting the luminance settings, with similar results.

As the values of μ and ν obtained from fitting data in **Step 1** and **Step 2** disagree, we also fit the model to the data from **Step 1** and **Step 2** simultaneously. These results were still satisfactory ($R^2 = 92\%$). The estimated parameter values were as follows; Relative overall brightness weight: $\alpha = 0.19 \pm 0.17$; Luminance weights corresponding to brightness and darkness, respectively: $\nu = 2.31 \pm 2.2$ and $\mu = 0.89 \pm 0.29$. The error bounds on the parameters were therefore relatively acceptable. The main discrepancy with the separate fits for **Step 1** and **Step 2** above, then, was in the value of μ. In should be pointed out, however, that when fit in this manner, the model predicted less transitivity than was observed in the data (see Discussion).

To check whether the augmented version of the brightness-darkness model introduced here can still account for the data presented in Vladusich et al. (2007), we attempted to 'postdict' the results of that study using the parameter values estimated from the luminance settings in **Step 2** above (Fig. 8). We found that the model explained the data reasonably well, with the only major deviations occurring for luminance settings in one condition (indicated by the yellow symbols in Fig. 8). Given the differences in stimuli, rating tasks and subjects employed in the two studies, this concordance seems reasonable. We conclude that the current version of the model preserves the useful explanatory properties of the model established in the Vladusich et al. (2007) study, even under the strong constraint of using the parameter values estimated from the luminance settings in **Step 2** above.

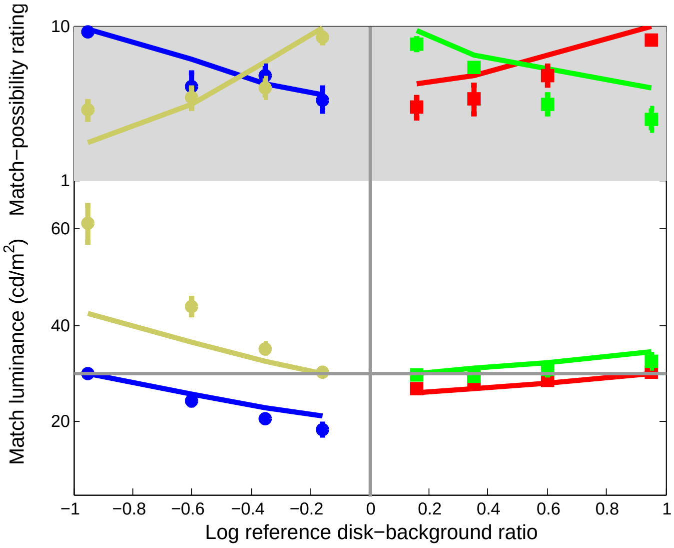

Figure 8: Model 'postdictions' for luminance settings and match-possibility ratings from Experiment 1 of Vladusich et al. (2007). Parameters are the same as those estimated from the luminance settings of **Step 2** above.

4. Computational analysis

4.1. Vector representation and the luminance frame

To better understand the psychophysical data, we plotted the projections of experimental stimuli onto brightness-darkness space, as given by the parameters estimated from fitting the model to the luminance settings in **Step 2** above (Fig. 9). To fix ideas, we represent the 2D vector encoding luminance information in a target region, k, as $\mathbf{l}_k$. We assume, for the present discussion, that the achromatic color, $\mathbf{a}_k$, of the region, k, is determined entirely by luminance, x_k, such that, $\mathbf{a}_k = \mathbf{l}_k = \{\phi, \psi\}$, where the brightness ($\psi$) and darkness ($\phi$) components of the vector representation are respectively defined as the weighted log luminance ratios of the luminance of region, k, and a pair of constants, k_b and k_d (Methods).

Now suppose we vary the luminance of region, k, continuously within some prescribed range, $x_{min} < x_k < x_{max}$, then the vector, $\mathbf{a}_k = \mathbf{l}_k$, varies as a function of luminance. In terms of the scalar components of the vector, the darkness value is high, and the brightness value low, at low luminance, $(\phi_k >> \psi_k)$, whereas the brightness value is high, and the darkness value low, at high luminance, $(\psi_k >> \phi_k)$.

The *achromatic color gamut* associated to region, k, is then defined by the linear function, $f_k : \phi_k = m_k \psi_k + c_k$, where ψ_k and ϕ_k represent brightness and darkness values of region, k, respectively. A discretely sampled version of this line, using equal log luminance steps, is shown in Fig. 9, assuming the maximum and minimum luminance values, $x_{min} = 5 \ \frac{cd}{m^2}$ and $x_{max} = 85 \ \frac{cd}{m^2}$, used in the experiment. The parameters k_d and k_b scale brightness-darkness space to determine the brightness value at which the target region, k, is perceived as a *pure* shade of darkness, $\phi(\psi = 0)$, and the darkness value at which region, k, is perceived as a *pure* shade of brightness, $\psi(\phi = 0)$. All remaining points consist of positive values of both brightness and darkness, appearing various shades of gray (Vladusich et al., 2007).

The line, f_k, specified by the values of k_d and k_b can be conceptualized as a 'reference frame' in brightness-darkness space, which we term the *luminance frame*. We set these values arbitrarily to $k_d = 85 \ \frac{cd}{m^2}$ and $k_b = 5 \ \frac{cd}{m^2}$ for the purposes of scaling the figure to optimize the display of figural details, and leave to future work the issue of determining the actual values of k_d and k_b.

4.2. Simultaneous contrast as vector summation

Suppose we have a pair of physically identical disks (labelled i and j), with luminance values, $x_i = x_j = x_k$, surrounded by a pair of rings (labelled p and q) with luminance values defined as follows, $x_{min} > x_i = x_j > x_{max}$, $x_p = x_{min}$ and $x_q = x_{max}$. To analyze simultaneous contrast within this framework, consider how luminance and contrast information combine to determine the achromatic colors of the pair of disks, i and j. The luminance values of the disks i and j are the same, $\mathbf{l}_i = \mathbf{l}_j$. The contrast vectors corresponding to the border between disks, i and j, and rings p and q, are denoted as $\mathbf{c}_i$ and $\mathbf{c}_j$, respectively. The brightness and darkness components of these vectors are defined in terms of weighted log luminance ratios of the disk and ring luminance values (Methods). The contrast induced by the low-luminance ring makes disk,

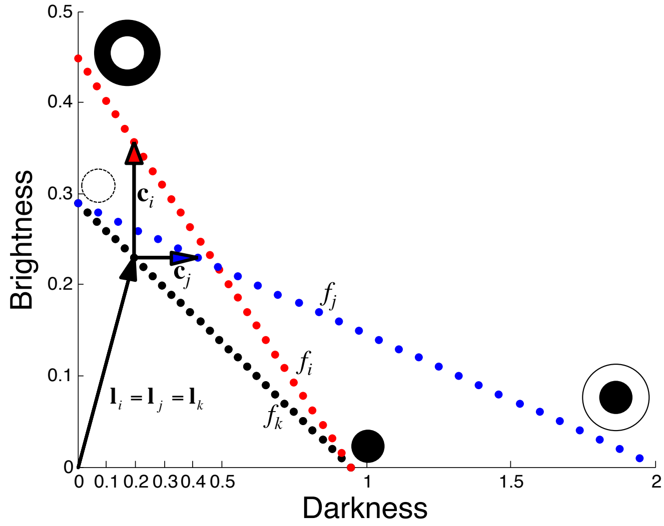

Figure 9: Simultaneous contrast and gamut relativity in brightness-darkness space. The figure is based on the parameter values estimated from the model fit to luminance settings in **Step 2** above. The arrow with the black head represents the luminance vector, $\mathbf{l}_i = \mathbf{l}_j = \mathbf{l}_k$, that is common to disks, i and j, and the arrows with red and blue heads indicate the contrast vectors, $\mathbf{c}_i \neq \mathbf{c}_j$, induced by the two rings, p and q, of low and high luminance, respectively. The achromatic colors, $\mathbf{a}_i \neq \mathbf{a}_j$, of disks, i and j, are thereby perceptually separated, with disk, i, appearing relatively brighter than disk, i, and disk, j, appearing relatively darker than disk, i. The dotted red and blue lines indicate equally spaced samplings of the linear functions, f_i and f_j, corresponding to lines of constant disk-ring contrast but variable disk luminance. Gamut relativity can be understood in terms of a family of linear 1D functions that 'slice' up 2D brightness-darkness space in different ways, depending on ring luminance. Here the black line represents achromatic color of a target region, p, in the absence of contrast (e.g. a *Ganzfeld*), whereas the red (blue) line denotes the achromatic color of a target region, i, viewed against a region of low (high) luminance. Note the different scales on the abscissa and ordinate.

