Bachelor Thesis

Comparison of two multiscale spatial filtering models

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Summary

1 Introduction

1.1 Light and the Visual System

In the environment, light is emitted by a source of illumination, such as the sun. Any surface on which this light falls will reflect a portion of it as *luminance*. This portion is called the *reflectance* of the surface. The luminance is therefore the result of *illuminance* and reflectance, as shown in Figure 1 a). A lightmeter can measure the amount of luminance reflected by a surface, but it cannot tell what the reflectance of this surface is, because the luminance could be the product of any combination of illuminance and reflectance.

$$L = I \cdot R \tag{1}$$

The formula 1 shows the problem from a mathematical perspective. L represents luminance, I and R illuminance and reflectance, respectively. It is simply impossible to solve for I and R, when only L is been measured, since for every R there is an I to produce the measured L (Adelson, 2000).
However, the human visual system can solve this problem. It is also processing only luminance, yet it is able to generate the perception of reflectance, which is referred to as lightness. Figure 1 b) shows an abstraction of this process.

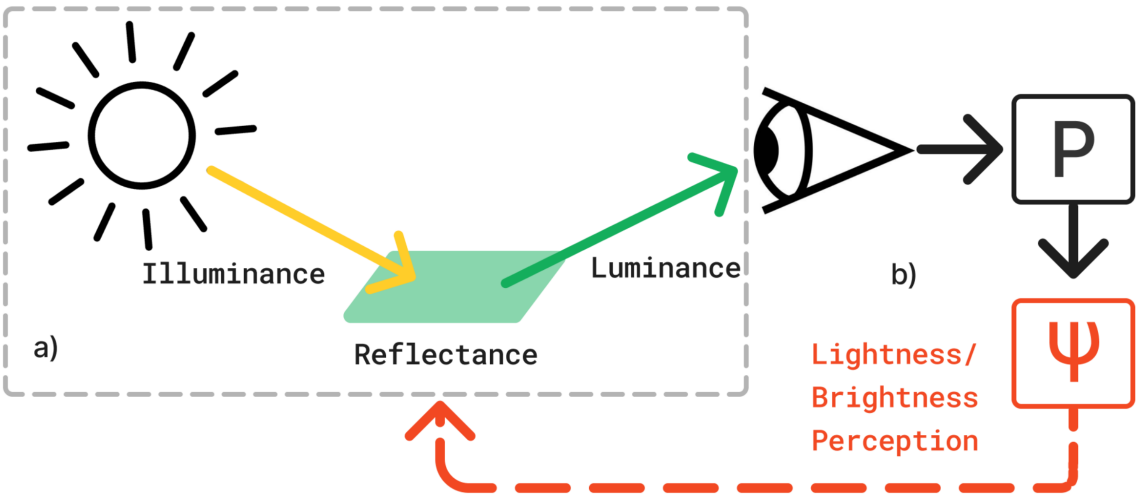


Figure 1: a) Relationship between illuminance, reflectance and luminance. Luminance is the result of illuminance and reflectance. b) The human visual system processes luminance through an unidentified mechanism, represented by P which is determining lightness and brightness perception ψ of the surface.

Next to lightness, humans also perceive brightness, which is the perception of luminance, seen in Figure 1 b). Unlike reflectance, luminance is directly available at the retinal image and brightness could in principle be derived from the retinal measurement. However, the visual system does not only consider the corresponding luminances when evaluating the perceived lightness and brightness of image areas, it also takes into account the luminances of the surrounding regions (Kingdom, 1997). As a result the perception can differ from the actual retinal information. The mechanisms through which the visual system accomplishes these tasks are the subject of current research and will be discussed further in the following sections.

