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Abschlussarbeit

Texture-based surface boundaries: An attempt to experimental quantification

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SELBSTÄNDIGKEITSERKLÄRUNG

Hiermit erkläre ich, dass ich die vorliegende Arbeit selbstständig und eigenhändig sowie ohne unerlaubte fremde Hilfe und ausschließlich unter Verwendung der aufgeführten Quellen und Hilfsmittel angefertigt habe.

Berlin, den 12. September 2023

Filipe Borges

ABSTRACT

Surface segmentation is the process of separating different parts of an image into separate regions. It is a challenging problem in vision research, and the mechanisms behind it are still an open question. For example, it is still not fully understood whether luminance-based natural texture boundaries are segmented in the same way as simple luminance steps. DiMattina and Baker (2021) explored this issue by measuring observers' segmentation performance on synthetic textures. Their stimuli consisted of light and dark micropatterns defining the segmentation boundary. Here I studied how these micropattern stimuli differ from luminance-based natural texture boundaries. Concretely, I explored if any differences in boundary sharpness could lead to significant differences in segmentation. I measured boundary detection accuracy of DiMattina and Baker's micropattern stimuli and luminance-based natural texture boundaries. Naive observers showed better boundary detection performance for the natural texture boundaries than the micropattern stimuli. Therefore, the micropattern stimuli might not be good analogs for luminance boundaries within natural textures.

ZUSAMMENFASSUNG

Bei der Oberflächensegmentierung werden verschiedene Teile eines Bildes in separate Bereiche unterteilt. Es handelt sich um ein herausforderndes Problem in der Sehforschung, und die Mechanismen dahinter sind immer noch offen. Es ist beispielsweise immer noch nicht vollständig geklärt, ob auf Luminanz basierende natürliche Texturgrenzen auf die gleiche Weise segmentiert werden wie einfache Luminanzschritte. DiMattina and Baker (2021) untersuchte dieses Problem, indem es die Segmentierungsleistung von Beobachtern auf synthetischen Texturen maß. Ihre Reize bestanden aus hellen und dunklen Mikromustern, die die Segmentierungsgrenze definierten. Hier habe ich untersucht, wie sich diese Mikromusterreize von luminanzbasierten natürlichen Texturgrenzen unterscheiden. Konkret habe ich untersucht, ob Unterschiede in der Grenzschärfe zu signifikanten Unterschieden in der Segmentierung führen könnten. Ich habe die Grenzerkennungsgenauigkeit der Mikromusterstimuli von DiMattina und Baker und der auf Luminanz basierenden natürlichen Texturgrenzen gemessen. Naive Beobachter zeigten eine bessere Grenzerkennungsleistung für die natürlichen Texturgrenzen als für die Mikromusterstimuli. Daher sind die Mikromusterreize möglicherweise

keine guten Analogien für Luminanzgrenzen innerhalb natürlicher Texturen.

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1 INTRODUCTION

In computer vision, segmentation is the process of grouping different parts of an image into meaningful sections based on their local features. These features can be the luminance of an image region or more complicated image features such as texture.

Luminance is the amount of light emitted or reflected to the observer from a surface. Consider for example Figure 1.1(a.1). It shows an image that is subdivided into two regions by a difference in luminance. The left half has a higher luminance than the right side. To visualize this difference it is instructive to look at the pixel intensity profile directly below the image. It depicts the mean luminance value at each position along a horizontal cross-section.

The term "texture" is more difficult to describe and can carry different meanings. One could say that textures are groups of micropatterns with similar features. For example, in Figure 1.1(c.1) by Wagemans and Rosenholtz (2015) the "L"-shaped elements and the "X"-shaped elements build 2 different segments. While textures and their features may be hard to describe, humans can easily see and differentiate between textures. Figure 1.1(b.1) shows an image of two natural textures side by side. Although both natural textures are relatively complex, the image is still easy to segment.

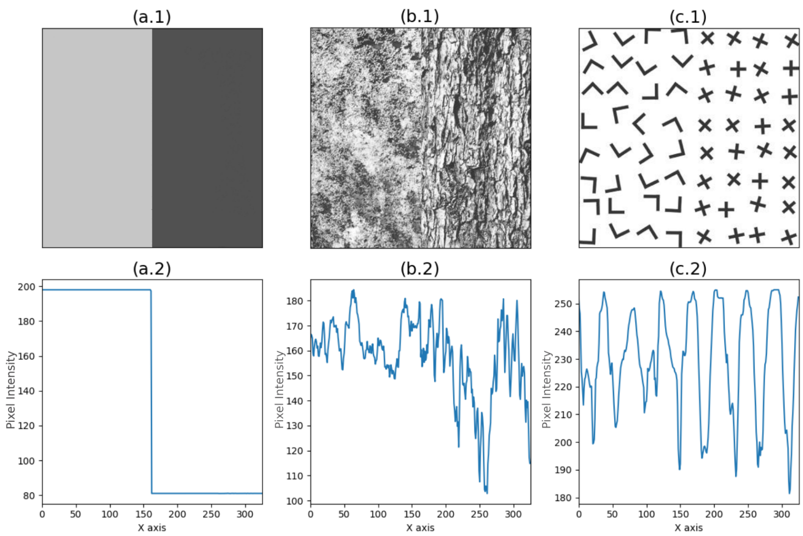


Figure 1.1: Examples of Segmentation and mean pixel intensity change across X-Axis. (a.1) Easily segments, two halves differ in their mean luminance. (b.1) Still segments fairly easy, even though natural textures are often more complex. Image by Wagemans and Rosenholtz (2015) (c.1) also segments easily, elements in each half have the same shape. Image by Wagemans and Rosenholtz (2015).

It still is an open question how the human visual system accomplishes texture segmentation. A good example of the complexity of this problem can be seen again in Figures 1.1(a) and 1.1(b), where two images and their mean pixel intensity profiles are presented. In Figure 1.1(a), the boundary between two surfaces is defined by differences in luminance, while in Figure 1.1(b) the boundary is defined by differences in texture. Figure 1.1(b) is easy for us to segment, but there is no clear luminance step at the boundary. It is still not clear if luminance-defined boundaries and texture-defined boundaries are segmented via the same mechanism.

Figure 1.1 shows the mean pixel intensity profiles of all mentioned examples. Even though all three images and their mean pixel intensity profiles are very different, all three examples are easy to segment. It is clear that our visual system can segment a wide variety of images.

Our visual system is sensitive to differences in luminance, and neurons respond to changes in luminance between adjacent areas of the visual field. Gabor filters are a commonly assumed model of how simple cells in the visual cortex detect edges and oriented features. These filters are also believed to be useful to model segmentation in humans. Essentially, 2D Gabor filters are a combination of a Gaussian kernel function and a planar sine wave of a particular frequency and orientation. An example of a Gabor filter can be seen in Figure 1.2.

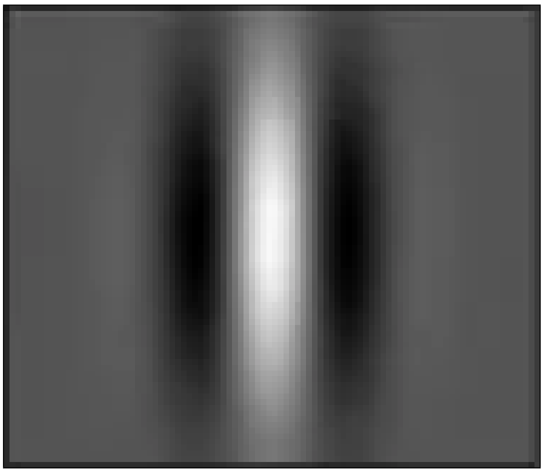


Figure 1.2: A basic example of a Gabor-shaped linear spatial filter. According to DiMattina and Baker (2021), Gabor-shaped linear spatial filters are a commonly assumed computational model of luminance boundary detection. It is unknown if this model is sufficient to detect texture-defined surface boundaries. Image by Shah (2018)

Gabor filters respond maximally when the input contains features that match the orientation of the filter. In Figure 1.3 we can see an illustration by Shah (2018). This image shows how filters with different orientations respond to a circle.

