

# Diffraction Shader

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# 1 Introduction

WIKI : [http://en.wikipedia.org/wiki/Electromagnetic\\_radiation](http://en.wikipedia.org/wiki/Electromagnetic_radiation)

Electromagnetic radiation (EM radiation or EMR) is one of the fundamental phenomena of electromagnetism, behaving as waves propagating through space, and also as photon particles traveling through space, carrying radiant energy.

EMR is characterized by the frequency or wavelength of its wave. The electromagnetic spectrum, in order of increasing frequency and decreasing wavelength, consists of radio waves, microwaves, infrared radiation, visible light, ultraviolet radiation, X-rays and gamma rays.

The eyes of various organisms sense a somewhat variable but relatively small range of frequencies of EMR called the visible spectrum or light. Higher frequencies correspond to proportionately more energy carried by each photon; for instance, a single gamma ray photon carries far more energy than a single photon of visible light.

EMR carries energy—sometimes called radiant energy—through space continuously away from the source

In general, EM radiation (the designation '*radiation*' excludes static electric and magnetic and near fields) is classified by wavelength into radio, microwave, infrared, the visible spectrum we perceive as visible light, ultraviolet, X-rays, and gamma rays. Arbitrary electromagnetic waves can always be expressed by Fourier analysis in terms of sinusoidal monochromatic waves, which in turn can each be classified into these regions of the EMR spectrum.

The behavior of EM radiation depends on its frequency. Lower frequencies have longer wavelengths, and higher frequencies have shorter wavelengths, and are associated with photons of higher energy. There is no fundamental limit known to these wavelengths or energies, at either end of the spectrum, although photons with energies near the Planck energy or exceeding it (far too high to have ever been observed) will require new physical theories to describe.

WIKI : [http://en.wikipedia.org/wiki/Radiant\\_energy](http://en.wikipedia.org/wiki/Radiant_energy) Radiant energy is the energy of electromagnetic waves.[1] The quantity of radiant energy may be calculated by integrating radiant flux (or power) with respect to time and, like all forms of energy, its SI unit is the joule. The term is used particularly when radiation is emitted by a source into the surrounding environment. Radiant energy may be visible or invisible to the human eye.

The term "*radiantenergy*" is most commonly used in the fields of radio-

metry, solar energy, heating and lighting,

WIKI : [http : //en.wikipedia.org/wiki/Radiance](http://en.wikipedia.org/wiki/Radiance) Radiance and spectral radiance are measures of the quantity of radiation that passes through or is emitted from a surface and falls within a given solid angle in a specified direction. They are used in radiometry to characterize diffuse emission and reflection of electromagnetic radiation. In astrophysics, radiance is also used to quantify emission of neutrinos and other particles. The SI unit of radiance is watts per steradian per square metre ( $\text{W} \cdot \text{sr}^{-1} \cdot \text{m}^{-2}$ ), while that of spectral radiance is  $\text{W} \cdot \text{sr}^{-1} \cdot \text{m}^{-2} \cdot \text{Hz}^{-1}$  or  $\text{W} \cdot \text{sr}^{-1} \cdot \text{m}^{-3}$  depending on whether the spectrum is a function of frequency or of wavelength.

Radiance characterizes total emission or reflection. Radiance is useful because it indicates how much of the power emitted by an emitting or reflecting surface will be received by an optical system looking at the surface from some angle of view. In this case, the solid angle of interest is the solid angle subtended by the optical system's entrance pupil. Since the eye is an optical system, radiance and its cousin luminance are good indicators of how bright an object will appear. For this reason, radiance and luminance are both sometimes called "*brightness*". This usage is now discouraged – see Brightness for a discussion. The nonstandard usage of "*brightness*" for "*radiance*" persists in some fields, notably laser physics

$$\text{Def } L = \frac{d^2\Phi}{dA d\Omega \cos(\theta)} \approx \frac{\Phi}{\Omega A \cos(\theta)}$$

## 1.1 Motivation

effect of diffraction, stam, genf, rendering snake skin

Introducation bla In phicss/bioligy

The purpose of this thesis is to render realtime the effect of diffraction on different snakes skins in a photorealistic manor. In oder to achieve this purpose we will rely J. Stam's formulation of a BRDF which basically describes the effect of diffraction on a given surface assuming one knows the hightfield on this surface. In our case, those heightfields are small patches of the nanostructure of the snake skin provided by GENEVA taken by MIKROSKOP. In his Paper, J. Stam assuming distribution on his heightfields whereas we require a an explicit provided hightfield of the surface or at least a small patch. Therefore, this work can be considered as an extension of J. Stam's derivations for the case one is provided by a explicit height field on a quasiperiodic structure. Since one goal of this work is to render in realtime,

we have to perform also precomputations which will require us to slightly modify Stam's main derivation.

Explain that this thesis has deep theoretical background, some derivations show derivation roadmap

## 1.2 Stams derivation

In his Paper Diffraction Shader, Jos Stam derives a BRDF which modeling the effect of diffraction for various analytical anisotropic refraction models using the scalar Kirchhoff theory and the theory of random processes. By employing the so called wave theory of diffraction [source 5 in stams paper] in which a wave is assumed to be a complex valued scalar. It's noteworthy, that Stam's BRDF formulation does not take into account the polarization of the light. Nevertheless, light sources like sunlight and light bulbs are unpolarized. In our simulations we will always assume we have given a directional light source, i.e. sunlight. Hence, we can use Stam's model for our derivations

A further assumption in Stam's Paper is, the emanated waves from the source are stationary - sunlight once again. Which implies the wave is a superposition of independent monochromatic waves. This implies that each wave is associated to a definite wavelength  $\lambda$ .

