TECHNISCHE UNIVERSITÄT BERLIN
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Abschlussarbeit

Investigating Model Predictions: Parametric and Stimuli Category Influence on ODOG, LODOG, and FLODOG

vorgelegt von
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zur Erlangung des akademischen Grades
Bachelor of science (B.sc.)
im Studiengang **Wirtschaftsingenieurwesen**

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03. Merz 2025

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Berlin, den 03. Merz 2025

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Abstract

This study investigates how variations in target size and spatial frequency influence the predictions of three low-level brightness perception models—ODOG, LODOG, and FLODOG—across different stimulus types. Using a set of brightness illusions categorized into contrast and assimilation groups, systematic parametric manipulations were applied to key stimulus features, such as element width and target size. The models' outputs were quantified by measuring predicted brightness differences between target regions. Results indicate that while smaller target sizes generally enhance contrast effects, larger targets tend to promote assimilation effects. However, these trends are not uniformly observed across all stimuli. Notably, the ODOG and LODOG models frequently predict stronger contrast effects even for stimuli theoretically expected to induce assimilation, whereas the FLODOG model—despite producing higher magnitude effects—displays a more balanced sensitivity to parameter variations. Furthermore, the anticipated differences between assimilation and contrast stimuli were not consistently reflected in the models' outputs, indicating that model predictions depend more on the specific attributes of individual stimuli than on their theoreticle grouping. The study highlights both the strengths and limitations of current computational models and underscores the need for further validation against psychophysical data to refine our understanding of human brightness perception.

Zusammenfassung

Diese Studie untersucht, wie Variationen in Zielgröße und räumlicher Frequenz die Vorhersagen dreier Modelle der Helligkeitswahrnehmung – ODOG, LODOG und FLODOG – in unterschiedlichen Stimulus-Typen beeinflussen. Mithilfe einer Reihe von Helligkeitsillusionen, die in Kontrast- und Assimilation-Gruppen unterteilt wurden, wurden systematische parametrische Modifikationen an zentralen Stimulusmerkmalen wie Elementbreite und Zielgröße vorgenommen. Die Modellvorhersagen wurden quantifiziert, indem die prognostizierten Helligkeitsunterschiede zwischen den Zielbereichen gemessen wurden. Die Ergebnisse zeigen, dass kleinere Zielgrößen tendenziell Kontrasteffekte verstärken, während größere Ziele Assimilationseffekte begünstigen. Diese Trends treten jedoch nicht in allen Stimuli einheitlich auf. Insbesondere neigen die Modelle ODOG und LODOG dazu, stärkere Kontrasteffekte vorherzusagen – selbst bei Stimuli, die theoretisch eine Assimilation erwarten ließen –, während das FLODOG-Modell trotz höherer Effektstärken eine ausgewogenere Empfindlichkeit gegenüber Parameteränderungen aufweist. Darüber hinaus spiegeln sich die erwarteten Unterschiede zwischen Assimilations- und Kontraststimuli in den Modellausgaben nicht konsistent wider, was darauf hinweist, dass die Vorhersagen der Modelle stärker von den spezifischen Eigenschaften einzelner Stimuli als von ihrer theoretischen Gruppierung abhängen. Die Studie hebt sowohl die Stärken als auch die Einschränkungen der aktuellen rechnerischen Modelle hervor und unterstreicht die Notwendigkeit weiterer Validierungen anhand psychophysikalischer Daten, um unser Verständnis der menschlichen Helligkeitswahrnehmung zu verfeinern.

1 Introduction and Background

Imagine walking past a white-walled house on a sunny day, as we see in Figure (1). Part of the wall is brightly lit by direct sunlight, while another portion sits in shadow. Although the wall's color is uniform, the section in the sun appears much brighter than the part in shade. This everyday observation highlights the interplay among luminance, reflectance, and illumination.

Figure 1: An image of a scene effectively illustrates the distinction between lightness and brightness. The walls of the house seem uniformly painted in a light color (a judgment of lightness), yet they appear brighter in some areas and darker in others due to the effects of shadows and shading (a judgment of brightness). Image credit: (Kingdom, 2010).

Luminance, reflectance, and illumination plays a critical role in how the human visual system interprets images and objects in our environment. Luminance, defined as the amount of light reaching the eye from a surface, results from the combination of surface reflectance and illumination. Reflectance, or albedo, is the proportion of light that a surface reflects, while illumination refers to the varying levels of light that can change both spatially and temporally across different scenes. However, observed luminance is inherently ambiguous because the same luminance can result from different combinations of reflectance and illumination (Kim et al., 2018; Kingdom, 2010). For example, a black surface in direct sunlight can reflect more light than a white surface in shadow, highlighting the challenge the visual system faces in interpreting luminance correctly to maintain consistent perceptions of an object's properties.

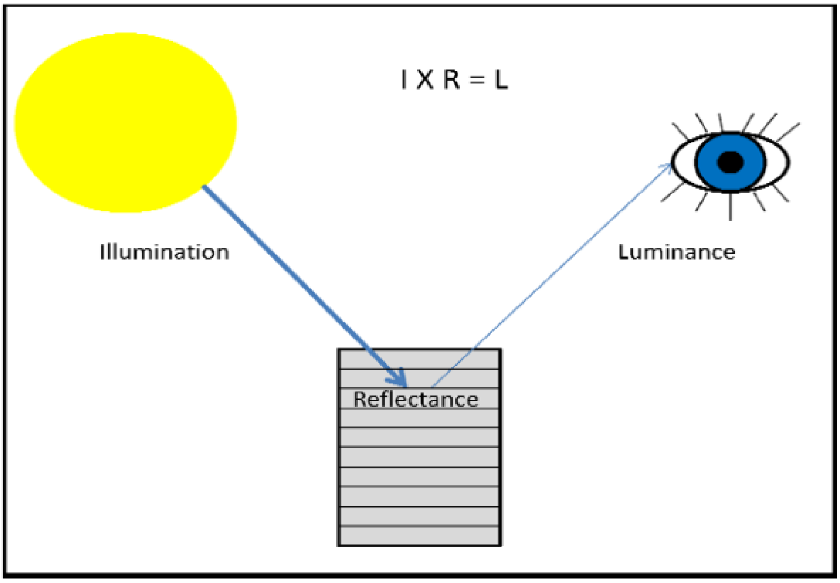

Figure 2: Illustration demonstrating the relationship between illumination, reflectance, and luminance. Illumination: varying levels of light that can change both spatially and temporally across different scenes. Reflectance: proportion of light that a surface reflects. Luminance: amount of light reaching the eye from a surface, results from the combination of surface reflectance and illumination. Image credit: (Riddle, 2011).

Despite the inherent ambiguity in luminance, reflectance, and illumination, our visual system generally achieves lightness constancy—perceiving stable reflectance properties of objects even under shifting lighting conditions (Gilchrist, 2007; Kingdom, 2010). As discussed above, the house walls appear uniformly painted (lightness), yet portions in direct sunlight look much brighter than those in shadow (brightness). This distinction between lightness and brightness highlights how our visual system interprets luminance information to differentiate changes in illumination from changes in surface reflectance. While lightness constancy helps us perceive the wall's reflectance as uniform, brightness perception allows us to note which areas are in shadow versus direct sunlight (Gilchrist, 2007; Kingdom, 2010). Understanding this interplay is crucial for explaining why our perceptions remain stable in a dynamic visual world filled with ever-changing lighting conditions.

Brightness illusions are visual phenomena in which identical luminance regions appear different (Adelson, 2000). They emerge because the visual system must resolve ambiguous signals arising from the interplay of surface reflectance and illumination (Kingdom, 2010). By examining these illusions, we can infer how the brain computes reflectance and luminance and gain insight into the strategies our visual system employs to make sense of the world (Adelson, 2000).

These illusions often involve patterns containing simple geometric shapes, such as squares, rectangles, or circles arranged in configurations with varying shades of gray or contrasting colors, where the target's brightness appears different despite having the same physical intensity. For example, as shown in Figure (3), gray targets placed on different backgrounds can look lighter or darker depending on their surroundings, even though their physical luminance remains unchanged (Kingdom, 2010). Unlike physical experiments, brightness illusions can be easily created, manipulated, and measured in experimental settings. Researchers can quantify these illusions by asking participants to indicate which patch appears brighter or by having them adjust the luminance of one patch until it matches the brightness of another. This straightforward methodology makes lightness and brightness illusions ideal for testing theories of human visual perception.

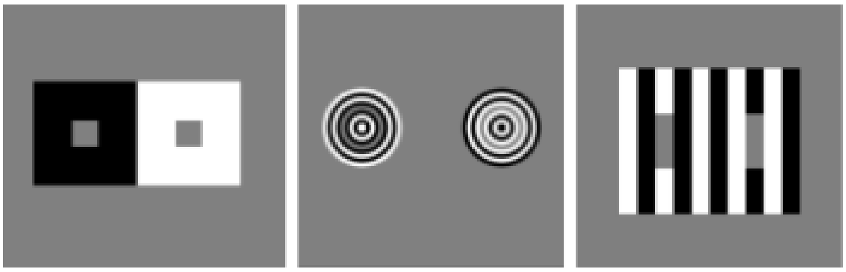

Figure 3: From left to right: Simultaneous Brightness Contrast (SBC): A gray square is placed on a black background on the left and on a white background on the right. The target appearing darker when placed on a black background and brighter when placed on white background on the right (showing contrast effect). Circular: Two sets of concentric circles, with alternating black and white rings and a gray target as the middle ring. The target ring between the black rings appearing darker than the one between the white ones (showing assimilation effect). White's illusion: gray targets are placed over alternating black and white stripes, appearing darker when positioned on white stripes and lighter when placed on black stripes (showing White's effect). Image credit: (Kobayashi & Shapiro, 2024).

Illusions can be divided into two main observed phenomena. Brightness contrast is a phenomenon in which a target appears lighter when surrounded by a darker background and darker when surrounded by a lighter background (Adelson, 1993; Kingdom, 2010; Robinson et al., 2007). As illustrated in Figure (3), left, a gray square target placed on a black and on a white background can appear to vary in brightness. The target appears darker when placed on a black background and brighter when placed on a white background on the right. On the contrary, assimilation refers to a phenomenon in which the perceived brightness of a target area shifts toward the brightness of its surrounding area. In this case, a region appears lighter when bordered by lighter areas and darker when surrounded by darker regions (Adelson, 1993; Kingdom, 2010; Robinson et al., 2007), like in Figure (3), middle, where the gray target rings in the middle of two concentric circles appear to assimilate with its surrounding.