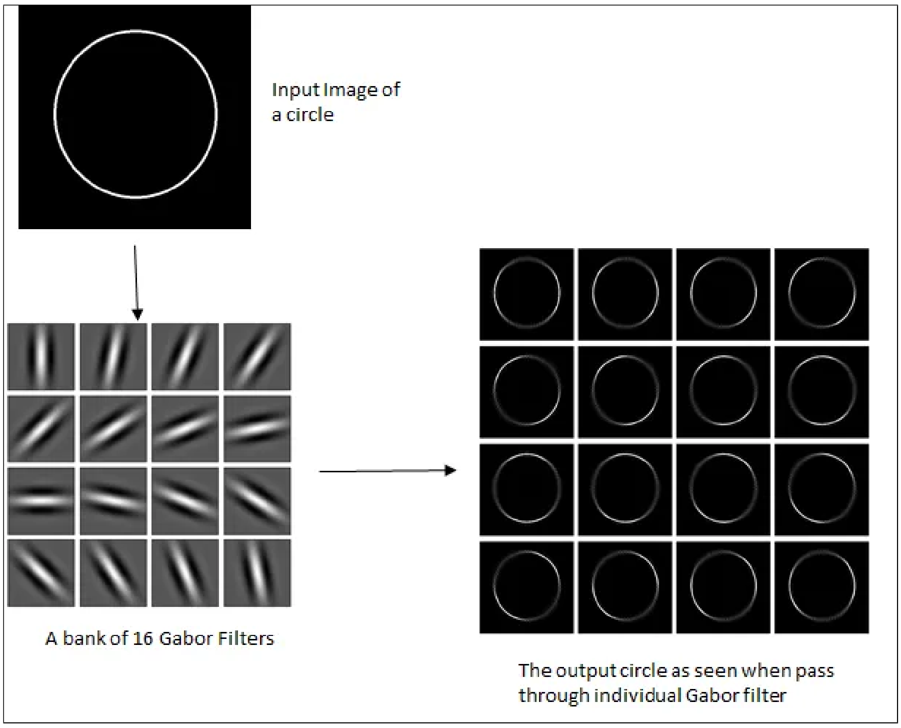


Figure 1.3: How Gabor filters of different orientations detect features of the circle that match the filters orientation. Image by Shah (2018)

Gabor filters can provide at least some information about a luminance-defined boundary. While such simple Gabor filters may be enough to segment simple luminance-defined boundaries, natural textures are more complex and often contain many different features. It is still unclear if such a simple filter is enough to model texture boundary detection in humans. In the next section, I will explain how DiMattina and Baker explored this problem.

1.1 DIMATTINA AND BAKER, AND PERCEIVED BOUNDARIES

DiMattina and Baker (2021) introduced a study to investigate potential differences in luminance texture segmentation compared to simple luminance steps. The authors introduced the terms "Luminance Step Boundary" (LSB) (Figure 1.4a) and "Luminance Texture Boundary" (LTB) (Figure 1.4c) to differentiate between the two types of luminance cues. The former refers to a simple luminance step and the latter refers to a luminance difference within a noisy texture.

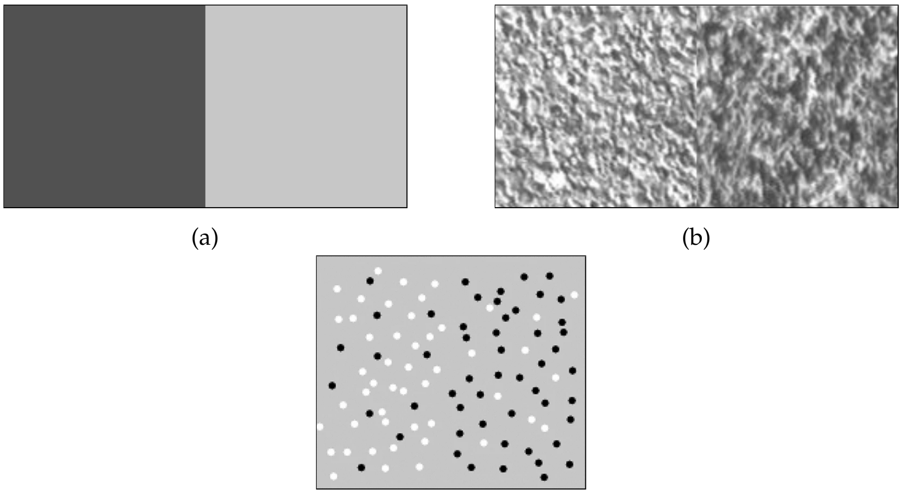
The authors explain how different natural surfaces can have varying mean luminance without an apparent sharp boundary between them. DiMattina and Baker exemplify this by placing natural textures from the Brodatz dataset next to each other (Figure 1.4b). The left texture has 21% higher mean luminance than the left texture.

The researchers motivate their study with natural textures, but in their experiments, they use simple, digitally synthesized textures

(Figure 1.4c). Figure 1.5 shows the luminance profiles for both types of stimuli, and it is evident that they are quite different. The rate of luminance decrease is much steeper at the boundary of the natural texture than in the artificial one. The two types of stimuli also differ perceptually. In my personal observation, I perceive a sharp boundary for the natural texture (Figure 1.4b) but not in the synthetic one (Figure 1.4c).

Moreover, the experimental tasks do not probe boundary detection directly, which is the main goal of the study. The authors used the same task for all experiments. In the task, observers classified a single displayed stimulus as being either left- or right-oblique. Figure 1.6 shows examples of both types of stimuli. The stimuli consist of two regions with differing mean luminance. The boundary between both regions was either oriented at $-45°$ (left-oblique) or $+45°$ (right-oblique).

It may be the case that the experiment did not measure boundary detection with much accuracy. Stimuli were oriented at only 2 orthogonal angles ($+45$ and -45). Fine changes in boundary detection accuracy are not probed. Therefore, it is still an open question if a task that probes boundary detection directly and with finer accuracy would produce similar results.



(a) (b) (c)

Figure 1.4: Examples of LSB and LTB

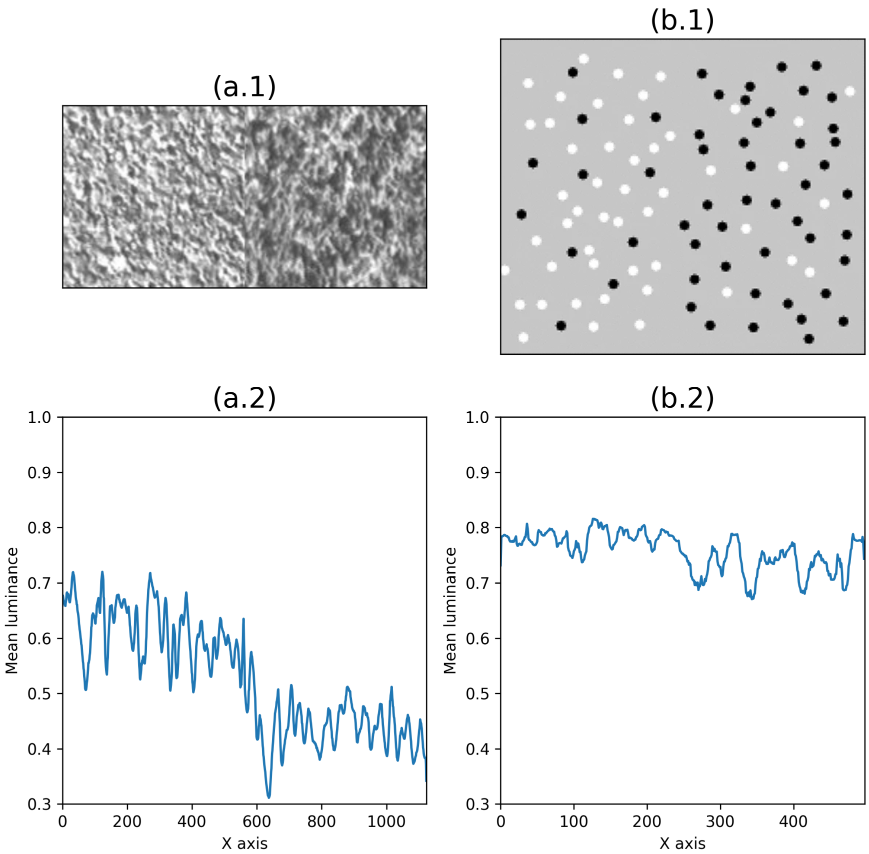
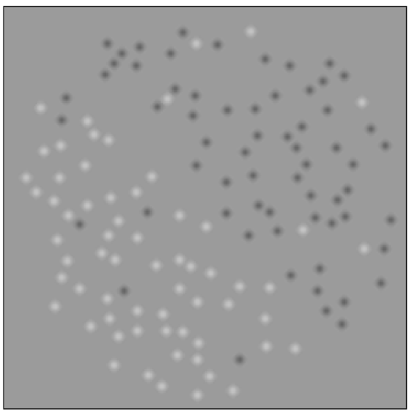
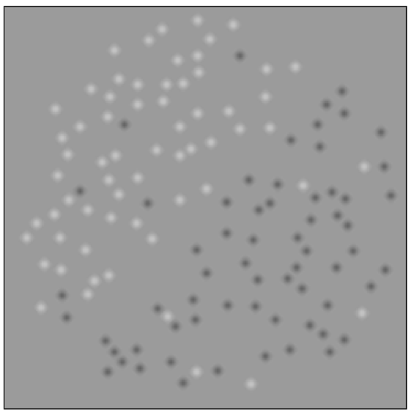