Mention Helmholtz equation, which has the solution  $k = \frac{2\pi}{\lambda}$  which is the wavenumber

Stam starts his derivations by above's assumptions and by applying the Kirchhoff integral, which describes the reflected field and the Huygen's principle, which states, when somebody knows the wavefront at a given moment, the wave at a later time can be deduced by considering each point on the first wave as the source of a new disturbance.

$$\psi_2 = \frac{ike^{iKR}}{4\pi R} (F\mathbf{v} - \mathbf{p}) \cdot \int_S \hat{\mathbf{n}} e^{ik\mathbf{v}\cdot\mathbf{s}} d\mathbf{s} \quad (1)$$

In optics, when dealing with scattered waves, one does use differential scattering cross-section rather than a BRDF which has the following identity:

$$\sigma^0 = 4\pi \lim_{R \rightarrow \infty} R^2 \frac{\langle |\psi_2|^2 \rangle}{\langle |\psi_1|^2 \rangle} \quad (2)$$

Relationship between the BRDF and the scattering cross section is the following:

$$BRDF = \frac{1}{4\pi} \frac{1}{A} \frac{\sigma^0}{\cos(\theta_1)\cos(\theta_2)} \quad (3)$$

Whereas  $\theta_1$  and  $\theta_2$  are the angles that the vectors  $\hat{\mathbf{k}}_1$  and  $\hat{\mathbf{k}}_2$  make with the vertical direction.

ADD FIGURE for  $\mathbf{k}_1, \mathbf{k}_2$

where  $R$  is the distance from the center of the patch to the receiving point  $\mathbf{x}_p$ ,  $\hat{\mathbf{n}}$  is the normal of the surface at  $\mathbf{s}$  and the vectors:

$$\mathbf{v} = \hat{\mathbf{k}}_1 - \mathbf{k}_1 = (u, v, w)$$

$$\mathbf{p} = \hat{\mathbf{k}}_1 + \hat{\mathbf{k}}_1$$

During his derivations, Stam provides a analytical representation for the Kirchhoff integral by using his assumptions. He restricts himself to the reflection of waves from height fields  $h(x, y)$  with the assumption that the surface is defined as an elevation over the  $(x, y)$  plane using the surface plane approximation. Which will lead him to the following identity for the Kirchhoff integral

$$\mathbf{I}(ku, kv) = \int \int \frac{1}{ikw} (-p_x, -p_y, ikwp) \quad (4)$$

whereas

$$p(x, y) = e^{ikwh(x, y)} \quad (5)$$

We observe that the integral is a Fourier transform by  $-iku$  and  $-ikv$  which will lead us to his final derivation, using the identity of BRDF, and computing the limits:

$$BRDF = \frac{k^2 F^2 G}{4\pi^2 A w^2} \langle |P(ku, kv)|^2 \rangle \quad (6)$$

Where

$$G = \frac{(1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{\cos(\theta_1)\cos(\theta_2)} \quad (7)$$

and  $P(x,y)$  is the Fourier transform of the function  $p(x,y)$  from above.  
This identity for the BRDF is the starting point for our derivations.

### **1.3 Related Work**

see paper listing

### **1.4 Thesis Outline**

describe what is which chapter



## 2 Theoretical Background

### 2.1 Definitions

#### 2.1.1 Signal

A signal is a function that conveys information about the behavior or attributes of some phenomenon. In the physical world, any quantity exhibiting variation in time or variation in space (such as an image) is potentially a signal that might provide information on the status of a physical system, or convey a message between observers

#### 2.1.2 Fourier Transformation

The Fourier-Transform is a mathematical tool which allows to transform a given function or rather a given signal from defined over a time- (or spatial-) domain into its corresponding frequency-domain.

Let  $f$  an measurable function over  $\mathcal{R}^n$ . Then, the continuous Fourier Transformation, denoted as FT,  $\mathcal{F}\{t\}$  of  $f$  is defined as, ignoring all constant factors in the formula:

$$\mathcal{F}\{w\}_{FT} = \int_{\mathcal{R}^n} f(x) e^{-iwt} dt \quad (8)$$

whereas its inverse transform is defined like the following which allows us to obtain back the original signal:

$$\mathcal{F}\{w\}_{FT}^{-1} = \int_{\mathcal{R}^n} \mathcal{F}\{w\} e^{iwt} dt \quad (9)$$

By using fourier analysis, which is the approach to approximate any function by sums of simpler trigonometric functions, we gain the so called discrete time fourier transform (in short DTFT). The DTFT operates on a discrete function. Usually, such an input function is often created by diitally sampling a continius function. The DTFT itself is operation on a discretized signal on a continious, periodic frequency domain and looks like the following:

$$\mathcal{F}\{w\}_{DFT} = \sum_{-\infty}^{\infty} f(x) e^{(-iwk)} \quad (10)$$

we can further discretize the frequency domain and will get then the discrete fourier transformation (in short DFT) of the input signal:

$$\mathcal{F}\{w\}_{DFT} = \sum_{n=0}^{N-1} f(x)e^{(-i\omega_n k)} \quad (11)$$

Where the angular frequency  $\omega_n$  is defined like the following  $\omega_n = \frac{2\pi n}{N}$  and  $N$  is the number of samples within an equidistant periode sampling.