An intriguing phenomenon that is hard to refer to as contras or assimilation is White's effect see (3) right figure. In White's illusion, gray targets are placed over alternating black and white stripes, appearing darker when positioned on white stripes and lighter when placed on black stripes. The direction of effect depends on the point of comparison; when compering to the specific stripe on which the gray target lies, the effect appears to be one of contrast. However, when compering to the flanking stripes, the gray target seems to merge with its surroundings, appearing lighter when adjacent to lighter stripes and darker when flanked by darker ones (contrast phenomena). Do to this duality, White's effect can be interpreted as contrast or assimilation depending on the elements the targets are compared to.

Expanding on the distinction between contrast and assimilation effects, recent empirical work by Kobayashi and Shapiro (2024) has investigated how different lightness illusions relate to one another. By examining the correlations among the perceived magnitudes of a diverse set of lightness illusions, their exploratory factor analysis revealed that a two-factor solution best describes the data. One latent factor was primarily associated with illusions that yield a contrast effect, while the other corresponded mainly to assimilative phenomena. Notably, White's illusion did not load exclusively on either factor but instead showed moderate contributions from both, suggesting that there are perceptual appearances that may result from an interplay of contrast and assimilation processes.

Theoretical frameworks been development to explain the underlying mechanisms that drive contrast and assimilation effects. These frameworks range from high-level cognitive theories, incorporating high-level cognitive processes and knowledge associated with the image, such as Gilchrist's anchoring theory, which posits that the brightest area in a scene is perceived as white and other areas are scaled relative to it (A. Gilchrist et al., 1999), to Anderson's Scission theories, which suggests the brain splits surfaces into layers like reflectance, transparency, and illumination (Anderson & Winawer, 2005). The low-level processes theories focus on processes occurring in the retina and early visual pathways, where local interactions between luminances help determine the perception (Adelson, 1993). More recent integrative models combine these high-level processes with low-level visual mechanisms, emphasizing that perception arises from interactions between early visual processing and scene interpretation (Kingdom, 2010). While these high-level cognitive theories offer suggestions about how perception works, low-level models provide relatively easy testable mechanisms grounded in early visual processing, allowing for direct computational predictions of human perception.

An example of a low-level model that successfully predict human perceptual responses is the ODOG family. The Oriented Difference of Gaussian (ODOG) model, introduced by Blakeslee and McCourt, provides an explanation for brightness perception through spatial filtering mechanisms (Blakeslee & McCourt, 1999; Blakeslee et al., 2005; Kim et al., 2018). The ODOG model receives an achromatic image as input and generates an output image by utilizing a set of seven ODOG filters applied at six different orientations to analyze the image. The ODOG filters used in these models emulate the center-surround inhibition, a mechanism where light in the center of the receptive field excites the neuron while light in the surrounding area inhibits it, helping the visual system detect contrasts and edges (Kuffler, 1953). After filtering, the model combines the outputs across different spatial frequencies and applies a normalization process within each orientation (Blakeslee & McCourt, 1999; Robinson et al., 2007). The LODOG model is variation of the ODOG model that uses localized rather than global normalization, generally reducing the magnitude of the predicted effects compared to ODOG. This approach is more neurally plausible, as it emphasizes the impact of neighboring regions on perceived brightness. Finally, FLODOG incorporates both local and frequency-dependent normalization, making it highly sensitive to spatial frequency changes (Robinson et al., 2007). Thus, ODOG, LODOG and FLODOG provide accurate and biologically plausible predictions of brightness perception.

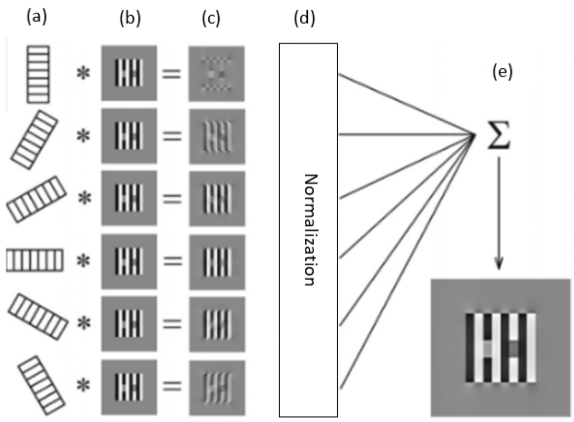

Figure 4: Schematic overview of (F)(L)ODOG model: In (a), a set of orientation-specific filters is shown. These filters are applied to the input stimulus (b), producing orientation-dependent response images (c) via convolution. Next, the root-mean-square (RMS) contrast of each filter output is normalized (d) so that responses at different orientations can be directly compared. Finally, these normalized outputs are summed across orientations (e) to generate the model's overall brightness prediction.(Blakeslee & McCourt, 1999; Kingdom, 2010).

Because models like ODOG, LODOG, and FLODOG rely on spatial filtering, the geometry of the input stimulus likely influences their brightness predictions. These models have already proven successful in predicting important aspects of brightness perception in various illusions (Blakeslee & McCourt, 1999; Kobayashi & Shapiro, 2024). Recent work by Ollech (2024) examined how varying the spatial frequency (black-and-white alternation in the stimulus, see Figure (5)) and the target size (the physical dimensions of the target elements in the stimulus, see Figure (5)) affects model outputs.

The ODOG, LODOG, and FLODOG models predict varying effects depending on these parameters. For example, according to Ollech (2024) the ODOG and LODOG models consistently predict contrast effects at lower spatial frequencies and assimilation effects at higher spatial frequencies. As the spatial frequency increases, these models simulate the smoothing of the details, resulting in stronger assimilation effects. Similarly, target size significantly influences model predictions. Smaller targets enhance assimilation effects, while larger targets lead to contrast effects. This occurs because smaller targets promote the integration of information over a limited area, whereas larger targets emphasize low-frequency details. Notably, the FLODOG model predicts a stronger assimilation effect across stimuli at high spatial frequencies, although its response to changes in target size is less consistent than ODOG and LODOG (Ollech, 2024). These predictions align with human studies, such as those by Blakeslee and McCourt (Blakeslee & McCourt, 1999), where the assimilation effects are more pronounced at high spatial frequencies and smaller target sizes.

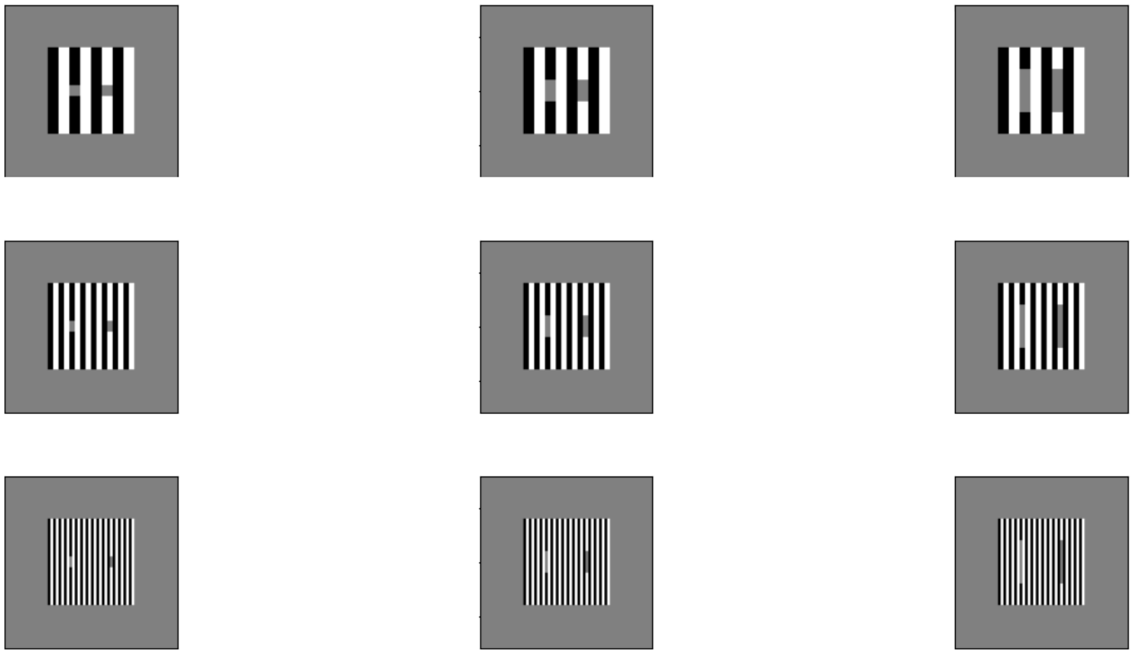

Figure 5: White's illusion: As we move down across the grid, the spatial frequency increases, meaning the vertical stripes become progressively narrower, representing finer details and sharper edges. This change reflects the transition from low spatial frequency on the top, where the patterns are broad and generalized, to high spatial frequency on the bottom, where more intricate details emerge. Conversely, as we go right in the grid, the target size increases, meaning the overall size of the gray rectangle grows larger, encompassing a greater area. At the left side of the grid, the smaller target sizes highlight more compact forms, while on the right side, the larger target sizes showcase broader features. This visualization demonstrates how spatial frequency and target size can vary independently, influencing how we perceive fine details versus large, generalized shapes.

Based on the findings of Ollech (2024) and Kobayashi and Shapiro (2024) this research aims to explore how do the predictions of the models (ODOG, LODOG, and FLODOG) change with different parameters like target size and frequency, and is there a difference between stimuli categories such as assimilation and contrast? The findings provide insights into the models' sensitivity to different types of illusions and parameter variations, offering a deeper understanding of how these models approximate human visual perception. Ultimately, this work will contribute to refining computational approaches in visual science and improving the accuracy of model-based predictions of visual phenomena. The models exhibit more consistent behavior in their predictions when stimulus parameters are varied within theoretically/empirically grouped stimuli (e.g., assimilation, contrast), as compared to between different stimulus groups. While these parameter variations may influence the magnitude and direction of the models' predictions, the predictions are expected to remain more stable within each stimulus group.

2 Methodology

This research investigated how variations in specific visual parameters (spatial frequency and target size) affect the consistent behavior of the models predictions within empirically grouped brightness illusions (assimilation vs. contrast).