Figure 1.5: Natural and synthetic texture luminance profile



(a)



(b)

Figure 1.6: Examples of (a) left- and (b) right-obliques used in DiMattina and Baker's task.

1.2 OBJECTIVES AND HYPOTHESIS

The objective of the thesis is to evaluate if DiMattina and Baker's synthetic stimuli are suitable analogs for natural texture-defined surface boundaries. This is important to determine whether the findings from this study can be applied to natural texture segmentation.

This thesis is an exploration of the differences in boundary sharpness between natural textures and DiMattina and Bakers' synthetic textures. I will investigate if the lack of a clear boundary in synthetic textures leads to different segmentation mechanisms than those observed in natural textures.

If synthetic and natural texture segmentation use different mechanisms, then human capacity to define segmentation boundaries will significantly vary between the two. I will test this hypothesis by performing an experiment in which observers are asked to accurately define the boundary between segments of natural and synthetic surfaces.

Concretely, the aim is to design and perform an experiment that compares boundary detection performance between Luminance Step Boundaries, Natural Texture Boundaries and DiMattina and Baker's micropattern stimuli. Additionally, the task should probe boundary detection directly and be sensitive to fine changes in boundary detection performance.

2 METHOD

2.1 STIMULI

All stimuli are circular cutouts of square images with a diameter of 256 pixels. Each stimulus is divided in half, with the boundary positioned at an angle ranging from 0 to 179.9 degrees, as shown in Figure 2.1.

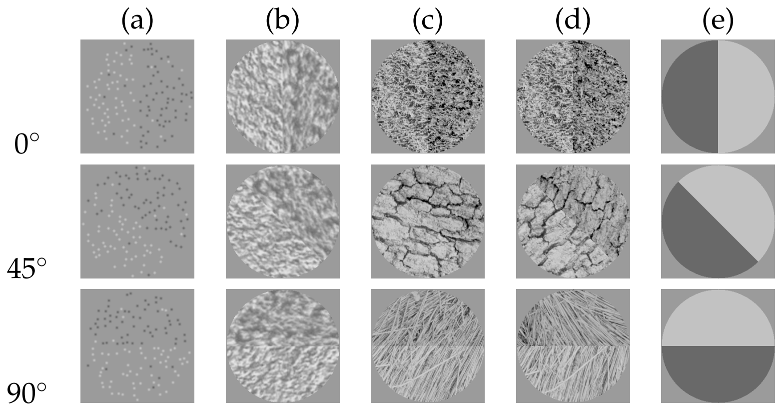


Figure 2.1: Examples of Stimuli at various degrees of rotation. (a) Synthetic micropattern stimuli. (b) Stimuli based on DiMattina and Baker's motivational texture pair. (c) Luminance-Boundary Brodatz Natural texture stimuli. (NLB) (d) Luminance-Texture-Boundary Brodatz Natural Texture stimuli (NLTB) (e) Control stimuli

2.1.1 *Micropattern stimuli*

The micropattern stimuli were created according to DiMattina and Baker (2021)'s description of "Luminance texture boundary (LTB) stimuli". The stimuli were synthesized by placing 64 non-overlapping black and white micropatterns on opposite vertical halves of a circular disc. The micropatterns consist of an 8-pixel 2D Gaussian (σ = 2 pixels). The micropattern maximum amplitude A was set to the maximum used by DiMattina and Baker at $A = \pm 0.25$ (W/B) dimensionless luminance units with respect to the gray mid-point (0.5). The proportion of "unbalanced" micropatterns π_U determines how many micropatterns have an opposite (black/white) counterpart on the other side of the stimulus boundary. π_U ranges from 0 (both halves of the stimulus have the amount of black and white micropatterns) to 1 (each half contains only black or only white micropatterns). The background luminance is set at a gray mid-point (0.5). In total 5 sets of micropattern stimuli were created. Each set only varies in the proportion of "unbalanced" micropatterns π_U. The π_U values were taken from DiMattina and Baker's paper (π_U = 0.2, 0.4, 0.6, 0.8). Additionally, π_U = 1 was added to maximize the mean luminance difference between both halves. In addition, the micropattern placement guarantees that there is no mean luminance difference across the anti-diagonal perpendicular to the image boundary. Examples of all micropattern stimuli described and their mean luminance profiles are shown in Figure 2.2.

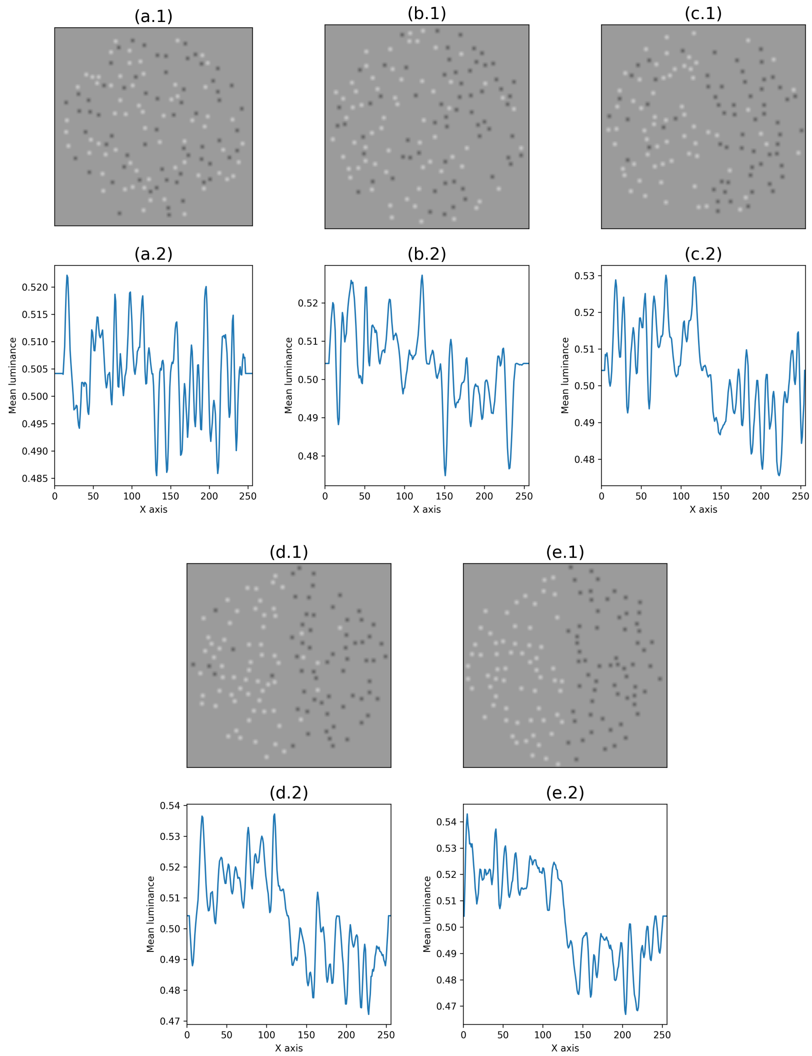


Figure 2.2: Examples of micropattern stimuli and their mean luminance profiles. Images a, b, c, d and e have values π_U = 0.2, 0.4, 0.6, 0.8 and 1.0 respectively.