### 2.1.3 Convolution

$$(f * g)(t) = \int_{\mathcal{R}^n} f(t)g(t - x)dx \quad (12)$$

Note that the Fourier transform of the convolution of two functions is the product of their Fourier transforms. This is equivalent to the fact that Convolution in spatial domain is equivalent to multiplication in frequency domain. Therefore, the inverse Fourier transform of the product of two Fourier transforms is the convolution of the two inverse Fourier transforms

### 2.1.4 BRDF

The bidirectional reflectance distribution function, in short BRDF, denoted as  $f_r(\omega_i, \omega_r)$  is a four dimensional function that defines how light is reflected at an opaque surface. The function takes a negative incoming light direction,  $\omega_i$ , and outgoing direction,  $\omega_r$ , both defined with respect to the surface normal  $\mathbf{n}$  and returns the ratio of reflected radiance exiting along  $\omega_r$  to the irradiance incident on the surface from direction  $\omega_i$

$$f_r(\omega_i, \omega_r) = \frac{dL_r(\omega_r)}{dE_i(\omega_i)} \quad (13)$$

$$= \frac{dL_r(\omega_r)}{L_i(\omega_i)\cos(\theta_i)dw_i} \quad (14)$$

where  $L$  is radiance, or power per unit solid-angle-in-the-direction-of-a-ray per unit projected-area-perpendicular-to-the-ray,  $E$  is irradiance, or power per unit surface area, and  $\theta_i$  is the angle between  $\omega_i$  and the surface normal,  $\mathbf{n}$ . The index  $i$  indicates incident light, whereas the index  $r$  indicates reflected light.

The reason the function is defined as a quotient of two differentials and not directly as a quotient between the undifferentiated quantities, is because other irradiating light than  $\mathrm{d} E_i(\omega_i)$ , which are of no interest for  $f_r(\omega_i, \omega_r)$ , might illuminate the surface which would unintentionally affect  $L_r(\omega_r)$ , whereas  $\mathrm{d} L_r(\omega_r)$  is only affected by  $\mathrm{d} E_i(\omega_i)$ .

### 2.1.5 Taylor Series

Taylor series is a representation of a function as an infinite sum of terms that are calculated from the values of the function's derivatives at a single point.

The Taylor series of a real or complex-valued function  $f(x)$  that is infinitely differentiable at a real or complex number  $a$  is the power series:

$$\mathcal{T}(f; a)(x) = \sum_{n=0}^{\infty} \frac{f^n(a)}{n!} (x - a)^n \quad (15)$$

### 2.1.6 The Effect Of Diffraction

+ mention fraunhofer diffraction, fresnel diffraction?

### 2.1.7 BRDF - Spectral Rendering

In Computer Graphics, spectral rendering is where a scene's light transport is modeled considering the whole span of wavelengths instead of R,G,B values (still relating on geometric optic, which ignore wave phase). The motivation is that real colors of the physical world are spectrum; trichromatic colors are only inherent to Human Visual System.

## 2.2 Derivations

### 2.2.1 Taylor Series Approximation

Based on J. Stam's Paper about Diffraction shaders we will show that there is an approximation of his equation (5),  $\mathbf{p}(\mathbf{x}, \mathbf{y})$ , for a explicitly given heightfield  $\mathbf{h}(\mathbf{x}, \mathbf{y})$ . This approximation is achieved by using Taylor-Series and using this identity we will further be able to approximate the Fourier-Transformation of  $\mathbf{p}(\mathbf{x}, \mathbf{y})$ , denoted as  $\mathbf{P}(\mathbf{u}, \mathbf{v})$ . Finally we will give an error bound for this approximation.

### 2.2.2 Taylor Series of p

Given  $p(x, y) = e^{ikwh(x, y)}$  from Stam's Paper where  $h(x, y)$  is here a given heightfield. Also given the definition  $e^y = 1 + y + \frac{y^2}{2!} + \frac{y^3}{3!} + \dots = \sum_{n=0}^{\infty} \frac{y^n}{n!}$  where  $y$  can be real or even complex valued - note this identity can either be derived by power series or by Taylor-Series (using the derivatives of the exp-function and developing the Taylor-Series around the point  $a=0$ ). Let us now set  $y = ikwh(x, y)$  where  $i$  is the imaginary number. For simplification, let us denote  $h(x, y)$  as  $h$ . It follows by our previous stated identities:  $e^y = 1 + (ikwh) + \frac{1}{2!}(ikwh)^2 + \frac{1}{3!}(ikwh)^3 + \dots = \sum_{n=0}^{\infty} \frac{(ikwh)^n}{n!}$ . Hence it holds  $p(x, y) = \sum_{n=0}^{\infty} \frac{(ikwh(x, y))^n}{n!}$ .

### 2.2.3 Fourier Transformation of function p

Let us now compute the Fourier Transformation of  $p(x, y)$  from above:  $\mathcal{F}\{p\}(u, v) = \mathcal{F}\left\{\sum_{n=0}^{\infty} \frac{(ikwh(x, y))^n}{n!}\right\} = \mathcal{F} \text{ lin Operator } \sum_{n=0}^{\infty} \mathcal{F}\left\{\frac{(ikwh(x, y))^n}{n!}\right\} = \sum_{n=0}^{\infty} \frac{(ikwh)^n}{n!} \mathcal{F}\{h(x, y)^n\}$ .

Hence it follows:  $P(\alpha, \beta) = \sum_{n=0}^{\infty} \frac{(ikwh)^n}{n!} \mathcal{F}\{h^n\}(\alpha, \beta)$ .

**NB:**  $\mathcal{F}\{h^n\}(u, v)$  denotes the two dimensional Fourier Transformation of  $p(x, y)$  and can be numerically computed by the two dimensional **DFT** or rather by the two dimensional **FFT** over  $h(x, y)$ .

