Estimating illuminance flow: the case of scale-selection

Bachelor thesis (15 ECTS)

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Abstract

Light has been researched by many fields such as physics, philosophy, psychology, pictorial arts and psychophysics. The latter brought about the concept of the physical light field which can be summarized as a function that measures the distribution of light in a certain space on every possible point (x,y,z,). An aspect of the physical light field is illuminance flow which is a robust indicator of the light field computed through a series of algorithms. On the other hand, research has shown that people also quite clearly observe the visual light field. This concept is different from the physical light field because the visual light field is defined in, for example, the empty space between objects and therefore has no physical existence. With this information, a research was conducted investigating the visual light field within paintings. The perceptual results obtained from that research were used in the present paper as material to be compared with illuminance flow calculations of the same paintings. Previous research suggested that there might be a relation between the scale on which the algorithm calculates the illuminance flow and the perceptual data. This would provide us with a 'perfect scale' on which the algorithm operates. In the present paper, the relation between scale selection and perceptual data was investigated after which the question arose whether there is also a relation between the performance of the participants in the perceptual experiment and the performance of the algorithm. The algorithmic calculations were executed using Mathematica, and the scale of the algorithm was varied over all the calculations. The results of the algorithm were documented in SPSS and correlation analysis was conducted. The results showed no evidence for a perfect scale because there was no relation between the calculated orientation of the algorithm and the average orientation of the perceptual data. There was however a significant relation between the standard deviation of the perceptual data and the confidence of the algorithm which suggests there is a relation in the performance of both. This led to the conclusion that the harder it is for participants to estimate the illuminance flow in a painting, the lower the confidence of the algorithm becomes. Because the first hypothesis was rejected, suggestions for future research have been made mainly regarding the constancy of the stimuli.

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1. Introduction

Pink Floyd's masterpiece, *The Dark side of the Moon*, my favourite album and possibly the best rock album ever made, is partly as successful as it is due to its iconic cover art. If it weren't for Sir Isaac Newton the cover might have looked entirely different if not non-existent. Newton was a scientist who you probably know for his three laws of motion. But besides that, he had a great impact on physical understanding of light. In this thesis, the concept of light will be my main concern, especially perception of light fields. Before threading into detail, I would like to briefly address several historical concepts regarding light.

Newton's views on the physical understanding of light were very different than those of his peers at the time. A fellow scientist and outspoken antagonist of Newton, Robert Hooke, stated that light was made up of waves and by doing so, he sided with his predecessor René Descartes (Hooke, 1672, p. 10). Newton did not accept the wave theory of light but instead spoke of light particles we now call photons. The proponents of the wave theory stated that when light travels through glass it's waves get disrupted resulting in a slightly less pure beam of light at the other side. Hence, the further it travels through glass, the more corrupted it becomes, that's why a prism shows a rainbow. Newton wanted to disprove the theories by both Descartes and Hooke and to do so he refracted a light beam with a prism and then refracted the coloured light beams with another prism in order to show that light is indeed made up of particles that together appear white (Ede & Cormack, 2012, pp. 167-168).

It would take about two hundred years for both the theories of Hooke and of Newton to be proven wrong. This was done by Thomas Young and his double slit experiment, see figure 1. In this experiment a light source was put in front of a screen with two slits. By opening the slits, the light could pass through the screen on another screen behind it. If only one slit is opened a regular stroke of light is observed on the screen. If Newton's particle theory would have been right it wouldn't matter if the second slit would open, the same stoke of light would have been observed. Yet, when the second slit is opened an interference pattern is observed. For now this observation is showing evidence in favour of the wave theory. Later on in scientific history, this experiment will show evidence for an integration of the particle- and wave-theory.

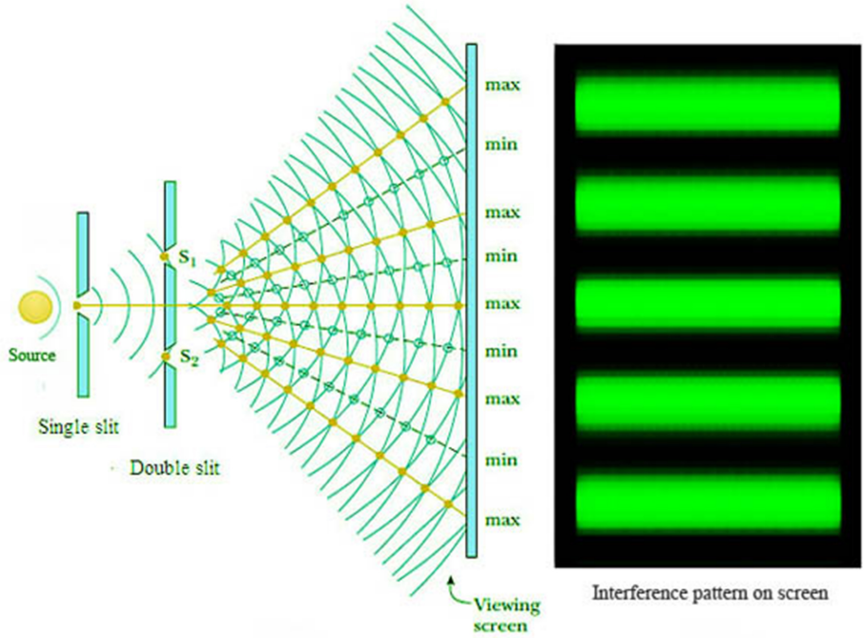


Figure 1. A schematic prepresentation of Young's double slit experiment setup. Adapted from *Liberty.me* by D. Robison, 2015. Retrieved from http://libguides.gw-umc.edu/c.php?g=27779&p=170358. Adapted with permission

Thomas Young also laid the fundamentals of the theory of trichromatic vision by proposing that there are three types of photoreceptors located in the eye of the human. In ensuing Thomas Young, a German scientist named Hermann von Helmholtz, took light from the physical to the psychophysical realm and proposed a theory of colour vision. He might not have been the first but he was, however, one of the most notable: *"the resultant of all various light stimuli so far as sensations are concerned can be completely represented as a function of three variables"* (Helmholtz, 1962, p. 426). This fundamental statement led to further development of the theory of trichromatic vision. Helmholtz developed did this by elaborately describing the anatomy of the eye in the first part of his *'Physiologischen Optik"* (1962). Nowadays we know that there are indeed three types of photoreceptors, called cones, which differ in sensitivity to S-, M- and L-wavelengths due to a difference in photopigments inside the cones (Wolfe, Kluender, Levi, Bartoshuk, Herz, Klatzky, Lederman & Merfeld, 2012, p. 144). These wavelengths respond to respectively blue, green and red light. In the second part of his *Optik*, Helmholtz discusses the concept of *'inferred illumination'* that is important for the cause of this paper. The theory of inferred illumination assumes that one cannot derive wavelength distribution reaching the eye from a surface, because the light that reaches the eye is a product of the illuminant and the reflecting properties of the surface. The only way to correctly resolve the issue at hand is to assume the elements to be illuminated by the same light source, i.e. illuminant. Hence one must *infer* the light unto the surfaces cued

by the level of illuminance and chromaticity of the surrounding surfaces. (Helmholtz, 1962 in Schirillo, 2013, p. 907) More about this concept will be explained in the course of this paper.

Next to Helmholtz I would like to discuss another notable scientist by the name of Marcel Minnaert. Not only because his name rings a bell for almost every student from my University (there's a massive building named after him), but mainly because Minnaert wrote a tripartite theory of *'Natuurkunde van 't vrije veld'*. The first part is called '*Licht en kleur in het landschap'* concerning the psychological aspects of light and colour. The title says *'in het landschap'* because Minnaert was not concerned with means to measure, extract from statistics or theorize about light. He took light out of the area of physics and into human experience as he was interested in everything about light that we could see using our own eyes (Minnaert, 1974, p.8). He makes a remark saying that you would be amazed about the abundance of observations that remain. Almost everything that can be observed in the Dutch outdoors is described and explained in this volume, from observations about the colour of the beach to the coming of frost at the beginning of winter. About the latter he says he is intrigued about how frost can transform walls and trees into a surface that scatters the light into a thousand directions. And that the smaller the angle is we look at it, the shinier it becomes (1974, pp. 373-374). It is this wonderment that, in combination with the vast knowledge about the subject, that made this book into a practical guide to light (in the outdoors). He finds himself to describe roughly every aspect of light where at one point he discusses Boys and the intriguing soap bubble. He recommends everyone to go out and a blow a soap bubble:

> "*Let vooral op de dubbele weerspiegeling van de heldere hemel; op het silhouette van uw eigen hoofd dat zich donker tegen die lichte achtergrond aftekent, en op de merkwaardig vervormde dakenlijnen der huizen; op het zeer vergrote beeld van uw hand, die het buisje vasthoudt waaraan de bel hangt; op de weerspiegeling van het punt waar de bel aan het buisje vastzit; op de bijzondere duidelijkheid der aan de hemel zo wazige onbepaalde wolkenmassa's. Maar geniet vooral ook van de prachtige kleurspelingen waarin alle lichte partijen iriseren, in wisselde tinten der rijker en rijker worden…. tot de bel barst.*" (1974, pp. 32-33)

Minnaert here gives an insight into the discussion of interference and 'Newton's Light'. The way Minnaert describes the problem of interference is rather remarkable to me. We have seen two ways, a physical and a psychophysical one, in describing the different colours, how they

exist and how they are to be perceived, but in theory. Minnaert, on the other hand, describes this by interference in an oil spill. He explains how people can experiment on this by themselves. The way to do this is to measure an oil drop on the asphalt and as it lies there is stretches out and becomes thinner. The colours you see will change over time as the oil drop thins (1974, pp. 241-244). As you measure time and write down what colours you see in a table you will have a different, yet valid spectrum of light as a function of time. We have now had a small introduction into some scientific views on light. I would like to add a third category which is rather non-scientific, the philo-artisic views on light.

Artists, specifically painters, seemed to have a hand at the essence of light perception before scientists did. Take for example Caravaggio or Rembrandt who used light in their paintings to shape three-dimensional objects and highlight elements or to create drama (Collins, 2008). Given this fact, the question remains how they did their job in translating physical light to a painting. A lot of thought about light produced by philosophers was done through reflection on paintings like those by Caravaggio or Rembrandt. Although the various philosophical views on light differ a lot from each other I would like to highlight one view in particular. This concerns the view of Maurice Merleau-Ponty, a renowned phenomenologist.

Merleau-Ponty was sharply against the scientific method, which is rather typical to being a phenomenologist. The reason for this is that phenomenologists think that by questioning an object the way scientists do, it loses all its *meaning* to us. I'll elaborate: scientists examine a phenomenon in a way that first of all they assume it exists (something that is not so evident in philosophy) and secondly, that it has some universality in it. This is what philosophers call the naturalistic attitude, or naturalism (Husserl, 2008). So, what scientists try to do is examine a phenomenon as if it were a universal thing on which they can base a theory that categorises all the phenomena of the same sort. For example theories about colour perception: we observed cones in a human retina, so therefore all human beings perceive colour in this way. As I've said, phenomenologists criticize this by saying that it loses all it's meaning. What they mean by this is that it loses all the value of what it is to experience the phenomenon at hand. It will be shown in this research that even though the artists knew how to recreate light with oil on canvas, they did not always do this is in a way that was identical to the physical truth. A phenomenologist wouldn't agree with this statement like this because there might be a *meaningful* reason the light is painted is this way.