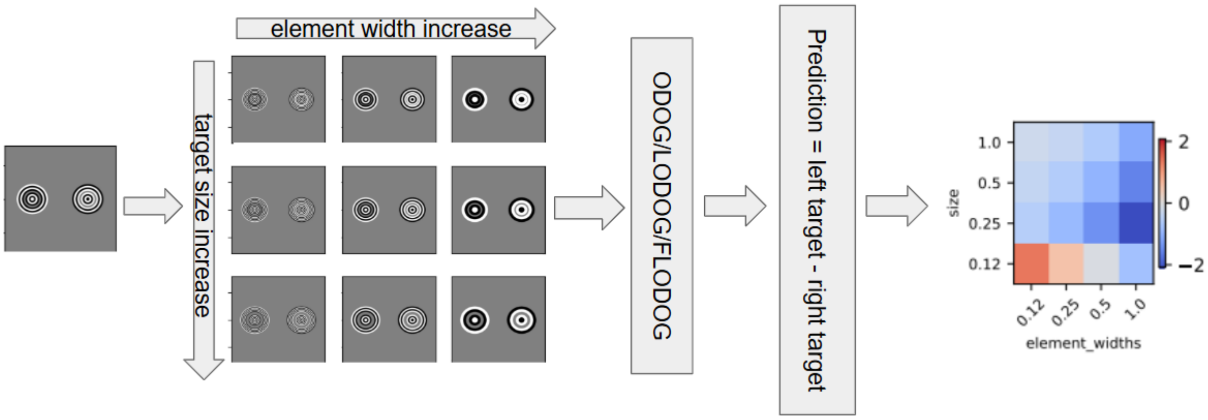

Figure 6: Workflow: First, selection of the stimuli from the Kobayashi and Shapiro (2024) research. Next, parametric variations of this stimulus are created, altering the features spatial frequency or target size. These varied stimuli are then processed by the ODOG, LODOG, and FLODOG models (middle-right), producing model outputs. From these outputs, the predicted brightness values in the target areas are extracted, calculated and assembled into a heatmap (right).

The study will involve three main phases: (1) generating and manipulating brightness illusions within these groups, (2) applying the computational models to these manipulated stimuli, and (3) evaluating the behavior of the models' predictions in response to these manipulations.

2.1 Stimulus selection

The visual stimuli for this study were selected based on two main criteria: Their relevance in previous studies - I chose stimuli that according to Kobayashi and Shapiro (2024) research had in the factor loading matrix a high loading and same direction of effect. Ease of manipulation - This simplicity allows for controlled alterations in parameters such as target size, and spatial frequency without introducing unintended distortions. These features ensure consistency across variations, making them suitable for systematic analysis and modeling in comparison to the other ones. Contrast group: SBC, Radial, and Grating Induction illusions as in Figure (7). Assimilation group: Circular, Dungeon, Yazdanbakhsh, and the Checkerboard illusions as in Figure (8).

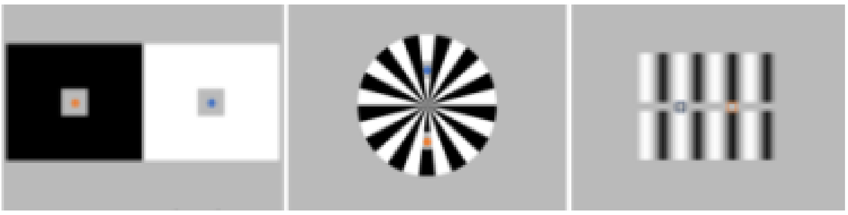

Figure 7: From left to right: SBC - A simultaneous brightness contrast illusion where two identical gray squares are placed on different backgrounds. One gray square is positioned on a black background, while the other is on a white background; Radial - A radial pattern with alternating black and white wedges that radiate outward from the center. Two small gray circles are positioned near the center of the pattern, one on a black wedge and the other on a white wedge; and Grating induction illusions - Alternating vertical black and white grating, with two gray squares placed in the center on one of the white stripes (Kobayashi & Shapiro, 2024)

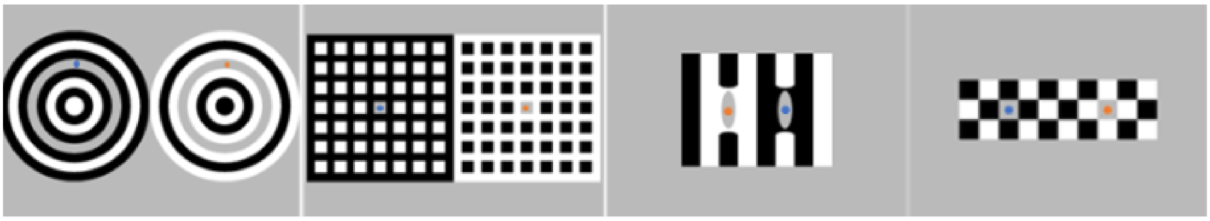

Figure 8: From left to right: Circular - Two sets of concentric circles (bullseye patterns) in black and white. In the center of each pattern, there are two gray concentric circles; Dungeon - Two grids made of black and white squares, with the left grid containing black lines on a white background and the right grid featuring white lines on a black background. Two gray squares are placed in different squares; Yazdanbakhsh - Vertical black and white bars, with two colored gray squares placed in between the bars; and Checkerboard illusions - A simple black-and-white checkerboard pattern, with two gray squares placed in different squares. (Kobayashi & Shapiro, 2024)

2.2 Stimulus parameter variations

I used the Schmittwilken et al. (2023) package to generate stimuli. Then I systematically manipulated the spatial frequency by adjusting the element width, which controls the alternation between black and white regions, and the target size, which defines the physical dimensions of the gray target area. Among the various parameter combinations created, one configuration was chosen to closely match the parameter variation used by Kobayashi and Shapiro (2024), ensuring direct comparability with their findings. The specific implementation of these adjustments varies across different stimulus types, as the definition of element width and target size depends on the structural characteristics of each stimulus (see Table (1)).

For Simultaneous Brightness Contrast (SBC) stimuli (Figure (7), 1st from left), the target size is defined by the size of the square-shaped target (in degrees visual angle). For the Radial stimuli (Figure (7), 2 from left), the target size is the thickness of the target rings, while the element width is calculated as half the radius of the pins (both in degrees visual angle). For the Grating Induction (Figure (7), 1st from right) and Yazdanbakhsh

(Figure (8), 2 from right) stimuli, the element width parameter corresponds to the width of the stripes (in degrees visual angle), while the target size is represented by the height of the gray target (in degrees visual angle). For the Checkerboard stimuli (Figure (8), 1st from right), the element width is defined by the size of the individual squares (in degrees visual angle), and the target size corresponds to the dimensions of the diamond-shaped overlay within the gray area. For the Dungeon stimuli (Figure (8), 2 from left), the element width parameter is the size of the squares in the figure (in degrees visual angle), and the target size is the extent of the gray diamond-shaped layer surrounding the pattern. For the Circular stimuli (Figure (8), 1st from left), both the target size and the element width parameter refer to the thickness of the rings (in degrees visual angle).

$$\text{half\_pin\_radius} = \frac{r_{\max}}{2} \cdot \theta_{\text{segment}}, \quad \text{where} \quad \theta_{\text{segment}} = \frac{2\pi}{\text{number of pins}} \tag{1}$$

Stimulus Type	**Element Width**	**Target Size**
Grating Induction	Width of stripes	Height of the gray target
Yazdanbakhsh	Width of stripes	Height of the gray target
Checkerboard	Size of squares	Dimensions of the diamond overlay
Dungeon	Size of squares	Extent of the gray diamond layer
White's Effect Circular	Thickness of rings	Thickness of target rings
Simultaneous Brightness Contrast (SBC)	–	Size of the square target
White's Effect Radial	Half the radius of the pins	Thickness of target rings

Table 1: Overview of the parametric variations for each stimulus type. (See Appendix)

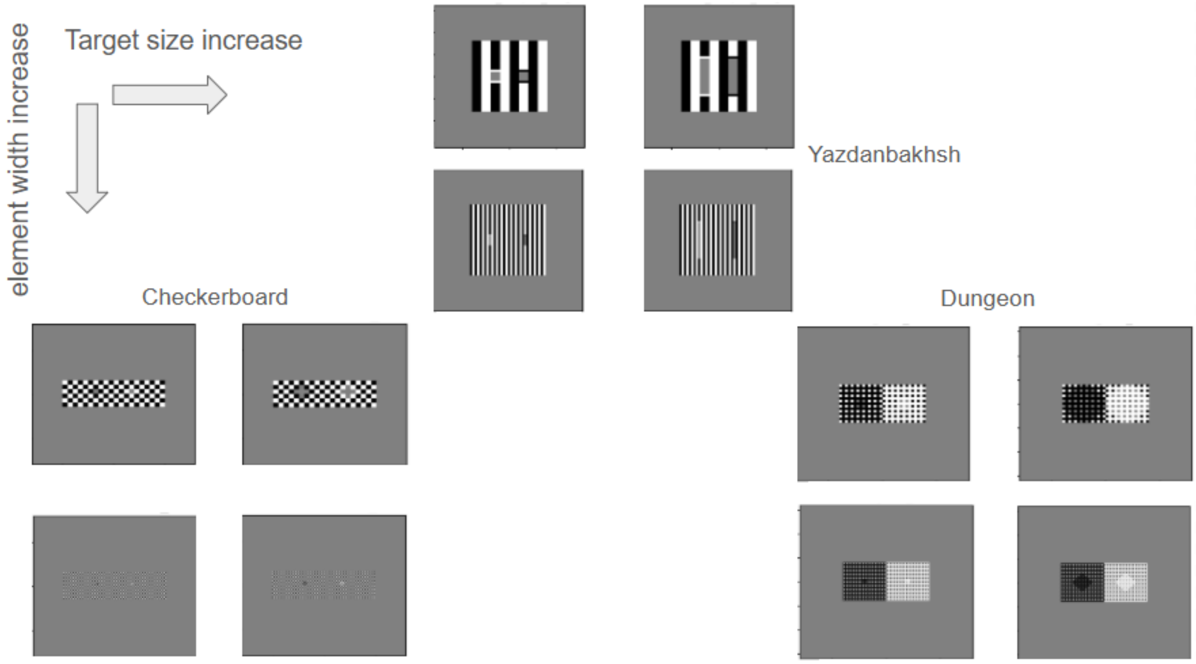

Figure 9: The figure consists of three stimulus groups, each demonstrating systematic variations in element width and target size: Top-left quadrant (Checkerboard stimuli group): The element size decreases from left to right as the figure is divided into fewer squares, while the target size increases with the addition of a diamond-shaped overlay in the gray region. Top-right quadrant (Dungeon stimuli group): The element width decreases from top to bottom, while the target size increases from left to right by adjusting the square-like pattern size and the extent of the gray diamond-shaped layer. Lower quadrant (Yazdanbakhsh stimuli group): The target size, represented by the height of the target shape, increases from left to right, while the element width, defined by the stripe width, decreases from top to bottom.

