FACULTY
OF MATHEMATICS
AND PHYSICS
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BACHELOR THESIS

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Design and Prototypical Implementation of a Radiometrically Calibrated Light Source to Perform Dark-light Adaptation Measurements of the Human Eye

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Specialization:	Computer Graphics, Vision and Game Development

Prague 2023

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I would like to thank my supervisor Dipl.-Ing. Thomas Klaus Nindel, PhD. for his patience and very much appreciated valuable advice and suggestions.

Title: Camera Model for Light-dark Adaptation of the Human Eye

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Abstract: The thesis is about obtaining absolute radiometric values of a scene using only a digital camera. A further usage of this data to calibrate a screen to perform experimental dark adaptation measurements of the human eye is proposed. To get the radiometric values, or to be exact, radiance values, the camera response function (CRF) of the camera used had to be found first. The CRF determines how the light hitting the camera sensor affects the brightness of the pixel values of the captured image. Using the inverse CRF function we were able to get the radiance from the pixel values. The thesis also contains a description of what factors affect the dark adaptation itself.

Keywords: dark-light adaptation, radiometry, radiometric self-calibration, camera, human eye

Contents

Introduction

Background

Dark adaptometry tests are important medical procedures that help with diagnosis of some eye disorders, for example help with diagnosis of age-related macular degeneration (AMD) in its early stages. Dark adaptation measurements can also be used in computer graphics to simulate the eye's behaviour when, for example, entering a dark indoors from a bright lit outdoors. Such feature can already be found in Unreal Engine 4.25 and higher. Measurements of the dark adaptation are done by testing a person's ability to see light at various intensities; the time, when a person notices the light, and the intensity of the light is recorded and from this data resulting dark adaptation measurement is formed. To conduct this test, the intensity of the light (or more precisely, its radiance) must be known.

Radiance is also very important radiometric unit in a field of photography. Digital cameras convert scene radiance into pixel values through an image acquisition process. This process includes converting light captured by a camera sensor (irradiance) to pixel values using a camera response function (CRF). This function is unique to every sensor and is hardly ever linear. This is because of various non-linearities that occur during the capture and storage of the gained data. Such non-linearities for example include conversion of analogue voltages to digital values or build-in film-like responses of a camera sensor to light. Acquisition of this function, if not provided by a manufacturer, is an interesting task in itself.

Now, could digital cameras be used to measure the radiance values of a scene, or just a light? How could the obtained data be used to conduct dark adaptation measurements?

These problems are what this thesis tries to solve.

Goals of the Thesis

The main goal of this thesis is the computation of the absolute radiance values from taken photographs and how to use these values to calibrate a screen for purposes of experimental the dark adaptation measurements of the human eye. To do this the CRF of the digital camera used must be found.

1 Related Work

To compute the absolute radiance values from photographs, the CRF of the digital camera used to capture those images must be known first. The recovery of this function can be done by taking a photograph of a subject of known relative reflectance such as the ColorChecker [1].

Not always is such a thing in disposal however, so algorithms that try to recover the CRF using only a provided camera were developed. Such algorithms are a work of Mitsunaga and Nayar [1], and Debevec and Malik [2]. Both algorithms are described in detail further in the thesis but they both work on a principal of taking multiple photos of different exposures. Algorithms differ in assumption if the exposure time is known or not. Based on this, different recovery methods are then used.

Both of these algorithms however do not fully solve our goal of finding out absolute radiance values as the result of the algorithms is scaled and/or relative. The result of the algorithm by Mitsunaga and Nayar is a scaled intensity value (from 0 to 1) for a scaled pixel value (also from 0 to 1); so the result is actually the inverse to the CRF. The result of the algorithm by Debevec and Malik is also the inverse function of the CRF - a log exposure for a pixel value (from 0 to 255); this could be easily addressed however, the problem with this is that the algorithm assumes the middle pixel value to have unit exposure – the horizontal position of the resulting curve is arbitrary. Some conversion to absolute values must be found.

Since we are trying to find out if the resulting radiance values could be used for dark adaptation, what follows is a brief overview of how the dark adaptation is measured for medical testing. Dark adaptation in medicine is measured using devices called dark adaptometers. The measurement itself is done in a dark room, where a patient is asked to look into the measuring device. In the beginning of the test, the patient's eyes are bleached with a bright flash of light. This means that the photosensors in the person's eyes get saturated and become insensitive to more incoming light. Then, a gradually brightening blinking spot will start to appear. When the patient notices the light, they push a button. During the test, the patients' eyes should remain fixated on a target (usually of a red colour) [3][4].

Some types of dark adaptometers even enable testing of the dark adaptation anywhere. An example of such device is the AdaptDx Pro. This device works on the same principle as described above but resembles more a VR headset, the outside light is blocked with a rubber eye cups, similar to ones that can be found on professional video cameras [5].

Another attempt to make dark adaptation tests even more accessible was done by Pundlik and Luo [6]. They were testing if dark adaptation measuring was possible with a mobile app. The app, again, was working on the same principle as other dark adaptometers. For purposes of their studies, they chose a Samsung smartphone with an OLED screen which provides them with a larger luminance range then common LCD screens do. To calibrate the phone's screen, they used a spectrometer, which is something we in this thesis try to do with a digital camera.

2 Method

In this chapter we describe the process of obtaining the absolute radiance values of a photographed scene. But before we get to that, the background needed is covered. This includes what radiance as a radiometric unit is and what are other radiometric units; what affects the amount of light captured by the camera sensor and how to get the camera response function.

2.1 Radiometry

Radiometry is the field of science that deals with the measurement of light. On contrary to photometry, it does not take into consideration the properties of the human eye. Brief overview of the most important quantities follows:

The smallest quantum of light that can be emitted from a light source is called *a photon*. The energy of a photon of a wavelength λ is:

$$e_\lambda = \frac{hc}{\lambda}.$$

Where h is the Planck constant (≈ 6.626×10^{-34} J·s) and c is the speed of light in a vacuum. Its unit is the joule [7, 8].

Spectral energy Q [J] is an energy of collection of photons (n_λ) of a certain wavelength λ. This energy can be computed as [7]:

$$Q = \int_0^\infty n_\lambda e_\lambda d\lambda.$$

Radiant flux Φ [W = J·s^{-1}] is a quantity describing the amount of energy emitted or received during a unit of time.

$$\Phi = \frac{dQ}{dt}$$

Irradiance E [W·m^{-2}] is the amount of radiant flux received by a unit area (on the contrary, radiant flux emitted from a unit area is called *radiosity*).

$$E = \frac{d\Phi_i}{dA}$$

Radiance L **[W·sr^{-1}·m^{-2}]** is the most important radiometric quantity. Although the irradiance tells us how much light hits the surface, we need something more analogous to what our eyes see, that is, we need to know how much light comes from a specific direction [8]. Radiance serves this very purpose. The equation for radiance is:

$$L(x, \vec{\omega}) = \frac{d^2\Phi}{\cos\Theta dA d\vec{\omega}}.$$

$L(x, \vec{\omega})$ is the radiance at a point x and at an incoming/outgoing direction $\vec{\omega}$. Area perpendicular to this direction is $\cos\Theta dA$.