### 2.2.4 Approximation of function P

Next we are going to look for an  $N \in \mathbb{N}$  s.t.  $\sum_{n=0}^N \frac{(ikwh)^n}{n!} \mathcal{F}\{h^n\}(\alpha, \beta) \approx P(\alpha, \beta)$ . is a good approximation. We have to prove two things:

1. Show that there exist such an  $N \in \mathbb{N}$  s.t the approximation holds true.
2. Find a value for  $B$  s.t. this approximation is below a certain error bound, for example machine precision  $\epsilon$ .

### 2.2.5 Proof Sketch of 1.

By the **ratio test** (see [1]) we can show that the series  $\sum_{n=0}^N \frac{(ikwh)^n}{n!} \mathcal{F}\{h^n\}(\alpha, \beta)$  converges absolutely:

**Proof:** Consider  $\sum_{k=0}^{\infty} \frac{y^k}{k!}$  where  $a_k = \frac{y^k}{k!}$ . By the definition of the ratio test for series it follows:  $\forall y : \limsup_{k \rightarrow \infty} \left| \frac{a_{k+1}}{a_k} \right| = \limsup_{k \rightarrow \infty} \frac{y}{k+1} = 0$

Thus this series converges absolutely, no matter what value we will pick for  $y$ .

### 2.2.6 Part 2: Find such an $N$

Let  $f(x) = e^x$ . We can formulate its Taylor-Series, stated above. Let  $P_n(x)$  denote the  $n$ -th Taylor-Polynomial,  $P_n(x) = \sum_{k=0}^n \frac{f^{(k)}(a)}{k!} (x - a)^k$ , where  $a$  is our developing point (here, in this case  $a=0$ ). We can define the error of the  $n$ -th Taylor-Polynomial to be  $E_n(x) = f(x) - P_n(x)$ . That error is the actual value minus the Taylor polynomial. It holds true:  $|E_n(x)| = |f(x) - P_n(x)|$ . By using the Lagrangian Error Bound - (see source [2]) it follows:  $|E_n(x)| \leq \frac{M}{(n+1)!} |x - a|^{n+1}$  with  $a=0$ , where  $M$  is some value satisfying  $|f^{(n+1)}(x)| \leq M$  on the interval  $I = [a, x]$ . Since we are interested in an upper bound of the error and since  $a$  is known, we can reformulate the interval as  $I = [0, x_{max}]$ , where  $x_{max} = |i| * k_{max} * w_{max} * h_{max}$ , since we are interested in computing an error bound for  $e^{ikwh(x,y)}$ . From Stam's Paper about diffraction shader we know some parameters for the length, width and height for a given sample patch, i.e. heightfield  $h(x,y)$  and when using those parameters are able to find an explicit number for  $x_{max}$ .

Facts we are using from Stam's Paper:

- Height of bump: 0.15micro meters
- Width of a bump: 0.5micro meters
- Length of a bump: 1micro meters
- $k = \frac{2\pi}{\lambda}$  is the wavenumber and  $\lambda \in [\lambda_{min}, \lambda_{max}]$  its wavelength hence  $k_{max} = \frac{2\pi}{\lambda_{min}}$
- $w$  is a component of the vector  $\vec{v} = \vec{k}_1 - \vec{k}_2 = (u, v, w)$ , where  $\vec{k}_1$  and  $\vec{k}_2$  are **normalized** direction vectors and this each component can have a value in range  $[-2, 2]$ .
- for simplification, assume  $[\lambda_{min}, \lambda_{max}] = [400nm, 700nm]$ .

Hence  $x_{max} = |i| * k_{max} * w_{max} * h_{max} = k_{max} * w_{max} * h_{max} = 2 * (\frac{2\pi}{4 * 10^{-7}m}) * 1.5 * 10^{-7} = 1.5\pi$  and it follows for our interval  $I = [0, 1.5\pi]$ . Next we are going to find the value for  $M$ . Since the exponential function is monoton growing

(on the interval I) and the derivative of the **exp** function is the exp function itself, we can find such an M:  $M = e^{x_{max}} = \exp(1.5\pi)$  and  $|f^{(n+1)}(x)| \leq M$  holds. With  $|E_n(x_{max})| \leq \frac{M}{(n+1)!} |x_{max} - a|^{n+1} = \frac{\exp(1.5\pi) * (1.5\pi)^{n+1}}{(n+1)!}$  we now can find a value of n for a given bound, i.e. we can find an value of  $N \in \mathbb{N}$  s.t.  $\frac{\exp(1.5\pi) * (1.5\pi)^{N+1}}{(N+1)!} \leq \epsilon$ . With Octave/Matlab we can see:

- if  $N=20$  then  $\epsilon \approx 2.9950 * 10^{-4}$
- if  $N=25$  then  $\epsilon \approx 8.8150 * 10^{-8}$
- if  $N=30$  then  $\epsilon \approx 1.0050 * 10^{-11}$

### 2.2.7 Conclusion

With this approach we have that  $\sum_{n=0}^{25} \frac{(ikwh)^n}{n!} \mathcal{F}\{h^n\}(\alpha, \beta)$  is an approximation of  $P(u, v)$  with error  $\epsilon \approx 8.8150 * 10^{-8}$ . This means we can precompute 25 Fourier Transformations (for example via FFT2) and then sum them up in order to approximate  $P(u, v)$  and  $\epsilon \approx 8.8150 * 10^{-8}$ . This approach will allow us to speed up our shader. Furthermore we see that when we just take 5 more iterations, we will reduce the error bound to the dimension of  $10^{-11}$ .