In this research, I would like investigate whether there is a relation between the physically true light and the inconsistent light in paintings, and whether it has an effect on light perception within paintings by human observers. This will be done by comparing the illuminance flow of a painting with observers' inferences of the visual light field within that

painting. How the illuminance flow of a painting is to be calculated will be explained in this paper after which it will be compared with perceptual data taken from a research conducted by Kartashova, de Ridder, te Pas, Schoemaker & Pont (2015). The concepts I have mentioned briefly will be further explained in the course of the paper, before providing a theoretical background on the subject.

1.1 Scientific Relevance

This research might have implications for several scientific fields. First of all, of course, cognitive psychology. Significant findings in a possible relation between physical data and human observations will give yet another insight in how our perceptive system works. For example, if a relation between observers' inferences of visual light fields and the calculation of illuminance flow is detected, one might conclude that the two operate on the basis of the same mechanism. This will be of importance for future research in, for example, selecting relevant stimuli. Secondly, findings in this paper will be relevant for the field of artificial Intelligence. Consider computer vision but also our ever-going quest for autonomous robots. The fact that human artists depicted real scenes on canvas in some form of what appears to be innate knowledge we humans possess, but had yet to be described by scientists, shows us that there is a layer to human perception that is hard to understand by science. Making robots appear human does not lie merely in passing a Turing test, it also lies in things like these, complex human perception for example. Aside from that, means for calculating and reproducing light have been a subject of investigation in the field of computer vision. The plenoptic function of the light field is now used to create physically true light fields on computer screens (more about the plenoptic function will be discussed in the section 'Physical Light Field'). That is why further research into light fields is important because findings that further support the possibility to recreate light on computer screens is evidently relevant for field of computer vision.

2. Theory

2.1 Lightness, brightness and colour constancy

To provide a theoretical background for this paper I would first like to discuss three basic aspects of light: lightness brightness and colour constancy. These aspects are relevant for further research discussed in this paper, and are also relevant for conveying a natural scene in a painting. To start off with an example, start by imaging an empty white room with a lamp hanging from the ceiling in the centre. One will see the light radiating from the lamp

itself and reflecting upon the walls of the room. But to see the light *in* the room one has to hold up some kind probe, as in an object, on which the light will fall and become visible. The empty space surrounding the object however, does not appear to be coloured nor to be black or void, nor does the space in the room where there's no probe. In his highly interesting paper '*We Infer Light in Space'* James Schirillio detects the issue that the literature does not take into account the empty space surrounding surfaces and objects, as mentioned earlier. Schirillo borrows the term 'infer' from Helmholtz (1866/1962) meaning that human observers are aware of the light that is reflected by the surface and are thus perceiving a certain chromaticity.

Among others Schirillo discusses Alan Gilchrist who in 1977 wrote his paper '*Perceived Lightness Depends on Perceived Spatial Arrangement'*. In this paper, he argues against the popular view that depth perception does not have any role in the perception of surface lightness. Gilchrist wants to prove his 'coplanar ratio hypothesis' which assumes that perceived lightness is primarily determined by the ratios within perceived planes (Gilchrist, 1977). In other words, the illumination falling on multiple surfaces in the same depth plane are of the same level, they're constant. Therefore, depth perception must occur before lightness perception. Gilchrist proved his hypothesis by conducting two experiments. In the first experiment the observer would look through a pinhole and see a near wall which was dimly illuminated and a far wall that was brightly illuminated. The experimental setup could be manipulated so that the test surface could appear to be lying in either the plane of the near or the far wall. Observers had to rate the apparent lightness of the test surface on a 16-step Munsell scale on which black was 2 and white was 9.5. This resulted in the test surface appearing white (9.0) in the case of the near wall and almost black (3.5) in the case of the far wall. That means observers assume that a surface must be equally illuminated as the other surface lying in that plane, hence the term coplanar. The relevance of this research will become clear in the next two paragraphs.

To further investigate the subject, lightness has been proven to be an important cue for estimating the spatial distribution of light (Boyaci, Maloney & Hersh, 2003, 2004; Ripamonti, Bloj, Hauck, Kiran, Greenwald & Maloney, 2004; Snyder, Doerschner & Maloney, 2005). Back in 2006 Boyaci, Doerschner & Maloney developed what they called the Equivalent Lighting Model. This model describes that the human visual system adequately estimates spatial and spectral distribution of certain components of lighting. In their aforementioned paper, they address the question *"what sources of information in the scene does the visual system use to develop an estimate of [Equivalent Lighting Model]?"* These cues were identified in threefold, namely: "*cast shadows, surface shading (attached*

shadows) and the virtual image formed in the surface of a specular object." (Boyaci, et al., 2006, p. 107) In their experiment, an observer had to set the lightness on a test patch (an achromatic, Lambertian surface) so that it would match the scene. This task was repeated three times for which the conditions were based on the three hypothetical cues I have just mentioned. In other words, they have to set the lightness cued by, for example, a cast shadow. The authors concluded that the visual system does indeed use cues to estimate the lighting of a scene. Which cues a certain observer uses seems to be depended on whether they have learned to use this cue at all. This is a rather important observation because it gives insight into what cues observers might using while examining light in a painting.

Important to take into consideration is that there is a difference between *brightness* and *lightness*. Schirillo describes this best: "*Lightness refers to the perceived reflectance of a surface.* (…) *Brightness, on the other hand, refers to the perceived luminance of a surface region.*" (Schirillo, 2013, p. 906). In the paper Schirillo refers to Arend and Goldstein who categorise the distinction as lightness being a judgement of the surface and brightness being a sensory judgment (1987, p. 2281). This means that the difference exists in the perceived intensity of the reflectance bouncing of a surface versus the perceived light intensity of that surface (region) itself.

To further elaborate on the subject of lightness and brightness I will now discuss two researches that have used Mondrian stimuli. A Mondrian stimulus is an image that consists of several squares with different chromaticities, just like a painting by the Dutch artist Piet Mondriaan might look. In 1993 Schirillo & Shevell did a research in which the squares of the Mondrians varied in greyness from white to black. The observer would view two Mondrians through a haploscope. On half of the trails the disparity of the test patch shifted causing the test patch to appear either in the 'near', highly illuminated, or 'far', dimly illuminated, depth plane. Results showed that observers set the illuminance of the test patch that appeared in the 'near' depth plane to be 16% higher than in the 'far' depth plane. In this experiment the effect that is observed was due to the inference of light by the observers that is dictated by a square in the same plane. Given that the observers set the test patch to match its coplanar illuminance, and thus setting it bright in a near plane suggests that they have a representation of distribution of light intensities throughout three-dimensional space (Schirillo, 2013).

Schirillo & Shevell briefly discuss Gilchrist theory I've mentioned earlier. They agree with the fact that local contrast isn't enough for determining lightness. But they also propose that the lightness judgments done on the basis of the stimuli that Gilchrist used might cause the observers to infer the illumination on the test from a retinally adjacent coplanar grey scale (Schirillo & Shevell, 1993). The method used in their research, however, was different

because it had no retinally adjacent coplanar surround which means there is a possibility that coplanarity solely provides information about illuminance. This provides proof for a contrary hypothesis to Gilchrist namely that lightness is determined by coplanar luminance ratios. In other words, illuminance is determined by brightness, not lightness when a test does not share coplanar retinally adjacent edges. Schirillo (2013) concludes that this effect is established because we infer the level of illumination from the spatial average of surface brightness: "*observers infer differences in the levels and chromaticities of the illuminant(s) within a volume of space.*" (Schirillo, 2013). This provides us with yet another clue about how light perception in paintings might work.

In research in brightness, another concept that has been developed using Mondrian stimuli has been called *recognized visual space illumination,* or RVSI. The important property of the RVSI is its size. The size of the RVSI is a concept that is expressing the perception of brightness (Mizokami, Ikeda & Shinoda, 1998). When the RVSI expressed to be high, it means that the space is to be perceived as very bright. Also, the RVSI is constructed from the *initial visual information* which includes the appearance objects in the space, the luminaires illuminating the space and the windows through which the daylight enters (Ikeda, 1998). This is a very relevant finding regarding the fact that this is indeed what happens in photorealistic paintings, not in abstract ones but maybe does happen in paintings that are somewhere in between. Think about it, when observing a landscape by Cézanne the first thing you do is try and recognize what objects are depicted before inferring space. So, the way the RVSI is constructed can be seen in figure 2. In their research, Mizokami et al. (1998) tested the RVSI hypothesis. In order to prove the theory, they set up an experiment consisting of two rooms in which two grey test patches appeared at various locations in the room. The front room had walls, floors and furniture that had lower apparent lightness than the back room resulting in a smaller RVSI. The results showed that when the patches were moved from the back room toward the front room, the apparent lightness increased, which proved their theory. Mizokami et al. emphasize the point that that since the research has shown that there is clearly a relation to RVSI and apparent lightness of the test patch, lightness research should be done in a three-dimensional fashion rather than two-dimensional, opposing Gilchrist. Schirillo (2013) adds that the conclusion of Mizokami et al. means that our representation of the illumination distribution in space is organised in a gradient-like manner.

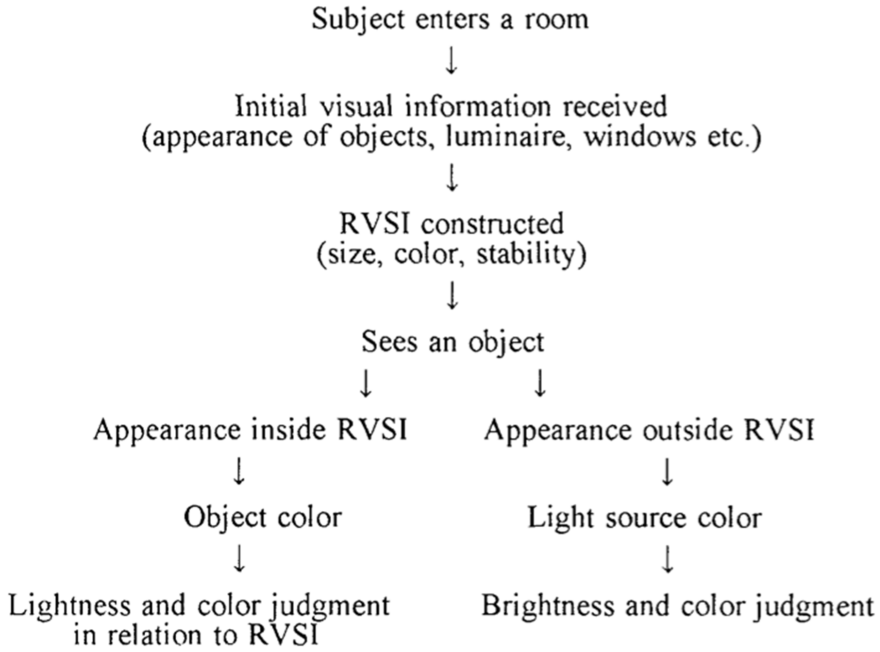


Figure 2. Flow chart to show the construction of RVSI and color perception. Adapted from "*Phenomena of Apparent Lightness Interpreted by the Recognized Visual Space of Illumination",* by M. Ikeda et al., 1998, *Optical Review,* Volume 5, p. 381. Department of Photonics, Faculty of Science and Engineering, Ritsumeikan University, 1-1-1, Nojihigashi, Kusatsu, Shiga, 525-8577 Japan.