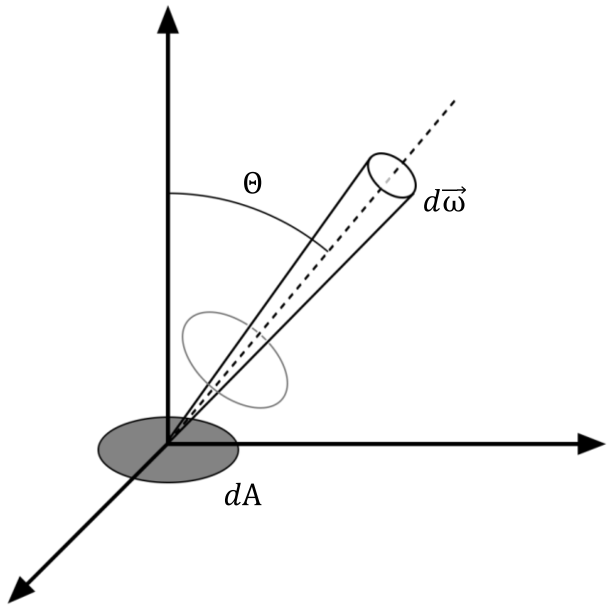

Figure 2.1: Radiance.

A great property of radiance that is it does not change with distance. We see objects to have the same "colour" regardless of how far we observe them [7, 8].

2.2 Exposure in Photography

Exposure is the amount of light that reaches the camera's sensor or film and determines how bright the final picture will be. If not enough light reaches the sensor the picture will appear dark, *underexposed.* On the other hand, if too much light reaches the sensor, the photos are *overexposed*. In the Figure 2.2. example of underexposed photo, photo with correct exposure and a overexposed photo can be seen.

Figure 2.2: Underexposed photo (left), correctly exposed photo (centre), overexposed photo (right).

The exposure is affected by how the photographer sets the camera's **shutter speed**, **aperture size** and **ISO** (these three settings are also called *the exposure triangle*) [9, 10].

2.2.1 Shutter Speed

Shutter speed is the amount of time for which the camera's shutter is open. The longer this time is, the more light gets to the sensor and the result photo becomes brighter. This time can be as short as 1/1000 of a second or can take up to several minutes.

One thing to keep in mind when setting up the shutter speed is a motion blur. There are two kinds of motion blur – *a camera blur* and *a subject blur*. The first one occurs, for example, when you hold the camera in hands. During longer shutter speeds it is impossible to hold the camera completely still and even a slight shake can result in blurry photos. This however can be solved by using a tripod. A subject blur can occur when the capturing subject moves itself, for example a playful cat or a flower moving in the wind (see Figure 2.3). In these cases, it is necessary to set the shutter speed to a lower value, for example photos of sport athletes are taken at speeds of around 1/1000 s [9, 10].

Figure 2.3: Example of a subject blur.

2.2.2 Aperture

Aperture is an opening through which light travels to the camera. Size of the opening is adjusted by the aperture blades.

Function of the aperture is very similar to the pupil in our eyes which at low light intensities dilates to let more light in and narrows when exposed to a bright light.

Aperture is measured in a *f-number* (also called *f-stop*). For example, an aperture can be of f/22, f/8, f/2 and so on, where the higher number indicates a smaller opening (it is because these numbers are fractions).

Besides controlling the brightness of an image, aperture size also changes depth of field. Depth of field is the amount of scene that is in focus. Small aperture opening, such as f/16, yields large depth of field and a large aperture opening, such as f/1.7, gives shallow depth of field (see Figure 2.4) [9, 10].

Figure 2.4: Photos taken with f/1.7 (left) and f/16 (right).

2.2.3 ISO

ISO says how much the light sensor within the camera is sensitive to light. Lower ISO means the sensor is less sensitive and higher ISO means more sensitive. Examples of ISO values are ISO100 (usually the base sensitivity in cameras), ISO200, ISO1600.

With increasing ISO however comes also more digital noise which makes photos grainy (see Figure 2.5). Sometimes though this is more acceptable in comparison with a completely dark image [9, 10].

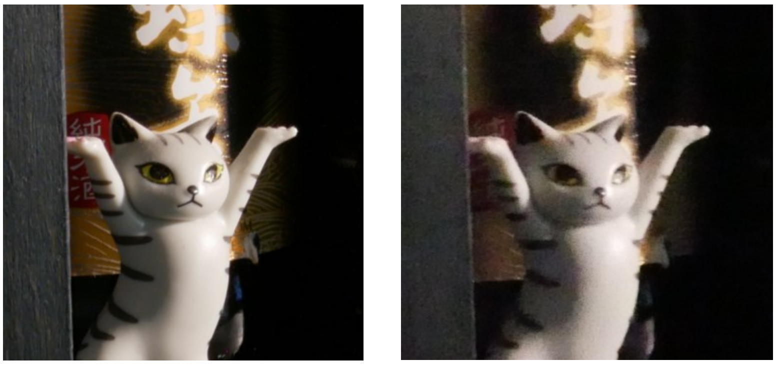

Figure 2.5: Detail of photos taken with ISO200 (left) and ISO25600 (right).

2.3 Camera Response Function Recovery

To express the relationship between a scene and a captured values on a photo, we need to find out *a camera response function* (*CRF*) f. This response function f maps exposure H to the pixel values of the captured image. Exposure H is a product of the irradiance E captured by the camera sensor and the exposure time Δt (which is a shutter speed set during the acquisition of the image). Once we find the CRF of the camera, we are able to obtain the exposure H of any pixel as $H = f^{-1}(pixel\ value)$. From here, if we know the exposure time Δt, we can easily get the irradiance E and sequentially the radiance L.

There are many ways to find out the CRF from which the most universal algorithms were created by Mitsunaga and Nayar [1] and by Debevec and Malik [2]. These two algorithms are described below.

2.3.1 Radiometric Self Calibration Algorithm by Mitsunaga and Nayar

In the beginning it should be noted that the result of this algorithm is not the camera response function but its inverse. This however is no problem as we are more interested in the inverse function anyway (so throughout this section we will call this function the response function f).

The algorithm gets the response function from a series of photographs of various exposures of the same arbitrary scene. No precise knowledge of exposure setting is needed, the only requirement that the photos must fulfil is that, when the images are ordered from the darkest to the lightest, the pixel values M between images do not decrease.

The idea behind this algorithm is that the response function can be modelled as some high-order polynomial because the measured brightness increases or stays constant with increasing exposure:

$$H = f(M) = \sum_{n=0}^{N} c_n M^n.$$

So, the problem of finding the response function is transformed to finding the order N and the coefficients c_n.