I compared my synthesized stimuli with the examples given by DiMattina and Baker in their Nature publication to validate the faithfulness of my implementation. The tests performed are limited as all provided examples of DiMattina and Baker's stimuli are compressed JPEG files.

Figure 2.4 compares the mean luminance and standard deviation of DiMattina and Baker's stimuli with the newly created ones for different proportions of unbalanced micropatterns p_U. The mean luminance difference between the two sets of stimuli consistently remains below 0.009 luminance units, and the standard deviation consistently falls below 0.005 range. Minor differences observed might be due to JPEG compression artifacts or potential errors during the process of cutting out stimuli from larger images using GIMP for comparison.

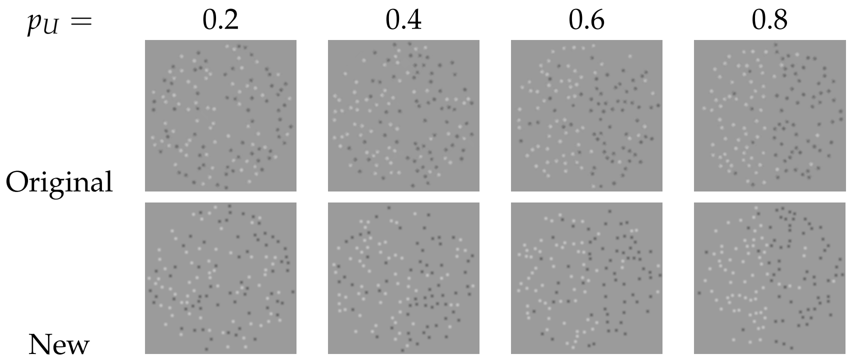


Figure 2.3: Visual comparison of the newly created micropattern stimuli with the examples present in DiMattina and Baker's paper.

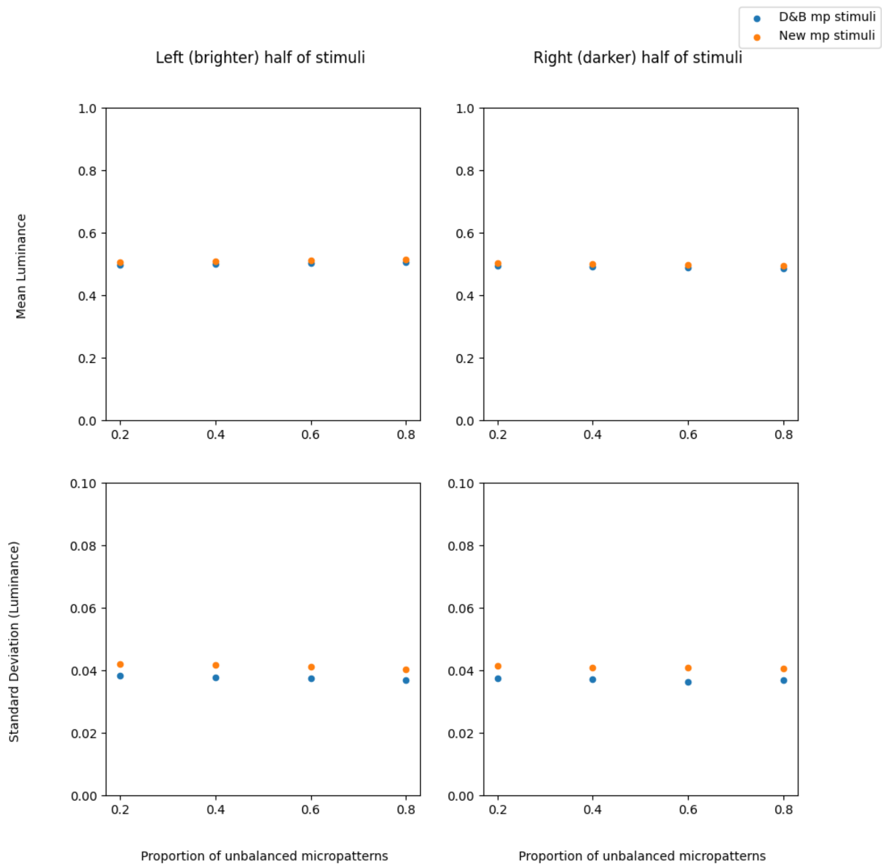


Figure 2.4: Micropattern stimuli implementation test. Comparison of (blue) original stimuli synthesized by DiMattina and Baker and (orange) the new implementation based on DiMattina and Baker's description.

2.1.2 *DiMattina and Baker's LTB example*

The stimulus shown in Figure 2.5 is a circular crop of the natural texture pair presented as a motivational example in DiMattina and Baker's study. Both textures were sourced from the Brodatz (1966) dataset originally. The image used for this stimulus was downloaded from DiMattina and Baker's paper on nature.com[1]. The crop has a diameter of 256 pixels to match all other stimuli. The right half of the stimulus is darker than the left one by 0.1065 dimensionless luminance units.

1 https://www.nature.com/articles/s41598-021-89277-2/figures/1

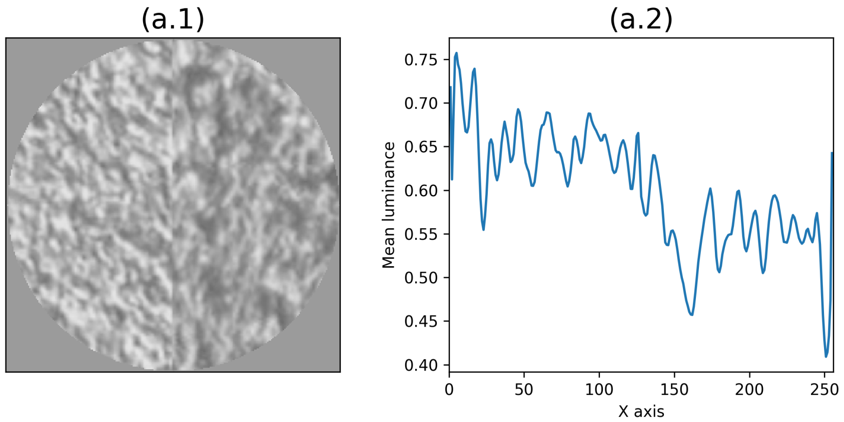


Figure 2.5: Stimuli based on DiMattina and Baker's motivational texture pair at various degrees of rotation.

2.1.3 *Natural textures*

To assess natural textures as described by DiMattina and Baker, I used images from the Brodatz (1966) dataset. Specifically, I utilized images from Volume 1 of the USC-SIPI-Database published by the University of Southern California and Institute (Accessed March 13, 2023). The images were not taken from the original book but are instead scans of glossy prints purchased from the author. While the images are mostly not equal to the ones in the original book by Brodatz (1966), they are the same textures.

Two sets of natural texture stimuli were created, distinguished by their boundaries: luminance-based (NLB) and a combination of luminance and texture (NLTB).

2.1.3.1 *Natural textures with a luminance-based boundary (NLB)*

For each image, the right half was darkened by 0.1065 dimensionless luminance units to match the texture pair used by DiMattina and Baker described in the previous section. This results in a luminance-defined boundary within a continuous texture (NLB). Example stimuli are shown in Figure 2.7.

2.1.3.2 *Natural textures with a luminance and texture-based boundary (NLTB)*

To create luminance and texture-defined boundaries (NLTB), I extracted two opposite subsections from each image, darkened the right half, rotated them randomly, and joined half-disk cutouts of them. Figure 2.6 illustrates this process. This results in a boundary defined by slight differences in texture. Example stimuli are shown in Figure 2.8.