i, appear brighter, whereas the contrast induced by the high-luminance ring makes disk, j, appear darker. The achromatic colors of disks, i and j, are then given by the vector sum of luminance and contrast vectors, $\mathbf{a}_i = \mathbf{l}_i + \mathbf{c}_i$, and $\mathbf{a}_j = \mathbf{l}_j + \mathbf{c}_j$. As the contrast vectors are unequal, $\mathbf{c}_i \neq \mathbf{c}_j$, so too are the achromatic color vectors, $\mathbf{a}_i \neq \mathbf{a}_j$. The luminance, contrast and achromatic color vectors defined above are displayed in Fig. 9, again assuming values of the model's free parameters estimated from the luminance settings in **Step 2** above.

4.3. Simultaneous contrast and gamut relativity

As shown in Fig. 9, as the luminance value, x_i, of disk, i, surrounded by the low-luminance ring, p, increases from low to high, the lengths of both the luminance vector, $\mathbf{l}_i$, and contrast vector, $\mathbf{c}_i$, increase, ensuring that the length of the achromatic color vector, $\mathbf{a}_i$, increases. Conversely, the length of the orthogonal contrast vector, $\mathbf{c}_j$, associated with disk, j, surrounded by the high-luminance ring, q, decreases. We define a pair of linear functions, $f_i : \psi_i = m_i\phi_i + c_i$ and $f_j : \psi_j = m_j\phi_j + c_j$, forming 1D 'slices' through brightness-darkness space. These lines correspond to the color gamuts associated to disks, i and j, given the respective rings, p and q. Thus, by virtue of the orthogonality of contrast vectors, simultaneous contrast defines independent reference frames in brightness-darkness space for incremental and decremental contrasts, which we call *increment frames* and *decrement frames*.

Discretely sampled versions of these lines are shown in Fig. 9 in order to emphasize the relationship between the mathematical descriptions of points in terms of vectors and linear functions. In general, we may specify families of increment and decrement frames, each corresponding to a differently parameterized linear function that depends on the value of ring luminance. All increment frames share the same slope but differ in y-intercept, as do all decrement frames.

4.4. Gamut relativity and relative color matches

According to the model, gamut relativity constrains the way that relative color matches are established between pairs of points representing colors within separate reference frames. Let the line, f_i, represent the color gamut available to subjects attempting to adjust the luminance of disk, i, to match a specific color of disk, j, as given by a point, $p_j = \{\phi_j, \psi_j\}$, on the line, f_j. It is clear from the geometry of the lines in Fig. 10 that an absolute color match is not possible. The best a subject can do, then, is to set the point, p_i, to obtain the closest possible match to the point, p_j, such that the point, p_i, minimizes the perceptual distance, $d_{i,j}$, subject to the constraints provided by the function, f_i, as shown in Fig. 10. Due to the much higher overall weight applied to darkness compared to brightness, $\frac{\alpha}{1-\alpha} > 6$, the match is much more highly weighted towards darkness. The shallow-sloped 1D slices of brightness-darkness space corresponding to increment and decrement frames (note the different scales on the abscissa and ordinate in Fig. 9 and Fig. 10) ensure that darkness values are more heavily weighted in any comparison of points representing colors belonging to different reference frames.

Fig. 10 also plots the achromatic colors corresponding to all disk-ring stimuli in the experiment, along with the linear functions (the 1D 'slices' of the 2D color space) corresponding to the color gamut available to subjects for each luminance value of ring, p, based on parameter values estimated from the **Step 2** data. As indicated above, these slices are generally concatenations of linear functions, corresponding to increment frames and decrement frames, respectively. Each red dot denoting disk, i, lies *approximately* on the point on each relevant 1D slice that most closely approaches the blue dot denoting disk, j, consistent with the notion that subjects attempted to minimize the perceptual distance between points representing individual achromatic colors.

4.5. Testing the prediction of relative color matches

The model suggests that "brightness" matches reflect the minimal perceptual distances between points representing reference and match achromatic colors in brightness-darkness space. To test

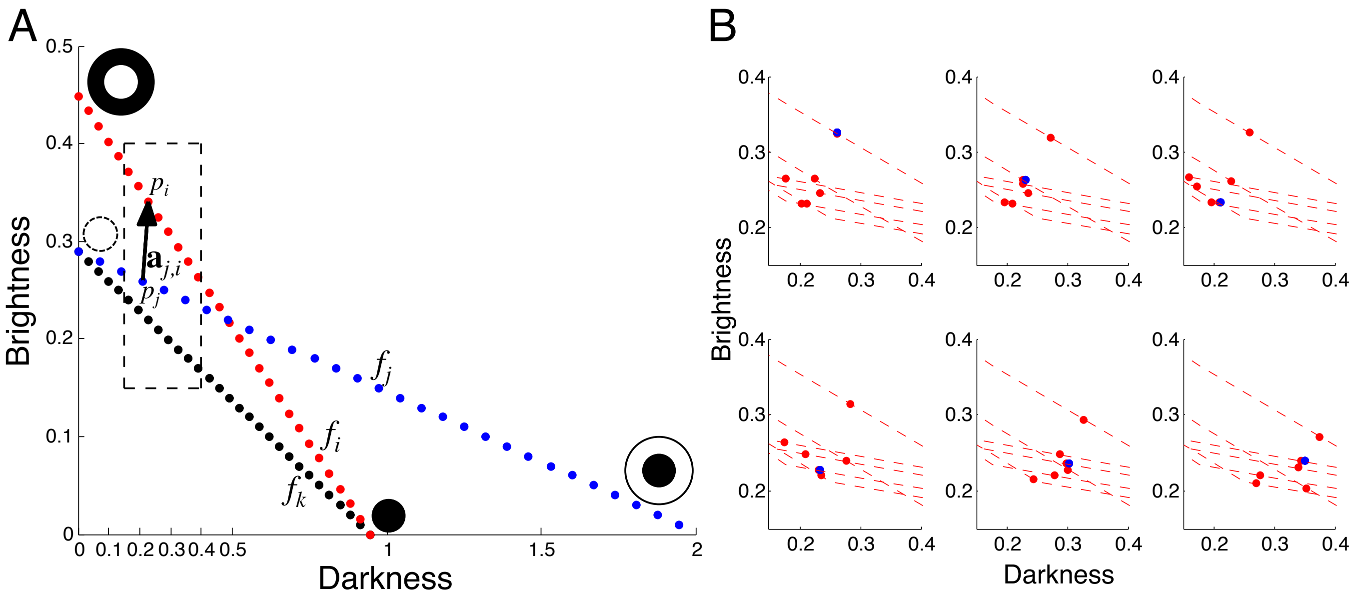

Figure 10: Gamut relativity and relative color matches in brightness-darkness space. (A) Subjects set the luminance, x_i, of the disk, i, to minimize the absolute value of the Euclidean vector, $\mathbf{a}_{j,i} = \mathbf{a}_j - \mathbf{a}_i$, between points, p_j and p_i, representing disk colors. The gamut function, f_i (red dots), constrains the subject to set the point representing the color, p_i, of the disk, i, to minimize the distance to the point representing the color, p_j, of the reference disk, j, on the gamut function, f_j (blue dots). The model suggests that subjects are heavily biased towards matching the darkness component of achromatic colors. The dashed black rectangle illustrates the region to which subjects restricted their color matches in the experiment. Note the different scales on the abscissa and ordinate. (B) Plot of achromatic colors in brightness-darkness space corresponding to the data shown in Fig. 7, as denoted by the dashed rectangle in (A). The blue dots represent the color of disk, j, and the red dots represent the color of disk, i. Dashed red lines are the 1D slices that denote the color gamut available to subjects for each value of ring luminance. The clustering of red dots is consistent with the conjecture that subjects set luminance to approximately minimize the perceptual distance between points representing colors in brightness-darkness space.