**NB:** More explanation about how the shader itself works during our discussion.

### 2.2.8 Sources

- [1] [http://en.wikipedia.org/wiki/Ratio\\_test](http://en.wikipedia.org/wiki/Ratio_test)
- [2] <http://math.jasonbhill.com/courses/fall-2010-math-2300-005/lectures/taylor-polynomial-error-bounds>

### 2.2.9 Our derivations

EXPLAIN: Why do we want a formulation for  $L_\lambda(w_r)$  in some words. what does it represent?

$$\text{Definition of } BRDF(w_i, w_r) := f_r(w_i, w_r) = \frac{dL_r(w_r)}{dE_i(w_i)} = \frac{dL_r(w_r)}{L_i(w_i) \cos(\theta_i) dw_i}$$

Hence, we can dervie the following expression:

$$\begin{aligned}
f_r(w_i, w_r) &= \frac{dL_r(w_r)}{L_i(w_i)\cos(\theta_i)dw_i} \\
\Rightarrow f_r(w_i, w_r)L_i(w_i)\cos(\theta_i)dw_i &= dL_r(w_r) \\
\Rightarrow \int_{\Omega} f_r(w_i, w_r)L_i(w_i)\cos(\theta_i)dw_i &= \int_{\Omega} dL_r(w_r) \\
\Rightarrow L_r(w_r) &= \int_{\Omega} f_r(w_i, w_r)L_i(w_i)\cos(\theta_i)dw_i
\end{aligned}$$

We assume, that our incident light is a directional light source like sun-light and therefore its radiance is given as  $L_{\lambda}(w) = I(\lambda)\delta(w - w_i)$  where  $I(\lambda)$  is the intensity of the relative spectral power for the wavelength  $\lambda$ . Thus we get for our the brdf formulation:

$$L_{\lambda}(w_r) = \int_{\Omega} BRDF_{\lambda}(w_i, w_r)L_{\lambda}(w_i)\cos(\theta_i)dw_i \quad (16)$$

$$= BRDF_{\lambda}(w_i, w_r)I(\lambda)\cos(\theta_i) \quad (17)$$

where  $w_i$  is the solid angle for the incoming light,  $\theta_i$  is the angle of incidence,  $w_r$  is the solid angle for the reflected light,  $\lambda$  wavelength,  $\Omega$  is the hemisphere we of integration for the incomming light. Radiance reflected by given surface in given direction:  $L_{\lambda}(w_i)$  is the incomming radiance,  $L_{\lambda}(w_r)$  is the reflected radiance

For the  $BRDF(w_i, w_r)$  we are going to use the formulation dervied by Stam described above which looks like this using the fact that wavenumber  $k = \frac{2\pi}{\lambda}$ :

$$\begin{aligned}
BRDF(w_i, w_r) &= \frac{k^2 F^2 G}{4\pi^2 A w^2} \langle |P(ku, kv)|^2 \rangle \\
&= \frac{k^2 F^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)}{\cos(\theta_1)\cos(\theta_2)4\pi^2 A w^2} \langle |P(ku, kv)|^2 \rangle \\
&= \frac{4\pi^2 F^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)}{\cos(\theta_1)\cos(\theta_2)4\pi^2 A \lambda^2 w^2} \langle |P(ku, kv)|^2 \rangle \\
&= \frac{F(w_i, w_r)^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)}{\cos(\theta_1)\cos(\theta_2)A \lambda^2 w^2} \langle |P(ku, kv)|^2 \rangle
\end{aligned}$$

where  $\hat{\mathbf{k}}_t$  represents a unit vector whose spherical coordinates are given by the solid angle  $t$ . Since we are going to integrate over a sphere  $\Omega$  we can write the component  $w = (\cos(\theta_i) + \cos(\theta_r))$  SHOW WHY WE ARE ALLOWED TO WRITE IT LIKE THIS => SPHERICAL COORDINATES DIFFERENCE  $(k_1 - k_2) = (u, v, w)$  and so on. this our identity for  $L_r(w_r)$  will lead us to the following identity using our identity :

$$\begin{aligned} L_\lambda(w_r) &= \frac{F(w_i, w_r)^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{A \lambda^2 \cos(\theta_i) \cos(\theta_r) (\cos(\theta_i) + \cos(\theta_r))^2} \left\langle \left| P_{cont}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle \cos(\theta_i) I(\lambda) \\ &= I(\lambda) \frac{F(w_i, w_r)^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{\lambda^2 A (\cos(\theta_i) + \cos(\theta_r))^2 \cos(\theta_r)} \left\langle \left| P_{cont}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle \\ &= I(\lambda) \frac{F(w_i, w_r)^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{\lambda^2 A (\cos(\theta_i) + \cos(\theta_r))^2 \cos(\theta_r)} \left\langle \left| T_0^2 P_{dtft}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle \end{aligned}$$

$P_{cont}$  is the continuous inverse Fourier transform for the Taylor series of our high-field representing the nano structure, i.e.  $P(k, l) = \mathcal{F}^{-1}\{p\}(k, l)$  and  $P_{dtft}$  is the discrete-time inverse Fourier Transform for the same problem domain and  $T_0$  the sampling distance for the discretization of  $p(x, y)$  assuming equal and uniform sampling in both dimensions  $x, y$ .

### 2.3 Relative BRDF

reason why relative brdf: In order to scale the reflectance such that we are able to texture. convex combination reflectance with texture. Scale illumination.