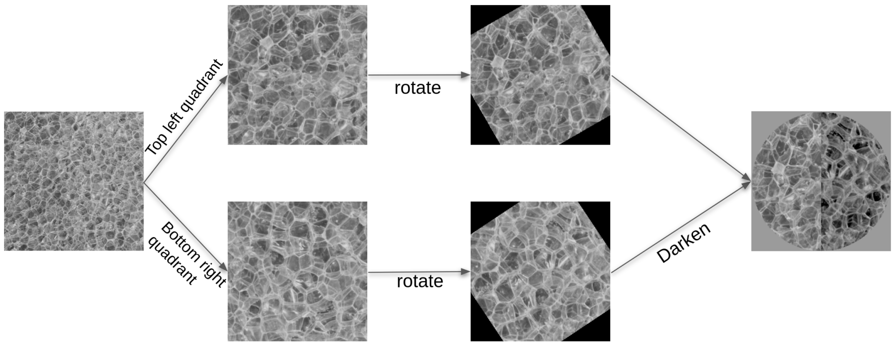


Figure 2.6: Creation of Luminance- and Texture defined natural texture (NLTB) stimuli

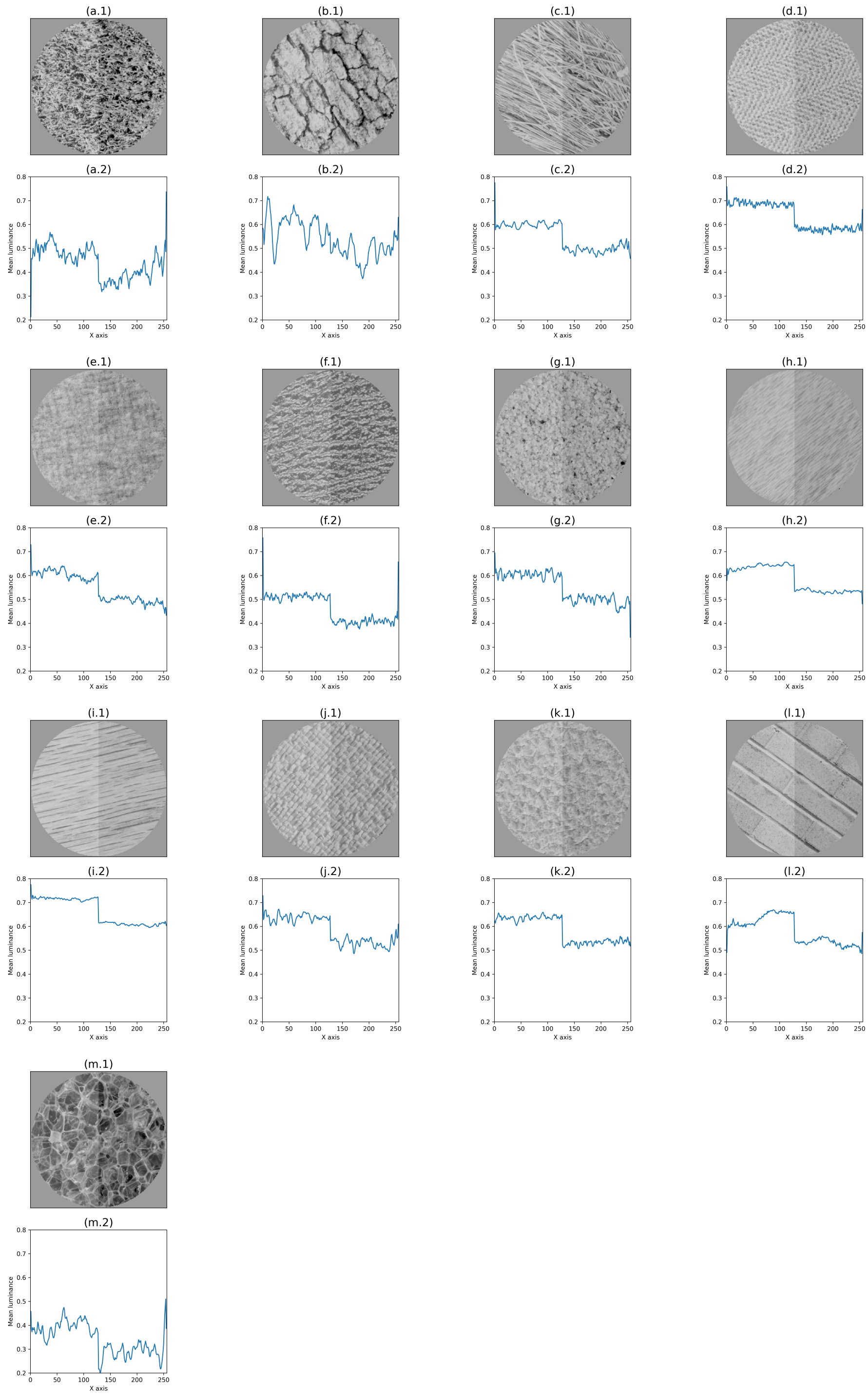


Figure 2.7: Natural textures with a luminance-based boundary (NLB) and their mean luminance profiles.

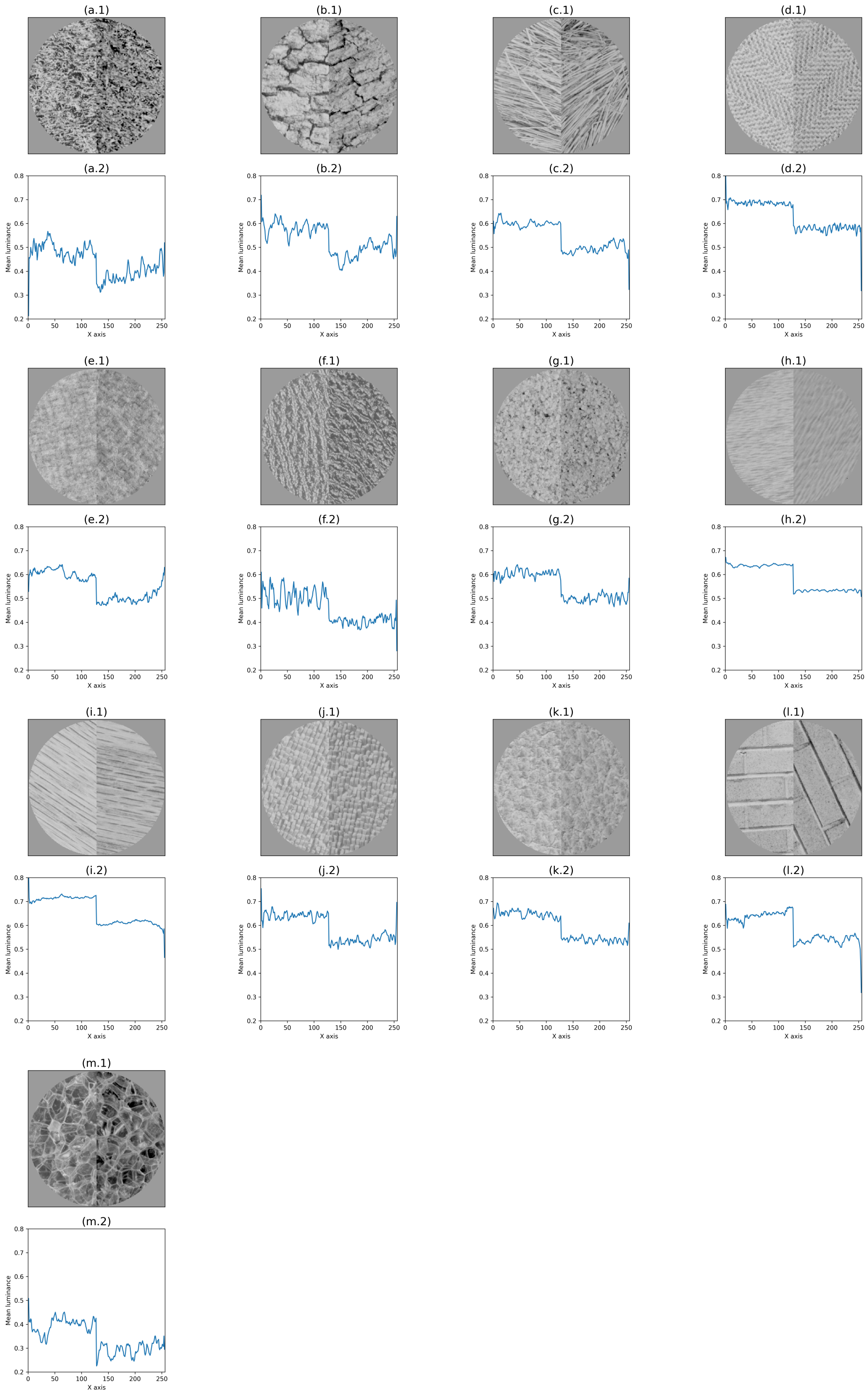


Figure 2.8: Natural textures with a luminance and texture-based boundary (NLTB) and their luminance profiles.