this prediction, we turned to the vast published literature on "brightness" matching in center-surround displays (Gilchrist, 2006). We chose an experiment that was similar in design and task to that described in **Step 2** of the current experiment (Arend and Goldstein, 1987), and attempted to predict subjects' luminance settings in that experiment, based on the model parameters estimated from **Step 2** above (Fig. 11).

We calculated the minimum Euclidean distances between reference and match colors in the center-surround "brightness" matching condition of Arend and Goldstein (1987) by sampling a set of discrete luminance values spanning the entire luminance range of the experiment ($\approx 0.01 \frac{cd}{m^2}$ to $\approx 50 \frac{cd}{m^2}$). (We set $k_d = 50 \frac{cd}{m^2}$ and $k_b = 0.01 \frac{cd}{m^2}$ for the purposes of scaling Fig. 11 to optimize the display of figural details). The resulting model predictions (Fig. 11) bear a remarkable resemblance to subjects' luminance settings. The model correctly predicts, in particular, that incremental targets—those targets belonging to the more-negatively sloped increment frames in Fig. 11—are matched approximately according to target luminance (slope ≈ 1). Decremental targets—those targets belonging to the less-negatively sloped decrement frames in Fig. 11—are, by contrast, matched according to a weighted sum of target luminance and contrast (the reference center-surround contrast being constant for all luminance values of the match surround). As many published experiments have confirmed these basic observations (Gilchrist, 2006), we conclude that substantial evidence exists to support the proposal that subjects' luminance settings in standard "brightness" matching experiments reflect minimal perceptual distances between achromatic colors in brightness-darkness space.

5. Discussion

We have shown here that the conventional assumption concerning the 1D nature of the achromatic color gamut is not supported by data from our color matching experiment. The failure of subjects to establish equivalent and transitive color matches, coupled with our modeling work, instead supports the proposal that the achromatic color gamut is relative, depending on surround luminance. These data also provide additional support for the proposal that brightness and darkness constitute the dimensions of achromatic color space (Vladusich et al., 2007). The augmented brightness-darkness model presented here suggests how local luminance and contrast information are combined by the visual system through vector summation, and how gamut relativity constrains color matching behavior between reference frames specified by different surround luminance values. The model thereby provides a novel geometrical approach to simultaneous contrast. The model also correctly predicts a wide body of data indicating that incremental and decremental targets are associated with different matching behaviors (Gilchrist, 2006). Below we discuss some strengths and weaknesses of the current study.

5.1. Some limitations of the model

Although the model fit subjects' luminance settings in the current experiment well, the predictions of match quality left room for improvement. In our modeling of **Step 1**, for example, the model incorrectly predicted that subjects should rate incremental disk-to-background matches as being very low in quality, whereas subjects actually rated these matches as highly as decremental matches. In our modeling of **Step 2**, the greatest discrepancy with the data pertained to matches in which either the reference or match configurations manifested low disk-ring contrast. In order to explain the transitivity in luminance settings between **Step 1** and **Step 2**, furthermore, we required the model to be fit to the luminance settings from each step separately. When fit to the data from both steps simultaneously, the model predicted much stronger transitivity than is actually observed in the data.

With respect to our modeling of **Step 1**, a clue to the model's infidelity may be found in the phenomenology of the task; namely, disk-to-background matches are associated with a *perceptual bistability* whereby disk appearance depends on the assignment of the disk-ring edge to ei-

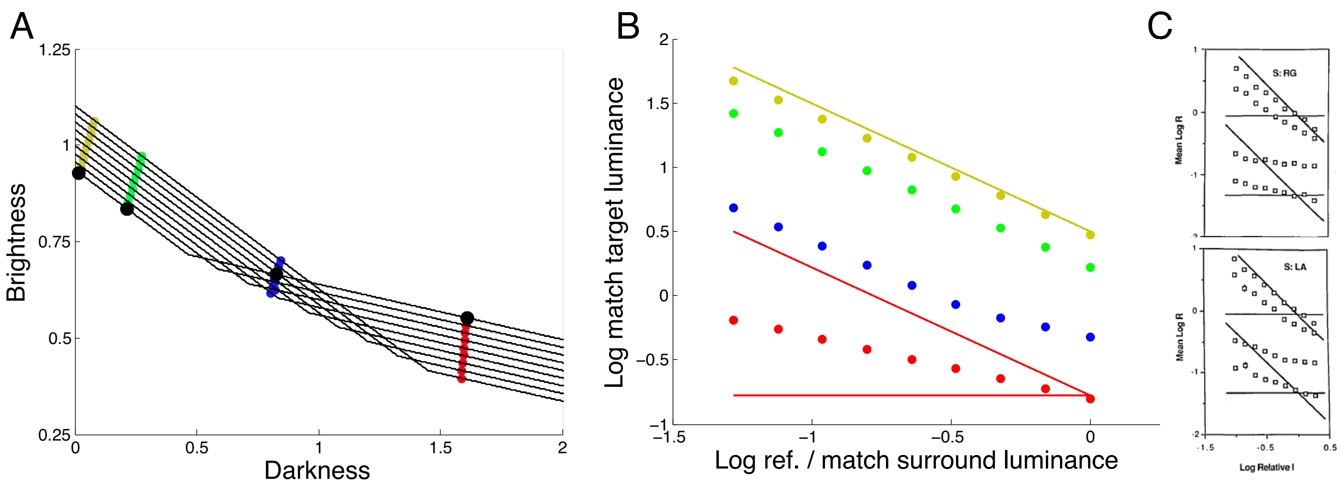

Figure 11: Test of the model prediction that subjects' luminance settings minimize the perceptual distance between reference and match colors. (A) Based on the parameter values estimated in **Step 2** of the current experiment, we calculated the minimum Euclidean distances between reference and match colors in the center-surround "brightness" matching condition of Arend and Goldstein (1987). This was done by discretely sampling potential match luminance settings within the range specified by the experimental stimuli. Each black line shows the color gamut associated with the target match region as the luminance of the region is varied. The large black dots denote the colors of the four target reference regions used in Arend and Goldstein (1987). Minimal-distance color matches for incremental targets correspond to colored dots above the black dots, whereas minimal-distance color matches for decremental targets correspond to colored dots positioned below the black dots. The figure is scaled according to the highest and lowest luminance values used in the experiment. (B) Predicted luminance settings based on the minimal-distance selection procedure. Each colored dot represents a luminance setting. The horizontal red line denotes perfect contrast matching, and the negatively sloped red and yellow lines denote perfect luminance matching. (C) Comparison data from Arend and Goldstein (1987). The model predicts the data very well, particularly the observation that increments are matched approximately according to target luminance, whereas decrements are matched approximately according to a weighted sum of target luminance and contrast.