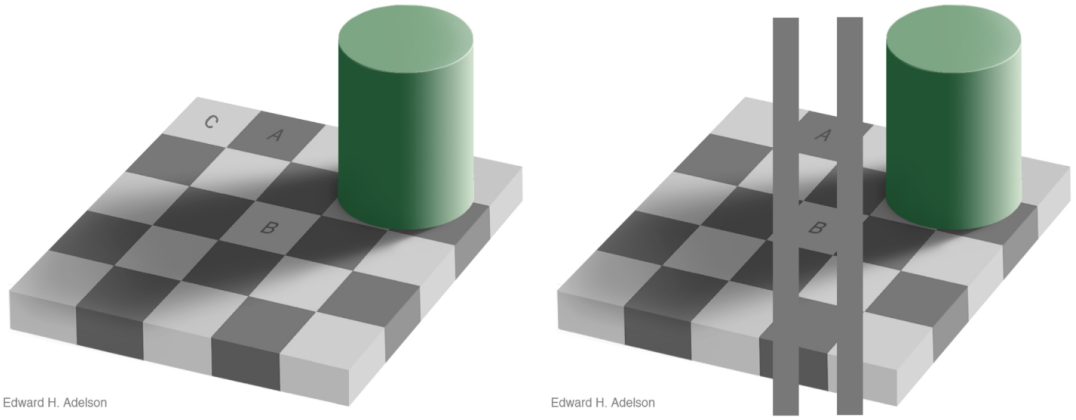
Figure 2: Lightness and brightness are distinguishable when illumination is visible. *"The walls of the house appear uniformly white — a lightness judgment — yet are brighter in some places than others — a brightness judgment"*. Quote and picture from Kingdom (2014).

The distinction between lightness and brightness becomes apparent when information about illumination is visible, as seen in Figure 2. *"The walls of the house appear uniformly white — a lightness judgment — yet are brighter in some places than others — a brightness judgment"* (Kingdom, 2014). This distinction is important because brightness is about the relationship between the object and its environment. In other words, it reveals how the object is exposed to illumination. Lightness, on the other hand, represents the intrinsic properties of the object, such as color, regardless of the environment.

Since reflectance is only implicitly perceivable, it can lead to uncertain situations. For instance, a shadow can dim an area so that a white surface within the shadow reflects the same amount of light as a black surface in full illumination next to it. Despite this, human observers can usually distinguish between the white and the black surface (Arend, 1993).

This phenomenon is illustrated by Edward H. Edelson's *checkerboard shadow illusion*, shown in Figure 3. The two patches A and B on the checkerboard in Figure 3a appear to have different colors, even though they are emitting the same light, as shown in Figure 3b.

The cylinder seems to cast a shadow, even though there is no real light source, since the image is just a two-dimensional representation of the scene. However, the visual system is designed to process images coming from three-dimensional scenes with illumination and shadows and so it processes the checkerboard shadow illusion with all the available information about depth and illumination. To logically follow the processing, one can say, that patch B reflects the same amount of light as patch A (seen in Figure 3b), but is located in the shadow of the cylinder and therefore must have a higher reflectance. In other words, the visual system needs to react to differences in illumination and compensate for them in order to estimate the reflectance. This behavior ensures that the perception of a scene is closely related to the reflectance of its surfaces and is largely unaffected by the illumination.



(a) (b)

Figure 3: (a) The Checkerboard shadow illusion image; (b) proof image (Adelson, 1995).

In everyday life, illusions in brightness and lightness perception are rare, likely due to the vast amount of information that the visual system can make use of. Shading, shadowing, and spatial depth can guide the perception of brightness and lightness, like in the checkerboard shadow illusion. However, there are illusions with less information available for the visual system, which need a different explanation.

1.2 Low-Level Vision

One very simple illusion is the classic *simultaneous contrast illusion*, as seen in the upper part of Figure 4. Two identical grey squares appear to be different in brightness, depending on their surroundings. The lack of information about illumination and spatial depth is crucial in comparison with the checkerboard shadow illusion. The parts of the visual system, which are processing illumination or spatial depth, will have no information available in the simultaneous contrast illusion. Here the idea of detecting illumination and compensating for it will fail, hence a different explanation is needed.

An explanation for the simultaneous contrast illusion is offered by neural units in the retina. Hering (1834 —1918) was the first describing their *center surround fields*, which compare luminance areas with their surrounding areas. With that they could account for the simultaneous contrast illusion. The lower part in Figure 4 illustrates the principle. The blocks under the illusion represent neurons responding to areas of the illusion image. The surrounding blocks subtract and the center block adds their responses to the fourth block underneath. When the surrounding blocks are sensing the darker surrounding of the left patch, their response is small and so the subtraction is small. As a result the left summing block receives a higher response, correlating with a human observer experiencing the left patch to be brighter. On the right patch the surrounding blocks are sensing bright surroundings and so the subtraction is higher and the summing block receives a lower response, also correlating with a human observer experiencing the right patch to be darker.