This is done iteratively. First, images are ordered from the one with the lowest exposure to the one with the highest, then let's consider $R_{i,i+1}$ to be a ratio between exposures between images i and $i+1$. The exposure ratio is then related to the response function as:

$$\frac{f(M_{p,i})}{f(M_{p,i+1})} = R_{i,i+1},$$

where $M_{p,i}$ is the pixel value of the pixel p in the image i. Now, if we rewrite the above using the polynomial model, we get:

$$\frac{\sum_{n=0}^{N} c_n M_{p,i}^n}{\sum_{n=0}^{N} c_n M_{p,i+1}^n} = R_{i,i+1}.$$

From this, if we know the ratios $R_{i,i+1}$ we can recover the response function by formulating an error function ϵ, where I is the total number of images and P number of pixels:

$$\epsilon = \sum_{i=1}^{I-1} \sum_{p=1}^{P} \left[\sum_{n=0}^{N} c_n M_{p,i}^n - R_{i,i+1} \sum_{n=0}^{N} c_n M_{p,i+1}^n \right]^2.$$

Coefficients c_n are then obtained from ϵ using partial derivations.

Problem that arises is that the ratios $R_{i,i+1}$ are not known to us. So, now comes the iterative part that was mentioned in the beginning: first we take a guess of what the ratios might be (a good one is between 0.45 and 0.55) and then using the computed coefficients $c_n^{(k)}$ in iterative step k we update the ratios as:

$$R_{i,i+1}^{(k)} = \frac{\sum_{p=1}^{P} \frac{\sum_{n=0}^{N} c_n^{(k)} M_{p,i}^n}{\sum_{n=0}^{N} c_n^{(k)} M_{p,i+1}^n}}{P}.$$

The iteration stops when the difference between response functions obtained in iterative steps k and $k+1$ is small enough.

This process may find coefficients but does not give the order of the polynomial. This is solved by running this algorithm repeatedly for different values of N and finding the one that returns the lowest error ϵ.

2.3.2 The Algorithm by Debevec and Malik

This algorithm also uses a series of photographs of the same arbitrary scene but now the exposure times Δt must be known. Also, the result of this algorithm is again the inverse of the camera response function.

If we denote f to be the camera response function, $M_{p,i}$ to be a pixel value of pixel p in the photo i and exposure $H = E_p \Delta t_i$ we can write:

$$M_{p,i} = f\left(E_p \Delta t_i\right). \tag{2.1}$$

Because f is assumed to be monotonic, it is invertible. Also, if we take the natural logarithm of both sides, we get:

$$\ln f^{-1}\left(M_{p,i}\right) = \ln E_p + \ln \Delta t_i. \tag{2.2}$$

For simplification, we will write $\ln f^{-1}$ as g.

Now, to recover the function g and the irradiances E_i, we try to minimize this function:

$$O = \sum_{p=1}^{P} \sum_{i=1}^{I} \left[g\left(M_{p,i} - \ln E_p - \ln \Delta t_i\right]^2 + \lambda \sum_{m=M_{min}+1}^{M_{max}-1} g''(m)^2, \tag{2.3}$$

where P is the number of pixels, I number of photographs, scalar λ is a smoothness term and M_{min} and M_{max} being minimal and maximal pixel values.

The first term serves to satisfy the set of equations from (2.2) in a least squares sense. The second term ensures that the function g is smooth, here we use $g''(m) = g(m-1) - 2g(m) + g(m+1)$. The smoothness term λ should be chosen according to the expected noise in the photographs.

The equation (2.3) is not perfect though. Constraint that needs to be added is that $g(M_{mid}) = 0$, where $M_{mid} = 0.5(M_{min} + M_{max})$. This constraint establishes a scale factor. Next, we can anticipate the function $g(m)$ to be less smooth around the M_{min} and M_{max} values which could result in worse fitting of the data by the function g.

Because of this we establish a weighting function $w(m)$:

$$w(m) = \begin{cases} m - M_{min}, & m \leq 0.5(M_{min} + M_{max}) \\ M_{max} - m, & m > 0.5(M_{min} + M_{max}) \end{cases}. \tag{2.4}$$

The equation (2.3) now looks like this:

$$O = \sum_{p=1}^{P} \sum_{i=1}^{I} \{w(M_{p,i})[g(M_{i,p}) - \ln E_p - \ln \Delta t_i]\}^2 + \lambda \sum_{m=M_{min+1}}^{M_{max}-1} [w(m)g''(m)]^2. \tag{2.5}$$

The last thing that needs to be addressed is the pixel selection for this algorithm to work properly. Given the computational complexity, it is not advised to use all pixels, but too few pixels could also lead to problems. To ensure sufficiently overdetermined system, this must hold: $P(I-1) > (M_{max} - M_{min})$. Pixels should also be chosen in a way that the pixel values are reasonably evenly distributed from M_{min} to M_{max}.

2.3.3 Examples of Resulting Camera Response Functions

To find the CRFs of our cameras we opted to use the latter algorithm as it is computationally less demanding.

Example of a set of images which were used to calibrate the cameras can be seen in Figure 2.6. The images capture the same scene and the only camera setting that changes throughout the photos is the shutter speed, otherwise f-number and ISO remain the same.

Cameras tested were Flir Blackfly S BFS-U3-19S4M and Panasonic Lumix DMC-GX80. The resulting CRF of the Panasonic camera can be seen in Figure 2.7. – the x axis shows the log exposure (the logarithm is the natural logarithm), the unit exposure was assumed to be for middle pixel value (127), for more detail see [2]; the CRF shows almost symmetrical sigmoidal shape with a reasonably linear middle range and compressed tails.

The result for the Flir camera can be seen in the Figure 2.8, here again is unit exposure assumed to be at pixel value 127; this time the CRF seems to be rather quadratic.