We have now discussed two aspects of psychological light theory that might be of importance for the cause of this paper, namely lightness and brightness and their role in perception of three-dimensional space. Colour constancy would be the third important aspect of light that I would like to discuss. The theory of colour constancy is used to describe our subjective experience of colours the real world. Take for example a Granny Smith apple. It appears green to us in the morning, in the afternoon or at sunset. Nevertheless, the colours of the light that radiate onto this apple vary during each part of the day. The fact that the apple keeps appearing to us as a green object (if you are not colour-blind of course), is due to colour constancy. This process is very relevant, not only because it taught us a lot about how the human visual system works, but also because the artists I mentioned earlier knew how to master this in order to conceive a 'real' scene in their painting.

In order to determine whether there's a relation between human observation of light in paintings and their physical truth, there are other aspects of light we need to discuss. Apparently, artists had mastery over the abovementioned aspects of light before scientists put pen to paper but there's more to light than lightness, brightness and colour constancy. In the following chapter I will first discuss the aspects of physical light that are important to us (the light field, illuminance orientation and illuminance flow) followed by their visual counterparts and finally describing what the possible relation between the visual and the physical light field might be.

2.2 Light fields

2.2.1 The Physical Light Field

Long before Schirillo wrote his paper '*We infer light in space'* (2013), Andrey Gershun described what he called *light fields*. He saw that within the theoretical field of *photometry*, to measure light, theories and problems are treated in a mathematical way. Gershun's theory of the light field can be summarized as a function that measures the distribution of light in a certain space on every possible point (x,y,z,). He explains that *"We may define a physical field as a part of space, studied from the standpoint of a definite physical process happening within that space*" (Gershun, 1936, p. 56) follow by an introduction of the light field "*which is studied from the standpoint of transmission of radiant energy within that space*." This means that photometry should not only limited their research to theories concerning concepts of emission of and absorption of light. But that the body that transmits the light is just as important. Light fields also differ from electromagnetic fields. The study of the light field focuses on bodies of finite size consisting within *elementary emitters* rather than forces caused by them which is the case with electromagnetic fields. An example of an elementary emitter is an atom-photon cluster (Basharov, 2009).

Edward Adelson and James Bergen (1991) were curious about this understanding of light and extended Gershun's theory into a *plenoptic function*. It has been called this way because it describes everything (*plenus*) that can be seen (*optic*). The function is equivalent to a holographic movie. A holographic movie is an accumulation of every way in which a certain object can be represented in a visual reproduction. Take for example a bottle sitting on a table. One could take a black and white picture of it through a pinhole camera. The light reflecting off the surface of the bottle (and the table) radiates through space, from which a certain amount of that radiation enters through the aperture onto the photosensitive residue at the other side of the camera. The inverted image then seen is the light averaged over the overall light in the room in two directions (*x* and *y*), hence the image gives information about the light in two dimensions. A third dimension would be the addition of colour to the image which gives information about the intensity of each wavelength present. Creating a movie of multiple coloured pictures would add another dimension to the information received about the light, namely time. Lastly a fifth element is added, depth, turning the movie into a holographic film which gives us, in terms of Adelson, all the possible information there is about light (Adelson, 1991). The construction of these five dimensions into the plenoptic function deems it possible to measure the exact *physical* light field.

Other relevant research concerning the physical light field was done by Mury, Pont and Koenderink (2007) who confirmed their hypothesis that low-order spatial components of the light field are more constant within a scene than is the case with high-order components. Low-order spatial components are for example the structure of the grass in a field or the texture of a stone brick wall. High-order components on the other hand are more global components over the image. This means that the physical light field might stay constant within a field of grass but can differ from the light field on the wall next to it. The geometry of the scene has a great effect on this. When the geometry of a light scene is relatively constant, the lower-order components of the light field within the scene will be too (Mury et al. 2007). Mury et al. measured this in an experiment where panoramic pictures of three types of scenes were analysed. For each scene pictures were taken under clear sky and overcast sky. This resulted in two different types of illumination, namely collimated and diffuse. A collimated light beam is a beam of which each ray is parallel to the other. With a clear sky the light source, the sun, is undisrupted resulting in a primarily collimated beam. When the sky is overcast, the primary light source is greatly occluded and the sun's beam is being refracted into what is called diffuse lighting, it is scattered in all the directions. Mury et al. (2007) concluded that light fields vary less under an overcast sky than in the case of clear sky. The reason for this difference in perceptual variation is that light field variation is mainly caused by a secondary light source. The effect of a secondary light source on a scene is larger when the primary light source is a collimated beam. This is because in the case of diffuse lighting, the light is already scattered and directed almost everywhere. A second light source would have a lesser effect on the lighting in the scene than in the case where the primary light source is a collimated beam in generally one direction.

Koenderink, van Doorn, Kappers, te Pas & Pont (2003) have found that observers are quite good at judging the direct of illumination for obliquely illuminated natural surfaces. This is relevant because this is often the case in a painting or picture of a 'natural' scene which is the subject of this study. In this research observers were asked to identify the direction of the illumination within a certain picture by adjusting the shading on a probe which was presented next to the picture. The results showed that observers are good at judging the direction of the illumination. Although Koenderink et al. (2003) must add that observers made a lot of 180° mistakes which results in the conclusion that observers can't really judge *direction* but rather *orientation* (2003, p. 993) (more about this is section 2.2.2 of this paper). This is however, never the case in a real scene because an isolated object is often a detail which is situated with in a scene that functions as the relevant context for judging the shading on the detail. The authors then conclude that this information serves as proof that

observers took the pictures to be texture rather than a part of a scene. The importance of these observations will later be clarified in section about the visual light field.

2.2.2 Illuminance flow

We have now seen an introduction in a way of describing the physical light field, its different components and how one can measure light field and its orientation. Further study in the direction of illumination brought Sylvia C. Pont and Jan J. Koenderink (2003) to research on a topic called illuminance flow. This concept translates as a 'robust indicator of the light field' computed through a series of algorithms. The authors describe that the light field can be of various nature, meaning that the source can be diffuse, collimated or a mixture of both. The latter is the case in the real world, where the sun functions as a collimated beam. As has been shown, shading is a rather import cue for estimating the direction of illuminance. About the cause of shading in the real world, the authors write the following: *"In a collimated beam the shading is due to shadow (occlusion of the source) and the attitude effect due to Lambert's cosine law."* (Pont, 2003, p. 90). When the light source is rather diffuse, the shading is due to a phenomenon called vignetting. This means that the object occludes the light source partially creating shade surrounding the object rather than a drop shadow in the case of a collimated beam. Either way it texturizes an image due to the shading caused by for example a rough surface.

A rough surface can be called Lambertian, which means that it adheres to Lambert's cosine law and reflects a ray of light diffusely. The direction of the light on a Lambertian surface causes a dipole-like structure. An example of this is a *hill* that is illuminated from one side and when observed from the front, one will see a 'dipole'. This means that one side is illuminated and the contrary side is darkened. The order in which this is observed is due to the illumination direction. This also goes for a *depression,* which is the opposite of a hill. This leaves us only one difference between the two, which exists in the polarity direction of the dipole. If the direction of the light comes from the left a hill will be light on the left, dark on the right (frontally observed) and a depression will be observed as dark on the left, light on the right. A random Gaussian surface, which is a surface that has been used to illustrate illuminance flow estimation, can be seen as a collection of random hills and depressions. Thus, a random Gaussian surface is a collection of dipoles with a random polarity but of the same orientation.

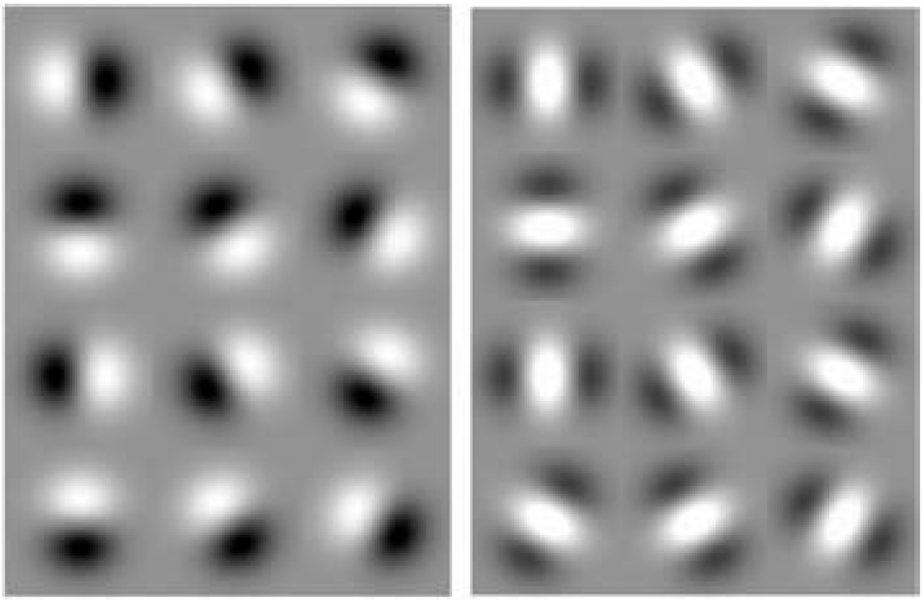


Figure 3. At the left a set of "edge detectors", at the right a set of "line detectors". These operators suffice to compute the illuminance flow via the squared gradient or Hessian. Adapted from *"Illuminance Flow".* by S. C. Pont & J.J. Koenderink, 2003, *CAIP 2003, LNCS 2756*, pp.90-97.

Measuring and comparing all these dipoles results in a certain dipole illumination pattern, the left image of figure 3. This pattern gives rise to the first order of information or the first-order statistics, namely the illumination direction. From here we cannot yet compute the illuminance flow of an image, we need second-order statistics. This information is computed by autocorrelation of the dipoles. Autocorrelation is a mathematic tool for detecting correlation patterns within a given region. These patterns combined give a field of orientations which Pont et al. call the "illuminance flow" (2003). These second order statistics are calculated with either one of two algorithms, so called gradient based or Hessian based. In do not want to thread further into the mathematical detail on these algorithms, but the details can be found in the appendix. What is of importance is that the gradient based algorithm functions as an edge detector, whereas the Hessian serves as a line detector. In their 2007 paper, Koenderink, van Doorn and Pont concluded that it is the edge detector, not the line detector, us humans use in our primary visual cortex to detect illuminance flow. For this reason, only the calculations from the gradient based algorithm will be used in this research.