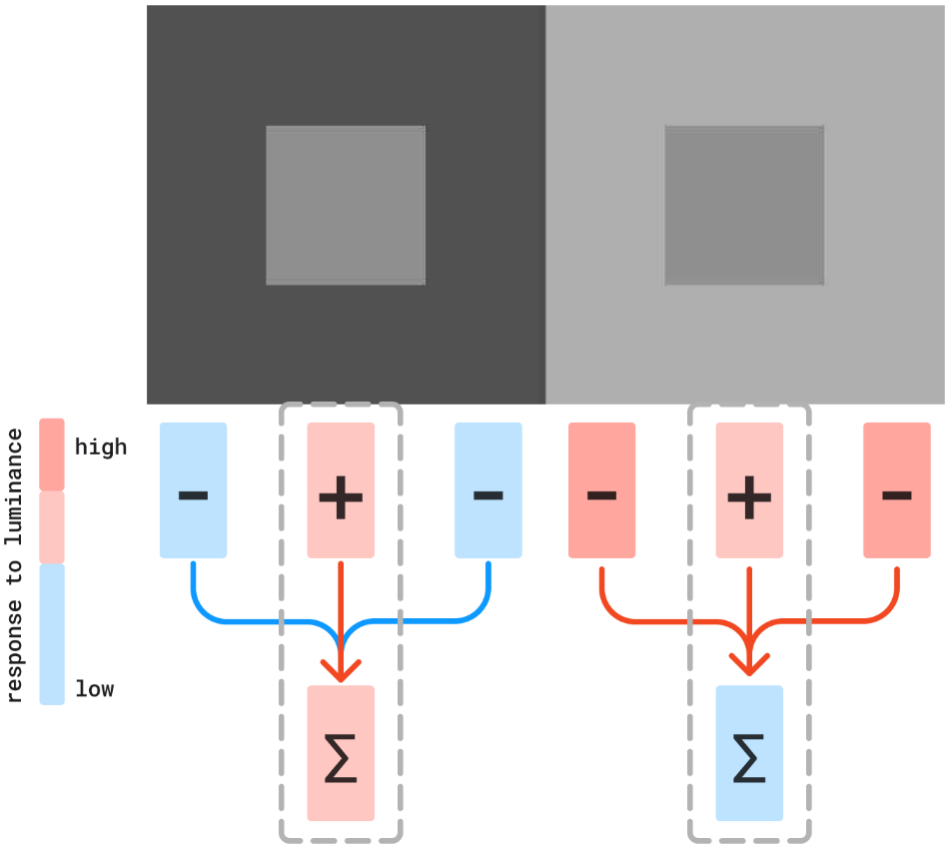


Figure 4: Above: The simultaneous contrast effect. Two identical grey patches appear to be different in brightness, depending on their surrounding. The left patch appears brighter than the right patch.
Below: The principle of center surround fields. The blocks on each side represent neurons, where the surrounding blocks subtract and the center block adds their responses to the fourth block underneath. On the left side the center response is medium (light red), corresponding to the left patch in the illusion, while the surround response is low, corresponding to the surrounding dark gray in the illusion. The summation results in a medium response. On the right side the center is the same, but the surround response is higher (dark red) and so the summation in the fourth block is lower. The responses of the patches in the illusion depends on their surrounding.

Simple mechanisms like the center surround fields could be responsible for human brightness perception[1]. They exist in different sizes and their outputs are also interacting with each other. This complex neural processing results in so called *sensory channels*, where each channel is selectively sensitive to different sizes of contrast areas, also referred to as spatial frequencies (Sachs et al., 1971). Large center surround fields will respond to low spatial frequency information like large objects and gradual changes across the image. Small center surround fields will respond to high spatial frequency information like fine details and edges.
The organization of center surround fields can isolate specific image properties and the interaction of their outputs provides a mechanism to process the retinal information in a much more meaningful way. This has inspired researchers to investigate the computational modeling of center-surround fields and their interactions.