2.2 APPARATUS

Stimuli were presented in a dark room on a 1920×1080, 24-inch VIEW-Pixx LCD monitor with a refresh rate of 120 Hz. All stimuli were adapted so the gray mid-point stayed at 100 cd/m2. This was done using calibration measurements of the monitor. Observers were situated 133 cm from the monitor using a chin-rest. Observers' responses were registered with a regular computer keyboard. Observers were able to rotate a red line by 0.1 degrees by using the left and right arrow keys. Once at the desired angle, the observers confirmed their response by pressing the space bar.

2.3 EXPERIMENTAL PROTOCOL

To investigate whether the different stimuli are segmented using similar mechanisms, I designed the task to enable precise measurements of segmentation accuracy. In each trial, a random-angle stimulus was presented, and participants were asked to align a vertical red line with the stimulus boundary using the arrow keys on the keyboard. Each key press rotated the line by 0.1 degrees clockwise or counterclockwise. Holding down an arrow key rotated the red line rapidly in the corresponding direction. See Figure 2.9 for an example of the initial configuration and a perfectly aligned red line. The stimuli shown in the example are the control stimulus, a micropattern stimulus and a natural texture boundary stimulus. All stimuli are set at different random angles.

Observers performed 164 psychophysical trials. These include the synthetic stimuli with proportions of unbalanced micropatterns $p_U = \{0.2, 0.4, 0.6, 0.8, 1.0\}$, the texture pair used by DiMattina and Baker, the newly created NLB and NLTB stimuli, and control stimuli. For each participant, the order of all stimuli, including repeats, and the angle of each stimulus were randomized.

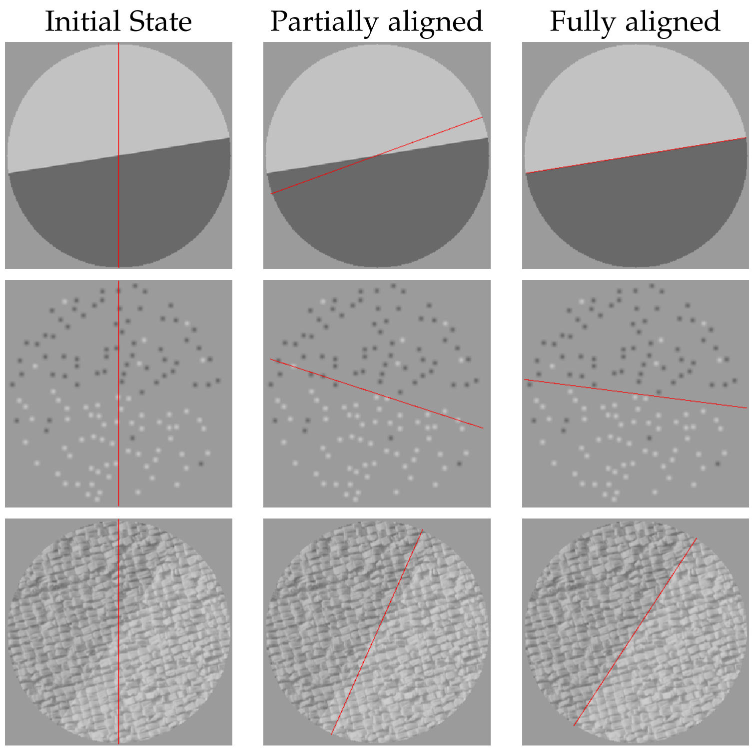


Figure 2.9: Task Example. The figure shows the initial configuration of each trial and aligned examples. The shown stimuli are the control stimulus, one micropattern stimulus with $p_U = 0.8$ and one NLB stimulus

3 RESULTS

The objective of this experiment was to compare boundary perception performance across different texture stimuli. The focus was to compare natural texture stimuli with micropattern stimuli and to observe how different approaches to natural texture stimuli generation differ from each other. Figures 3.1 and 3.2 show the boundary detection performance of all observers (O1-O4) across all stimuli sets. Performance is measured in angle deviation between the stimulus angle and the angle of the red line aligned by the observer.

The micropattern stimuli resulted overall in the worst performance compared to the control and the natural texture stimuli. Both mean angle deviation and variability increased with a lower proportion of unbalanced micropatterns. Unexpectedly, mean performance was slightly better for a $p_U = 0.8$ than $p_U = 1.0$ for 2 naive observers (O1 and O2).

The natural texture stimuli, on the other hand, had low and consistent angle deviations. All three natural texture stimuli groups showed similar mean performance. While mean performance stayed consistent among all natural stimuli groups, the luminance-based boundary stimuli (NLB) resulted in a significantly higher standard deviation. Additionally, perfect alignment (angle deviation $= 0$) only occurred for natural texture stimuli.

All naive observers (O1-O3) were consistent with each other. However, the experienced observer (O4) performed significantly better for the micropattern stimuli than all naive observers.

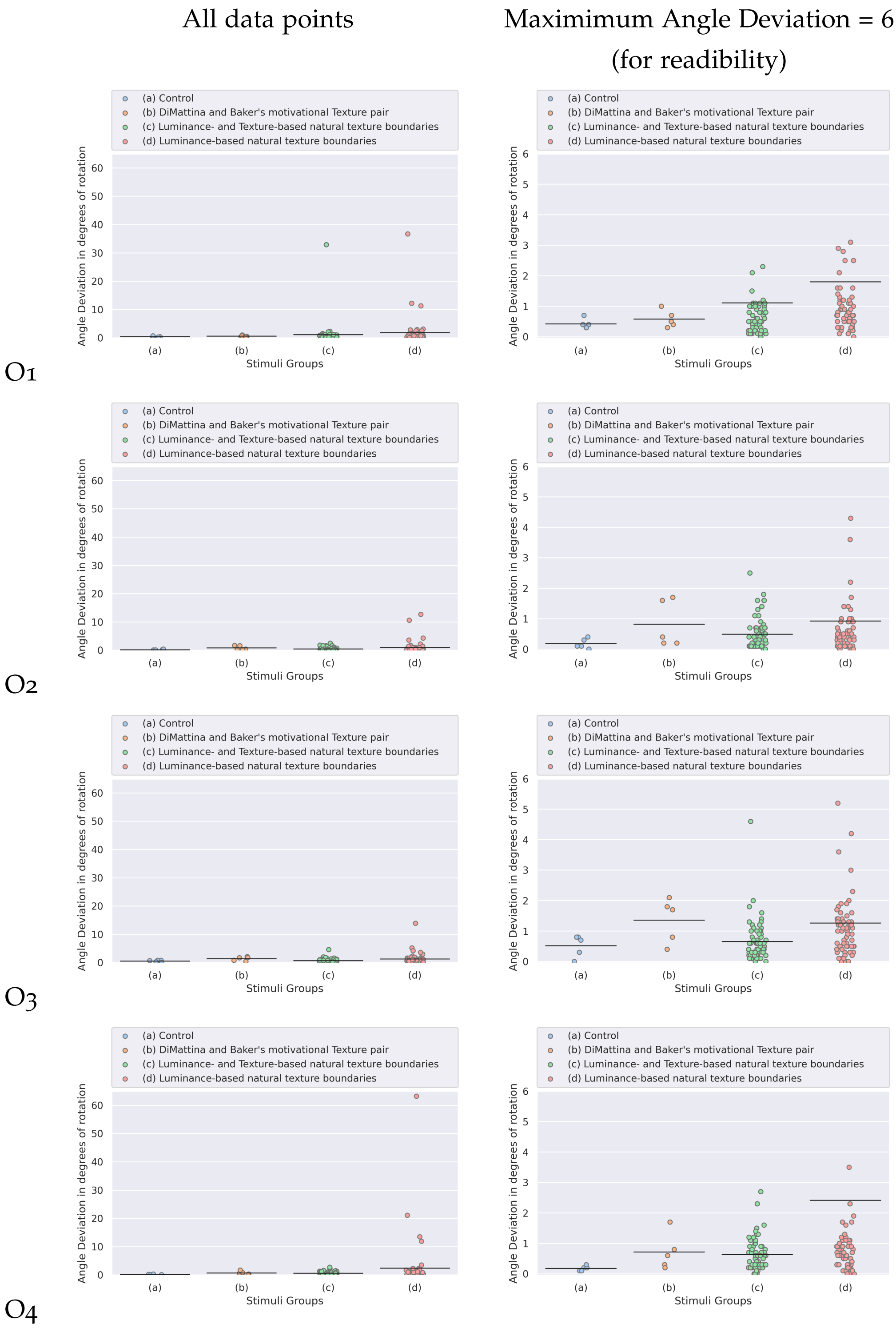


Figure 3.1: Performance for natural texture stimuli for each observer. Each row shows the performance of one observer. The left column is scaled, so all data points are visible. The right column is scaled, so fine performance differences between stimuli groups are visible. The black lines show the mean angle deviation for each stimulus group. Observers 1-3 are naive observers. Observer 4 is experienced with the experiment and the stimuli.