Lastly there is yet another research on illumination direction that interests us which has shown that we are indeed quite good at estimating illumination orientation but not where there is deformation of the pattern. This causes us to be inconsequent (Van Doorn, Koenderink, Todd & Wagemans, 2012). In this research the inconsistency was tested in an experiment using grouped textons (see figure 4.) As I have mentioned earlier, textons can cause observers to make 180° mistakes (Koenderink et al. 2003). In this case that means that observers can either describe a texton as concave or convex. Notable is that when these textons are grouped together in a similar fashion (in the same direction), the textons seem to

synchronise which means that the entire group is observed in the same way, so completely concave or completely convex. On the other hand, when the pattern in which the textons were organised was rotated or deformed, the effect disappeared (see figure 4). This led to the conclusion that observers use illuminance flow patterns to tell the orientation of the illuminance. But that the human visual system only groups unidirectional, convergent and divergent illuminance flow patterns and not deformed or rotational flow patterns. These findings have interesting implications for the cause of this paper because it suggests that people make local estimates as well as group those local estimates. For example, look at the second picture (in figure 4) on the left where one texton has a different direction compared to the other textons. You can see that the middle texton is concave compared to the rest, which shows the previously mentioned implication that people in fact make local estimates as well as group those estimates. Whether local estimation will be the case within paintings is debatable because the stimuli used in the abovementioned research are very simple in comparison with a painting. Subjective judgment of whether a picture is a scene or a texture might have an effect on this.

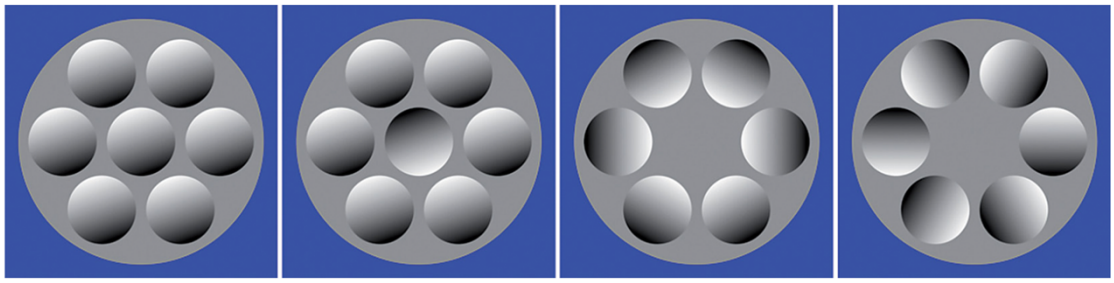


Figure 4. Four groups of 'textons'. From left to right: same gradient direction, or uniform illuminance flow; an outlier in the center; concurrent gradient directions or divergent illuminance flow; rotational illuminance flow. Adapted from "*The Visual Light Field"* by J. van Doorn et al. 2012, *i-Perception*, volume 3, p.486.

Important to take note of is that illuminance flow and illuminance direction research has been done on reproductions of a 3D scene or object on a 2D surface, a computer screen. Therefore, Xia, Pont & Heyndrickx researched illuminance flow in 'real scenes' (2014, 2016). They have set up several experiments using a box with three chambers, see figure 5. Because of this setup they could make a probe in room C 'appear' to be in room B. Contrary to previous research, instead of manipulating the light on the probe on a computer screen, they have managed to manipulate the light field in a real scene. Because they have proved their experimental setup to be valid and because their results were congruent with previous research, it is safe to conclude that observers are also sensitive to light intensity, direction and diffuseness in real scene (2014).

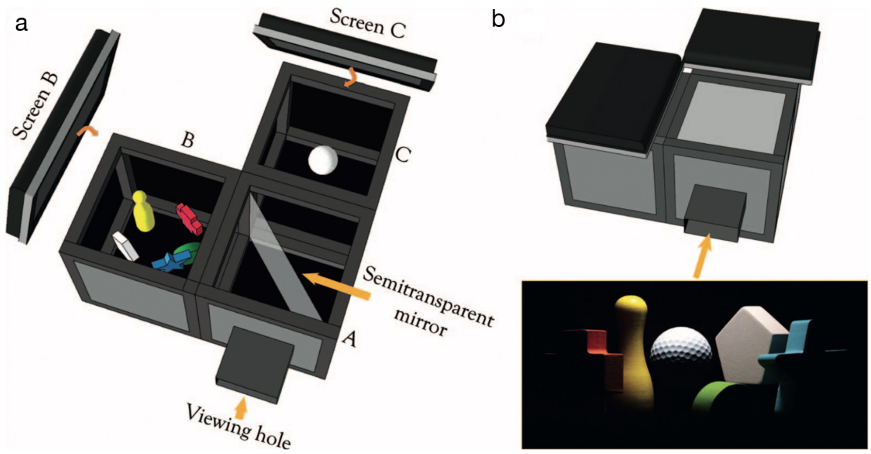


Figure 5. Illustration of the setup used in the research by Xia et al. Details about the dimensions of the objects can be found in their paper. Adapted from "*Effects of scene content and layout on the perceived light direction in 3D spaces.*" by Xia, L., Pont, S. C., & Heynderickx, I. (2016). *Journal of Vision*, 16(10):14, 1–13, doi:10.1167/16.10.14.

In a follow-up paper Xia et al. aimed to investigate the potential effect of scene content and layout on the perceived light direction in a similar experimental design. The difference with this design was that the pentagon like shape in the back of the scene varied in complexity, see figure 6. Due to this variation, the number of (visible) faces on varied from shape to shape. The fact that more faces were visible created more steps in the creation of the shading pattern which caused more veridical estimation of the light direction. For us this is relevant because cues to the light direction of the shading are provided by illuminance flow. This give rise to one of the reasons why scale-selection might be relevant in illuminance flow estimation. If scale-selection is in fact important, analysis of scale selection will also reveal at what scale human observers estimate illuminance flow. Because the selection of the scale might cause the calculation by the algorithm to focus on each surface individually instead of globally.

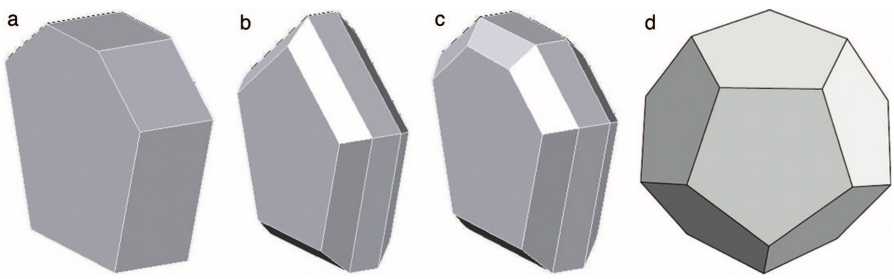


Figure 6. The four shapes used in Experiment 2. Shape I, II, and III were developed starting from the pentagon body by (a) cutting its top, (b) cutting its edges, (c) first cutting its top and then its edges, (d) Shape IV, a pentagonal dodecahedron with a globally spherical shape. Adapted from *"Effects of scene content and layout on the perceived light direction in 3D spaces"* by L. Xia, S, Pont & I. Heynderickx, 2016, *Journal of Vision*, 16(10):14, 1–13, doi:10.1167/16.10.14

2.2.3 The Visual Light Field

I have now provided a background on the physical light field. The *visual* light field on the other hand, is not a part of the physical world but nevertheless is quite clearly observed. A way to measure and describe the visual light field will be discussed in this paragraph. In 2007 a paper was published by Koenderink, Pont, van Doorn, Kappers and Todd that considered the visual light field instead of the physical light field. The authors explain that we observe the visual light field because of what they call *chiaroscuro*, borrowing the term from the world of pictorial art. Chiaroscuro is, for example, seen in paintings by masters as Rembrandt, Rubens and Caravaggio and refers to a technique that uses high contrast between light and dark in paintings. By using this term, the researchers do not refer to the painting technique but refer to a definition of the visual light by Schöne. It means that certain objects that are visible to the observers are to be perceived as illuminated by the visual field (Schöne, 1979 in Koenderink et al., 2007).

In order to measure the visual light field an experiment was conducted where the researchers set up six penguins in a blacked-out room. From this set-up three different scenes were created in which the physical light field was measured in six different locations. Observers then had to set a probe that was presented in a picture of a scene to fit the scene according to the visual light field (see figure 7). The results showed that "*observers have a notion of the structure of the light field, even at locations in empty space, quite remote from any visual object.*" (Koenderink et al., 2007, p.7).

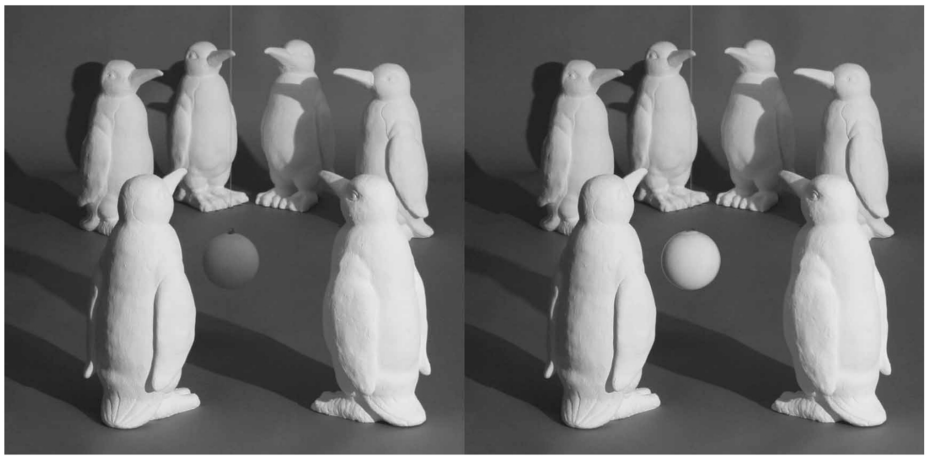


Figure 7. The left image shows a scene where the probe fits the scene and is 'physically correct. The right image shows a probe where this is not the case and is therefore physically wrong. Adapted from "*The Visual Light Field"* by J.J. Koenderink et al., 2006, *Perception advance onlien publication,* p.8, Helmholtz Institute

By means of this research method, Kartashova et al. (2015) studied the inferences of light by a human observer in the empty space of a painting. In other words, they studied the visual light field in paintings. The researchers conducted an experiment in which they tested the perception of light qualities for two conditions: a) for a position in empty space in a painting and b) on the convex cutout of the painting that was replaced by the probe in the first condition. This was a difference between a full image condition and a cutout condition. The difference in conditions results in a difference in cues to be used to determine the light field on the test probe. In the case of a cutout condition, the observer solely depends on the light field that is depicted on this particular detail of the image, see figure 8. On the other hand in case of the full image condition, the overall light field within the image can be used. Hence the importance of texture/scene dichotomy. The results of this experiment was a set of illumination settings by 16 different observers. These settings were used in the present research to be compared with the calculated illuminance flow of the picture.