[1]The terms brightness and lightness become synonymous without information about illumination and will be used interchangeably in the following sections, as we will discuss only such illusions

1.3 Modelling Human Vision

The basic idea of center surround fields is to compare luminances with their surround luminances. Since computers handle image data as discrete pixel values, it is mathematically straight forward to model this comparison with algorithms. A common approach is to design a convolution filter, representing the center surround field and convolve it with the image pixel values. In Figure 5 the principle of a convolution on a grayscale image is shown. The filter values are applied on the input pixels by an element-wise multiplication. In the example of Figure 5 the filter is comparing every pixel with its direct neighboring pixels.

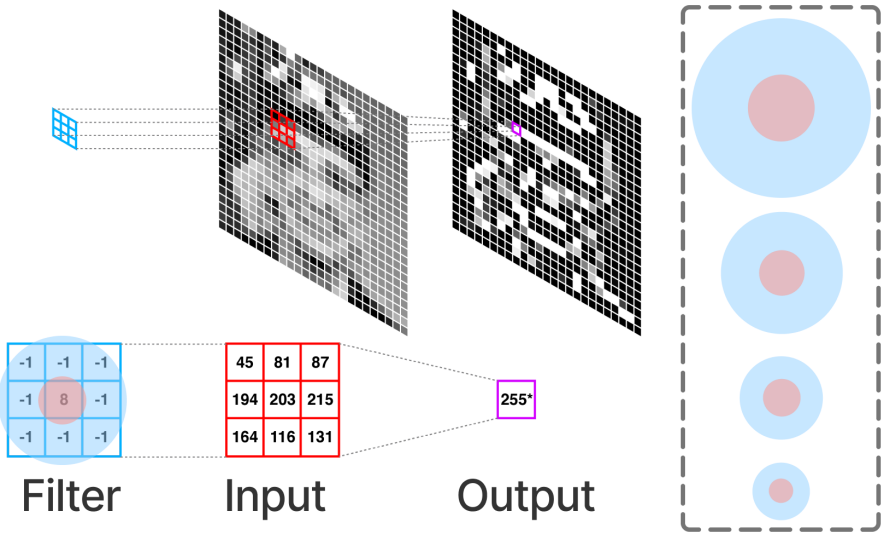


Figure 5: Applying a convolution on an image is a common approach to model center surround fields. Every pixel of the input image is multiplied with the center value of the filter (8) and then summed up with every surround pixel multiplied with the corresponding value in the filter (-1). The resulting sum is the new pixel value for the output image at the position of the original pixel. the left Figure is inspired by Gundersen (2017). The right side shows a filterbank, existing of multiple filters in different sizes.

To address the benefits of different sized center surround fields of the retina, it is sufficient to create multiple filters of varying sizes. On the right in Figure 5 a so called filterbank is shown. Each of the different sized filters will be applied on the input image and generate its own output, similar to the sensory channels of the visual system. Larger filters will compare more pixels and will respond stronger to low spatial frequencies. Smaller filters will respond to high spatial frequencies. The outputs from all the filters of a filterbank are representing the image information decomposed by frequencies. In order to reconstruct the image, it is sufficient to sum the filter outputs. The reconstructed image is identical to the original image, since all information is kept during the process.

To replicate human perception the DOG (Difference Of Gaussian) model from Blakeslee and McCourt does a reweighting of the filter outputs before reconstruction (Blakeslee & Mccourt, 1997). Inspired by the contrast sensitivity function of the human visual system, it attenuates lower frequencies. As a consequence the output image is no longer identical to the input image. In fact for the simultaneous contrast illusion the left patch is brighter and the right patch is darker, aligning with the human perception of the illusion.