ther figure (the ring) or ground (the background). When the disk-ring edge appears to 'belong' to the disk, the disk and background colors appear quite dissimilar, whereas when the disk-ring edge appears to 'belong' to the ring, the disk and background colors appear perceptually grouped and quite similar (Fig. 1). This suggests that the contrast information derived from the disk-ring edge may play a flexible role in the computation of disk color, depending on the perceptual 'frame' of the subject. Were contrast information to be eliminated from the computation of disk color, for example, then according to the brightness-darkness model, luminance information alone would determine disk color (the luminance frame). The predicted match quality would therefore be high, as an absolute color match within the luminance frame would be possible. This explanation of the observed match quality ratings does not, of course, explain why subjects set disk luminance higher or lower than the background value (i.e. perceived simultaneous contrast). A more complete explanation would therefore require that subjects initially perceive simultaneous contrast in the disk (the increment frame), and so adjust disk luminance accordingly, but when the time comes to set their match-quality rating, contrast information no longer plays a significant role in computing disk color. This could occur, for example, if disk and background colors were more likely to become perceptually grouped as their color similarity increased. Further psychophysical and modeling work is clearly required to test these assumptions. In any case, the task of matching disk color to background color seems to offer some interesting new opportunities for the investigation of simultaneous contrast.

With respect to our modeling of **Step 2**, a clue to the model's infidelity comes from the observation that low-contrast edges in center-surround displays tend to induce a percept that has been likened to a form of *perceptual transparency* (Ekroll et al., 2002, 2004; Ekroll and Faul, 2009; Ekroll et al., 2011; Koenderink, 2003). The effect is apparent, for example, in Fig. 1, where the low-contrast disks appear 'fuzzy and 'indistinct', relative to the 'sharp' and 'distinct' appearance of high-contrast disks. It seems reasonable to assume that subjects took into account perceptual 'clarity' in their ratings of match quality. Given that the model predictions of match quality were based *only* on the perceptual distance between reference and match colors, the model's failure to account for these data points is expected.

We suggest that future psychophysical and modeling studies employ the similarity-rating method to assess the perceptual distances between arbitrary pairs of targets (Logvinenko and Maloney, 2006; Vladusich et al., 2007), while having subjects simultaneously rate the transparency of targets. The resulting data could then be used to test the assumption that transparency reduces the perceptual similarity between targets when one or both targets has low contrast. To the extent that subjects' match-quality ratings at low contrast are related to the emergence of perceptual transparency, then, the brightness-darkness model must be amended to account for the stimulus conditions under which transparency occurs. This topic remains a primary consideration for future work.

5.2. Achromatic color matching and rating tasks

Our use of color matching and quality ratings was motivated by the aim to understand the relationship between achromatic color relativity and the experience of unsatisfactory matches that seemed to us ubiquitous in previous matching experiments. We propose, however, that future experiments make greater use of quality, similarity, or dissimilarity, rating tasks (Logvinenko and Maloney, 2006; Vladusich et al., 2007), thereby avoiding extant problems with color matching tasks (Ekroll et al., 2002, 2004; Ekroll and Faul, 2009; Ekroll et al., 2011), or at the least combine these rating tasks with matching tasks.

One advantage of rating tasks is that subjects are able to directly quantify the perceptual distance between pairs of target colors, providing the experimenter with more information than can be obtained from luminance settings alone. A second advantage is that rating data is itself much easier to fit with models than luminance settings. This is because the equations required to model rating data do not require the experimenter to solve for the unknown luminance setting. As stimulus conditions and model complexity increase, it is often not possible to solve such equations directly. The modeling of rating data, in which one must only compute the difference between two sets of equations, each corresponding to one of the two targets, is generally a trivial problem to solve. The major disadvantage of rating techniques, in the absence of a matching task, is that the subject must perform a large number of trials, $t = rn^2$, where n is the sampling resolution of the stimulus gradations presented to the subject and r is the desired number of replicates. Thus, even for 10 samples each of a pair of targets, the subject must perform $100r$ trials.

5.3. Comparison with standard models

Our psychophysical data are inconsistent with a large class of models of simultaneous contrast and related phenomena in achromatic color perception that embody the assumption that the achromatic color gamut is 1D (Arrington, 1996; Blakeslee and McCourt, 1997, 1999, 2004; Bressan, 2006; Cohen and Grossberg, 1984; Dakin and Bex, 2003; Gilchrist et al., 1999; Gilchrist, 2006; Grossberg and Todorović, 1988; Hamada, 1985; Heinemann and Chase, 1995; Land and McCann, 1971; Moulden and Kingdom, 1990; Pessoa et al., 1995; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Rudd and Popa, 2007; Rudd, 2010; Spehar et al., 1996; Vladusich et al., 2006b; Whittle, 1986, 1992). These models typically treat darkness as the negative of brightness, and with few exceptions (Pessoa et al., 1995), do not incorporate local luminance signals into the computation of achromatic colors. They therefore suffer from the same problem as the previous version of the brightness-darkness model (Vladusich et al., 2007), in that they incorrectly predict that subjects can make absolute color matches in conventional simultaneous contrast displays (Fig. 5), and are, furthermore, inconsistent with psychophysical data on mixed-polarity simultaneous contrast (Vladusich et al., 2007).

5.4. The dimensions of achromatic color space

Our modeling framework suggests that brightness and darkness constitute the dimensions of achromatic color space. Alternative models of 2D achromatic color space have, however, been proposed (Evans, 1959, 1964; Heggelund, 1974a,b, 1992; Gilchrist, 2006; Logvinenko and Maloney, 2006). Logvinenko and Maloney (2006), for example, presented psychophysical data and a descriptive model supporting the notion that achromatic color space is composed of two dimensions, and argued that brightness and lightness constitute the perceptual dimensions underlying this color space. The authors' data also indicated that the achromatic color gamut available to subjects performing a color matching task depended on illumination intensity. In our experiment, subjects viewed simple disk-ring configurations that appeared against a background of uniform and constant luminance on a computer monitor. We did not introduce any cues that may have induced strong impressions of surface lightness and illumination in the 'match' and 'reference' configurations (Arend and Goldstein, 1987), and we instructed subjects to match brightness, rather than lightness (Arend and Goldstein, 1987; Arend and Spehar, 1993a,b). Together with our modeling of the psychophysical data presented herein, these considerations suggest that brightness and lightness may not be the appropriate computational descriptors to apply in the case of simple, computer-generated stimulus configurations.

A detailed computational analysis of the issues raised in Logvinenko and Maloney (2006) falls outside the scope of the current article and will instead be presented in a follow-up article. For the present purposes, it suffices to say that the brightness-darkness model, and the concept of gamut relativity, can be extended to account for properties of achromatic color constancy, the dimensionality of achromatic colors, and the effects of task instruction on color matching behavior (Arend and Goldstein, 1987; Arend and Spehar, 1993a,b; Gilchrist, 2006; Heggelund, 1974a,b, 1992; Logvinenko and Maloney, 2006).

5.5. *The asymmetry between brightness and darkness*

The incorporation of luminance information into the brightness-darkness model requires us to revise existing qualitative definitions of brightness and darkness. Rather than referring to the perceived luminance of contrast *increments* and *decrements*, respectively, brightness and darkness are computationally (re)defined as the sum of weighted luminance and contrast information. Our modeling results suggest that the *overall weight* applied to darkness is approximately 6 times greater than the overall weight applied to brightness, as $\frac{\alpha}{1-\alpha} > 6$. As the *contrast* weights applied in the brightness and darkness dimensions were set to unity, the total weight applied to incremental and decremental contrasts is equal to the overall weight values. This is consistent with a large body of psychophysical data suggesting that decremental contrasts are more heavily weighted than incremental contrasts (Bowen et al., 1989; Burr, 1987; De Weert and Spillmann, 1995; Gilchrist, 2006; Hamada, 1985; Magnussen and Glad, 1975a,b; Moulden and Kingdom, 1990; Shevell, 1989; Wook Hong and Shevell, 2004; Vladusich et al., 2006b, 2007; Whittle, 1986).