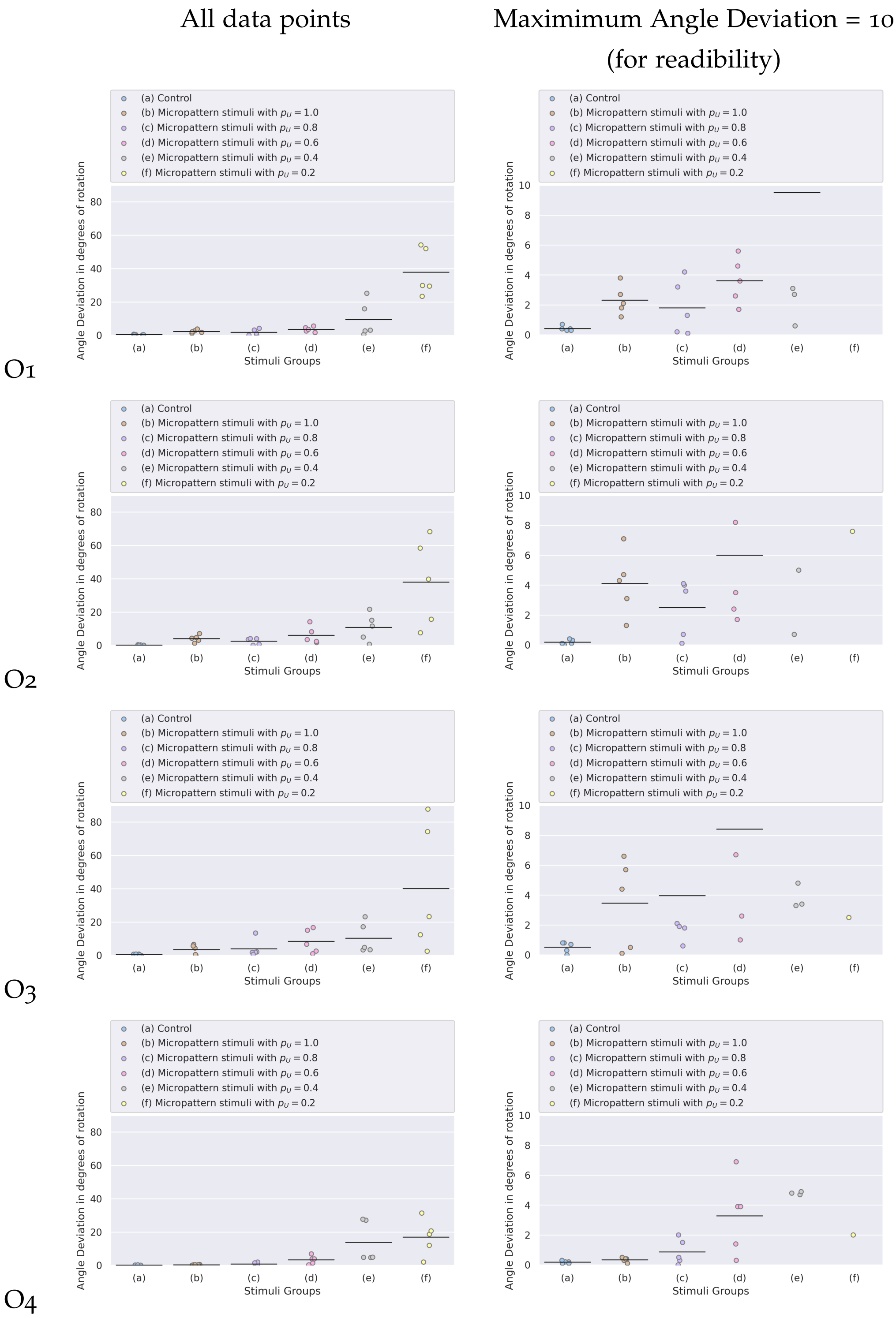


Figure 3.2: Performance for micropattern stimuli for each observer. Each row shows the performance of one observer. The left column is scaled, so all data points are visible. The right column is scaled, so fine performance differences between stimuli groups are visible. The black lines show the mean angle deviation for each stimulus group. Observers 1-3 are naive observers. Observer 4 is experienced with the experiment and the stimuli.

3.0.1 *Different Natural Texture Boundaries*

The natural luminance-based (NLB) and texture-luminance-based boundary (NLTB) stimuli were created using a set of 13 different textures. Figure 3.3 shows the boundary detection performance of all observers (O1-O4) across all used textures. Performance was consistent among all natural luminance-texture boundary (NLTB) stimuli. The luminance-based boundary (NLB) stimuli set also showed consistent results, except for one clear outlier texture. Removing the outlier texture lowers the standard deviation considerably and brings the variability of the stimuli set much closer to the values of the remaining natural texture stimuli sets.

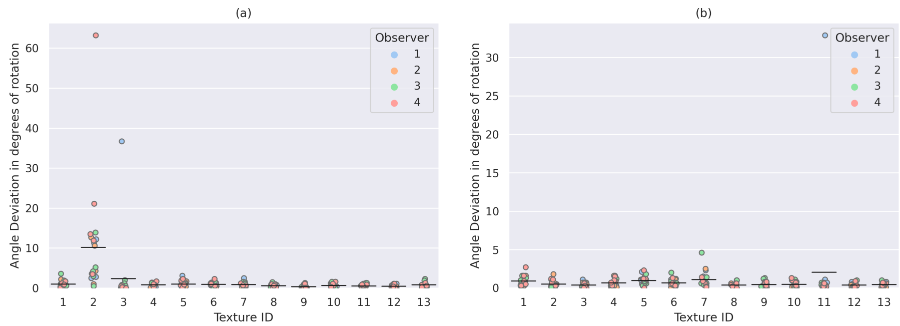


Figure 3.3: Performance differences between textures. (a) Luminance-based boundary (NLB) stimuli (b) Texture and Luminance-based boundary (NLTB) stimuli. The black lines show the mean performance of all observers for each stimulus group

3.0.2 *Effect of p_U on micropattern stimuli*

Figure 3.4 shows the performance for the micropattern stimuli as the proportion of unbalanced micropatterns (p_U) changes. These findings align with the research conducted by DiMattina and Baker. Notably, lower values of p_U exert a significant impact on observer performance, with a noticeable decline occurring when p_U falls below or equals 0.6.

Of particular interest, stimuli characterized by $p_U = 0.2$ yielded the poorest performance results, representing the only micropatterns associated with complete misjudgments (angle deviations > 45°). Notably, 30% of trials featuring $p_U = 0.2$ exhibited an angle deviation exceeding 45°. No stimuli with $p_U > 0.4$ resulted in angle deviations surpassing 45°.