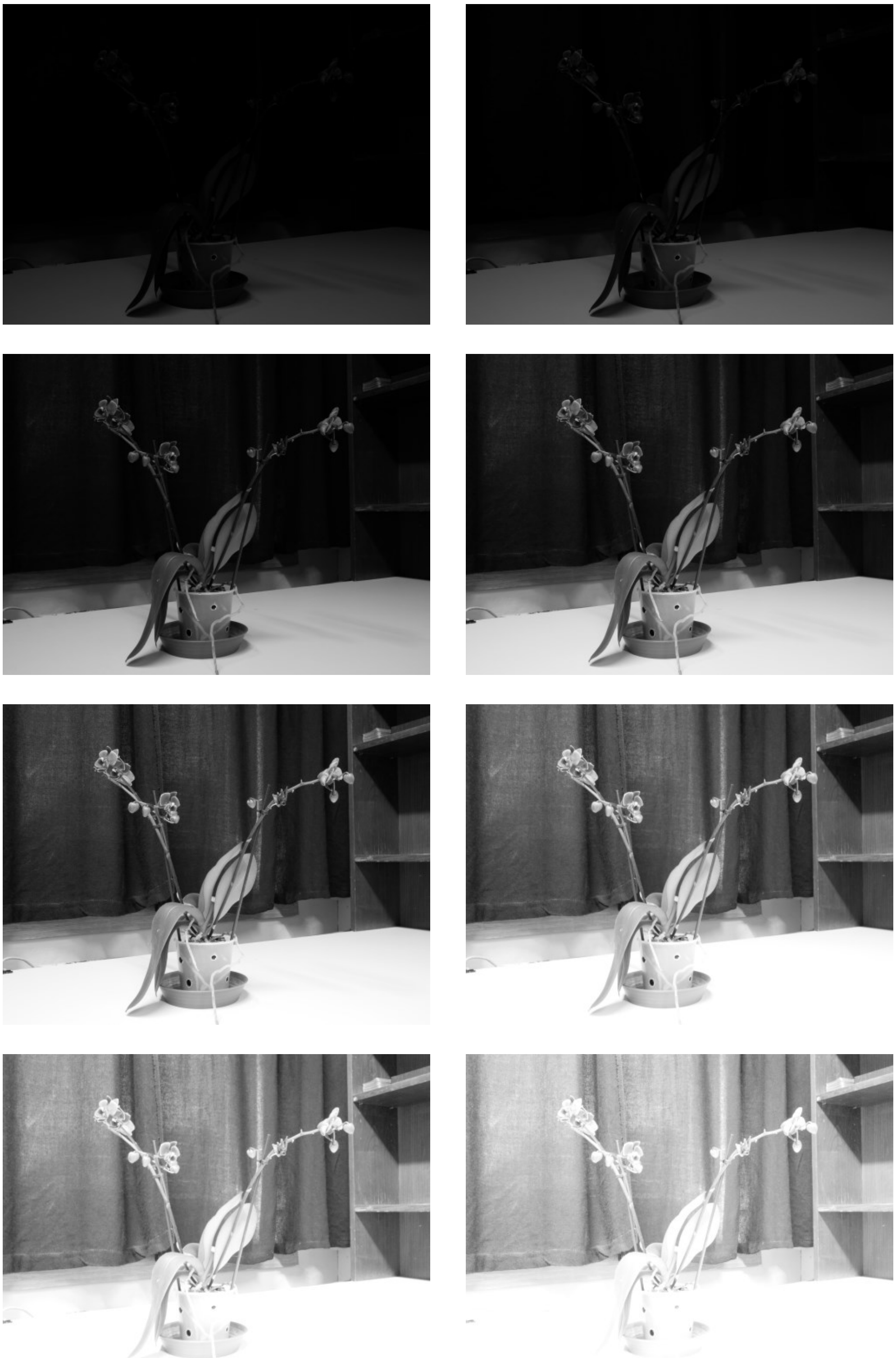

Figure 2.6: Set of images used to find CRF.

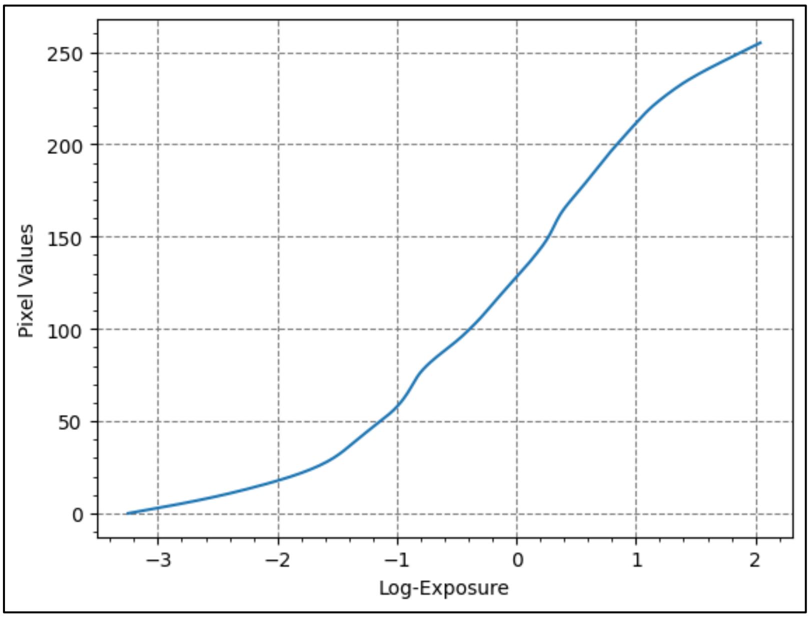

Figure 2.7: Resulting CRF of the Panasonic camera using algorithm by Debevec and Malik [2].

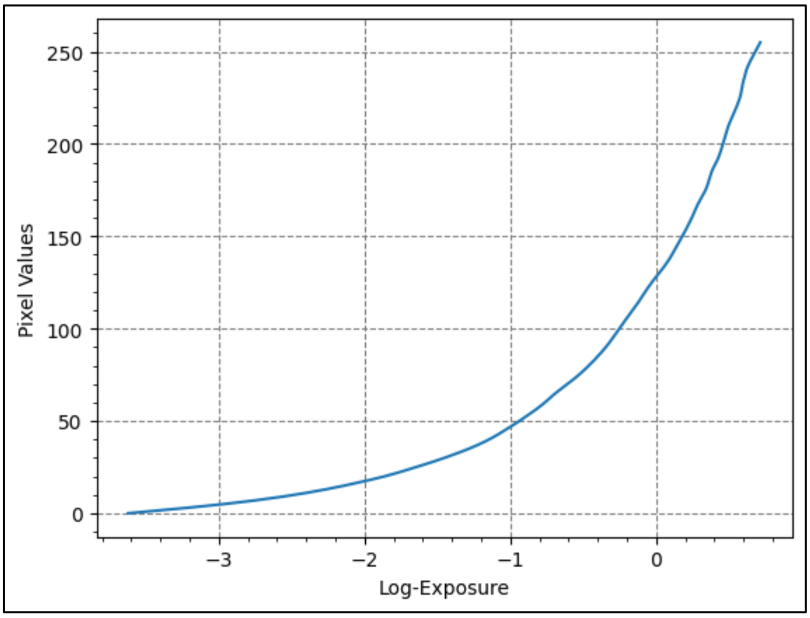

Figure 2.8: Resulting CRF of the Flir camera using algorithm by Debevec and Malik [2].

2.4 Obtaining the Absolute Values

As described previously, the algorithms have one major flaw and that is that the resulting radiant exposure to pixel value mapping is scaled and/or relative. For the purposes of this thesis though we need the absolute values that correspond to individual pixel values.

To do this we take monochromatic photos and take advantage of a built-in reflective light meter in the used camera. But what is a light meter?

2.4.1 Light Meters

Light meters are devices that measure how much light is in the scene that the photographer wants to take a photo of. Light meter tells the photographer how to set their camera so that the final photo has a correct exposure.