Our results are, however, more general than those of previous studies, as the brightness-darkness model allows us to calculate the separate contributions of luminance and contrast to brightness and darkness. The respective luminance weights applied to brightness and darkness, ν and μ, differed only by a factor of 2, with $\nu \approx 1.8$ and $\mu \approx 0.9$. Given these values, and factoring in the unity contrast weights, we calculate that darkness is approximately 4 times more heavily weighted than brightness. We term this asymmetry the *darkness bias*.

5.6. *"Brightness" matching in the increment and decrement frames*

The concept of gamut relativity leads to the prediction that "brightness" matches in simple center-surround displays reflect minimal perceptual distances between reference and match colors in brightness-darkness space. It is important to note, in this respect, that such "brightness" matches are strongly influenced by the darkness bias. Due to the darkness bias, "brightness" matches performed in the increment frame are most strongly influenced by target luminance, whereas "brightness" matches performed in the decrement frame are influenced by both target luminance and contrast. This can be seen, for example, in Fig. 9 and Fig. 10, where the decrement frame is far more discriminable from the luminance frame than is the increment frame. This proposal thereby unifies a large body of psychophysical data showing that the achromatic colors of incremental targets are closely associated with luminance information, whereas the achromatic colors of decremental targets are closely associated with a combination of luminance and contrast information (Arend and Goldstein, 1987; Arend and Spehar, 1993a,b; Bressan and Actis-Grosso, 2001; Gilchrist, 2006; Heinemann, 1955; Jacobsen and Gilchrist, 1988a,b; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Rudd and Popa, 2007; Vladusich et al., 2006b, 2007; Wallach, 1948; Whittle, 1986, 1992).

The model also provides a new way to predict whether subjects will perform opposite-polarity matches (match increment to decrements, or *vice versa*), as subjects routinely did in **Step 2** of the present psychophysical experiment. According to the model, such matches will occur when the achromatic color of the target reference region lies within the "cross-over nexus" between increment and decrement frames. As shown in Fig. 11 (blue data points), the cross over from same-polarity to opposite-polarity matches is associated with a change in the slope of the "brightness" matching function. An indication of such a change in slope is evident, for example, in the data of subject L.A. shown in Fig. 11.

It is clear from the discussion above that the use of the term "brightness" as an instructional construct within a given psychophysical context need not correspond to the technical usage within a given computational context. According to the brightness-darkness model, greater weight is placed on darkness than brightness during "brightness" matching tasks. It would therefore be more correct to say that subjects match darkness, rather than brightness, when instructed to match "brightness" in simple center-surround displays.

5.7. The case for luminance information

While the role of contrast information in achromatic color perception is well established, classical and recent evidence supports the hypothesis that luminance information also plays a role in achromatic color perception (Barlow and Verrillo, 1976; Bolanowski, 1987; Gilchrist et al., 1999; Gilchrist, 2006; Knau and Spillmann, 1997; Li and Gilchrist, 1999; Masin, 2003; Shapiro et al., 2004, 2005; Shapiro, 2008; Shapiro and Knight, 2008). The capacity to distinguish between bright and dim illumination levels, for instance, provides circumstantial evidence supporting the role of luminance in achromatic color perception (Gilchrist, 2006). Psychophysical experiments using *Ganzfeld* stimuli provide direct empirical support for the role of luminance information, as subjects in such experiments perceive "brightness" to vary with the luminance of the field in a manner consistent with Steven's law (Barlow and Verrillo, 1976; Bolanowski, 1987; Knau and Spillmann, 1997; Gilchrist, 2006). It is nonetheless clear that a great deal of controversy in the literature has arisen due to the assumption that contrast information alone determines achromatic colors, as embodied in Wallach's ratio principle (Wallach, 1948), particularly with respect to differences observed using incremental and decremental targets (Bressan and Actis-Grosso, 2001; Gilchrist, 2006; Heinemann, 1955; Jacobsen and Gilchrist, 1988a,b; Rudd and Arrington, 2001; Rudd and Zemach, 2004; Wallach, 1948).

One study that has been cited (Gilchrist, 2006) as evidence *against* a role for luminance is that of Whittle and Challands (1969). Noting that experimental subjects often have difficulty making satisfactory color matches between targets viewed against backgrounds differing in luminance, these authors used a dichoptic presentation paradigm to fuse different backgrounds presented to each eye, creating a single background with a unitary gray shade. Targets presented separately to each eye were fused with the background from the other eye. Under these conditions, subjects were able to match the targets with ease, the data being consistent with Wallach's ratio principle (Wallach, 1948): Subjects matched the luminance ratio defined by target and background regions presented *to each eye*.

The brightness-darkness model presented here can be augmented in a simple way, however, to provide an argument against the interpretation of the Whittle and Challands (1969) data solely in terms of contrast information. Assuming that the visual system sums the luminance information received from each eye at the same visual field location, as in *binocular brightness summation* (Engel, 1967; Bolanowski, 1987), then the model predicts that subjects will adjust target luminance presented to one eye to match the target-background luminance ratio presented to the other eye. Suppose we have a pair of targets (labelled i and j) presented to left and right eyes, with luminance values, x_i and x_j, respectively surrounded by backgrounds (labelled p and q) with luminance values, x_p and x_q, such that the reference target (say j) is a local contrast decrement. The summed darkness values, ϕ_i and ϕ_j, corresponding to the left- and right-eye targets, i and j, are

$$\phi_i = \alpha\left(\beta_i \log\frac{x_p}{x_i} + \mu \log\frac{k_d^2}{x_i x_q}\right) \tag{10}$$

and

$$\phi_j = \alpha\left(\beta_j \log\frac{x_q}{x_j} + \mu \log\frac{k_d^2}{x_j x_p}\right) \tag{11}$$

From this construction, setting $\phi_i = \phi_j$, and assuming a decrement-to-decrement match, such that $\beta_i = \beta_j$, the model predicts that subjects perform color matches according to Wallach's ratio principle (Wallach, 1948), as we can derive the equality $\frac{x_p}{x_i} = \frac{x_q}{x_j}$. A similar argument applies to the brightness dimension. As such, the above analysis negates a major argument against the notion of a luminance signal that contributes to achromatic color perception. It also suggests that absolute achromatic color matches are possible under certain, albeit somewhat contrived, circumstances.

5.8. The scaling of brightness-darkness space

The parameters k_d and k_b were assumed to be constants in this study, canceling out in the calculation of our solutions to the color matching equations, and therefore having no tangible influence on the results. In displaying achromatic colors in brightness-darkness space, however, we were forced to assign specific values to k_d and k_b. In our modeling of the current psychophysical data, we set $k_d = 85\ \frac{cd}{m^2}$ and $k_b = 5\ \frac{cd}{m^2}$, whereas in our modeling of the Arend and Goldstein (1987) data, we set $k_d = 50\ \frac{cd}{m^2}$ and $k_b = 0.01\ \frac{cd}{m^2}$. The scaling of brightness-darkness space is, nonetheless, an important computational issue, though it is difficult to say at this juncture how the values of k_d and k_b should be chosen in general, or indeed whether these parameters should be considered constants or functions of image luminance or contrast. We provide a partial solution to these issues in a follow-up article that deals with the concept of gamut relativity in a more general way than is appropriate here.