Let us examine what  $L_\lambda(w_r)$  will be for  $w_r = w_0 := (0, 0, *)$  i.e. specular reflection case, denoted as  $L_\lambda^{spec}(w_0)$ . When we know the expression for  $L_\lambda^{spec}(w_0)$  we would be able to compute the relative reflected radiance for our problem by simply dividing  $L_\lambda(w_r)$  by  $L_\lambda^{spec}(w_0)$ , denoted as

$$\rho_\lambda(w_i, w_r) = \frac{L_\lambda(w_r)}{L_\lambda^{spec}(w_0)} \quad (18)$$

But first, let us derive the following expression:



$$\begin{aligned}
L_{\lambda}^{spec}(w_0) &= I(\lambda) \frac{F(w_0, w_0)^2 (1 - \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ 0 \\ -1 \end{pmatrix})^2}{\lambda^2 A (\cos(0) + \cos(0))^2 \cos(0)} \langle |T_0^2 P_{dtft}(0, 0)|^2 \rangle \\
&= I(\lambda) \frac{F(w_0, w_0)^2 (1 + 1)^2}{\lambda^2 A (1 + 1)^2 1} |T_0^2 N_{sample}|^2 \\
&= I(\lambda) \frac{F(w_0, w_0)^2}{\lambda^2 A} |T_0^2 N_{sample}|^2
\end{aligned}$$

Where  $N_{samples}$  is the number of samples of the dtft.

Thus, we can plug our last derived expression into the definition for the relative reflectance radiance in the direction  $w_r$  and will get:

$$\begin{aligned}
\rho_{\lambda}(w_i, w_r) &= \frac{L_{\lambda}(w_r)}{L_{\lambda}^{spec}(w_0)} \\
&= \frac{I(\lambda) \frac{F(w_i, w_r)^2 (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{\lambda^2 A (\cos(\theta_i) + \cos(\theta_r))^2 \cos(\theta_r)} \langle |T_0^2 P_{dtft}(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda})|^2 \rangle}{I(\lambda) \frac{F(w_0, w_0)^2}{\lambda^2 A} |T_0^2 N_{sample}|^2} \\
&= \frac{F^2(w_i, w_r) (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{F^2(w_0, w_0) (\cos(\theta_i) + \cos(\theta_r))^2 \cos(\theta_r)} \langle \left| \frac{P_{dtft}(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda})}{N_{samples}} \right|^2 \rangle
\end{aligned}$$

for simplification and a better overview, let us introduce the following expression, the so called gain factor

$$C(w_i, w_r) = \frac{F^2(w_i, w_r) (1 - \hat{\mathbf{k}}_1 \cdot \hat{\mathbf{k}}_2)^2}{F^2(w_0, w_0) (\cos(\theta_i) + \cos(\theta_r))^2 \cos(\theta_r) N_{samples}^2} \quad (19)$$

Using this substitute, we will end up with the following expression for the relative reflectance radiance

$$\rho_{\lambda}(w_i, w_r) = C(w_i, w_r) \langle \left| P_{dtft}(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}) \right|^2 \rangle \quad (20)$$

using the previous definition for the relative reflectance radiance  $\rho_{\lambda}(w_i, w_r) = \frac{L_{\lambda}(w_r)}{L_{\lambda}^{spec}(w_0)}$  which we can rearrange to the expression

$$L_\lambda(w_r) = \rho_\lambda(w_i, w_r) L_\lambda^{spec}(w_0) \quad (21)$$

Let us choose  $L_\lambda^{spec}(w_0) = S(\lambda)$  such that it has the same profile as the relative spectral power distribution of CIE Standard Illuminant *D65*. Further, when integration over  $\lambda$  for a specular surface we should get *CIE<sub>X</sub>YZ* values corresponding to the white point for *D65*

the corresponding tristimulus values using CIE colormatching functions for the *CIE<sub>X</sub>YZ* values look like:

SEE HOW THIS DEFINITION DIFFERS FROM THE WIKIDEF AND HOW WE COULD END UP WITH A SIMILAR DEFINITION.

$$X = \int_\lambda L_\lambda(w_r) \bar{x}(\lambda) d\lambda \quad (22)$$

$$Y = \int_\lambda L_\lambda(w_r) \bar{y}(\lambda) d\lambda \quad (23)$$

$$Z = \int_\lambda L_\lambda(w_r) \bar{z}(\lambda) d\lambda \quad (24)$$

where  $\bar{x}$ ,  $\bar{y}$ ,  $\bar{z}$  are the color matching functions

Using our last finding for  $L_\lambda(w_r)$  and the definition for the tristimulus values we can actually derive an expression for computing the colors for our brdf model. Since X, Y, Z are defined similarly, it satisfies to derive an explicit expression for just one tristimulus term, for example X. The other two will look the same, except that we have to replace all X with Y or Z respectively. Therefore, we get:

$$\begin{aligned}
X &= \int_{\lambda} L_{\lambda}(w_r) \bar{x}(\lambda) d\lambda \\
&= \int_{\lambda} \rho_{\lambda}(w_i, w_r) L_{\lambda}^{spec}(w_0) \bar{x}(\lambda) d\lambda \\
&= \int_{\lambda} \rho_{\lambda}(w_i, w_r) S(\lambda) \bar{x}(\lambda) d\lambda \\
&= \int_{\lambda} C(w_i, w_r) \left\langle \left| P_{dtft}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle S(\lambda) \bar{x}(\lambda) d\lambda \\
&= C(w_i, w_r) \int_{\lambda} \left\langle \left| P_{dtft}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle S(\lambda) \bar{x}(\lambda) d\lambda \\
&= C(w_i, w_r) \int_{\lambda} \left\langle \left| P_{dtft}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle S_x(\lambda) d\lambda
\end{aligned}$$

Where we used the definition  $S_x(\lambda) \bar{x}(\lambda)$  in the last step.