There are two kinds of light meters: **reflective light meter** and **incident light meter**. All built-in light meters are reflective light meters and measure how much light is reflected off a subject. There also exist different metering methods such as Evaluative, Center-Weighted, and so on that can be set in a camera. Incident light meters are usually hand-held and measure light which falls on a subject. [11]

Both types of light meters use different equations to calculate proper exposure settings of a camera. Both equations are related to ISO speeds, but reflective light meters are also related to the scene luminance and incident light meters are related to the subject illuminance. The equations are as follows (coming from ISO 2720:1974):

<u>For reflective light meters:</u>

$$\frac{N^2}{t} = \frac{LS}{K},$$

where N is the aperture (f-number), t is the exposure time in seconds, L is the average scene luminance and K is the reflective light meter calibration constant.

<u>For incident light meters:</u>

$$\frac{N^2}{t} = \frac{ES}{C},$$

where the letters have the same meaning except E stands for the subject illuminance and C is the incident light meter calibration constant.

Because we use only the reflective light meter, in the following text we will use only the first equation.

2.4.2 Obtaining Luminance

From the equation for the reflective light meters, we can get luminance as:

$$L = \frac{N^2 K}{tS}. \tag{2.6}$$

To get needed values we use the internal light meter of our camera. While taking a photo we can see something like in Figure 2.9 on our camera screen.

Figure 2.9: Camera settings, a light meter is highlighted, [17].

The thing in the green box is the internal light meter. To obtain the correct exposure "the arrow" must be exactly in the middle. From this, we can easily get the f-number, exposure time and ISO speed for our equation (2.6). A little bit more problematic is how to know the K constant for this is hardly ever mentioned in the camera's hardware specification.

To get the K constant we can take a photo of something of known luminance (for example a computer monitor which maximum brightness is written in its hardware specification – usually around 300-350 nits). After this, K can be easily derived from the light meter equation.

2.4.3 Converting Luminance to Radiance

To get from radiometric values to photometric values a function called **photometric spectral luminous efficiency function $\boldsymbol{V(\lambda)}$** is used. This function gives spectral response to the human eye to various wavelengths of light. [12]

So, to compute luminance from radiance we use following equation:

$$L = K_m \int_{380}^{830} L_{e,\lambda} V(\lambda)\ d\lambda, \tag{2.7}$$

where $L_{e,\lambda}$ is a spectral radiance of wavelength λ and K_m is equal to 683 lm·W^{-1}.

However, we need it the other way around. To do this, we assume the $L_{e,\lambda}$ to be constant L_e. So, the above equation (2.7) becomes:

$$L = K_m \cdot L_e \int_{380}^{830} V(\lambda) d\lambda. \tag{2.8}$$

The definition of $V(\lambda)$ is:

$$V(\lambda) = 1.018 \cdot e^{-285.4(\lambda-0.559)^2}, \tag{2.9}$$

where λ is light wavelength in micrometres.

After evaluating the integral and plugging the value of K_m into equation (2.8), we can express luminance to radiance relationship as:

$$L_e = \frac{L}{683 \cdot 0.1068}. \tag{2.10}$$

Now if we know the average radiance of a scene, we can compute exposure of a pixel having a middle value. If pixel values range from 0 to 255, this value is 127 (the photos are monochromatic).

2.4.4 Computation of the Exposure of a Reference Pixel

Now, computing the exposure H of the average pixel is quite straightforward. First, from the radiance we compute the irradiance and from that we compute the exposure using the exposure time of the photograph.

We obtain the irradiance from:

$$E = L_e \frac{\pi}{4} \left(\frac{d}{f}\right)^2 \cos^4(\alpha), \tag{2.11}$$

where L_e is the radiance, d is the aperture diameter, f is the focal length of the lens and α is an angle between the lens optical axis and the pixel. Since most modern cameras are able to compensate for the vignetting effect at apertures f/8 and smaller we can leave it out of our equation. [2]

Then, exposure H is computed as:

$$H = Et, \tag{2.12}$$

where t is the exposure time.

2.4.5 Recovering the CRF with Absolute Values

Recovery of the CRF function from the Debevec and Malik algorithm is simple. We have the CRF curve but its position on x axis is arbitrary, so we just need to shift this curve. How to shift this curve is determined from previous computations, that is from equations (2.6), (2.10), (2.11), (2.12) – this gives us the exposure of one reference pixel and that is all we need to properly position the function's curve.

Although we decided to use the algorithm by Debevec and Malik or the recovery of the CRF, a method for recovering the absolute values from the second algorithm by Mitsunaga and Nayar is proposed as follows:

We need the reference pixel and the dynamic range of the camera. The dynamic range gives us a proper scale of the function and then we can position the curve according to the exposure of the reference pixel. The exposure of the reference pixel can be obtained again using previous computations. The dynamic range can be found by capturing a photograph of the correct exposure, a reference photo. This photograph has to have a region where the pixel values are around value 1, as well as a region where pixels are around a value 255 (the reason for them not being values 0 and 255 is to avoid regions that are clipped and out of the dynamic range). Then, we take photos that have pixels in these regions around the middle 127 value, one photo for each region type. Now, these photos are a result of a different exposure time. Since we know the exposure at the middle pixel value, we can compute irradiance of these regions and because the irradiance stays the same throughout photos, we can compute exposure for pixel values 1 and 254 as the product of obtained irradiances and the exposure time of the reference photo. The dynamic range is then the difference of the newly acquired exposures.

2.4.6 Test of the Plausibility of the Results

To test how correct the final curves are, we compare them with something of a known value. For example, with a photo of a LED of known radiant flux Φ_{LED}.

Now, we test if the known radiant flux Φ_{LED} and a radiant flux Φ_e from the formula (2.13) are equal.

$$\Phi_e = \sum_{n=1}^{N} \left(\frac{f^{-1}(Z_n)}{\Delta t} A \right) \tag{2.13}$$

Where N is the total number of pixels in the reference photo, f^{-1} is the inverse CRF, Z_n is the n-th pixel value and A is the area of a pixel.

This formula (2.13) comes from:

$$Z_i = f(E_i \cdot \Delta t),$$

where Z_i is the value of i-th pixel and E_i is the corresponding irradiance of this pixel. Then after expressing the irradiance using the radiant flux Φ_e we get:

$$Z_i = f\left(\frac{\partial \Phi_e}{\partial A} \cdot \Delta t\right),$$

where A is the area of a pixel. Assuming the irradiance to be constant over the area of a pixel, we can write:

$$Z_i = f\left(\frac{\Phi_e}{A} \cdot \Delta t\right).$$

From this we can express the inverse function f^{-1}:

$$f^{-1}(Z_i) = \frac{\Phi_e}{A} \cdot \Delta t.$$

And finally, if we sum over all the pixel values, we can express the radiant flux Φ_e using the formula (2.13).

3 Results

In this chapter we present the process of calculating the CRF with absolute values. To obtain the relative CRF the algorithm by Debevec and Malik [2] was used. The camera calibrated was Panasonic Lumix DMC-GX80.