2.3 Model application

In the second phase of the analysis, I applied the ODOG, LODOG, and FLODOG models to the stimuli using the multyscale package (Vincent, 2025) from the Department of Computational Psychology at Technische Universität Berlin, as well as parts of the implementation provided by Ollech (2024). Each stimulus variation was processed independently by each of the three models. The models take a grayscale image as input and generate a transformed output image that represents the model's predicted perceptual response. The multyscale package facilitates this process by implementing the multi-scale filtering steps that characterize these models.

2.4 Model predictions

The magnitude of the illusion where determined by measuring the difference in perceived lightness between two target areas. If L_1 represents the adjusted lightness of the first target area and L_2 represents the lightness of the second target area, the magnitude was calculated as:

$$\text{Magnitude} = L_1 - L_2 \tag{2}$$

A negative magnitude indicates that the left target area appears lighter than the right one, while a positive magnitude indicates that it appears darker. To ensure that positive values consistently reflect assimilation (i.e., appearing darker when adjacent to black) and vice versa, all stimuli were arranged so that the target on the black background always lies on the left side and the target on the white background on the right. For stimuli where the target is not only in direct contact with one color but also flanked by additional elements, the right-side figure was defined as the one where the target is positioned on the black region and flanked by white. Consequently, positive magnitudes reliably indicate an assimilation effect, and negative magnitudes denote contrast. These measures of perceived difference form the basis for subsequent analyses, where I evaluated how model predictions vary with stimulus type and parameter manipulations.

To analyze the collected data efficiently, I used pyton 3.11.4 whit pandas for data manipulation and processing, NumPy for numerical computations, and matplotlib for visualizing the results. Heatmaps were employed to determine whether the models' predictions are more consistent within stimulus groups (assimilation, contrast) or across different groups, and how the models' behavior changes with different parameter settings.

3 Results

To investigate the influence of spatial frequency and target size of selected brightness illusions, on the brightness predictions by the ODOG, LODOG and FLODOG models. In my experimental design, each model was applied to each stimulus variation. Then, for each model output (one for each stimulus variation), the predicted brightness was extracted for each of the two target patches. Then, for difference between these predicted brightness was taken as the as the predicted illusion strength. A metric value of zero indicates no illusion effect, a positive value reflects an assimilation effect, and a negative value represents a contrast effect. Therefore, the farther this metric diverges from zero, the stronger the predicted illusion.

For Simultaneous Brightness Contrast (SBC) stimuli as we see in Figure (10)), I observed that as the target size decreases, the effect predicted by the ODOG model steadily decreases from -19.52 for the smallest target size to -5.73 for the largest, indicating a reduced magnitude of contrast. Although these predictions approach a neutral (zero) effect, they do not transition into assimilation.

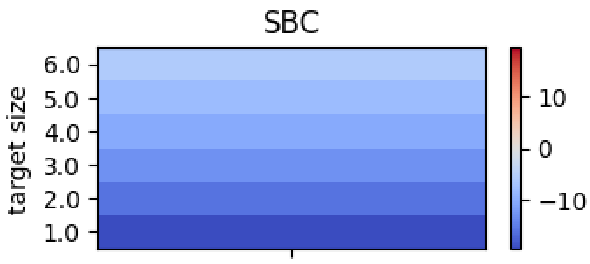

Figure 10: ODOG model for the SBC stimuli. The y-axis represents the target sizes, ranging from 1 to 6 degrees visual angle. Darker blue areas signify stronger contrast effects, while lighter shades suggest a weaker effect or a shift toward assimilation.

This pattern is also evident in other stimuli categorized within the contrast family as in Figure (11). In the Grating Induction stimulus, the results show that as the target size increases, the contrast effect becomes progressively weaker. The same pattern was observed across all element widths. For the smallest element width, the output is almost showing a neutral effect, by reaching a value of -0.997.

From the stimuli of the assumed contrast family (see 11), only the Radial stimulus (see 13) was misclassified by the model, failing to predict the contrast effect reported by human observers (Kobayashi & Shapiro, 2024). Instead, all variations generated an assimilation effect (positive predicted values).

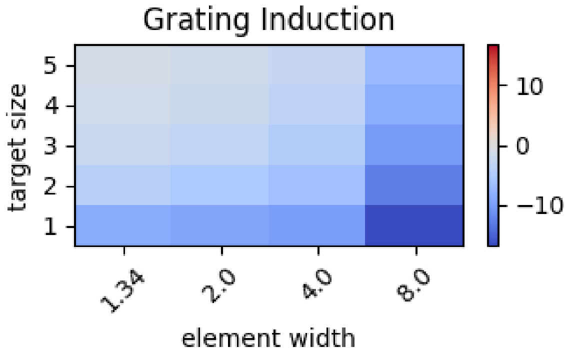

Figure 11: ODOG model predictions for the Grating Induction stimuli. The x-axis represents the element width in cycles per degree of visual angle, and the y-axis denotes the size of the target (both in degrees visual angle). The color scale denotes the magnitude and direction of the predicted effect, with red shades representing assimilation effects and blue shades indicating contrast effects. Darker blue areas signify stronger effects, while lighter shades suggest a weaker effect.

The ODOG model, on the other hand, failed to predict the direction of effect observed in human perception, as reported by Kobayashi and Shapiro (2024) and Blakeslee and McCourt (1999), for the four stimuli in the assumed assimilation family (see 6). Instead, it predicted them as contrast, with most variations yielding negative predicted values—opposite to the assimilation effect found in human observers.

A similar trend where a smaller target size leads to a stronger contrast effect and vice versa is observed in most of the stimuli tested in the assimilation theoretical group (see 12), with two notable exceptions. For the Yazdanbakhsh stimulus, in most variations the model predicts a brightness difference in the contrast direction, with the effect weakening as the target size increases. The model also predicts the difference in the brightness of the two variations with the largest targets (element width = 2.0) as assimilation rather than contrast, with predicted values of 0.73 and 1.42, respectively. In the Circular stimulus, a similar pattern is observed under most conditions, except when the target size is 0.125. For the initial range of sizes (1, 0.5, and 0.25), the predicted value is smallest for the largest target size, with predictions nearly reaching zero, resembling the behavior seen in the grating induction stimu lus. However, the Dungeon stimulus, displays a reversed trend: larger target sizes generally lead to stronger contrast effects, except for cases where the element width is 0.5 or 0.33 and the target size is 3. Similarly, the Checkerboard stimulus shows an inconsistent pattern. For an element width of 0.25, the predictions are unclear, while in other scenarios, the behavior appears reversed.

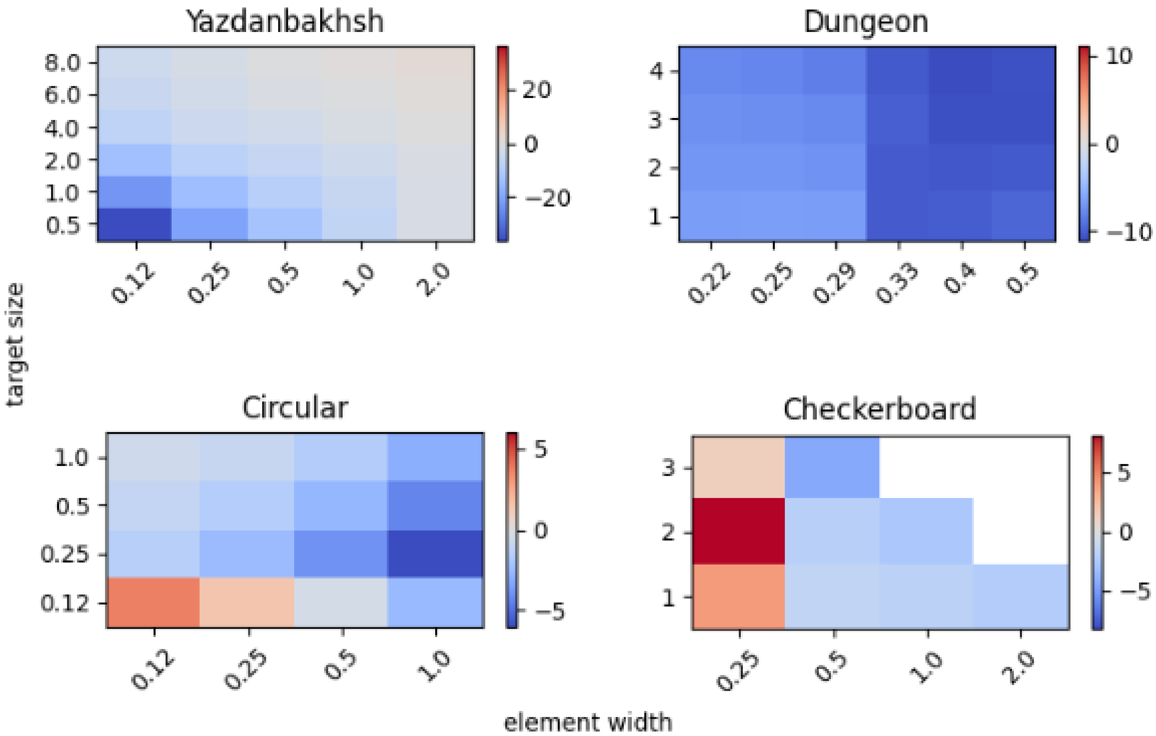

Figure 12: ODOG model's predictions for the assimilation stimuli: Yazdanbakhsh (right up), Circular (right down), Dungeon (left up), and Checkerboard (left down). In all heatmaps the x-axis represents the element width (degree of visual angle). For the y-axis, in all heatmaps except Dungeon, it indicates the target size (degree of visual angle), while in Dungeon it represents the "Manhattan radius" of the diamond target in cells. The color scale denotes the magnitude and direction of the predicted effect, with red shades representing assimilation effects and blue shades indicating contrast effects. Darker blue areas indicate stronger effects, while lighter shades represent weaker effects.

As shown in Figure (13) the Radial stimulus displays a behavior in which the magnitude of the contrast effect strengthens as the target size increases for each element width. With values from 0.7 for size equals 1 and element width equals 2.28 to 2.15 for size equals 5 and element width equals 2.28.

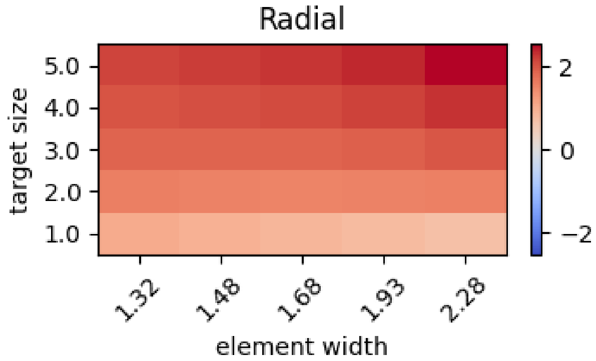

Figure 13: ODOG model predictions for the WE radial stimulus. The x-axis corresponds to the element width, calculated as half the radius of the pins. The y-axis represents the size of the ring target, increasing from 1 to 5 units (both in degrees visual angle).