5.9. Relationship to ON and OFF channels

The brightness-darkness model was originally (Vladusich et al., 2007) inspired by the concept of separate processing of contrast increments and decrements in the ON (on-centre off-surround) and OFF (off-centre on-surround) channels of the visual system (Barlow et al., 1957; Kuffler et al., 1957; De Valois and Pease, 1971; Magnussen and Glad, 1975a,b; Kinoshita and Komatsu, 2001; Kuffler, 1953; Schiller, 1992; Wang et al., 2007). Major obstacles remain, however, in elucidating the putative relationship between ON and OFF channels, on the one hand, and brightness and darkness perception, on the other. The ON and OFF channels, for instance, process information at the spatial scale of local receptive fields, whereas brightness and darkness are perceptual properties associated with extended surfaces (De Valois and Pease, 1971; Magnussen and Glad, 1975a,b).

According to the brightness-darkness model, furthermore, both luminance and contrast information contribute to achromatic color perception, whereas local ON and OFF responses are conventionally understood to be dominated by contrast information (Barlow et al., 1957; Chichilnisky and Kalmar, 2002; Kuffler et al., 1957; De Valois and Pease, 1971; Kuffler, 1953; Schiller, 1992). A considerable body of classical (Barlow and Levick, 1969; Barlow et al., 1978; Kayama et al., 1979; Papaioannou and White, 1972) and recent evidence (Geisler et al., 2007; Kinoshita and Komatsu, 2001; Mante et al., 2005; Peng and Van Essen, 2005; Rossi and Paradiso, 1999; Vladusich et al., 2006a; Xing et al., 2010; Yeh et al., 2009), however, supports a role for luminance information in shaping ON and OFF responses in mammalian lateral geniculate nucleus and primary visual cortex.

Available neurophysiological data are, furthermore, consistent with the prediction of the brightness-darkness model that luminance and contrast information combine linearly (Geisler et al., 2007; Mante et al., 2005), in a fashion that reflects the statistical independence of luminance and contrast information in natural scenes (Frazor and Geisler, 2006; Mante et al., 2005). Consistent with the darkness bias we describe in this article, neurophysiological data indicates that OFF cells are more numerous, and their responses greater, than ON cells in retina and visual cortex (Chichilnisky and Kalmar, 2002; Ratliff et al., 2010; Peng and Van Essen, 2005; Xing et al., 2010; Yeh et al., 2009). The darkness bias may, in this respect, reflect the statistical prevalence of contrast decrements, over increments, in natural scenes (Ratliff et al., 2010).

5.10. The appearance of luster at high contrast

According to the brightness-darkness model, a given image region can appear both *simultaneously brighter and darker* than another region (Vladusich et al., 2007), as in the demonstration shown in Fig. 12. Observers describe regions in which strong brightness and darkness components are simultaneously present variously as *glossy*, *lustrous*, *silver*, or *metallic*, whereas regions containing low levels of brightness and darkness appear *matte*, *dull* or *earthy*. Indeed, the model may help to explain the percepts of luster that arise through

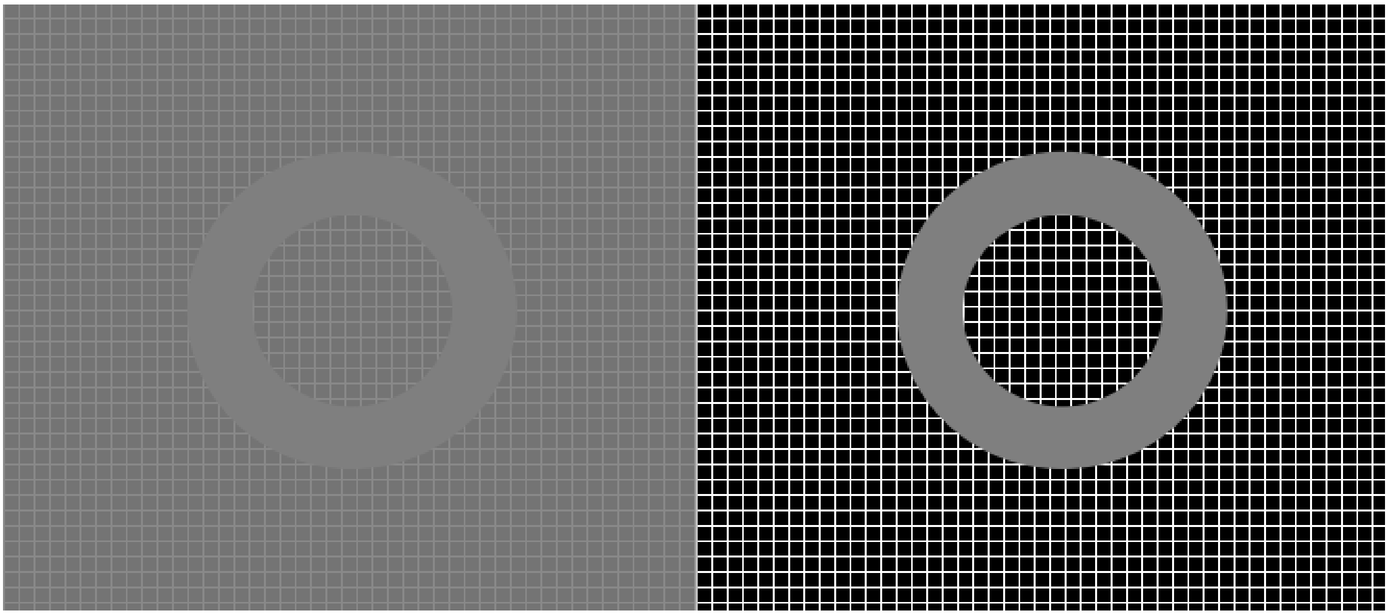

Figure 12: Mixed-polarity simultaneous contrast is associated with a lustrous or metallic appearance at high contrast and an earthy or dull appearance at low contrast. The gray rings are identical, but the ring on the left (right) is surrounded by texture of low (high) contrast. The model suggests that lustrous appearance occurs when brightness and darkness signals are simultaneously high, as during the binocular fusion of high-contrast targets with opposite contrast polarity (Anstis, 2000; Bancroft and Allen, 1925; Fry, 1931), during high-contrast increment-to-decrement flicker (Anstis, 2000; Magnussen and Glad, 1975b), or when luminance and contrast signals provide inconsistent information, as in certain versions of the Craik-O'Brien-Cornsweet effect (Burr, 1987). Pinna et al. (2002) presented a version of the Ehrenstein illusion that resembles the "scintillating luster" effect observed above. Closing one eye largely eliminates the scintillation effect, while preserving the lustrous appearance of the ring on the right side of the display.

binocular fusion of bright and dark image regions (Anstis, 2000; Harris and Parker, 1995; Bancroft and Allen, 1925; Fry, 1931), during presentation of targets flickering rapidly from bright to dark against a steady gray background (Anstis, 2000; Magnussen and Glad, 1975b), and in versions of the Ehrenstein illusion in which both brightness and darkness contrast signals are induced into a region (Pinna et al., 2002).

The augmented model developed herein extends this explanatory range to include cases in which luster arises when contrast signals in one dimension (e.g. brightness) and luminance signals in the other dimension (e.g. darkness) are simultaneously high. Burr (1987), for example, described certain versions of the Craik-O'Brien-Cornsweet display in which the percept of luster arises when brightness information from low-pass luminance signals and darkness information from high-pass contrast signals were simultaneously present in a target region.