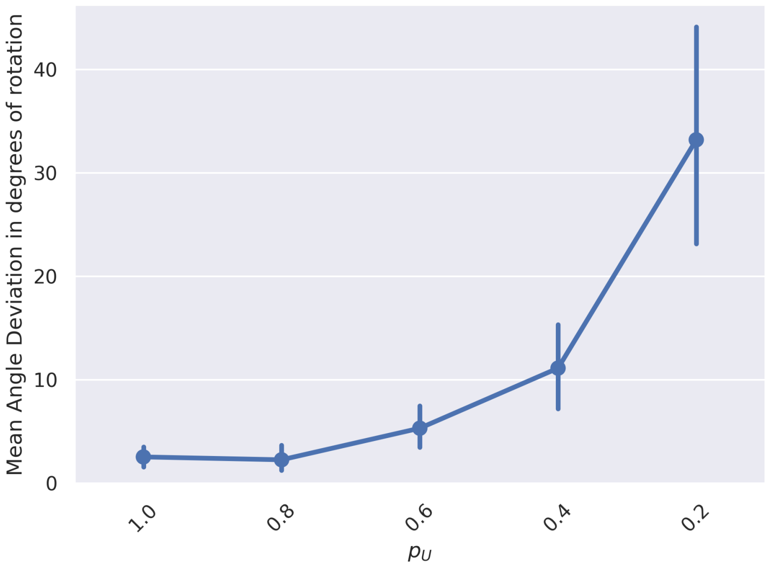


Figure 3.4: Task performance of micropattern stimuli. Performance of the 5 micropattern stimuli sets that were used. Each dot is the mean angle deviation in degrees of rotation. Each point contains 95% Confidence Interval error bars.

4 DISCUSSION

4.1 LUMINANCE TEXTURE BOUNDARIES

DiMattina and Baker set out to explore the mechanisms of natural texture segmentation in their paper. They compare two types of boundaries: sharp luminance boundaries, which have sudden changes in luminance, and natural texture boundaries, which they defined as regions with different mean luminances but no abrupt changes at the boundary. They exemplify natural texture boundaries with a pair of natural textures with different mean luminance. To parametrize the concept of natural texture boundaries DiMattina and Baker created micropattern stimuli. After visual inspection, the natural texture boundary seemed significantly sharper than the micropattern stimulus boundary. This thesis aimed to investigate whether DiMattina and Baker's micropattern stimuli are suitable analogs for natural texture boundaries. In particular, I tested whether any possible differences in stimulus boundary affect fine boundary detection performance.

The results show that naive observers can detect natural texture boundaries with finer accuracy than micropattern stimuli boundaries. This finding directly supports the hypothesis that the micropattern stimuli are segmented via different mechanisms than natural textures. Therefore, it is important to consider this difference when discussing the possible mechanisms behind natural texture segmentation, as DiMattina and Baker do based on their experiments on micropattern stimuli. Otherwise, their conclusions might be misleading.

One of the challenges of designing an experiment to measure natural texture segmentation is defining what constitutes a "texture". As this thesis focused on natural textures as understood by DiMattina and Baker, I created two sets of stimuli based on the Brodatz texture pair that they used as a motivating example. Both sets consist of textures from the Brodatz database and have subtle differences at the boundary. The first set has textures with only a luminance boundary (NLB) and the second set has a luminance boundary and slight texture differences (NLTB) created by rotating one half of the image. The performance on the texture pair used by DiMattina and Baker and both sets I created was very similar. This shows that my stimuli sets are good approximations of DiMattina and Baker's motivating texture pair. It also shows that the rotation introduced in the second set did not have a significant effect on performance, suggesting that the absolute difference in luminance between segments is the main cue for segmentation within these stimuli sets.

Moreover, all 13 textures used for the new stimuli sets showed very similar performance (with one exception that will be discussed later in this section). This reinforces the idea that texture differences do not have a strong influence on luminance boundary detection within textures.

4.2 PERFORMANCE DIFFERENCE BETWEEN NAIVE AND EXPERIENCED OBSERVERS

One further finding of the experiment was that the performance of micropattern stimuli segmentation varied significantly between the naive observers and the experienced observer. The experienced observer showed very good performance for the micropattern stimuli with a high proportion of unbalanced micropatterns. Since this happened only for the experienced observer, the high performance might be due to a different segmentation strategy. The same did not happen for the natural texture examples. The fact that performance changed with experience for the micropattern stimuli but not for any natural textures might again indicate that there are significant differences between both stimuli types. Additionally, naive observers had a limit on how well they could segment micropattern stimuli with high proportions of unbalanced micropatterns. Increasing the proportion of unbalanced micropatterns (p_U) from 0.8 to 1.0 did not improve their performance. This might suggest that boundary detection of micropattern stimuli might be limited by the lack of a perceivable line, unlike the natural texture stimuli.

4.3 PROBING SEGMENTATION BOUNDARIES

This experiment differs from DiMattina and Baker's experiment in that it directly probes boundary detection. DiMattina and Baker's task did not probe boundary detection directly and therefore did not make it possible to measure fine boundary detection accuracy. The experiment performed resulted in more information about the differences in segmentation of the different kinds of stimuli. Both experiments resulted in comparable but slightly different results with the micropattern stimuli. Performance for micropattern stimuli dropped in similar ways in both results with lower proportions of unbalanced micropatterns p_U. With DiMattina and Baker's task, all observers experienced missed guesses when confronted with p_U values of 0.5 or lower. However, in my experiment stimuli with $p_U = 0.4$ and $p_U = 0.6$ resulted in no angle deviations surpassing 45° (Angle deviation >= 45° would constitute a completely missed guess).

4.4 ADDRESSING THE OUTLIER STIMULUS

I found one clear outlier stimulus in the Luminance-based boundary (NLB) stimulus group. The outlier stimulus was based on texture number 02 from the USC-SIPI database from University of Southern California and Institute (Accessed March 13, 2023). I also used this texture to create a stimulus for the Luminance- and texture- boundary (NLTB) group, but it did not become an outlier. Figure 4.1 shows the original texture and both stimuli. The discrepancy might be due to the algorithm for creating the stimuli. I rotated the textures at different random angles for both groups. It is possible that the angle of rotation created a slight luminance gradient from left to right. This would result in a less sharp boundary in the middle when subtracting luminance on the right side, even though the mean luminance difference between both halves was similar.

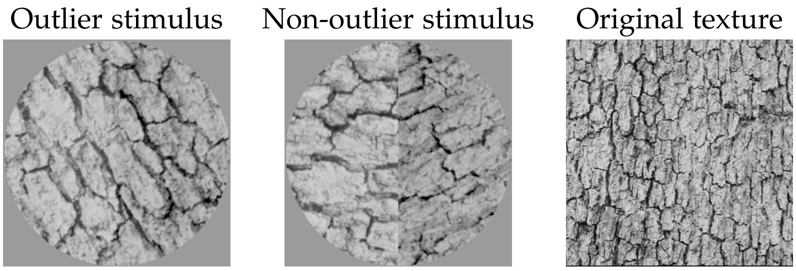


Figure 4.1: Outlier stimulus. The first image from the left is the outlier stimulus from the Luminace-defined boundary (NLB) stimulus group. The second image is based on the same texture and is from the Luminance- and texture-defined (NLTB) boundary stimulus group. The third image is the original texture from the USC-SIPI Brodatz database.

4.5 LIMITATIONS

This study has some limitations that should be acknowledged and possibly addressed in future research. First, the natural texture stimuli had a constant luminance difference at the boundary, which does not allow for a fair comparison of luminance difference with other factors that might be important for segmentation. It would also be of interest to measure how the impact of luminance difference would differ between natural texture stimuli and micropattern stimuli. Second, the data collection was unbalanced between micropattern stimuli and natural texture stimuli, which could introduce biases in the results. Third, it would be beneficial to have a higher number of both naive and experienced observers to better understand how experience would impact different kinds of stimuli. These limitations should be taken into account when interpreting the findings and drawing conclusions from this study.

4.6 CONCLUSION

In conclusion, this study has provided valuable insights into the mechanisms of natural texture segmentation and the suitability of micropattern stimuli as analogs for this process. The findings support the hypothesis that micropattern stimuli, as designed by DiMattina and Baker, differ significantly from natural texture boundaries in terms of fine boundary detection accuracy. This contrast emphasizes the importance of careful consideration when extrapolating conclusions from micropattern experiments to the broader context of natural texture segmentation.

Additionally, this research has provided crucial data directly probing boundary detection, a critical aspect not addressed in DiMattina and Baker's work. The comparison of results between the two experiments revealed subtle but significant differences in micropattern stimulus performance, particularly at lower proportions of unbalanced patterns, suggesting nuanced segmentation differences.

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