Figure 8. Example of the different experimental settings. Left is the full image condition and right is the cutout condition. The probe in the cutout condition obvisouly doesn't match the scene. Adapted from *"The Visual light field in paintings of Museum Prinsenhof: comparing settings in empty space and on objects"*, by T. Kartashova et al., 2015, *Human Vision and Electronic Imaging XX, edited by Bernice E. Rogowitz, Thrasyvoulos N. Pappas, Huib de Ridder, Proc. of SPIE-IS&T Electronic Imaging, SPIE Vol. 9394, 93941M,* p. 4.

2.3 A Relation Between Illuminance Flow and Subjective Light Inferences

In order to explain the possibly existing relation between illuminance flow and human observations I would first like to discuss the research that gave great indication for the existence of the relation. After that I will address the questions that arise from the information obtained in the present paper up until this point.

Comparing the calculated illuminance flow with subjective settings is a comparison of the physical and the visual light field. In 2016 Kartashova et al, conducted an experiment to investigate whether they could reconstruct the visual light field using the inference of local light by observers. Observers set the light on several probes in a picture of a scene. These settings gave the researchers the possibility of reconstructing the visual light field and therefore revealing which inferences of the structure of the physical light field observers

make. They concluded that it is in fact possible to make such a reconstruction, because after comparing the psychological data with physical measurements the authors found that human observers have a robust but simplified impression of the physical light field. This would in turn mean that comparison of physical calculations of the paintings and the settings of the observers could have a likewise similarity, and a similar method can be used to investigate whether this is the case.

This leads us to our primary objective of this paper, which is to determine whether there is a relation between on which illuminance flow is calculated and the settings of the observers in Kartashova's research (2015). It is almost inevitable that there is such a relation, but there is however the problem of pattern deformation in the case of the paintings. The reason for this is because of the number various objects depicted in the paintings that are used. And the fact that if you take a close look at the paintings, one will see that in none of them the light in the painting can ever exist in the physical world. There can be a problem because this will determine whether observers make local or global estimates.

Hence the rise of our second question, namely the importance of scale selection. If there is an existence of a relation, then there is a possibility that the analysis of the comparison between the settings and the calculation will unveil at what scale observers infer light. This might be relevant for future research because it will narrow down the experimental scope can help in further developing the algorithm.

The third and last question is whether confidence of the calculations by the algorithm are in anyway related to the performance of the observers. If there is a significant relation between performance of the observers and the confidence of the algorithm it will serve as evidence that the mechanism behind the algorithm is in fact relatable to the mechanism that our visual system uses to estimate illuminance flow.

On the basis of the background provided I expect there will be a correlation between the illuminance flow parameters and the observers' results. I expect the correlation to be strongest in the cutout conditions (from Kartashova's research) because there is little to no contextual distraction as compared to the without-cutout condition where the estimation of the illuminance will operate on the basis of different cues and may be disrupted by deformation patterns of the light field in the painting as a whole. If this will be true, a 'perfect scale' might be detected which means that that scale is the scale on which observers probably estimate illuminance flow in these paintings.

3 Methods

3.1 Material

The illuminance flow analyses that have been conducted in this research are done on the basis of the paintings used in a paper research by Kartashova et al. (2015). The original stimuli were obtained from photographs of five paintings of the museum Prinsenhof Delft from the "masters of Innovation" exhibition:

- The Quarrel between Ajax and Odysseus, *De twist tussen Ajax en Odysseus* (Leonaert Bramer, 1629 - 1631), further "Ajax";
- Fruits on a marble table with a blue cloth, *Vruchten op een marmeren tafel met een blauw kleed* (Willem van Aelst, 1649), further "Fruits";
- The Art of Painting, *De Schilderkunst* (Mary Waters, copy of a fragment of "The Art of Painting" by Johannes Vermeer, 1996), further "Girl";
- Woman with cat in interior, *Vrouw met kat in interieur* (Cornelis de Man, 1666), further "Cat";
- Woman with child at a window, *Vrouw met kind bij een raam* (Hendrick van der Burgh, circa 1650), further "Window".

The nicknames that were attributed in their research have been used in similar manner in this research. In figure 10 you can see all five pictures plus a mirrored version of "Ajax". The mirrored version was used to test for a possible bias in light direction perception. This picture will not be used in the present research.

In figure 10 you can see red circles in each picture. In the research by Kartashova (2015) these were the locations and sizes of the probes used. These same circles were in turn used in this research to draw up images of a mask in Photoshop CC 2017, see figure 9 for an example. These masks were used in calculating the illuminance flow of the images, more about this in the 'procedure' section. The Mathematica code required a square picture; therefore, all images were cropped using the 'square' function in Photoshop CC 2017.

The perceptual results of the research by Kartashova (2015) have, as I have mentioned, served as material in this paper. In their research the visual light field was expressed in tilt and angle. The results consisted of a large dataset, with multiple variables of which I have used the projected angle for each participant for each condition. In other words, I have used the illuminance orientation. This angle was expressed in 180° azimuth which means they varied anywhere from 0° to 180° and 0° to -180°. In order to calculate the average illuminance orientation for each condition I had to add 360° to all the negative numbers. For two conditions this would create a problem because their corrected angle was around 0°/360°.

This means that in computing the average of this condition would result in extremely large, incorrect standard deviations and a wrong mean angle, namely around 180˚. Therefore, for these two conditions only the average was computed using the original number and then increased by 360.

In order to calculate the illuminance flow, I adapted the algorithms constructed in the paper by Pont et al. (2003) that were translated into code by the authors using the programme Mathematica. This results in a workable method to calculate and visualize the illuminance flow of a picture on top of the picture itself. The entire code used to compute the illuminance flow can be found in the appendix.

Figure 9. An example of how a mask picture determines the coordinates used of the area in which the illuminance flow has to be calculated. The algorithm codes reads the black area as an area that it should not perform calculations on. If one would only read the numerical values that come out of the calculations, it will show up that in the black area there are no numbers for the pixels in this area.

Figure 10. The images of the pictures that were used in Kartashova et al. (2015). The red cricles indicate the size and location of the spherical probe used in their research and the size and location of the mask image used in this research. a) The Quarrel between Ajax and Odysseus, De twist tussen Ajax en Odysseus (Leonaert Bramer, 1629 - 1631), further “Ajax”; b) a mirrored image of The Quarrel between Ajax and Odysseus, De twist tussen Ajax en Odysseus (Leonaert Bramer, 1629 - 1631), further “Ajax”; c) Woman with child at a window, Vrouw met kind bij een raam (Hendrick van der Burgh, circa 1650), further “Window”; d) Woman with cat in interior, Vrouw met kat in interieur (Cornelis de Man, 1666), further “Cat”; e) The Art of Painting, De Schilderkunst (Mary Waters, copy of a fragment of “The Art of Painting” by Johannes Vermeer, 1996), further “Girl”; f) Fruits on a marble table with a blue cloth, Vruchten op een marmeren tafel met een blauw kleed (Willem van Aelst, 1649), further “Fruits”;

3.2 Procedure

All images, accompanied with their respective mask were loaded separately into Mathematica. I wanted to know the illuminance flow on a particular area of the painting. After the picture was imported, the accompanying mask would be imported. The algorithm would in turn use this as an overlay on top of the paining in order to determine at what locations it had to calculate the illuminance flow. There were three variables in calculating the illuminance flow: *sigma*, which translates to the scale of differentiation; *blur*, which translates to the scale of averaging of local estimates; and *mu*, which translates to the number of ellipses projected onto the image. As per default the number of ellipses (mu) was set to 32 pixels. The scales that were varied were the sigma (1,2,4,6,8 pixels) and blur (2,4,8,16 pixels). Next all the paintings with their accompanied masks were run through Mathematica with these different settings. For the algorithm to calculate the illuminance flow it would produce two variables, orG and confG. The first variable, orG is the second-order statistic of the painting. In other words, the auto correlated values of the dipoles. It gives rise to the orientation of the illuminance flow in the painting. The second variable, confG, is the value of the confidence on which the calculation of the orientation is done. For the cause of this research the values that these variables produced were averaged and the results were documented in Microsoft Excel 2015.

3.3 Analysis

At this point I had two sets of data, a perceptual data set containing the settings by Kartashova's participants and a modelled illumination flow set containing average illuminance flow orientations and confidences for each condition at every scale (sigma and blur). To analyse the data, I first transform the average calculated orientations from radians to degrees. Then I compute all the average orientations and standard deviations of Kartashova's data. Using SPSS Statistics. Using SPSS Statistics the mean orientations of the participants' settings were correlated with the mean calculated orientations. And also the mean confidence of the illuminance flow for each condition was correlated with the standard deviations of the participants' settings.

4 Results

The results are shown in the tables 1 and 2. I will briefly explain the variables:

- 'STD' stands for the standard deviation of the orientation of each sphere
- 'Mean' is the average direction for each sphere
- 'WC' is the Without Cut-condition, referring to Kartashova's research (2015)
- 'C' is the Cutout-condition, idem
- 'Orientation' is the orientation of the illuminance flow computed by the algorithm
- 'Confidence' is the confidence of the illuminance computed by the algorithm
- '2/4' and '8/16' refer to the settings of the scales (in pixels): sigma 2 and 8; blur 4 and 16.

As you can see in the tables only two scales were using to compare with the observers' settings. From observing the results derived from the illuminance flow computation, no clear 'perfect scale' was found for any of the spheres, only a somewhat linear regression from the smallest scale toward the largest scale. For this reason the choice was made to compare the results of Kartashova with the results of the illuminance flow calculations at the smallest and the largest scale. For the smallest scale not the combination of sigma 1 and blur 2 was chosen but respectively 2 and 4. This was done because the first scale would function as a line detector in some pictures with rough brushstrokes which would result in invalid results (Pont, 2007), for an example see figure 11. The large was chosen at this size and not bigger because if it would be extended, the number of pixels within the size of the mask would not fit. This would mean that the algorithm couldn't execute its calculations because there would be numbers missing that it was expecting.

First of all, table 1 shows that there is no significant correlation between the average orientation of the observers' settings and calculated orientation of illuminance flow by the algorithm. Figure 12 shows the four graphs that belong to the numbers found in table 1.

Secondly, table 2 however shows that there is a significant correlation that exists between the mean confidence of the calculated illuminance flow at the scale of sigma 8 and blur 16 and the standard deviation of the cutout conditions in Kartashova's research: $r = -.538$, $n = 21$, $p = 0.012$. This information can be found in table 2. Figure 13 shows the four graphs of the numbers found in table 2. In this figure, the fourth graph shows the significant correlation.

Table 1. Results of correlation analysis between the mean of the calculated of the illuminance flow and the mean settings by observers in Kartashova's research (2015).