5.11. Future directions

In a follow-up article, we conduct a computational study linking the asymmetry between brightness and darkness, or darkness bias, reported here to the phenomena of anchoring, scission and constancy in achromatic color perception (Adelson, 2000; Anderson, 2003; Anderson and Winawer, 2005, 2008; Arend and Goldstein, 1987; Gilchrist et al., 1999; Gilchrist, 2006, 1977, 1979; Gilchrist et al., 1983; Heggelund, 1974a,b, 1992; Logvinenko and Maloney, 2006). We show how, with the inclusion of a few simple, empirically supported modifications, the model can explain a wide body of psychophysical data on the perception of opaque, transparent and luminous achromatic colors, including data on gamut compression, insulation and luminosity in the Gelb effect (Gilchrist et al., 1999; Gilchrist, 2006), achromatic color constancy and the dimensionality of achromatic colors (Heggelund, 1974a,b, 1992; Logvinenko and Maloney, 2006), and the effects of task instruction on achromatic color matching behavior (Arend and Goldstein, 1987; Arend and Spehar, 1993a,b), all using the model parameter values estimated in the current article. The model therefore promises to provide a unified computational approach to achromatic color perception.

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7. References

Adelson, E.H., 2000. Lightness perception and lightness illusions. In M. Gazzaniga (Ed.), The new cognitive neurosciences (2nd ed., pp. 339– 351). Cambridge, MA: MIT Press .

Anderson, B.L., 2003. The role of occlusion in the perception of depth, lightness, and opacity. Psychol Rev 110, 785–801.

Anderson, B.L., Winawer, J., 2005. Image segmentation and lightness perception. Nature 434, 79–83.

Anderson, B.L., Winawer, J., 2008. Layered image representations and the computation of surface lightness. Journal of vision 8, 18.1–22.

Anstis, S., 2000. Monocular lustre from flicker. Vision Research 40, 2551–2556.

Arend, L.E., Goldstein, R., 1987. Simultaneous constancy, lightness, and brightness. J Opt Soc Am A 4, 2281–2285.

Arend, L.E., Spehar, B., 1993a. Lightness, brightness, and brightness contrast: 1. Illuminance variation. Perception & Psychophysics 54, 446–456.

Arend, L.E., Spehar, B., 1993b. Lightness, brightness, and brightness contrast: 2. Reflectance variation. Perception & Psychophysics 54, 457–468.

Arrington, K.F., 1996. Directional filling-in. Neural Comput 8, 300–318.

Bancroft, W.D., Allen, R.P., 1925. Metallic Luster. II. J. Phys. Chem. 29, 564–586.

Barlow, H.B., Fitzhugh, R., Kuffler, S.W., 1957. Dark adaptation, absolute threshold and Purkinje shift in single units of the cat's retina. J Physiol (Lond) 137, 327–337.

Barlow, H.B., Levick, W.R., 1969. Changes in the maintained discharge with adaptation level in the cat retina. J Physiol (Lond) 202, 699–718.

Barlow, R.B., Snodderly, D.M., Swadlow, H.A., 1978. Intensity coding in primate visual system. Exp Brain Res 31, 163–177.

Barlow, R.B., Verrillo, R.T., 1976. Brightness sensation in a ganzfeld. Vision Research 16, 1291–1297.

Blakeslee, B., McCourt, M.E., 1997. Similar mechanisms underlie simultaneous brightness contrast and grating induction. Vision Research 37, 2849–2869.

Blakeslee, B., McCourt, M.E., 1999. A multiscale spatial filtering account of the White effect, simultaneous brightness contrast and grating induction. Vision Research 39, 4361–4377.

Blakeslee, B., McCourt, M.E., 2004. A unified theory of brightness contrast and assimilation incorporating oriented multiscale spatial filtering and contrast normalization. Vision Research 44, 2483–2503.

Bolanowski, S.J., 1987. Contourless stimuli produce binocular brightness summation. Vision Research 27, 1943–1951.

Bowen, R.W., Pokorny, J., Smith, V.C., 1989. Sawtooth contrast sensitivity: decrements have the edge. Vision Research 29, 1501–1509.

Bressan, P., 2006. Inhomogeneous surrounds, conflicting frameworks, and the double-anchoring theory of lightness. Psychon Bull Rev 13, 22–32.

Bressan, P., Actis-Grosso, R., 2001. Simultaneous lightness contrast with double increments. Perception 30, 889–897.

Burr, D.C., 1987. Implications of the Craik-O'Brien illusion for brightness perception. Vision Research 27, 1903–1913.

Chichilnisky, E.J., Kalmar, R.S., 2002. Functional asymmetries in ON and OFF ganglion cells of primate retina. J Neurosci 22, 2737–2747.

Cohen, M.A., Grossberg, S., 1984. Neural dynamics of brightness perception: features, boundaries, diffusion, and resonance. Perception & Psychophysics 36, 428–456.

Dakin, S.C., Bex, P.J., 2003. Natural image statistics mediate brightness 'filling in'. Proc Biol Sci 270, 2341–2348.

De Valois, R.L., Pease, P.L., 1971. Contours and contrast: responses of monkey lateral geniculate nucleus cells to luminance and color figures. Science 171, 694–696.

De Weert, C.M., Spillmann, L., 1995. Assimilation: asymmetry between brightness and darkness? Vision Research 35, 1413–1419.

Ekroll, V., Faul, F., 2009. A simple model describes large individual differences in simultaneous colour contrast. Vision Research 49, 2261–2272.

Ekroll, V., Faul, F., Niederée, R., 2004. The peculiar nature of simultaneous colour contrast in uniform surrounds. Vision Research 44, 1765–1786.

Ekroll, V., Faul, F., Niederée, R., Richter, E., 2002. The natural center of chromaticity space is not always achromatic: a new look at color induction. Proc Natl Acad Sci USA 99, 13352–13356.

Ekroll, V., Faul, F., Wendt, G., 2011. The strengths of simultaneous colour contrast and the gamut expansion effect correlate across observers: evidence for a common mechanism. Vision Research 51, 311–322.

Engel, G.R., 1967. The visual processes underlying binocular brightness summation. Vision Research 7, 753–767.

Evans, R.M., 1959. Fluorescence and gray content of surface colors. J Opt Soc Am 49, 1049–1059.

Evans, R.M., 1964. Variables of perceived color. J Opt Soc Am 54, 1467–1474.

Frazor, R.A., Geisler, W.S., 2006. Local luminance and contrast in natural images. Vision Research 46, 1585–1598.

Fry, G., 1931. The stimulus correlate of bulky color. Am J Psychol 43, 618–620.

Geisler, W.S., Albrecht, D.G., Crane, A.M., 2007. Responses of neurons in primary visual cortex to transient changes in local contrast and luminance. J Neurosci 27, 5063–5067.

Gilchrist, A., Kossyfidis, C., Bonato, F., Agostini, T., Cataliotti, J., Li, X., Spehar, B., Annan, V., Economou, E., 1999. An anchoring theory of lightness perception. Psychol Rev 106, 795–834.

Gilchrist, A.L., 1977. Perceived lightness depends on perceived spatial arrangement. Science 195, 185–187.

Gilchrist, A.L., 1979. The perception of surface blacks and whites. Sci Am 240, 112–22, 124.

Gilchrist, A.L., 2006. Seeing black and white. Oxford University Press, USA.

Gilchrist, A.L., Delman, S., Jacobsen, A., 1983. The classification and integration of edges as critical to the perception of reflectance and illumination. Perception & Psychophysics 33, 425–436.

Grossberg, S., Todorović, D., 1988. Neural dynamics of 1-D and 2-D brightness perception: a unified model of classical and recent phenomena. Perception & Psychophysics 43, 241–277.

Hamada, J., 1985. Asymmetric lightness cancellation in Craik-O'Brien patterns of negative and positive contrast. Biological cybernetics 52, 117–122.

Harris, J.M., Parker, A.J., 1995. Independent neural mechanisms for bright and dark information in binocular stereopsis. Nature 374, 808–811.