The process of a screen calibration and more information about the dark adaptation is also described.

3.1 Results for the Algorithm by Debevec and Malik

The first thing we had to find out was the reflective light meter calibration constant K of our camera. To do this the camera was directed towards a monitor screen, which was set to the maximum brightness, and which displayed only a white colour. This allowed us to set correct exposure settings of our camera using the internal light meter. This was done on two different screens: a screen of a Lenovo laptop and a screen of AOC Q2778VQE monitor. The results for K came to be ranging from 14.3 to 18.3 (see Table 3.1 and Table 3.2).

Lenovo Screen

Luminance (nit)	F-number	Shutter speed	ISO	K
250	16	1/8	136	**16.6016**
250	5,6	1/60	136	**18.0697**
250	1,7	1/640	136	**18.3824**

Table 3.1: K obtained measuring a Lenovo laptop screen.

AOC Q2778VQE monitor screen

Luminance (nit)	**F-number**	**Shutter speed**	**ISO**	**K**
350	16	1/13	136	**14.3029**
350	5,6	1/100	136	**15.1786**
350	1,7	1/1000	136	**16.4706**

Table 3.2: K obtained measuring AOC Q2778VQE monitor screen.

Averaging the obtained values of K we get $K = 16.5$.

The next step was to obtain the luminance. After taking a photograph with the correct exposure, we got luminance from (2.6). Example of such photograph can be seen in Figure 3.1. Settings of the camera while taking this image were ISO200, f/16 and shutter speed 1/125 s. Because the manufacture ISO200 is actually ISO136, the resulting luminance was 3882.3529 cd·m^{-2}.

Figure 3.1: Example of a photo with correct exposure.

Now using (2.10) to convert the luminance to radiance, we got the radiance to be 53.2234 W·m^{-2}·sr^{-1}.

From here we could easily get the final exposure using (2.11) and (2.12). The final exposure was then calculated to be 1.30624×10^{-3} J·m^{-2}. This exposure corresponds to the middle pixel value, that is the pixel value of 127.

Now that we the exposure of one reference pixel we can adjust the function curve as described in previous chapter. Result of this operation can be seen in Figure 3.2, where is the final CRF with absolute values. Here the pixel value 127 corresponds to log exposure -6.6406; the log exposure, where the logarithm is the natural logarithm, was converted to absolute exposure. The camera setting needed to obtain this function is (manufacture) ISO200.

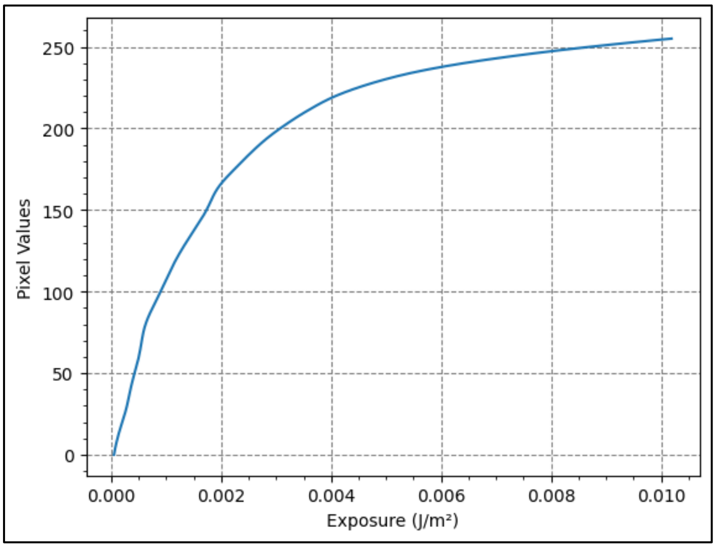

Figure 3.2: CRF of Panasonic camera set to ISO200, now with absolute exposure.

To demonstrate how to use this function to convert between a pixel value and its radiance let's assume an example where a photo was captured with (manufacture) ISO200, f/5.6, a shutter speed 1/250 s and a pixel with value 154 was selected.

From the obtained CRF we get the exposure of the pixel to be 1.792×10^{-3}. Then we get the irradiance E using this formula:

$$E = \frac{H}{t},$$

where H is the exposure and t is the shutter speed. The irradiance from this example then is 0.448 $\mathrm{W\cdot m^{-2}}$. And finally, we get the radiance L_e as:

$$L_e = \frac{E}{\frac{\pi}{4}\cdot\left(\frac{d}{f}\right)^2},$$

where d is the diameter of the aperture and f is the focal length of the lens used. The diameter is computed as the focal length divided by the f-number. So, we have $f = 0.02$ m and $d = 3.571\times10^{-3}$ m. The final radiance is then 17.892 $\mathrm{W\cdot sr^{-1}\cdot m^{-2}}$.

Now, to test the plausibility of the final CRF, we test it on photographs of a turned-on LED (see Figure 3.3) using the formula (2.13). As we can see in the photos, some areas are purely black or purely white. This is because of the small dynamic range of the camera. For this reason, values that were in the extremes (0 or 255) were not used to compute the radiant flux. The calculated radiant flux Φ is 1.1 mW, where the actual radiant flux from the LED's datasheet [13] is 5 mW.

This can be explained by the fact that not all light was captured by the camera – the LED was very bright so some values got clipped because they were out of the dynamic range of the camera, also some stray light did not arrive to the sensor at all.

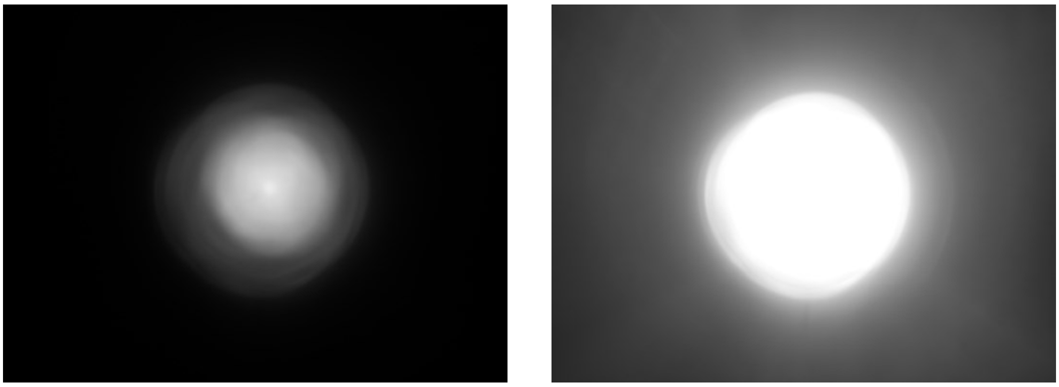

Figure 3.3: Photos with different shutter speeds of a turned-on LED of known radiant flux used to test the resulting CRF.

3.2 Calibration of a Screen for the Dark Adaptation Measurement

Now that we have a function which gives us the mapping of pixel values to the absolute radiance values, we can calibrate our monitor for purposes of an experimental dark adaptation measurement via a desktop application.