The influence of element width on the magnitude of the effect varies between stimuli and is generally less consistent. In Circular (for all variations except where target size = 0.12), Grating Induction and Checkerboard, a smaller element width generally leads to stronger assimilation effects and weaker contrast effects. However, in the Radial illusion, smaller element width result in weaker assimilation effects, while in the Yazdanbakhsh illusion, smaller element widths result in stronger contrast. Interestingly, for the Dungeon the pattern is less clear. Interestingly, for the Dungeon stimulus, the pattern is less clear. While, in general, variations with a larger element width tend to produce stronger contrast effects, there are many outliers—for example, when the element width is 0.4 and the target size is 1, 3, or 4, as well as when the element width is 0.5 and the target size is 1.

It is important to note that for the Radial stimulus, this effect is consistent as long as the length of the border of the target ring that flanks the contrasting color is greater than the border on which the target lies (see 14). It is not the case when for example the target size is 1 or for the case where target size = 2 and element width = 1.32. When $\Delta > 0$, the effect aligns with the general observation; otherwise, the trend reverses.

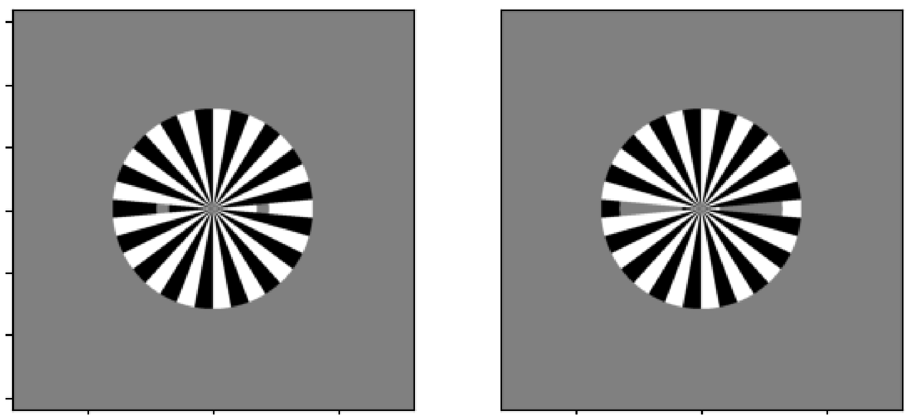

Figure 14: Two variations of the Radial stimuli. Left figure: the border of the target ring that flanks the contrasting color is smaller than the border on which the target lies. Right figure: the border of the target ring that flanks the contrasting color is greater than the border on which the target lies.

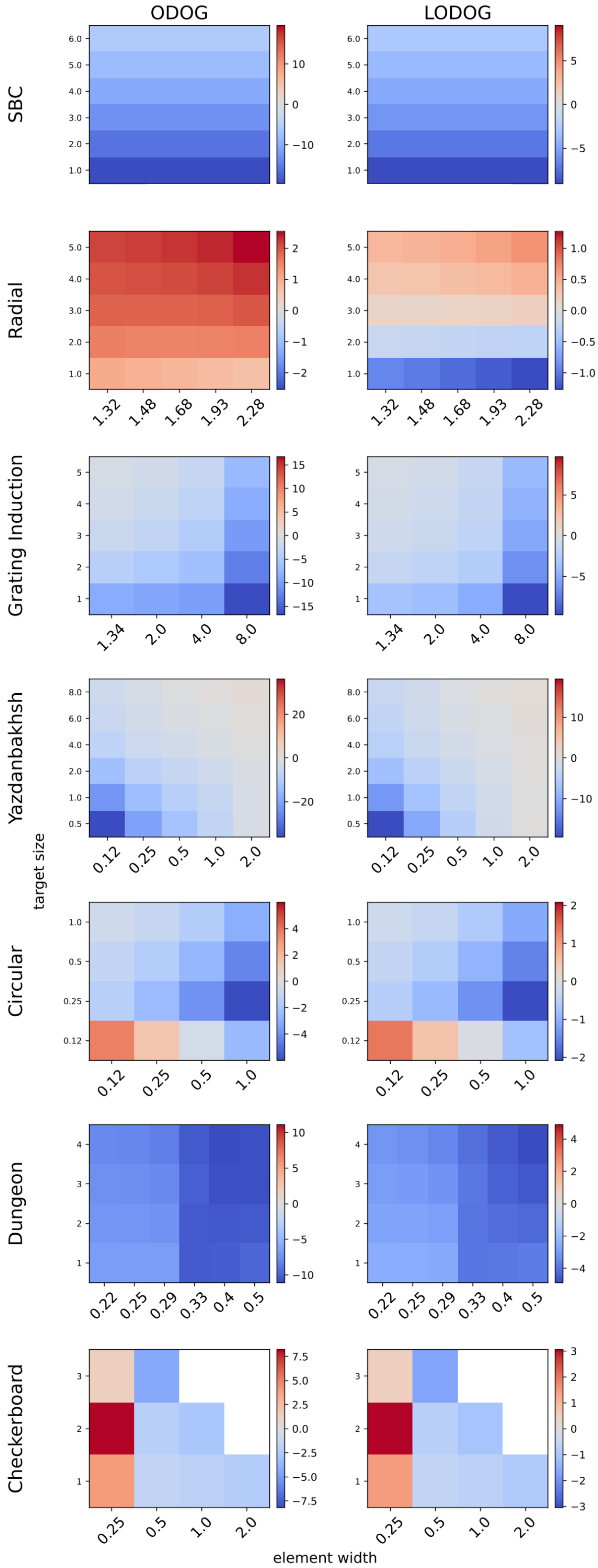

Figure 15: LODOG (right) and ODOG (left) model's predictions for the assimilation and contrast stimuli. From up to down: Yazdanbakhsh, Circular, Dungeon, Checkerboard, Radial, SBC and Grading Induction. The color scale denotes the magnitude and direction of the predicted effect, with red shades representing assimilation effects and blue shades indicating contrast effects. Darker blue areas indicate stronger effects, while lighter shades represent weaker effects.

With the LODOG model (see 15), we observe effects similar to those observed with the ODOG model in all stimuli. Here, like in ODOG the influence of a larger target size in all stimuli is a stronger assimilation and a weaker contrast except of Dungeon. Similarly, the influence of larger element width like in ODOG is a stronger assimilation and weaker contrast for Yazdanbakhsh and Radial, while it is the opposite for Circular, Grading Induction and checkerboard. In the case of Dungeon the effect of target size in LODOG is even clearer than in ODOG. Here, a larger element width leads to a stronger contrast effect other than the two exceptions at element width = 0.33 and 0.4 and target size = 1.

In general, for the LODOG model, the magnitude of both contrast and assimilation effects tends to decrease in the direction opposite to the dominant effect observed in the ODOG model. For example, for Yazdanbakhsh, we observe a decrease in magnitude from a range of -36.21 to 1.42 in ODOG to a range of -19.40 to 0.72 in LODOG. Similar patterns are evident in all the other stimuli. An exception to this trend is found in the Radial stimulus, where I also observe a shift to contrast for target sizes 1 and 2, with the magnitude changing from a range of 0.7 to 2.53 in ODOG to -1.26 to 0.41 in LODOG.

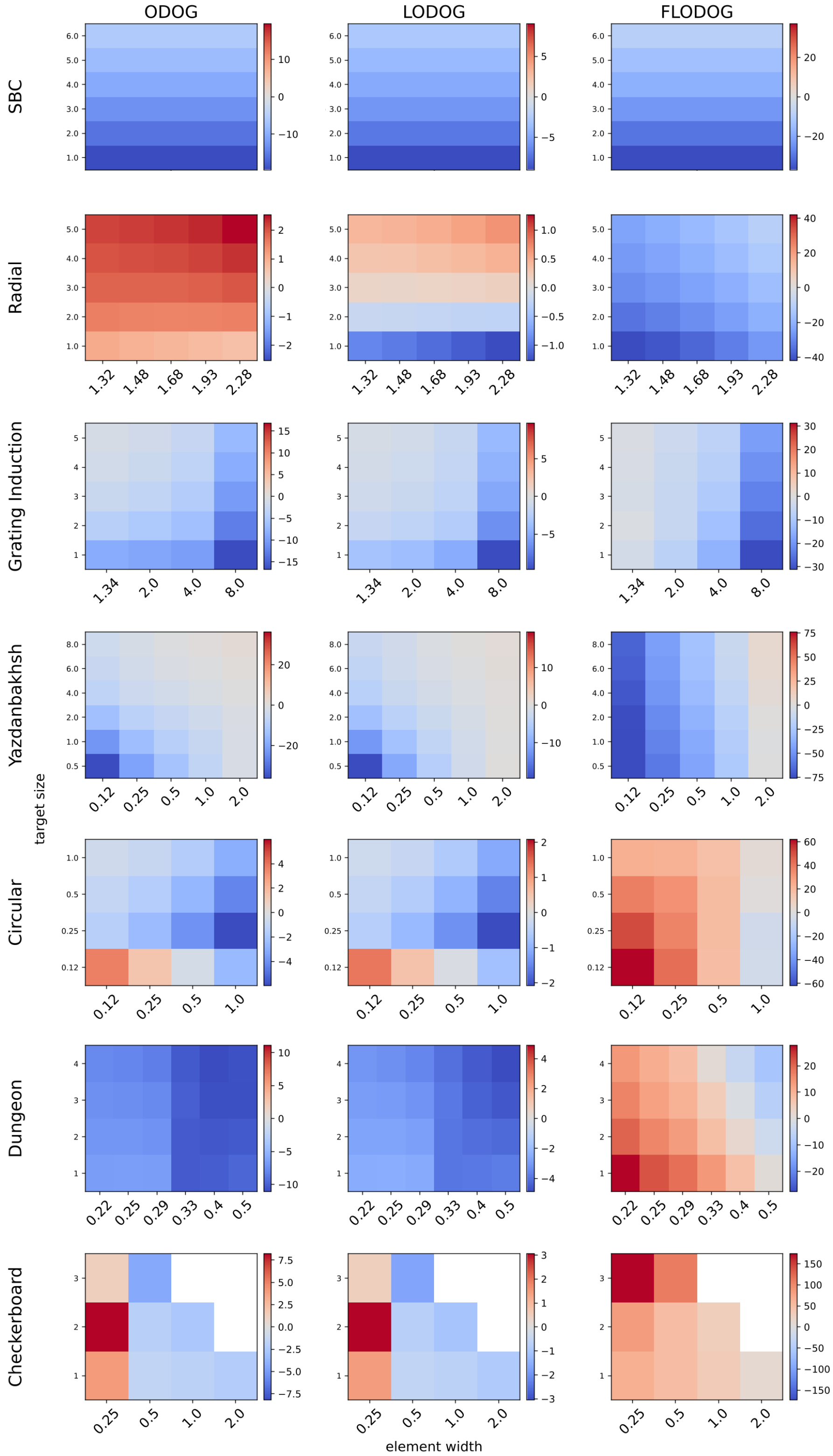

Figure 16: FLODOG model's predictions for the assimilation and contrast stimuli. From right to left, up to down: Yazdanbakhsh, Circular, Dungeon, Checkerboard, Radial, SBC, Grading Induction and Checkerboard. The color scale denotes the magnitude and direction of the predicted effect, with red shades representing assimilation effects and blue shades indicating contrast effects. Darker blue areas indicate stronger effects, while lighter shades represent weaker effects.