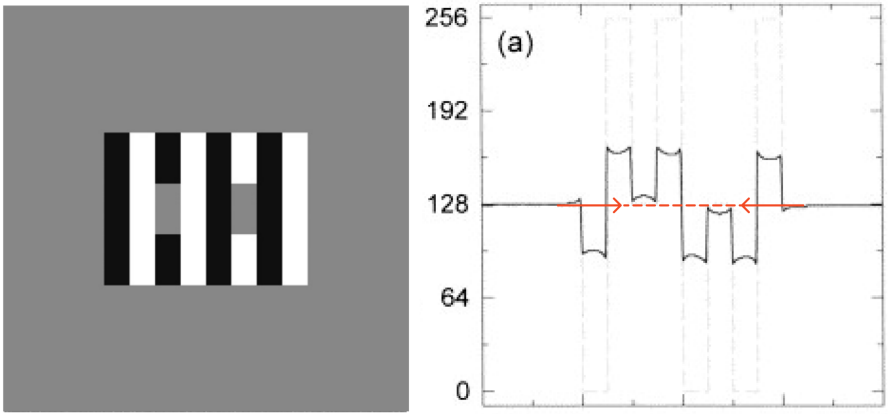


Figure 6: In White's Effect (left) the shift in perceived brightness is in the opposite direction compared to brightness contrast. Both patches are identical, but the left patch on the black bar appears to be brighter than the patch on the white bar, even if it shares most of its edges with white surfaces (White, 1979). The diagram on the right shows the processed White's Effect illusion by the ODOG model. The dashed line refers to the luminance profile across the horizontal center of the illusion. The solid line represents the models output along the same line. The red markers indicate that the models output is in accord with the human perception (Blakeslee & Mccourt, 1999).

The reweighting between decomposition and reconstruction appears to be a key mechanism of the DOG model making it capable of replicating human perception of the simultaneous contrast illusion. However, the DOG model cannot account for all brightness phenomena. For instance, the White's effect, illustrated on the left side of Figure 6, cannot be explained by Blakeslee and McCourt's initial model. One year later, in 1999, they developed an extended version of the model, called ODOG (Oriented Difference Of Gaussian), which can account for White's effect shown on the right side of Figure 6 (Blakeslee & Mccourt, 1999). Two changes are responsible for its new capabilities. They extended the filterbank by six different orientations for each filter, therefore they also changed the isotropic filters of the DOG model to anisotropic filters in order to be able to rotate them. The second change is a normalization step before reconstruction. The ODOG model will be discussed in more detail at a later point in the thesis.
The ODOG model became very famous and inspired a whole family of so-called spatial filtering models. Among them is a model with a different approach, the BIWaM (Brightness Induction Wavelet Model) model from Otazu. It doesn't use a filterbank to decompose the image, but rather convolves its filters within a wavelet transformation (Otazu et al., 2008).

1.4 ODOG and BIWaM

ODOG and BIWaM are oriented spatial-filtering models, highlighting the importance of low-level vision. Both models process an input image using filters, which are inspired by the center surround fields. As shown in Figure 7, their processing begins with the decomposition of the input image (Step 1), using spatially scaled and oriented filters. Each filter results in an channel that captures different orientations and spatial frequencies of the image. The channels are then processed (Step 2) by reweighting and normalization, each model has it own strategy. In the final step (Step 3) all outputs are merged to reconstruct the output image.