But before that, let's take a closer look at the process of dark adaptation and with that a brief look at our visual system.

3.2.1 Human Visual System and Visual Adaptation

The human visual system (HVS) consists of the eyes, the pathways connecting the visual cortex, and other parts of the brain. What is of the most importance for us now are the eyes as here happens the mechanism behind the dark-light adaptation.

Basic Anatomy of the human eye

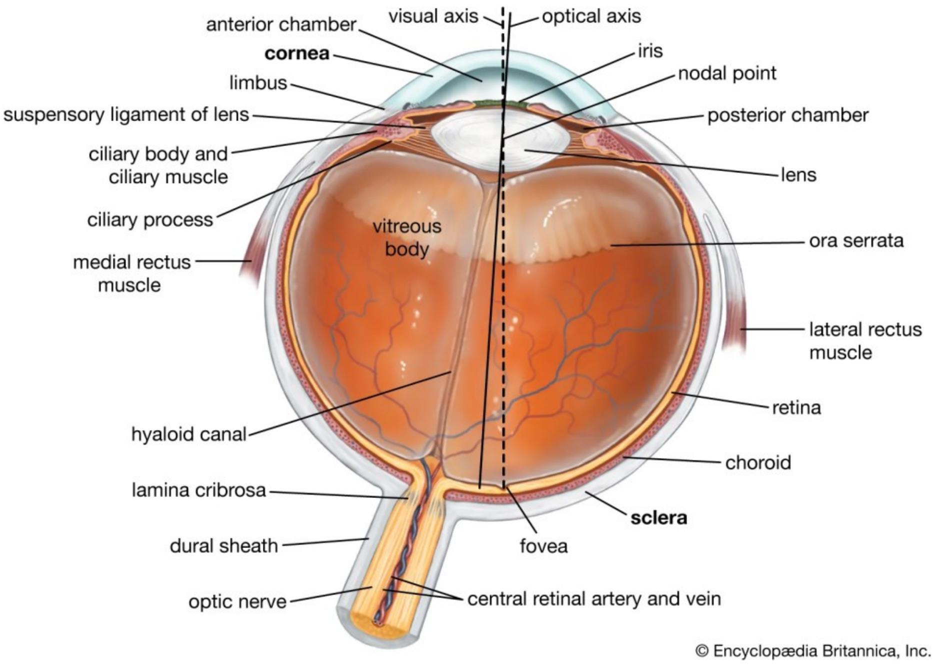

Figure 3.4: Cross section of the human eye, [18].

The eyeball sits in a bony structure called the orbit; here it is surrounded by extraocular muscles, fascia, fat, blood vessels and the lacrimal gland [14]. The adult eyeball, or the globe, is approximately 2.4 cm in diameter and consists of [3, 15]:

- **Three layers:**
  1. The external layer, formed by *sclera* and *cornea*.
  2. The intermediate layer, where *iris*, *ciliary body* and *choroid* can be found.
  3. The internal layer with the ***retina***.
- **Three chambers of fluid** (*anterior chamber*, *posterior chamber*, *vitreous chamber*)
- **Lens**

The Iris

The iris is a coloured circular muscle controlling the size of the pupil and as such controls the amount of light that enters the eye. The iris and the pupil are covered by the cornea. The cornea is transparent and of convex shape with optical power of 40 D (relaxed eye has approximately optical power of 60 D), this is caused by high refractive index of the cornea [3, 15].

Even though the iris controls the amount of light entering the eye, the pupil size change (from 2 mm in bright light to 8 mm in a dark) contributes only a factor of 16 to the light intensity reduction. This amount is in a range of about 10 billion to 1 insignificant and in the context of visual adaptation can be ignored. [16]

The Retina

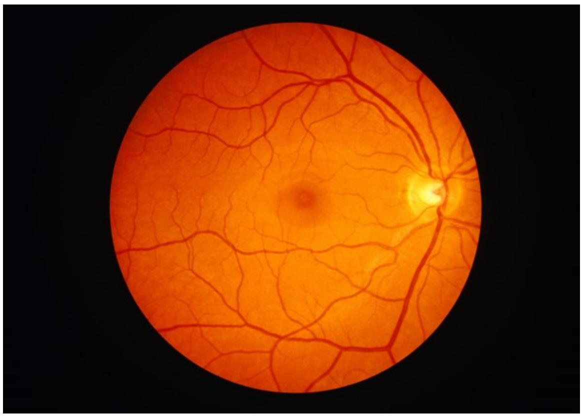

Figure 3.5: Photograph of the retina, [19].

The retina is a multilayered sensory tissue onto which light incoming to the light is focused [15]. In the above photo (Figure 3.5) of a healthy retina, we can observe the optic disc, also called the blind spot. It is because here the optic nerve meets the globe and as such no photoreceptors are present. From optic nerve also radiate major blood vessels that supply the retina with blood [3, 14, 15]. Approximately 17 degrees to the left from the optic disc we can see an avascular red spot, the fovea, the centre of the macula lutea. The surrounding area of 6 mm around the fovea is called the central retina and beyond that stretches up to the ora serrata the peripheral retina [3].

The retina consists of 10 distinct layers [15]. The ganglion cells lie innermost, and photoreceptors lie outermost against the retinal pigment epithelium (the RPE) and choroid [3]. The photoreceptors are of two kinds – the cones and the rods.

From the rod-dominant peripheral retina to the cone-dominated central retina the retina gets thicker as the density of photoreceptors increases. After that however the inner layers get shifted aside and a small depression is formed, the fovea [3, 15].

The fovea is the region of maximal visual acuity. The centre of the fovea, the foveola (or foveal pit) consists of only the cones, it is also here where the cones are concentrated at maximum density [3, 15].

Cones are photoreceptors responsible for acute and colour vision and **rods** are responsible for vision in a dim light and for the wide field of vision. In each human eye there are 6.3–6.8 million cones and 110-125 million rods [14, 15]. Both rods and cones play important roles in the dark-light adaptation.

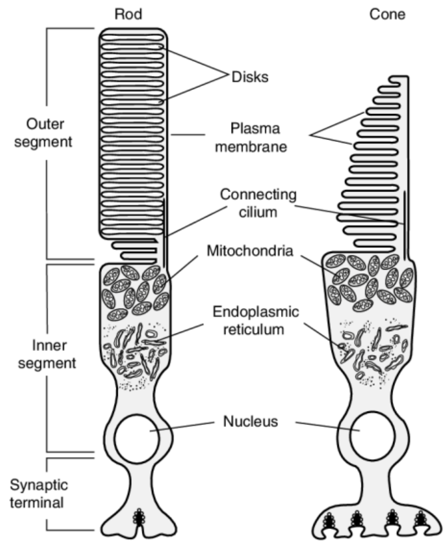

Figure 3.6: Rod and cone cells diagram, [20].