		Mean WC	Mean C	Orientation 8/16	Orientation 8/16
Mean WC	Pearson Correlation	1	-.241	-.338	-.184
	Sig. (2-tailed)		.292	.134	.424
	N	21	21	21	21
Mean C	Pearson Correlation	-.241	1	.102	.125
	Sig. (2-tailed)	.292		.659	.591
	N	21	21	21	21
Orientation 8/16	Pearson Correlation	-.338	.102	1	.179
	Sig. (2-tailed)	.134	.659		.437
	N	21	21	21	21
Orientation 2/4	Pearson Correlation	-.184	.125	.179	1
	Sig. (2-tailed)	.424	.591	.437	
	N	21	21	21	21

Table 2. Results of correlation analysis between the mean confidence of the calculated illuminance flow orientation and the standard deviation of the mean settings by observers in Kartashova's research (2015).

		STD WC	STD C	Confidence 8/16	Confidence 2/4
STD WC	Pearson Correlation	1	.025	.164	.206
	Sig. (2-tailed)		.915	.477	.370
	N	21	21	21	21
STD C	Pearson Correlation	.025	1	-.538*	.039
	Sig. (2-tailed)	.915		.012	.868
	N	21	21	21	21
Confidence 8/16	Pearson Correlation	.164	-.538*	1	.268
	Sig. (2-tailed)	.477	.012		.241
	N	21	21	21	21
Confidence 2/4	Pearson Correlation	.206	.039	.268	1
	Sig. (2-tailed)	.370	.868	.241	
	N	21	21	21	21

*. Correlation is significant at the 0.05 level (2-tailed).

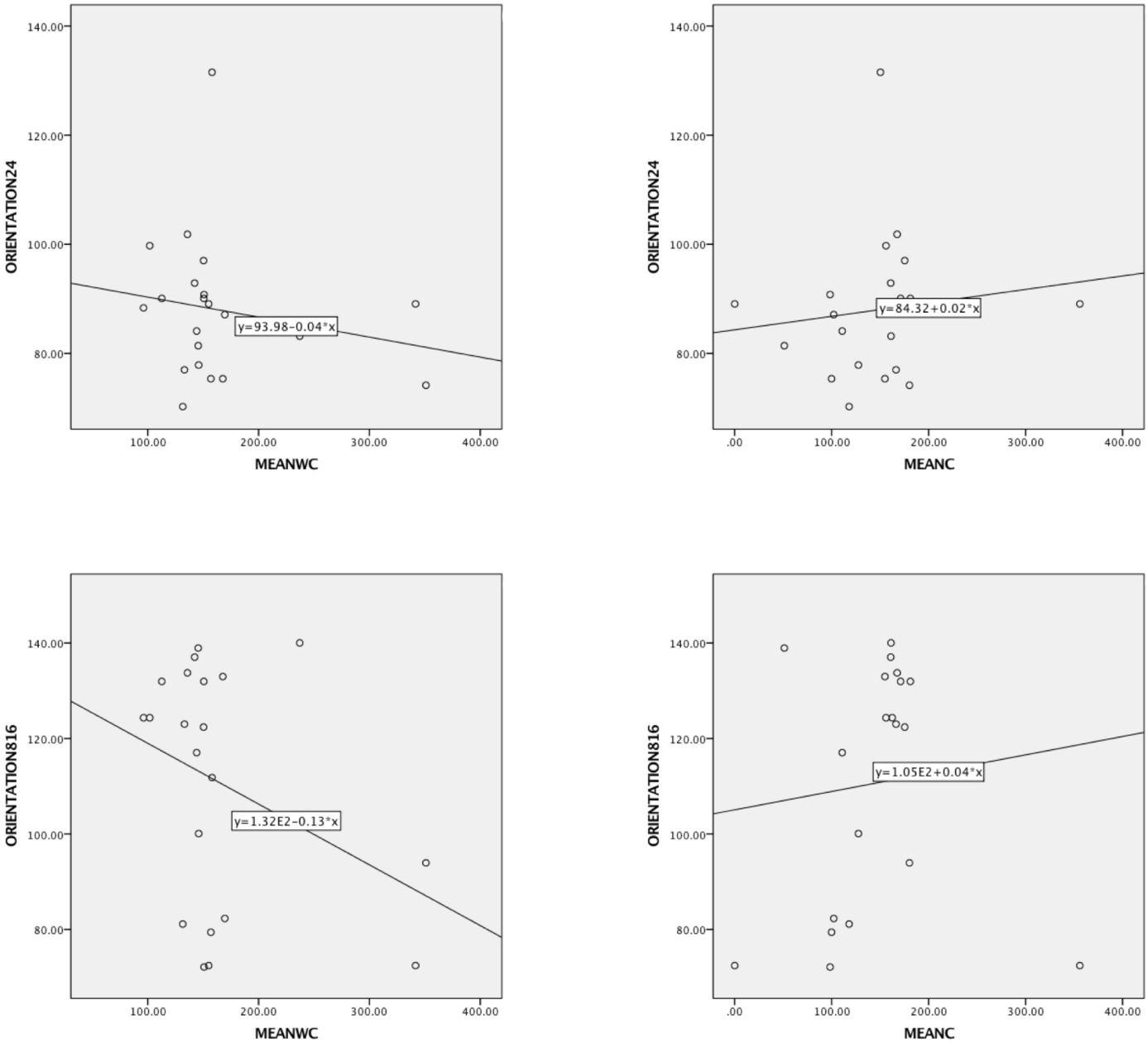


Figure 12. Four scatter plots showing the results presented in table 1: the mean orientation of the computed illuminance flow presented at the scales of 2/4 pixels and 8/16 pixels, compared with both the averages from the without- and with cutout conditions in Kartashova's reserach (2015).

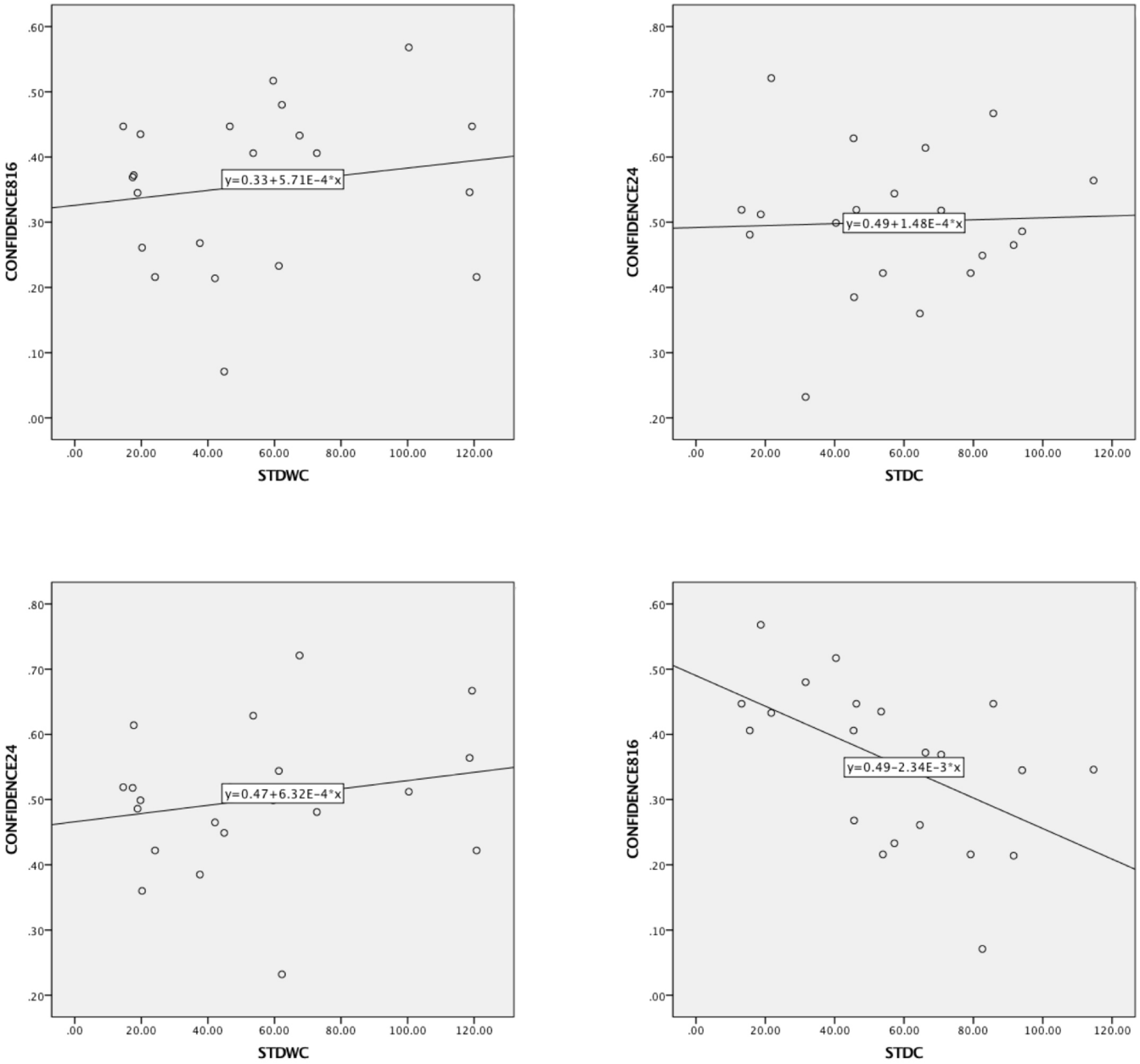


Figure 13. Four scatter plots showing the results presented in table 2: the mean confidence of the computed illuminance flow orientation presented at the scales of 2/4 pixels and 8/16 pixels, compared with both the standard deviations of the means from the without- and with cutout conditions in Kartashova's reserach (2015).

5 Discussion

I wanted to know whether there is a relation between the scale on which the algorithm operates and the perceptual data found in a research by Kartashova et al., (2015). Because of suggestions made in previous papers (Pont, 2007; Xia et al., 2016) I estimated that the correlations of the calculations and Kartashova's perceptual data would show a 'perfect scale'. Which means that it would have been the scale on which on average all the participants infer light on the spheres. Unfortunately, the results show that there is no clear correlation between the orientation of the calculations and the mean orientation of the participants. Although Kartashova et al. (2015) reported that although the observers are relatively consistent in their settings across paintings (depending on the painting's content), there is large between subject variation. This means that the average illuminance orientation over participants might not even come close the 'actual' or calculated orientation due to the large variation. In order to investigate a possible relation between the scale of on which the algorithm calculates the illuminance flow and the observers' settings, there has to be small within subject variance so their average orientational settings will have actual meaning. Alternatively, a within participant comparison could be conducted, but for that we would need more data per participant.

This leads us to the next question concerning whether the confidence of the algorithm's calculations was related to the performance of the participants. The results show that there is a correlation between the confidence of the large scale (8, 16 pixels) and standard deviations in the cutout conditions. This provides evidence to suggest that there is in fact a relation between the performance of the algorithm and the participants. This would mean that the greater the variance in between participants is, the lower the confidence of the algorithm will be. This is an important finding because it can be used in future selection of stimuli. With this information one can now make an estimation beforehand about whether there may or may not be great in between variance. There is another point about this I would like to highlight, because of findings in the paper van Doorn et al. (2012). Due to this paper it was expected that the results in the cutout condition would have had smaller standard deviations since there are little contextual references to compare the light field of the sphere with. The fact that the results in the cutout condition have more variance than the without-cutout condition suggests that even within the area of interest there is variation of the light field. This might mean that the material used is not suited for the cause of the paper. On this note I would like to continue with some recommendations for future research.