Unlike ODOG and LODOG, the FLODOG model (see 16) correctly predicts assimilation for the assimilation stimuli (almost all variations of 3 out of 4 stimuli); and correctly predicts contrast for Radial across all variations (except for a few variations of the Yazdanbakhsh stimuli). I observe a pattern similar to those seen with the ODOG and LODOG models across most stimuli, with notable exceptions in the Checkerboard, Dungeon and the Circular stimuli. For the Checkerboard stimulus, the model exhibits a clear assimilation effect, with both target size and spatial frequency strongly influencing the predictions. Specifically, the assimilation effect becomes stronger as the element width decreases (lower spatial frequency) and the target size increases, which is the opposite of what was predicted by the ODOG and LODOG models. In the Dungeon stimulus, instead of exhibiting a consistent contrast effect as in the other two models, the predictions shift predominantly toward assimilation. However, the influence of target size and element width remains the same, with the contrast effect weakening and the assimilation effect strengthening as target size and element width decrease. For the Circular stimuli we see that the direction of effect in the FLODOG model in this case is predominantly assimilation and not contrast like in ODOG and LODOG. Furthermore, we see that in this case unlike before a smaller target size and element width is leading to a stronger assimilation and weaker contrast effects.

I also observed that the FLODOG model produces a much larger magnitude of effect across all stimuli compared to the ODOG and LODOG models. For example, in the Dungeon stimulus the range shifts from -11.08 to -6.61 in ODOG to -9.35 to 27.71 in FLODOG. In the Circular stimulus, the range changes from 3.67 to -5.98 in ODOG to 61.86 and -6.15 in FLODOG. The largest difference was seen in the Checkerboard stimulus, where the range goes from -4.40 to 8.2 in ODOG to 9.68 and 173.54 in FLODOG.

4 Discussion

In this study, the research question was to determine how the predictions of the three low-level brightness perception models (ODOG, LODOG, and FLODOG) change in response to variations in target size and spatial frequency, and whether these changes differ between the assimilation and contrast theoretical stimuli groups. To address this, each model was applied to a range of selected stimuli (SBC, Radial, Grating Induction, Circular, Dungeon, Yazdanbakhsh, and Checkerboard), with systematic manipulations performed on target size alone or in conjunction with spatial frequency. A single metric was computed for each variation to capture both the direction (positive for assimilation, negative for contrast) and the magnitude of the predicted brightness differences.

Overall, our results show that FLODOG consistently provides predictions closer to human perceptual responses than ODOG and LODOG, as was also found in Robinson et al. (2007) and Kobayashi and Shapiro (2024). While ODOG and LODOG frequently exhibit a bias toward contrast effects—even in conditions where assimilation is expected—FLODOG, with its dual normalization mechanism, yields a more balanced outcome. These findings suggest that it is important to integrate both local and frequency-dependent normalization processes to more accurately predict the correct direction of effect.

The main results indicate that, overall, variations in target size and spatial frequency substantially modulate the models' predictions. Smaller target size is generally associated with weaker contrast effects, while larger target size tends to produce stronger assimilation effects. Notable exceptions include the Checkerboard stimulus in ODOG, the Checkerboard and Circular stimuli in LODOG, and the Circular and Dungeon stimuli in FLODOG. Interestingly, these findings are consistent with the results from Ollech (2024) thesis for the stimuli tested there.

On the influence of spatial frequency, the current results present a more nuanced pattern than what Ollech (2024) reported for White's effect, Bullseye, and Checkerboard stimuli. Ollech (2024) found that the models consistently predicted contrast effects at lower spatial frequencies and assimilation effects at higher spatial frequencies. However, our findings show that for ODOG and LODOG, a greater degree of black-white alternation (i.e., smaller element width) leads to stronger contrast and weaker assimilation effects in some stimuli (such as Radial, Dungeon, and Yazdanbakhsh), while for Circular, Grating Induction, and Checkerboard, the trend is reversed—smaller element widths result in stronger assimilation and weaker contrast effects. Moreover, for FLODOG, Circular exhibits the opposite influences of target size and element width compared to the other models.

In line with Ollech (2024), ODOG and LODOG perform similarly in most stimuli, predicting comparable effects, although ODOG typically exhibits greater magnitudes. Consistent with Ollech's findings, the FLODOG model produces much higher magnitude effects across the stimuli, suggesting a greater sensitivity to parameter variations. Furthermore, when comparing the dominant effect direction—defined as the outcome most frequently produced by varying the parameters for each stimulus—with the specific variation outcomes reported by Kobayashi and Shapiro (2024) for the ODOG, LODOG, and FLODOG models, we obtain consistent results regarding the correct and incorrect prediction of effects.

Overall, it seems that the models do not differentiate meaningfully between the theoretical assimilation group (Circular, Dungeon, Yazdanbakhsh and Checkerboard) and the theoretical contrast group (SBC, Radial and Grating Induction), as the effects of the target size and the black-and-white alternation parameter vary within groups but remain similar between stimuli from different groups. This suggests that the parameter's influence is more stimulus-specific than group-specific, challenging the notion of consistent behavior across theoretically defined categories.

Unlike ODOG and LODOG, in FLODOG, three out of the four stimuli in the theoretical assimilation group exhibit the same direction of effect. A possible reason why the Checkerboard stimulus shifts from assimilation to contrast in FLODOG is the much higher frequency of black-and-white alternation compared to the other stimuli. A similar behavior is observed in the Dungeon and Circular stimuli, where the black-and-white alternation occurs in two directions rather than just one. In contrast, for the Yazdanbakhsh and Radial stimuli, the black-and-white alternation is less pronounced and occurs in only one direction. This difference in alternation frequency appears to influence the model outputs, with stimuli that exhibit alternation in only one direction consistently maintaining their predicted direction of effect across all models in the ODOG family.

Furthermore, an overarching trend emerges across the models: they tend to predict contrast effects more readily than assimilation. For example, ODOG and LODOG frequently yield brightness-difference predictions that favor contrast, even for stimuli that are theoretically expected to produce assimilation (all four stimuli in the assimilation group where predicted as contrast). In contrast, FLODOG appears to counteract this tendency by incorporating mechanisms that increase its sensitivity to the relevant parameters, thereby predicting assimilation effects in three out of the four assimilation stimuli. This suggests that FLODOG may offer a more balanced account of brightness perception by effectively adjusting for the inherent bias toward contrast present in the other models, ultimately providing predictions that align more closely with theoretical expectations.

One primary limitation is the restricted set of stimuli used. In this study, illusions were chosen largely because they were straightforward to parameterize with Stimupy (e.g., by adjusting ring thickness or stripe width). This focus on relatively simple, repetitive patterns—such as checkerboards, radial pinwheels, and grating-like designs—facilitates systematic manipulation of target size and spatial frequency but excludes illusions whose effects depend on more irregular shapes, multi-layered backgrounds, or color manipulations like the Corrugated Mondrian or the snake illusions from Kobayashi and Shapiro (2024) work, as well as 3D illusions. As a result, the observed effects may be specific to these structured two-dimensional patterns and might not generalize to more complex or naturalistic contexts. Future research should therefore expand the stimulus set to include illusions with richer geometries, layered backgrounds, or three-dimensional cues, to determine whether the findings here extend beyond the specific subset of illusions tested.

that rely on more complex geometry, three-dimensional cues, or scene-based context (e.g., transparency illusions, shadow-based illusions, or naturalistic scenes). As a result, the observed effects may be specific to these highly structured, two-dimensional patterns and might not generalize to brightness illusions that involve partial occlusion, real-world shading, or higher-level cognitive factors. Future research should therefore examine a broader array of illusions, including those that require more intricate shapes or that occur in realistic settings, to determine whether the findings reported here extend to a wider range of brightness phenomena.

Moreover, an essential next step in validating these computational models is to directly compare their predictions with human perceptual data. Although the models are designed to mimic certain aspects of human brightness perception, without psychophysical data it is difficult to assess the extent to which the predicted effects correspond to actual perceptual experiences. Incorporating human observer experiments would not only help in verifying the models' accuracy but could also highlight potential areas where the models diverge from human performance, thereby guiding further refinement of the computational frameworks.

Finally, the presence of "outlier" predictions in certain parameter combinations warrants further investigation. Here, an "outlier" refers to a specific variation of the stimulus (i.e., a particular combination of target size and element width) that produces a model prediction sharply deviating from the general trend observed in the rest of the parameter space. For example, in the Circular stimulus under FLODOG, nearly all variations show a stronger assimilation effect as the target size decreases—except for two cases (element width = 1, target size = 0.25 or 0.125), where the predicted effect reverses from weak assimilation to contrast. However, this reversal is not apparent when I visually inspected the corresponding variations in Figure 16, and subjectively, these two conditions still appear to produce assimilation just like the others. This discrepancy suggests that the models may be overestimating certain effects, or that human perception compensates for these variations in ways the models do not account for. Future research should aim to explore the origins of these outliers, as understanding their cause could provide deeper insights into both the limitations of the present models and the broader mechanisms underlying brightness perception.