Also important for the dark-light adaptation process is the RPE as it regulates and recycles photopigments of the eye. Another very important function of the RPE is that it reduces light scattering by absorbing light that was not absorbed by the photoreceptors. [14, 15]

Light and Dark Adaptation

According to the luminance levels the vision is mediated by cones (*photopic vision*), rods (*scotopic vision*), or by both at the same time (*mesopic vision*) [3, 16]. This duplexity nature of our visual system can be seen in the threshold-versus-intensity (TVI) plot (see Figure 3.7). The first part shows the threshold for rods. In lower intensities – in the *scotopic range* – the rods are more sensitive and have lower thresholds, as the intensity increases the sensitivity of the rods becomes lower until they are completely saturated. Before that, the intensity gets into *photopic range* and cons become dominant in mediating vision. [16]

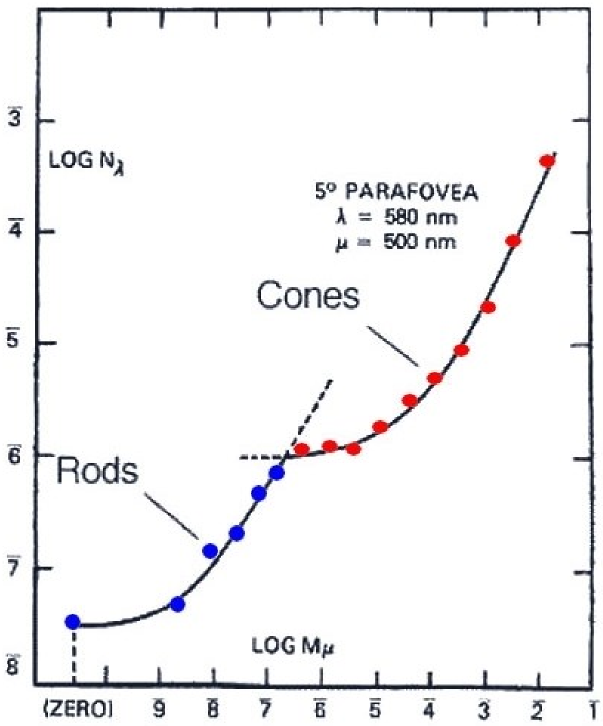

Figure 3.7: TVI plot, N_λ is the increment threshold and M_μ is the background luminance, [21].

This ranges are still very large in a sense of visual adaptation. This means that other mechanisms are at play.

When a photoreceptor absorbs light through photochemical reactions, their photopigments break down, which makes the photoreceptor insensitive until the photopigment is regenerated. This process is also called “bleaching”. In a case of rods, their photopigments are completely depleted when exposed to intensities above *mesopic range*. On the other hand, cone photopigments are not significantly reduced even after exposing them to a bright light. This does not however correlate with the lowering of sensitivity of cones as seen in the TVI plot [16].

What plays very important role in visual adaptation is *photoreceptor adaptation*. That is for example, when a dark-adapted photoreceptor gets exposed to a bright light it gets saturated and loses sensitivity to any additional light intensity. This does not last long, as the visual system adapts to a new background intensity [16].

Factors Affecting Dark Adaptation

When measuring dark adaptation, it is good to know factors that may affect the results. These factors are [3]:

- **Intensity and duration of pre-adapting light**

  Increasing the luminance will result in prolonged cone branch. The absolute threshold will also take longer to reach.

  Shorter exposure to pre-adapting light may result on obtaining only one rod branch. To get both cone and rod branches, the exposure to pre-adapting light must be longer (for example 5 minutes).

- **Wavelength distribution of the light**

  Because rod and cones are similarly sensitive to light of long wavelengths, the rod-cone break cannot be observed when using a bright red light for example. When using light of short wavelengths, however, the rod-cone break will be the most prominent as the rode are more sensitive to this type of light than the cones are.

Now that we understand the process of dark adaptation a little deeper and that we know what factors affect the adaptation, we can start the calibration of the screen.

3.2.2 Screen Calibration

From the previous section we know that the adaptation curve is affected by the wavelength of the light. After appropriate colour is chosen (for example blue), a test spot is displayed on a screen. Our goal is to measure how much radiance this test spot produces. To measure it, we take a monochromatic photo of the test spot of the colour we want to know the radiance of (as an example see Figure 3.8).

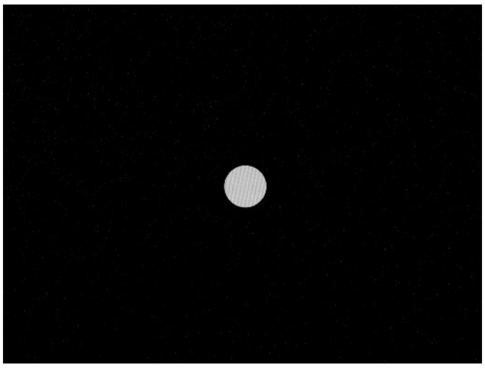

Figure 3.8: Monochromatic photograph of a test spot on a screen for its radiance value computation.

From the photo we can take a pixel value that corresponds to the test spot and find its exposure value from the CRF function. Then we can convert the exposure to radiance by first obtaining the irradiance and from that we get to the desired radiance L_e:

$$E = \frac{H}{t}$$

$$L_e = \frac{E}{\frac{\pi}{4} \cdot \left(\frac{d}{f}\right)^2}$$

Please note that if a f-number larger than 8 is used a factor of $\cos^4(\alpha)$ should be taken into consideration, especially if one would like to know a radiance of a pixel that lies closer to the edges of the photo as this is where the light fall-off (or vignetting) takes the greatest affect.

We do this computation process for the brightest test spot value, darkest test spot value and some intermediate values because it would be highly impractical to do this computation of what can be hundreds of photos.

4 Conclusion

The main goal of this thesis was to obtain the absolute scene radiance values using only a digital camera. To achieve this, the CRF of the digital camera used had to be found. This was done successfully using the algorithm by Debevec and Malik [2]. Next step was to obtain the absolute values from this algorithm as its initial results were relative. This was done using the internal light meter in the camera – using the formulas established in ISO 2720:1974 it is possible to correlate exposure settings of a camera to the captured scene luminance. Using this, we obtained a reference value for exposure which then was used to get from relative values to absolute values. The final results for the camera Panasonic Lumix DMC-GX80 were presented and tested on photographs of a LED of known radiant flux.

Another topic that this thesis was about, was using the measured radiance values for a calibration of a screen for purposes of experimental dark adaptation measurements. The screen calibration process was described. Because of the limitations of the current study, the usage of this process for exact measurements that could be used, for example in the medical field, is yet to be studied.

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6 List of Figures

7 List of Tables

8 List of Abbreviations

AMD	Age-related Macular Degeneration
CRF	Camera Response Function
DA	Dark Adaptation
HVS	Human Visual System
RPE	Retinal Pigment Epithelium
TVI	Threshold-Versus-Intensity
VR	Virtual Reality