### 2.3.1 Taylour approximation for BRDF

Using  $P_{dtft} = \mathcal{F}^{-1}\{p\}(u, v)$  defined in the section of the taylor approximation we get for the tristimulus value  $X$ , we will get:

$$\begin{aligned}
X &= C(w_i, w_r) \int_{\lambda} \left\langle \left| P_{dtft}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 \right\rangle S_x(\lambda) d\lambda \\
&= C(w_i, w_r) \int_{\lambda} \left| \sum_{n=0}^N \frac{(wk)^n}{n!} \mathcal{F}^{-1}\{i^n h^n\}\left(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}\right) \right|^2 S_x(\lambda) d\lambda
\end{aligned}$$

### 2.3.2 Sampling: Gaussian Window

Let  $window_g$  denote the gaussian window with  $4\sigma_s \mu m$  where  $\sigma_f = \frac{1}{2\pi\sigma_s}$  let us further substitute  $\mathbf{t}(\mathbf{x}, \mathbf{y}) = i^n h(x, y)^n$

$$\mathcal{F}_{dtft}^{-1}\{\mathbf{t}\}(u, v) = \mathcal{F}_{fft}^{-1}\{\mathbf{t}\}(u, v) window_g(\sigma_f) \quad (25)$$

Therefore we can deduce the following expression from this:

$$\begin{aligned}
\mathcal{F}_{d\mathbf{t}f\mathbf{t}}^{-1}\{\mathbf{t}\}(u, v) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F_{fft}^{-1}\{\mathbf{t}\}(w_u, w_v) \phi(u - w_u, v - w_v) dw_u dw_v \\
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \sum_i \sum_j F_{fft}^{-1}\{\mathbf{t}\}(w_u, w_v) \delta(w_u - w_i, w_v - w_j) \phi(u - w_u, v - w_v) dw_u dw_v \\
&= \sum_i \sum_j \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F_{fft}^{-1}\{\mathbf{t}\}(w_u, w_v) \delta(w_u - w_i, w_v - w_j) \phi(u - w_u, v - w_v) dw_u dw_v \\
&= \sum_i \sum_j F_{fft}^{-1}\{\mathbf{t}\}(w_u, w_v) \phi(u - w_u, v - w_v)
\end{aligned}$$

where  $\phi(x, y) = \pi e^{-\frac{x^2+y^2}{2\sigma_f^2}}$

### 2.3.3 Aplitude smooting

Let us consider the so called 1-dimensional Box-function with length  $T$  which is defined as the following: ADD AN IMAGE OF BOXFUNCTION

$$Box(x) = \begin{cases} 1 & \text{if } x \leq T \\ 0 & \text{if } else \end{cases}$$

We assume, that our given heighfield can be represented as a 2-dimensional box-function. Note that we can use any explicit given constrained 2-dimensional function and will get some identities like we get from the box-function.

Further we are assuming that we can model the overall surface be assuming this heighfield being distributed in a periodic manor. Therefore, the whole surface can be represented like this  $f(x) = \sum_{n=0}^N Box(x + nT_1, y + mT_2)$  assuming the given heighfield has the dimensions  $T_1$  by  $T_2$ . But let us first consider the 1-dimensional Box-function case before deriving an identity for the Fourier transform of our 2-dimensional Box-function, i.e. the fourier transform of our heighfield.

Note: A function  $f$  periodic with periode  $T$  means:  $\forall x \in \mathcal{R} : Box(x) = Box(x + T)$

A so called bump can be represented by our 1-dimensional Box-function. We assume periodicity which is equaivalent to:  $f(x) = \sum_{n=0}^N Box(x + nT)$

We are interested in the 1-dimensional inverse Fourier transform of the 1-dimensional Box-function:

$$\begin{aligned}
\mathcal{F}^{-1}\{f\}(w) &= \int f(x)e^{iwx}dx \\
&= \int_{-\infty}^{\infty} \sum_{n=0}^N \text{Box}(x+nT)e^{iwx}dx \\
&= \sum_{n=0}^N \int_{-\infty}^{\infty} \text{Box}(x+nT)e^{iwx}dx
\end{aligned}$$

Next, apply the following substitution  $x+nT=y$  which will lead us to:

$$\begin{aligned}
x &= y - nT \\
dx &= dy
\end{aligned}$$

Plugging this substitution back to the equation from above we will get

$$\begin{aligned}
\mathcal{F}^{-1}\{f\}(w) &= \int f(x)e^{iwx}dx \\
&= \sum_{n=0}^N \int_{-\infty}^{\infty} \text{Box}(y)e^{iwy-nT}dy \\
&= \sum_{n=0}^N e^{-iwnT} \int_{-\infty}^{\infty} \text{Box}(y)e^{iwy}dy \\
&= \sum_{n=0}^N e^{-iwnT} \mathcal{F}\{f\}(w) \\
&= \mathcal{F}^{-1}\{f\}(w) \sum_{n=0}^N e^{-iwnT}
\end{aligned}$$

We used the fact that the term  $e^{-iwnT}$  is a constant when integrating along  $dy$  and the identity for the inverse Fourier transform of the Box function. Next, let us consider  $\sum_{n=0}^N e^{-iwnT}$  further:

$$\begin{aligned}
\sum_{n=0}^N e^{-iwnT} &= \sum_{n=0}^N (e^{-iwnT})^n \\
&= \frac{1 - e^{-iwnT(N+1)}}{1 - e^{-iwnT}}
\end{aligned}$$

We recognize the geometric series identity for the left-handside of this equation. Since our series is bounded we can derive our right-handside.