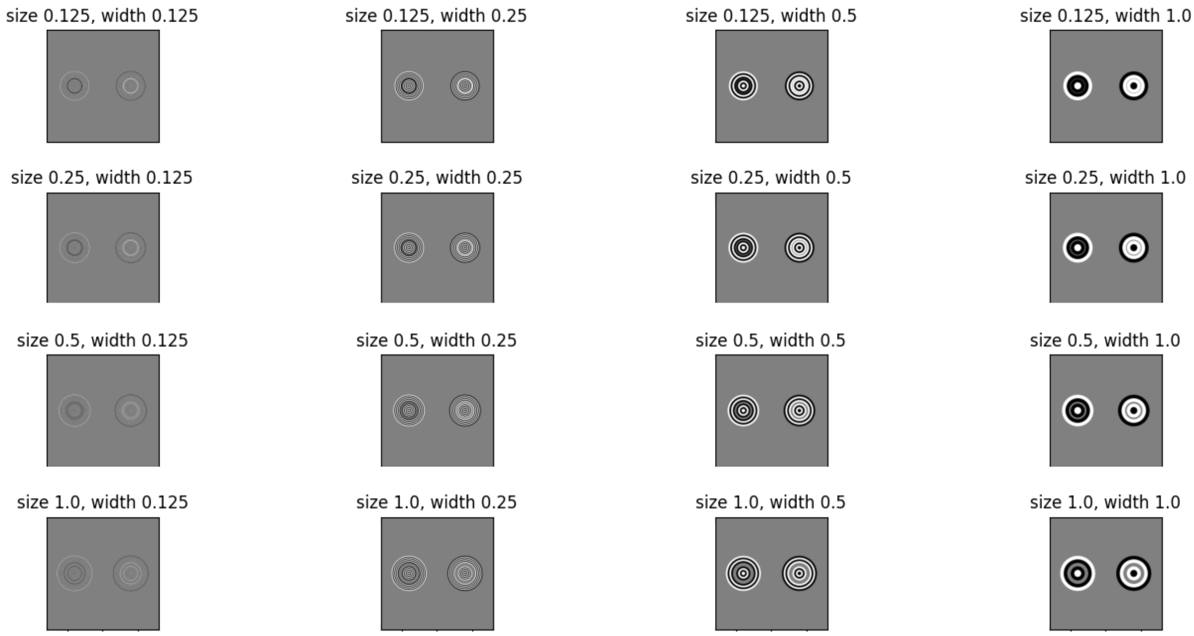

Figure 17: Different circular variations: Element width (width) increases as you move to the right, while the target size (size) increases as you move down. The two variations that were predicted as contrast by FLODOG are in the fourth column, second and third rows.

In summary, this research underscores the complex interplay between spatial frequency, target size, and brightness perception in computational models. By dissecting how the ODOG, LODOG, and FLODOG models respond to parametric variations, the study provides a nuanced view of low-level visual processing that extends our understanding of brightness illusions. The insights gained here not only highlight the models' strengths and limitations but also pave the way for future work that integrates broader stimulus sets and human perceptual data. This work contributes to the evolving dialogue between computational modeling and empirical research, driving us toward a more comprehensive framework for understanding how the human visual system interprets complex visual scenes.

A Appendix

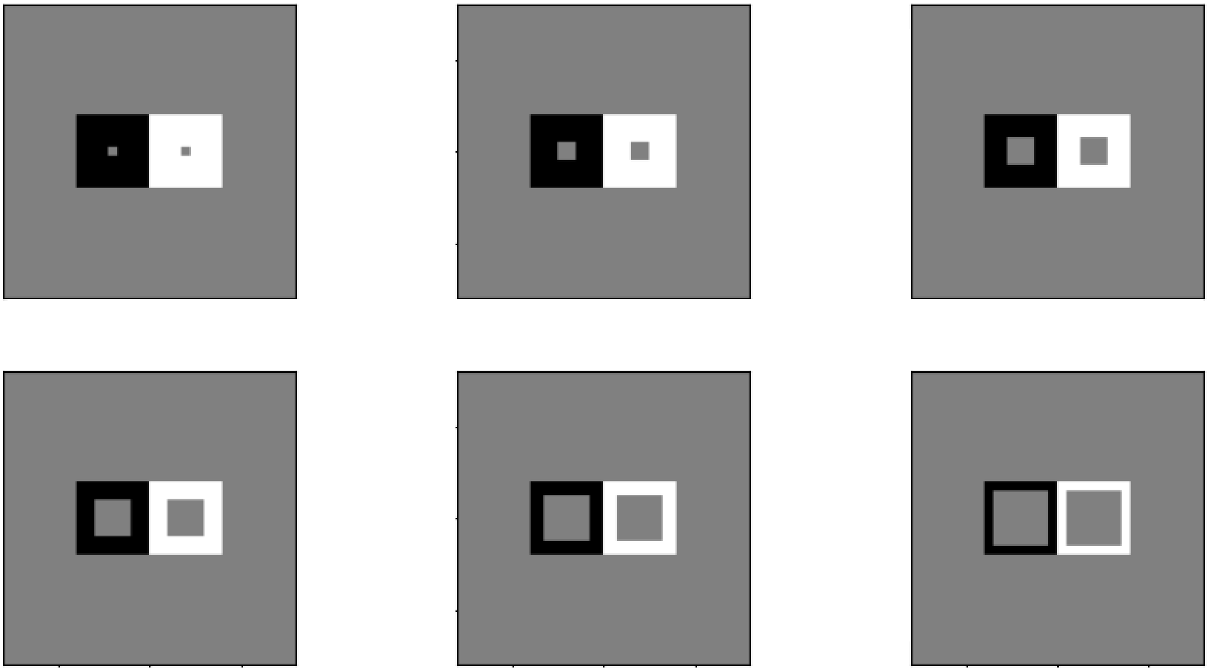

Figure 18: SBC: Target size gets bigger as we go right. values: target size- 1.0, 2.0, 3.0, 4.0, 5.0, 6.0

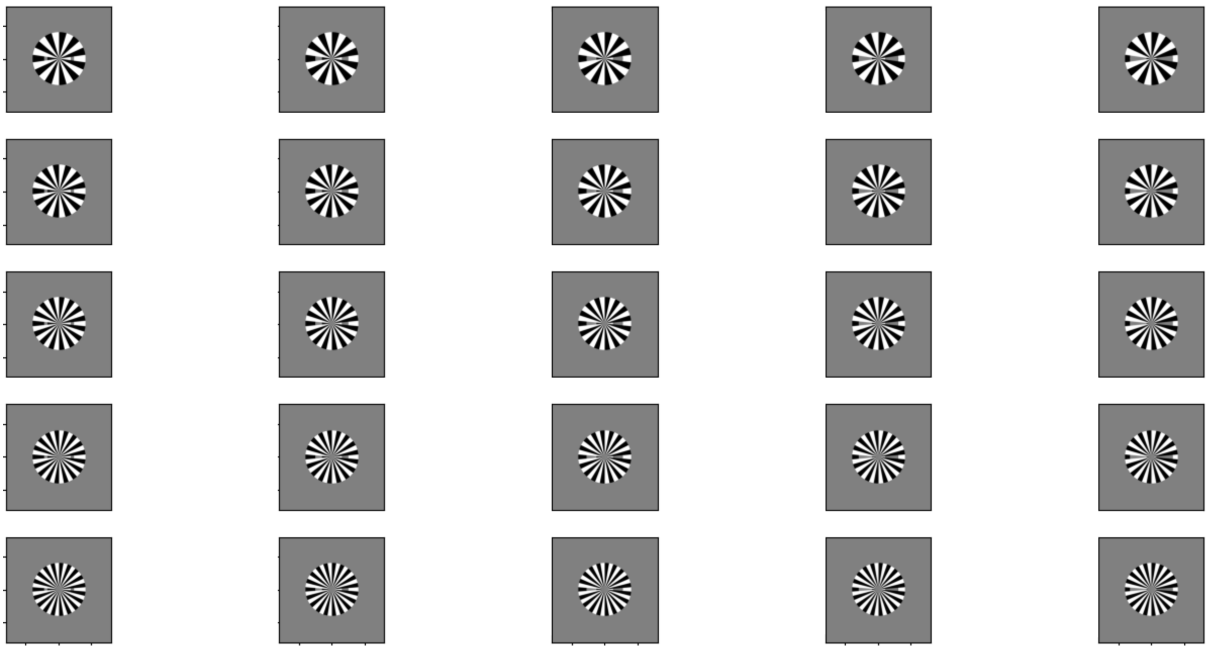

Figure 19: Radial: The target size increases as we move to the right. The element width decreases from top to bottom. Values: target size- 1.0, 2.0, 3.0, 4.0, 5.0; element width- 1.0, 2.0, 3.0, 4.0, 5.0

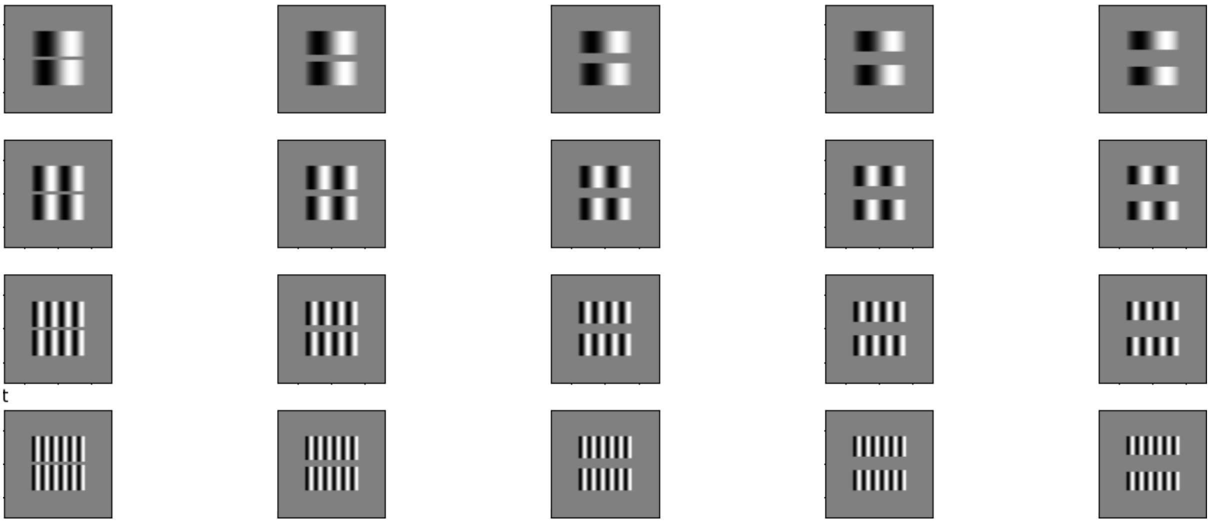

Figure 20: Grating Induction: The target size increases as we move to the right. The element width decreases from top to bottom. Values: target size- 1.0, 2.0, 3.0, 4.0, 5.0; element width- 1.0, 2.0, 3.0, 4.0, 5.0