To further investigate the importance of scale selection and the relation between calculated orientation and the observers' settings, an extension in the material must be made.

The variation in the paintings was relevant for the research by Kartashova but not for our cause. So in order to get the right material a vast selection of similar looking paintings has to be made. The similarity in the future paintings should consist in the content of the paintings. In our material, the location of the spheres were on such different objects in the paintings which resulted in large variation of the stimuli and thus the mechanism that our visual system uses to estimate the illuminance orientation might have been different between stimuli. I here refer to the scene/texture dichotomy. A suggestion for the selection of future painting content would be roundish objects. As the results have shown there was a higher confidence in the 'Ajax' painting than there was in the 'Fruits' painting (which had a lot of round objects). I still think round objects are necessary but the low confidence in 'Fruits' was due to the darkness and low contrast of the painting, not the shape of the objects. This causes difficulty in calculating the illuminance flow because there is little variance in chromaticity of the shading pattern. Therefore bright paintings should be selected, and only round objects should then be selected to serve as stimuli. This might result in only one or two stimuli per painting, so more than 5 paintings must be selected. I also recommend running the paintings through the algorithm beforehand. If the confidence of the painting is low, it should be discarded.

6 Conclusion

In this thesis the main objective was to determine whether there was a relation between an algorithm that calculates illuminance flow and settings of illuminance direction of a visual light field inferred by human observers within paintings. The original researchers on illuminance flow, Pont & Koenderink, who described their theory in 2003 wrote several consecutive studies (Pont 2007; Xia et al., 2016) in which they suggested there might be a relation there.

Secondly, the question arose whether there would be a 'perfect scale' on which the algorithm operates. If there was in fact a perfect scale it would mean that it is very probable that humans make illuminance flow estimations at this scale. A perfect scale here refers to a scale on which the calculations of the algorithm are in line with settings of the observers. In other words, it would mean that on average the participants infer light at this scale. This would have had implications for future research. Unfortunately, I could not confirm the existence of a 'perfect scale' since there was no clear relation between scale selection and the settings of the observers in Kartashova's (2015) research regarding orientation.

A third prediction was confirmed, namely the fact that there's a relation between performance of the observers and the performance of the algorithm: the variance of the settings grows larger as the confidence of the algorithm's calculations grow smaller. In other

words, the lower the confidence gets on which the algorithm calculates the illuminance flow, the harder it was for observers to estimate the light field. Recommendations for future research have been made mainly regarding the consistency of the stimuli. The results showed that even in small area estimations there was still large variation in between subjects. This means that future stimuli should be chosen on the basis of consistency in between stimuli but also within the stimulus. The latter means that if, for example, a certain object in a painting is chosen to act as a stimulus, there should only be one light field, on the single object that is depicted. This would result is valid calculations because the algorithm averages all the orientations. If there are two light fields, there is no true orientation because the two different directions are averaged. Therefore, future paintings have to be bright and the objects chosen to be stimuli should be round or at least the same shape as the probe used to infer the visual light field on. Also, the correlation that was found could help select future stimuli because if a calculation of the stimulus will have a high confidence, participants will probably estimate illuminance flow in a likewise manner.

7 Appendix

7.1 Mathematica code for computing illuminance flow

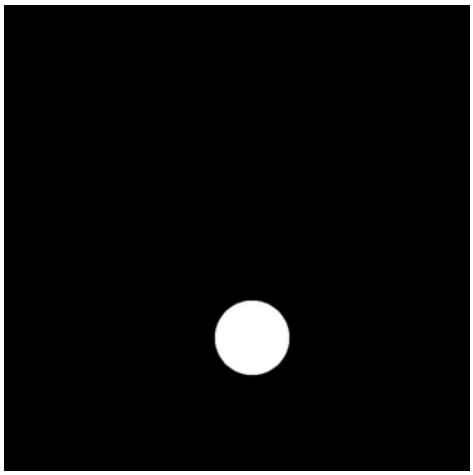
Kernels

```
showInbetweenResults = True;
```

Global settings

```
imageFile = ImageResize[Import[
   "/Users/imac/Library/Mobile Documents/com~apple~CloudDocs/Documents/LAS
     2016-2017/4 Blok 3/Scriptie/Mathematica/Pictures
     Squared/1WINDOW_MASK/Window_sq.png"], {320, 320}]
```


```
maskFile = ImageResize[Import[
   "/Users/imac/Library/Mobile Documents/com~apple~CloudDocs/Documents/LAS
     2016-2017/4 Blok 3/Scriptie/Mathematica/Pictures
     Squared/1WINDOW_MASK/Window_mask2.jpg"], {320, 320}]
```



Methods

Plot Light Field

```
plotLightField[orientationImage_, confidenceImage_, opts___] :=
  ListDensityPlot[
   image,
   Mesh -> False, Frame → False,
   PlotRange → All, ColorFunction → GrayLevel,
   Epilog → Table[
     Module[
      {x, y, d},
      d = n / (m + 1);
      x = Round[j * d * Sqrt[3] / 2];
      y = Round[If[OddQ[j], i * d, i * d + d / 2]];
      If[
       x ≤ n && y ≤ n > 0.5,
       icon[orientationImage[[y, x]],
        confidenceImage[[y, x]], {x, y}, iconScalingFactor],
       {}
      ]
     ],
     {i, 1, m + 2}, {j, 1, m + 2}
    ],
   opts,
   ImageSize → {512, 512}
  ];
```

Plot Orientation

```
orientationPlot[orientationImage_] :=
  Show[ListDensityPlot[
    orientationImage,
    Mesh → False,
    Frame → False,
    ColorFunction → cf,
    ColorFunctionScaling → False
   ]];
```

The Ellipses + S

```
icon[or_, conf_, loc_, scale_] :=
 Module[
  {phi, curve, k = 30, e1, e2, a, lambda1, lambda2},
  a = If[conf > 0.99, 0.99, conf];
  lambda1 = Sqrt[conf] * Sqrt[(1 + a) / (1 - a)];
  lambda2 = Sqrt[conf] / Sqrt[(1 + a) / (1 - a)];
  e1 = {Cos[or], Sin[or]};
  e2 = {Sin[or], -Cos[or]};
  curve = Table[loc + scale * (lambda1 Cos[phi] e1 + lambda2 Sin[phi] e2),
    {phi, 0, 2 Pi, 2 Pi / k}];
  {
   GrayLevel[1],
   Polygon[curve],
   GrayLevel[0],
   Line[curve]
  }
 ]
```

Make Gray Image

```
makeGrayImage[anImage_, upper_, lower_] :=
  Module[
   {mn, mx, a, b},
   mx = Max[Flatten[anImage]];
   mn = Min[Flatten[anImage]];
   a = (upper - lower) / (mx - mn);
   b = (lower * mx - upper * mn) / (mx - mn);
   Partition[
    Map[
     N[a * # + b] &,
     Flatten[anImage]
    ],
    Length[anImage]
   ]
  ];
```

Hue

```
cf[val_] := Hue[val / Pi]
```

Image Data

```
imageData[anImage_] :=
 Module[
  {nx, ny, iMin, iMax},
  {nx, ny} = Dimensions[anImage];
  {iMin, iMax} = limits[anImage];
  Print["Dimensions ", nx, " x ", ny, " pixels,"];
  Print["Intensity range ", iMin, " through ", iMax];
 ]
```

Limits

```
limits[aList_] := {Min[Flatten[N[aList]]], Max[Flatten[N[aList]]]}
```

Spatial partial derivatives

```
(* bovenste deel pagina 92 *)
partialDerivative[anImage_, xOrder_, yOrder_, blur_] :=
 Module[
  {nx, ny, σ},
  {nx, ny} = Dimensions[anImage];
  σ = N[blur];
  Sqrt[nx ny] *
   Chop[
    Re[
     InverseFourier[
      Fourier[anImage] *
       kernelSpectrum[xOrder, yOrder, σ, nx, ny]
     ]
    ]
   ]
 ]
```

Kernel Spectrum

```
kernelSpectrum =
  Compile[
   {
    {nx, _Integer},
    {ny, _Integer},
    {σ, _Real},
    {xres, _Integer},
    {yres, _Integer}
   },
   i = (xres - 1)/2;
   j = (yres - 1)/2;
   tx = Table[ HermiteH[nx, x/(σ Sqrt[2])] e^(If[-x^2/(2 σ^2)<-200,-200,-x^2/(2 σ^2)]), {x, -i, i}];
   ty = Table[HermiteH[ny, y/(σ Sqrt[2])] e^(If[-y^2/(2 σ^2)<-200,-200,-y^2/(2 σ^2)]), {y, - j, j}];
   c = 1/(2 π σ^2) (-1/(σ Sqrt[2]))^(nx+ny);
   Fourier[
    RotateLeft[c * Outer[Times, ty, tx], {xres/2, yres/2}]
   ],
   {
    {x, _Real},
    {y, _Real},
    {c, _Real},
    {i, _Integer},
    {j, _Integer},
    {tx, _Real, 1},
    {ty, _Real, 1},
    {Fourier[_], _Complex, 2},
    {Table[_], _Real, 2}
   }
  ];
```

Illumination direction I(r)

```
orientation[m11_, m12_, m22_] := Mod[.5 ArcTan[m11 - m22, 2 m12], N[Pi]]
```

Confidence

```
confidence =
  Compile[
   {
    {m11, _Real},
    {m12, _Real},
    {m22, _Real}
   },
   h = {{m11, m12}, {m12, m22}};
   lambda = Eigenvalues[h];
   If[
    lambda[[1]] ≠ 0 && lambda[[2]] ≠ 0,
    Abs[(lambda[[2]] - lambda[[1]]) / (lambda[[2]] + lambda[[1]])],
    0
   ],
   {
    {lambda, _Real, 1},
    {h, _Real, 2},
    {Eigenvalues[_], _Real, 1}
   }
  ];
```

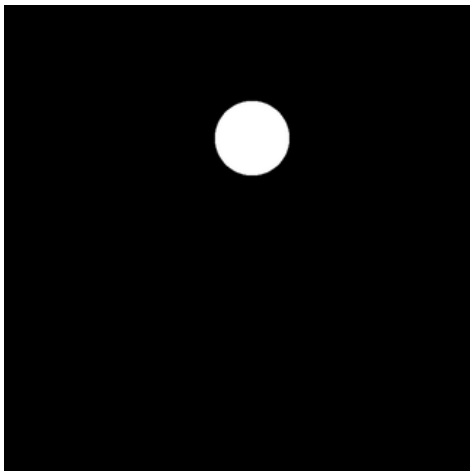
An Image

```
findTrend[anImage_] :=
  Module[
   {n, m, i, j, t},
   {n, m} = Dimensions[anImage];
   t[x_, y_] =
    Fit[
     Flatten[
      Table[
       {i, j, anImage[[i, j]]},
       {i, 1, n}, {j, 1, m}
      ], 1
     ],
     {1, x, y, x * y},
     {x, y}
    ];
   Table[
    t[i, j],
    {i, 1, n}, {j, 1, m}
   ]
  ];
```