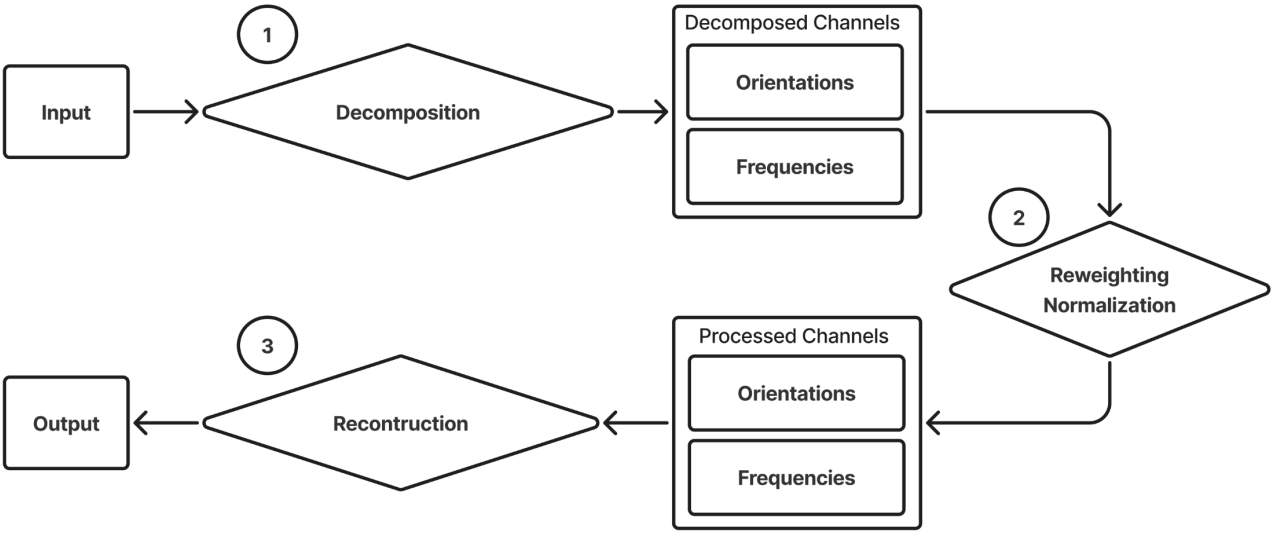


Figure 7: Structural overview of ODOG and BIWaM models, three steps to analyze

The ODOG model uses a filterbank consisting of 42 filters in seven different scales and six different orientations. These filters are applied on the input image by a convolution for every filter, to create the frequency specific and oriented channels. The outputs of the filters within the same orientation are summed, with weights that are determined by the spatial frequency. Lower frequencies receive smaller weights than higher frequencies, similar to the contrast sensitivity of the visual system. These responses are normalized by their root-mean-square energy, which is computed across all pixels and summed to yield the model output. As a consequence of the response normalization, orientations with little energy in the input image will have a proportionally larger influence on the model output (Betz et al., 2015).

For the decomposition in the BIWaM model, a wavelet transformation is used instead of a filterbank. This wavelet transformation also performs convolutions with different filters. Only three orientations are used, but a wider range of scales from 1 cpd (cycles per degree) to the Nyquist frequency. It iterates through the decomposition recursively, downsampling the image at each iteration but using the same filter. Therefore, it generates channels for different filter-to-image scales in each iteration, similar to the ODOG model. After decomposition, all channels are reweighted by a function that is also inspired by the contrast sensitivity function of the visual system. For normalization, they use factors generated for specific areas of the image, resulting in a local normalization. This could be a main difference between the models (Betz et al., 2015). In the final step, the BIWaM model merges the filter outputs to generate the output image.

ODOG and BIWAM may seem different at first glance, because of their distinct processing techniques. But some processes are similar to those in the other model. What exactly is making a difference? Is the decomposition and reconstruction interchangeably in both models, does the processing on the channels make the difference? These questions arise when dealing with both models and are the focus of this thesis. The aim is to explore whether they process identical information as a subset of the other, or if they address distinct concepts.

2 Research

A review of the publications revealed differences between the models, as listed in the table in Figure 8. To understand their impact, the plans in the next subsection are being developed.

2.1 Methods

For each step shown in Figure 7, the focus will be on the structural differences between the models. Adjusting the ODOG model to align it more closely with the BIWaM model, will reveal their importance step by step, shown in the diagram of Figure 8. The plan is to modify the source code for each part listed in the table of Figure 8 and to conclude every change by running the models with the modification on a set of illusions and comparing the outputs quantitatively.

Step (1-3)	ODOG	BIWaM
Decomposition (1)	Filterbank • Filter size changes • 6 orientations, 7 scales • Gaussian filter	Wavelet Transform • Image size changes (Downsampling) • 3 orientations, >7 scales • Gabor filter
Reconstruction (3)	• Summation	• Upsampling • Summation(?)
Processing (2)	• Weighting with $f^{0.1}$ • global Normalization	• Weighting with own CSF • Normalization in wavelet planes (?)