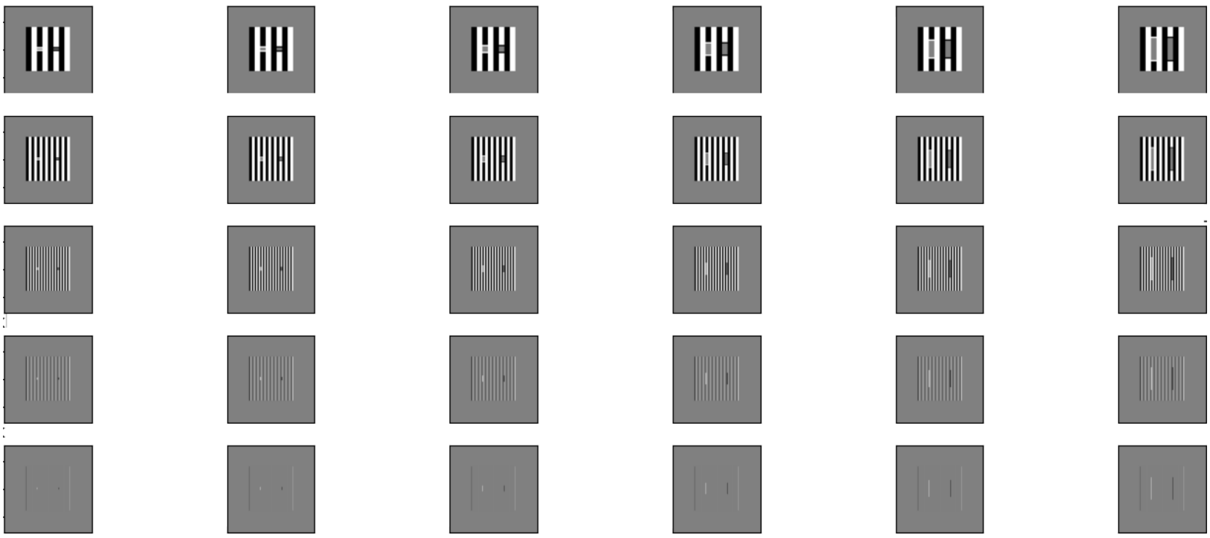

Figure 21: Yazdanbakhsh: The target size increases as we move to the right. The element width decreases from top to bottom. Values: target size- 0.5,1.0, 2.0, 4.0, 6.0, 8.0; element width- 0.125, 0.25, 0.5, 1, 2

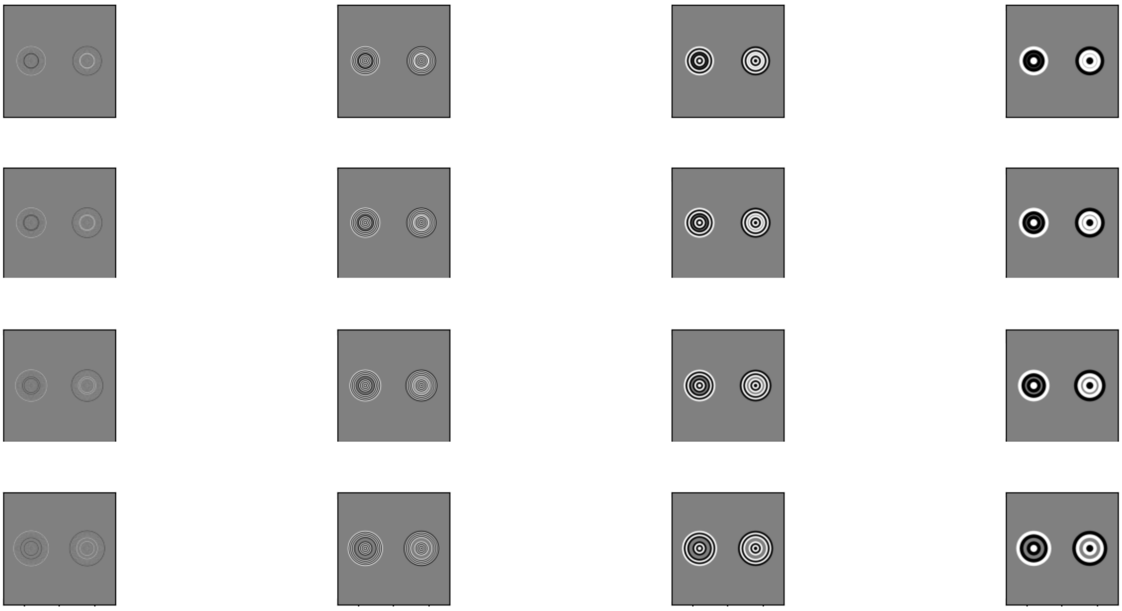

Figure 22: Circular: The target size increases from top to bottom. The element width increases as we move to the right. Values: target size- 0.125, 0.25, 0.5, 1; element width- 0.125, 0.25, 0.5, 1

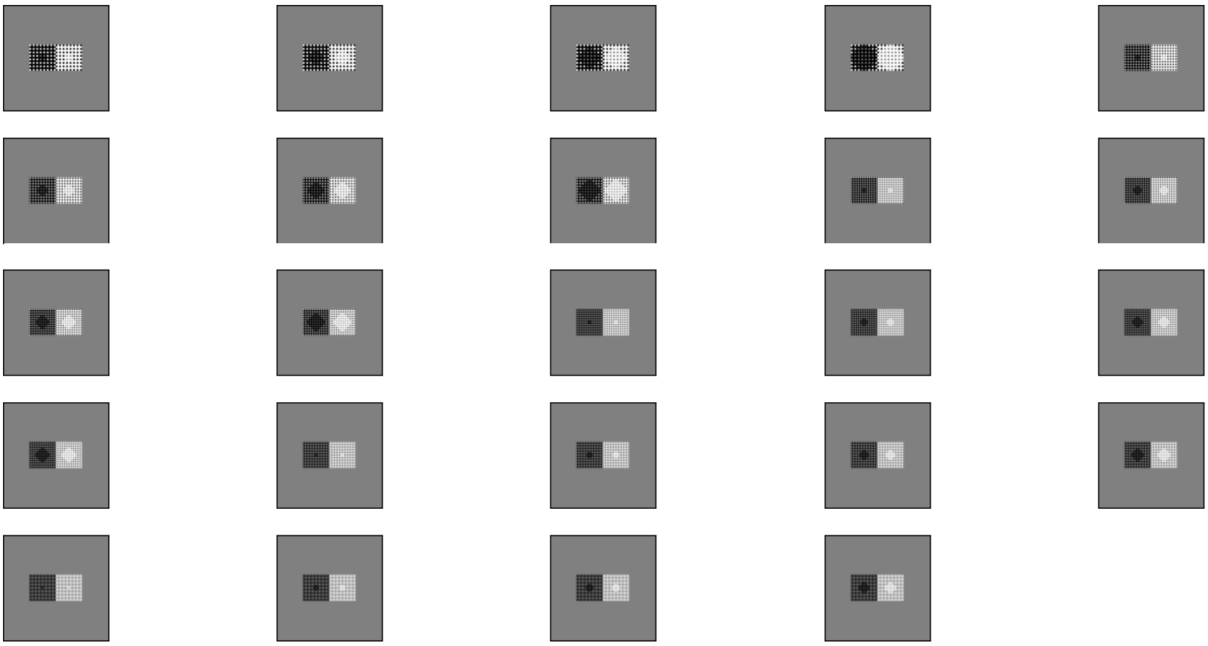

Figure 23: Dungeon: The target size increases as we move to the right. The element width decreases every four figures. Values: target size- 1, 2, 3, 4; element width- 0.22, 0.25. 0.29, 0.33, 0.4, 0.5

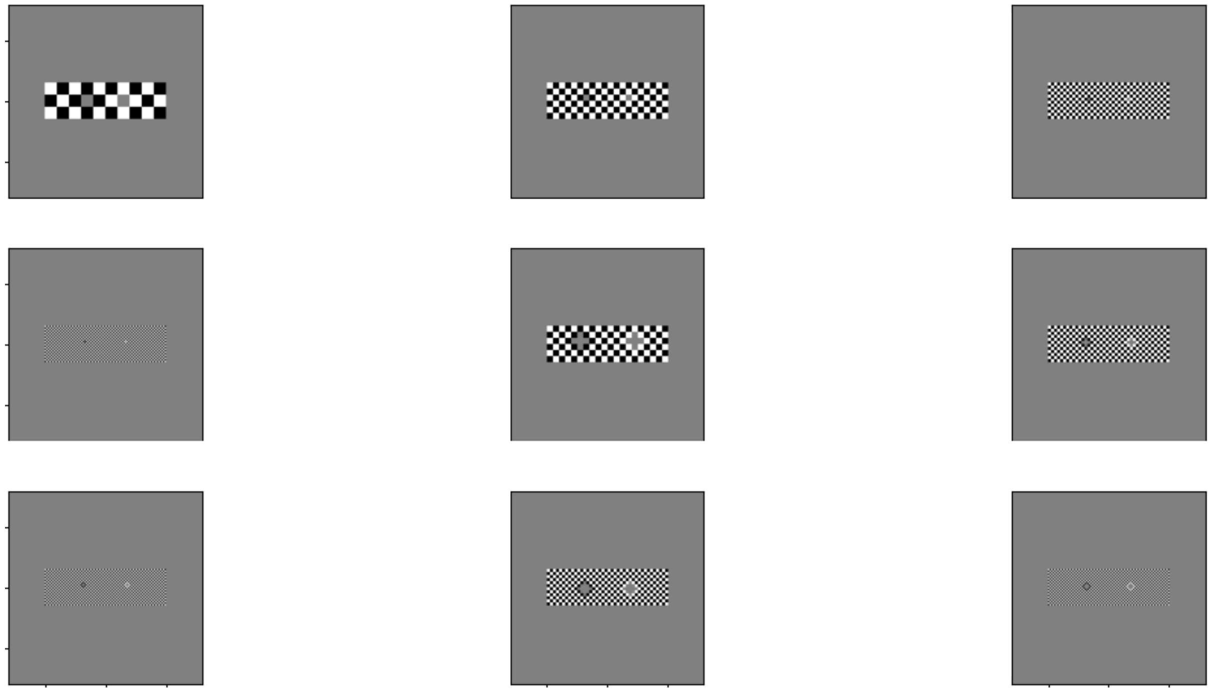

Figure 24: Checkerboard: The element width decreases as we move to the right in the following pattern—first, for the initial four figures, then for the next three, and finally for the last two. The target size remains constant for the first four figures, then increases for the next three, and finally for the last two.

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