Image

```
imageFile = ImageReflect[ColorConvert[imageFile, "Grayscale"]]
```

```
maskFile = ImageReflect[ColorConvert[maskFile, "Grayscale"]]
```



```
image = ImageData[imageFile];
tmp = Max[Flatten[image]];
image = Partition[Map[N[# / tmp] &, Flatten[image]], Length[image]];
image = Partition[Map[N[Log[1 + #]] &, Flatten[image]], Length[image]];
ListDensityPlot[image, Mesh → False, Frame → False]
Print[imageData[image]];
```

```
Dimensions 320 x 320 pixels,
Intensity range 0.0170944 through 0.693147
Null
```

```
mask = ImageData[maskFile];
tmp = Max[Flatten[mask]];
mask = Partition[Transpose[Flatten[mask, 1]][[1]], Length[mask]];
ListDensityPlot[mask, Mesh → False, Frame → False]
Print[imageData[mask]];
```

```
Transpose: The first two levels of
  {0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
    0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., ≪102350≫} cannot be transposed.
```

```
Dimensions 320 x 320 pixels,

Intensity range 0. through 1.

Null
```

```
trend = findTrend[image];
image = (image - trend) * mask;
trend = trend * mask;
ListDensityPlot[trend, Mesh → False, Frame → False, PlotRange → All]
 ListDensityPlot[image, Mesh → False, Frame → False, PlotRange → All]
imageData[image]
```

```
Dimensions 320 x 320 pixels,

Intensity range -0.190862 through 0.35381
```

The 1-jet

```
im10 = partialDerivative[image, 1, 0, sigma]
im01 = partialDerivative[image, 0, 1, sigma]
```

CompiledFunction: Compiled expression {{0. + 0. i, −5.94997 × 10^−7 − 0.000060604 i, −2.2934 × 10^−6 − 0.000116787 i, −4.85108 × 10^−6 − 0.000164661 i, ≪43≫, −1.87485 × 10^−15 − 3.77067 × 10^−15 i, −6.04759 × 10^−16 − 1.1869 × 10^−15 i, −1.90146 × 10^−16 − 3.64297 × 10^−16 i, ≪270≫}, ≪49≫, ≪270≫} should be a rank 2 tensor of machine−size real numbers.

CompiledFunction: Could not complete external evaluation at instruction 6; proceeding with uncompiled evaluation.

{ ··· 1 ··· }

large output | show less | show more | show all | set size limit...

CompiledFunction: Compiled expression {{0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, ≪21≫, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, 0. + 0. i, ≪270≫}, ≪49≫, ≪270≫} should be a rank 2 tensor of machine−size real numbers.

CompiledFunction: Could not complete external evaluation at instruction 6; proceeding with uncompiled evaluation.

{ ··· 1 ··· }

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Compute G^2 matrix

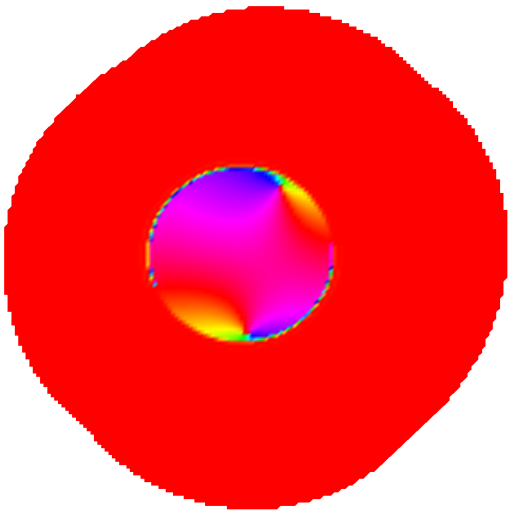
```
(
 g11 = Partition[Flatten[im10]^2, Length[image]];
 g12 = Partition[Flatten[im10] * Flatten[im01], Length[image]];
 g22 = Partition[Flatten[im01]^2, Length[image]];
)
```

```
ListDensityPlot[g11, Mesh → False, Frame → False]
ListDensityPlot[g12, Mesh → False, Frame → False]
ListDensityPlot[g22, Mesh → False, Frame → False]
```

Orientation of the illumination (azimuth modulo 180°)

```
orG =
 mask * Module[
   {nx, ny, ga11, ga12, ga22},
   {nx, ny} = Dimensions[g11];
   ga11 = partialDerivative[g11, 0, 0, blur];
   ga12 = partialDerivative[g12, 0, 0, blur];
   ga22 = partialDerivative[g22, 0, 0, blur];
   Table[
    orientation[
     ga11[[x, y]],
     ga12[[x, y]],
     ga22[[x, y]]
    ],
    {x, 1, nx}, {y, 1, ny}
   ]
  ]
```

```
orientationPlot[orG]
```



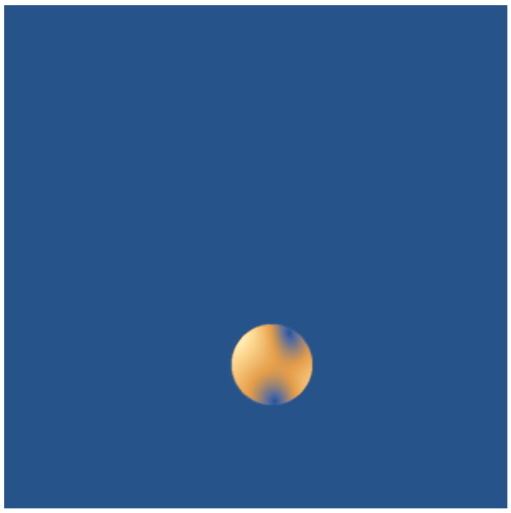
Confidence Measure

```
confG =
 mask * Module[
   {nx, ny, ga11, ga12, ga22},
   {nx, ny} = Dimensions[g11];
   ga11 = partialDerivative[g11, 0, 0, blur];
   ga12 = partialDerivative[g12, 0, 0, blur];
   ga22 = partialDerivative[g22, 0, 0, blur];
   Table[
    confidence[
     ga11[[x, y]],
     ga12[[x, y]],
     ga22[[x, y]]
    ],
    {x, 1, nx}, {y, 1, ny}
   ]
  ]
```

{ ··· 1 ··· }

large output | show less | show more | show all | set size limit...

```
ListDensityPlot[confG, Mesh → False, Frame → False]
```



Global setting

```
sigma = 8;(* scale of differentiation *)
blur = 16; (* scale of averaging of local estimates *)
m = 32; (* amount of ellipses *)
n = Length[image] (* in pixels *)
grayImageLowerLevel = 0.4;
grayImageUpperLevel = 0.8;
iconScalingFactor = 0.5 * (n / (m + 1))
```

```
320
```

```
4.84848
```

Results

```
flatconf = Flatten[confG]
flatorg = Flatten[orG]
```

```
{0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., ··· 102 318 ···, 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.}
```

large output | show less | show more | show all | set size limit...

```
{Indeterminate, Indeterminate, Indeterminate, Indeterminate, Indeterminate,
 Indeterminate, Indeterminate, Indeterminate, Indeterminate, Indeterminate,
 Indeterminate, ··· 102 378 ···, Indeterminate, Indeterminate, Indeterminate,
 Indeterminate, Indeterminate, Indeterminate, Indeterminate,
 Indeterminate, Indeterminate, Indeterminate, Indeterminate}
```

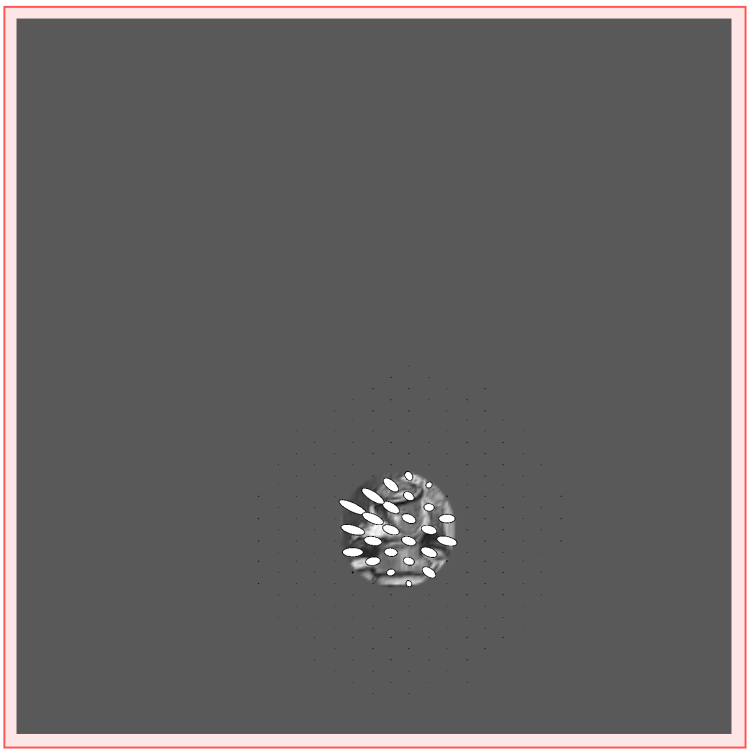
large output | show less | show more | show all | set size limit...

```
Mean[Select[flatorg, # > 0 &]]
Mean[Select[flatconf, # > 0 &]]
Variance[Select[flatorg, # > 0 &]]
Variance[Select[flatconf, # > 0 &]]
```

```
2.04257

0.268484

1.30937

0.0220378
```

Light Field Map From gradient

```
plotLightField[orG, confG]
```



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9. Formulier kennisneming plagiaat

Universiteit Utrecht

In de Onderwijs- en Examenregeling (artikel 5.15) is vastgelegd wat de formele gang van zaken is als er een vermoeden van fraude/plagiaat is, en welke sancties er opgelegd kunnen worden.

Onwetendheid is geen excuus. Je bent verantwoordelijk voor je eigen gedrag. De Universiteit Utrecht gaat ervan uit dat je weet wat fraude en plagiaat zijn. Van haar kant zorgt de Universiteit Utrecht ervoor dat je zo vroeg mogelijk in je opleiding de principes van wetenschapsbeoefening bijgebracht krijgt en op de hoogte wordt gebracht van wat de instelling als fraude en plagiaat beschouwt, zodat je weet aan welke normen je je moeten houden.

Hierbij verklaar ik bovenstaande tekst gelezen en begrepen te hebben.
Naam: Willem van der Maden Studentnummer: 4156278
Datum en handtekening: 16-6-2017

Dit formulier lever je bij je begeleider in als je start met je bacheloreindwerkstuk of je master scriptie.

Het niet indienen of ondertekenen van het formulier betekent overigens niet dat er geen sancties kunnen worden genomen als blijkt dat er sprake is van plagiaat in het werkstuk.