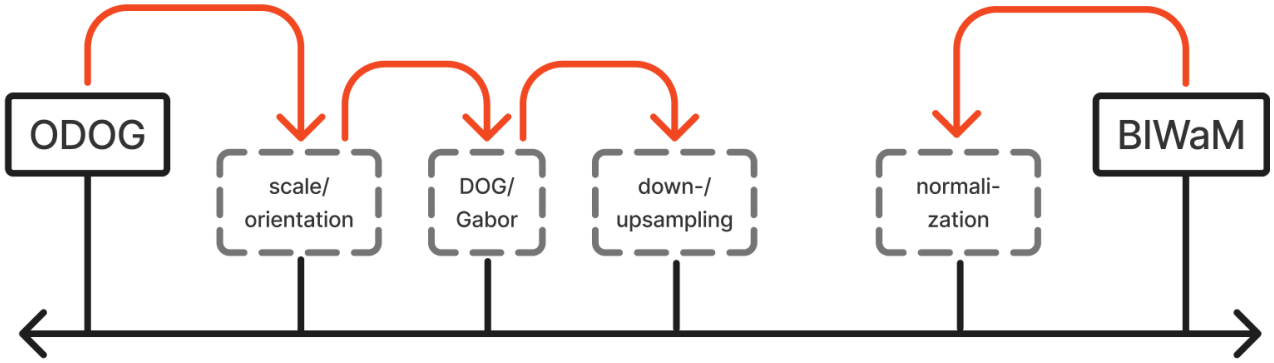


Figure 8: The table shows the already known differences between the models for each of the steps (1-3). The diagram below shows how i plan to narrow down the search for differences. By adjusting the models for each of the steps shown and concluding the impact by comparing the output, I wat to isolate the differences with the most impact.

Decomposition and Reconstruction

1. A wavelet transformation results in a function that is localized in both space and frequency. In the ODOG model the results of the filterbank will hold every spatial data for any frequency, in other words the responses of different frequencies will be a two-dimensional image itself, where the value at each pixel correlates to the presence of this frequency at this location. Can we find any details about wavelet transformation being the superior?
2. Looking at the functions used for convolution (Gabor and Difference of Gaussian) and change them in the source code could be informative.
3. The levels of decomposition in the wavelet transformation can be compared to the filterbank size. Adjusting them will show the influence in decomposition and the difference between the models.
4. The BIWaM uses a reverse wavelet transformation to reconstruct the output image, while the ODOG is summing up the channels it created during decomposition and processing stage. Where is the difference and could changing the source code show the differences to the processes?

Processing

1. To analyze the processing step for both models, it will be necessary to look at processing inside the wavelet planes versus processing in the filterbank output. Separatly to the processing itself, does it make a difference to compute the decomposed image inside a wavelet plane versus inside the filterbank channels?
2. The processing itself is different independent from where it is happening. Does the weighting in BIWaM really make a difference to the one the ODOG is using? To investigate this, a modification of the source code is necessary, e.g. changing the implementation of BIWaM and use a $f^{0.1}$ function to attenuate low frequencies, like in the ODOG model.
3. According to Otazu et al., *"this modified CSF takes into account the (spatial) surround information, so that the value of the contrast sensitivity increases when surround contrast decreases and vice versa."*, (Otazu et al., 2008). But aren't low frequencies filters applying the same logic? Kingdom mentioned: *"In multiscale spatial-filtering models remote context makes its impact via the coarse-scale (low-spatial-frequency) filters"* (Kingdom, 2014)

3 Structure of the thesis

1. Introduction
    a) Light an the Visual System
    b) Low-Level Vision
    c) Modelling Human Vision
    d) ODOG and BIWaM

4 Methods

1. **Recreation of published predictions for BIWaM**
    - Understanding the algorithm and parameter exploration.
    - Python reimplementation, to directly compare with ODOGs python implementation.
    - Recreate input stimuli from the paper using the Stimupy library.
    - Evaluate robustness of the BIWaM model to input variations.
    - Illusions tested: Two versions of SBC, two versions of White's effect, and the Todorovic illusion.
2. **Modification of parameters**
   BIWaM:
    - CSF parameters
    - Decomposition levels, window size, peak s.f.
    - A big window size does effectively end up in global normalization (?)
    - Wavelet filter functions (?)

   ODOG:
    - Number of scales and orientations
    - Filter functions
    - Down- and upsampling (?)
3. **Comparative testing**:
    - Applied both models to recreated stimuli and analyze outputs.
    - Adjusted parameters to align both models for direct comparison.