Heggelund, P., 1974a. Achromatic color vision–I: perceptive variables of achromatic colors. Vision Research 14, 1071–1079.

Heggelund, P., 1974b. Achromatic color vision–II: measurement of simultaneous achromatic contrast within a bidimensional system. Vision Research 14, 1081–1088.

Heggelund, P., 1992. A bidimensional theory of achromatic color vision. Vision Research 32, 2107–2119.

Heinemann, E.G., 1955. Simultaneous brightness induction as a function of inducing and test-field luminances. J Exp Psychol 50, 89–96.

Heinemann, E.G., Chase, S., 1995. A quantitative model for simultaneous brightness induction. Vision Research 35, 2007–2020.

Jacobsen, A., Gilchrist, A., 1988a. Hess and Pretori revisited: resolution of some old contradictions. Perception & Psychophysics 43, 7–14.

Jacobsen, A., Gilchrist, A., 1988b. The ratio principle holds over a million-to-one range of illumination. Perception & Psychophysics 43, 1–6.

Kayama, Y., Riso, R.R., Bartlett, J.R., Doty, R.W., 1979. Luxotonic responses of units in macaque striate cortex. J Neurophysiol 42, 1495–1517.

Kinoshita, M., Komatsu, H., 2001. Neural representation of the luminance and brightness of a uniform surface in the macaque primary visual cortex. J Neurophysiol 86, 2559–2570.

Knau, H., Spillmann, L., 1997. Brightness fading during Ganzfeld adaptation. J Opt Soc Am A 14, 1213–1222.

Koenderink, J.J., 2003. Another Babel. Perception 32, 391–394.

Kuffler, S.W., 1953. Discharge patterns and functional organization of mammalian retina. J Neurophysiol 16, 37–68.

Kuffler, S.W., Fitzhugh, R., Barlow, H.B., 1957. Maintained activity in the cat's retina in light and darkness. J Gen Physiol 40, 683–702.

Land, E.H., McCann, J.J., 1971. Lightness and retinex theory. J Opt Soc Am 61, 1–11.

Li, X., Gilchrist, A.L., 1999. Relative area and relative luminance combine to anchor surface lightness values. Perception & Psychophysics 61, 771–785.

Logvinenko, A.D., Maloney, L.T., 2006. The proximity structure of achromatic surface colors and the impossibility of asymmetric lightness matching. Perception & Psychophysics 68, 76–83.

Magnussen, S., Glad, A., 1975a. Effects of steady surround illumination on the brightness and darkness enhancement of flickering lights. Vision Research 15, 1413–1416.

Magnussen, S., Glad, A., 1975b. Temporal frequency characteristics of spatial interaction in human vision. Exp Brain Res 23, 519–528.

Mante, V., Frazor, R.A., Bonin, V., Geisler, W.S., Carandini, M., 2005. Independence of luminance and contrast in natural scenes and in the early visual system. Nat Neurosci 8, 1690–1697.

Masin, S.C., 2003. On the determinants of surface brightness. Psychon Bull Rev 10, 220–223.

Moulden, B., Kingdom, F., 1990. Light-dark asymmetries in the Craik-Cornsweet-O'Brien illusion and a new model of brightness coding. Spat Vis 5, 101–128.

Nosofsky, R.M., Kantner, J., 2006. Exemplar similarity, study list homogeneity, and short-term perceptual recognition. Memory & cognition 34, 112–124.

Papaioannou, J., White, A., 1972. Maintained activity of lateral geniculate nucleus neurons as a function of background luminance. Exp. Neurol. 34, 558–566.

Peng, X., Van Essen, D.C., 2005. Peaked encoding of relative luminance in macaque areas V1 and V2. J Neurophysiol 93, 1620–1632.

Pessoa, L., Mingolla, E., Neumann, H., 1995. A contrast- and luminance-driven multiscale network model of brightness perception. Vision Research 35, 2201–2223.

Pinna, B., Spillmann, L., Ehrenstein, W.H., 2002. Scintillating lustre and brightness induced by radial lines. Perception 31, 5–16.

Ratliff, C.P., Borghuis, B.G., Kao, Y.H., Sterling, P., Balasubramanian, V., 2010. Retina is structured to process an excess of darkness in natural scenes. Proc Natl Acad Sci USA 107, 17368–17373.

Rossi, A.F., Paradiso, M.A., 1999. Neural correlates of perceived brightness in the retina, lateral geniculate nucleus, and striate cortex. J Neurosci 19, 6145–6156.

Rudd, M.E., 2010. How attention and contrast gain control interact to regulate lightness contrast and assimilation: a computational neural model. Journal of vision 10.

Rudd, M.E., Arrington, K.F., 2001. Darkness filling-in: a neural model of darkness induction. Vision Research 41, 3649–3662.

Rudd, M.E., Popa, D., 2007. Stevens's brightness law, contrast gain control, and edge integration in achromatic color perception: a unified model. J Opt Soc Am A 24, 2766–2782.

Rudd, M.E., Zemach, I.K., 2004. Quantitative properties of achromatic color induction: an edge integration analysis. Vision Research 44, 971–981.

Schiller, P.H., 1992. The ON and OFF channels of the visual system. Trends Neurosci 15, 86–92.

Shapiro, A., Knight, E., 2008. Spatial and temporal influences on the contrast gauge. Vision Research 48, 2642–2648.

Shapiro, A.G., 2008. Separating color from color contrast. Journal of vision 8, 8.1–18.

Shapiro, A.G., Charles, J.P., Shear-Heyman, M., 2005. Visual illusions based on single-field contrast asynchronies. Journal of vision 5, 764–782.

Shapiro, A.G., D'Antona, A.D., Charles, J.P., Belano, L.A., Smith, J.B., Shear-Heyman, M., 2004. Induced contrast asynchronies. Journal of vision 4, 459–468.

Shevell, S.K., 1989. On neural signals that mediate induced blackness. Vision Research 29, 891–900.

Spehar, B., Debonet, J.S., Zaidi, Q., 1996. Brightness induction from uniform and complex surrounds: a general model. Vision Research 36, 1893–1906.

Vladusich, T., Lucassen, M.P., Cornelissen, F.W., 2006a. Do cortical neurons process luminance or contrast to encode surface properties? J Neurophysiol 95, 2638–2649.

Vladusich, T., Lucassen, M.P., Cornelissen, F.W., 2006b. Edge integration and the perception of brightness and darkness. Journal of vision 6, 1126–1147.

Vladusich, T., Lucassen, M.P., Cornelissen, F.W., 2007. Brightness and darkness as perceptual dimensions. PLoS Comput Biol 3, e179.

Wallach, H., 1948. Brightness constancy and the nature of achromatic colors. J Exp Psychol 38, 310–324.

Wang, Y., Xiao, Y., Felleman, D.J., 2007. V2 thin stripes contain spatially organized representations of achromatic luminance change. Cereb Cortex 17, 116–129.

Whittle, P., 1986. Increments and decrements: luminance discrimination. Vision Research 26, 1677–1691.

Whittle, P., 1992. Brightness, discriminability and the “crispening effect”. Vision Research 32, 1493–1507.

Whittle, P., Challands, P.D., 1969. The effect of background luminance on the brightness of flashes. Vision Research 9, 1095–1110.

Wook Hong, S., Shevell, S.K., 2004. Brightness contrast and assimilation from patterned inducing backgrounds. Vision Research 44, 35–43.

Xing, D., Yeh, C.I., Shapley, R.M., 2010. Generation of black-dominant responses in V1 cortex. J Neurosci 30, 13504–13512.

Yeh, C.I., Xing, D., Shapley, R.M., 2009. “Black” responses dominate macaque primary visual cortex V1. J Neurosci 29, 11753–11760.