5 Results

1. **Recreation of published predictions for BIWaM**:
    - Avilable Matlab implementation is another version (CIWaM).
    - Bad reproducibility led to extensive research and parameter exploration.
    - DWT function is highly optimized and undocumented -> took a lot of time to understand.
    - Python reimplementation behaves same as Matlab version (CIWaM).
    - Using CIWaM_per_channel function from CIWaM code as BIWaM representative.
    - **Predictions**
        - Available BIWaM predicts brightness illusions qualitatively, but not quantitatively.
        - Model outputs diverged from published results despite wide parameter adjustments.
        - This led to the question of whether the available model is different, or whether the parameters are different, or whether the re-created stimuli (as input) are different.
        - Tests indicated high robustness of BIWaM to input variations, suggesting that output differences are coming from differences in implementation rather than the re-created stimuli.
2. **Findings on parameter effects**:
    - Adjusting wavelet levels influenced decomposition depth but did not resolve discrepancies.
    - Modifying filters results in ...
    - Modifying window size results in ...
    - Modifying peak s.f. results in ...
3. **Findings on comparative testing**:
    - On the exact same stimuli the original models ....
    - With aligned parameters both models behave ...
4. **Potential differences between models**:
    - Studying the models showed that the following features of the models are causing differences

6 Discussion

1. **Linking differences in structure with results in behavior**
2. **Insights into decomposition**:
    - Information loss through downsampling does not appear to cause output differences.

References

Adelson, E. H., & Pentland, A. P. (1996). The perception of shading and reflectance.

Adelson, E. H. (1995). Checkershadow illusion. https://persci.mit.edu/publications

Adelson, E. H. (2000). Lightness perception and lightness illusions. *The New Cognitive Neurosciences, 2nd ed., M. Gazzaniga, ed. Cambridge, MA: MIT Press,* 339–351.

Arend, L. E. (1993). Lightness, brightness, and brightness contrast.

Betz, T., Shapley, R., Wichmann, F. A., & Maertens, M. (2015). Noise masking of white's illusion exposes the weakness of current spatial filtering models of lightness perception. *Journal of Vision*, *15*. https://doi.org/10.1167/15.14.1

Blakeslee, B., & Mccourt, M. E. (1997). Similar mechanisms underlie simultaneous brightness contrast and grating induction.

Blakeslee, B., & Mccourt, M. E. (1999). A multiscale spatial filtering account of the white effect, simultaneous brightness contrast and grating induction. www.elsevier.com

Brainard & Longere, K.

bibinitperiod. (2003). Colour constancy: Developing empirical tests of computational models. In R. Mausfeld & D. Heyer (Eds.), *Colour perception: Mind and the physical world* (pp. 308–326). Oxford University Press.

Gundersen, G. (2017). From convolution to neural network. https://gregorygundersen.com/blog/2017/02/24/cnns/

Hanson, A. R., & Riseman, E. M. (1977). *Recovering intrinsic scene characteristics from images*. Academic Press.

Kingdom, F. A. (1997). Simultaneous contrast: The legacies of hering and helmholtz [PMID: 9474338]. *Perception*, *26*(6), 673–677. https://doi.org/10.1068/p260673

Kingdom, F. A. (2014). Brightness and lightness. *MIT Press*, 499–509.

Murray, R. F. (2021). Lightness perception in complex scenes. https://doi.org/10.1146/annurev-vision-093019

Otazu, X., Vanrell, M., & Párraga, C. A. (2008). Multiresolution wavelet framework models brightness induction effects. *Vision Research*, *48*, 733–751. https://doi.org/10.1016/j.visres.2007.12.008

Robinson, A. E., Hammon, P. S., & de Sa, V. R. (2007). Explaining brightness illusions using spatial filtering and local response normalization. *Vision Research*, *47*, 1631–1644. https://doi.org/10.1016/j.visres.2007.02.017

Sachs, M. B., Nachmias, J., & Robson, J. G. (1971). Spatial-frequency channels in human vision. *J. Opt. Soc. Am.*, *61*(9), 1176–1186. https://doi.org/10.1364/JOSA.61.001176

White, M. (1979). A new effect of pattern on perceived lightness. *Perception, 8(4)*, 413–416. https://doi.org/10.1068/p080413