Since  $e^{-ix}$  is a complex number and every complex number can be written in its polar form, i.e.  $e^{-ix} = \cos(x) + i\sin(x)$  we can go even further, using the trigonometric identities that  $\cos(-x) = \cos(x)$  and  $\sin(-x) = -\sin(x)$ :

$$\frac{1 - e^{iwT(N+1)}}{1 - e^{-iwT}} = \frac{1 - \cos(wT(N+1)) + i\sin(wT(N+1))}{1 - \cos(wT) + i\sin(wT)}$$

Which is still a complex number  $(p + iq)$ . Every complex number can be written as a fraction of two complex numbers. This means that the complex number  $(p + iq)$  can be written as  $(p + iq) = \frac{(a+ib)}{(c+id)}$  for any  $(a + ib), (c + id) \neq 0$ . For our case, let us use the following substitutions:

$$a := 1 - \cos(wT(N+1)) \quad b = \sin(wT(N+1)) \quad (26)$$

$$c = 1 - \cos(wT) \quad d = \sin(wT) \quad (27)$$

hence it follows  $\frac{1 - e^{iwT(N+1)}}{1 - e^{-iwT}} = \frac{(a+ib)}{(c+id)}$ . By rearranging the terms it follows  $(a + ib) = (c + id)(p + iq)$  and multiplying the right handside out we get the following system of equations:

$$(cp - dq) = a \quad (28)$$

$$(dp + cq) = b \quad (29)$$

Which gives lead us we some further math (trick: mult first eq. by  $c$  and 2nd by  $d$ , then adding them together. using distributivity and we have the identity for  $p$  for example, similar for  $q$ ) to

$$p = \frac{(ac + bd)}{c^2 + d^2} \quad (30)$$

$$q = \frac{(bc + ad)}{c^2 + d^2} \quad (31)$$

Putting our substitution for  $a, b, c, d$  back into the current representation for  $p$  and  $q$  and using some trigonometric identities, this we then get:

$$p = \frac{1}{2} + \frac{1}{2} \left( \frac{\cos(wTN) - \cos(wT(N+1))}{1 - \cos(wT)} \right) \quad (32)$$

$$q = \frac{\sin(wT(N+1)) - \sin(wTN) - \sin(wT)}{2(1 - \cos(wT))} \quad (33)$$

Since we have seen, that  $\sum_{n=0}^N e^{-iwnT}$  is a complex number and can be written as  $(p + iq)$  and we know now the explicit identity for those  $p$  and  $q$  we get for the 1-dimensional Fourier transform of the 1-dimensional Box-function the following final identity:

$$\begin{aligned} \mathcal{F}^{-1}\{f\}(w) &= \mathcal{F}^{-1}\{f\}(w) \sum_{n=0}^N e^{-iwnT} \\ &= (p + iq) \mathcal{F}^{-1}\{Box\}(w) \end{aligned}$$

In order to derive next a identity for the Fourier transform for our 2-dim heighfield, we can proceed similarly, the only fact which changes is, that we are now in a 2-dimensional domain, i.e. we are about to compute a two-dimensional Fourier transform: Let us again us again a Box-function, this time a 2-dimensional Box-function  $Box(x, y)$  just for the sake of convenience.

$$\begin{aligned}
\mathcal{F}^{-1}\{f\}(w_1, w_2) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \sum_{n_2=0}^{N_1} \sum_{n_2=0}^{N_2} \text{Box}(x_1 + n_1 T_1, x_2 + n_2 T_2) e^{iw(x_1+x_2)} dx_1 dx_2 \\
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \sum_{n_2=0}^{N_1} \sum_{n_2=0}^{N_2} \text{Box}(y_1, y_2) e^{iw((y_1-n_1 T_1)+(y_2+n_2 T_2))} dy_1 dy_2 \\
&= \sum_{n_2=0}^{N_1} \sum_{n_2=0}^{N_2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \text{Box}(y_1, y_2) e^{iw(y_1+y_2)} e^{-iw(n_1 T_1+n_2 T_2)} dy_1 dy_2 \\
&= \sum_{n_2=0}^{N_1} \sum_{n_2=0}^{N_2} e^{-iw(n_1 T_1+n_2 T_2)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \text{Box}(y_1, y_2) e^{iw(y_1+y_2)} dy_1 dy_2 \\
&= \left( \sum_{n_2=0}^{N_1} \sum_{n_2=0}^{N_2} e^{-iw(n_1 T_1+n_2 T_2)} \right) \mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2) \\
&= \left( \sum_{n_2=0}^{N_1} e^{-iwn_1 T_1} \right) \left( \sum_{n_2=0}^{N_2} e^{-iwn_2 T_2} \right) \mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2) \\
&= (p_1 + iq_1)(p_2 + iq_2) \mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2) \\
&= ((p_1 p_2 - q_1 q_2) + i(p_1 p_2 + q_1 q_2)) \mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2) \\
&= (p + iq) \mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2)
\end{aligned}$$

Where we define  $p := (p_1 p_2 - q_1 q_2)$  and  $q := (p_1 p_2 + q_1 q_2)$ . For this identity we used green's integration rule which allowed us to split the double integral to the product of two single integrations. Also, we used the definition of the 2-dimensional inverse Fourier transform of the Box-function. We applied the same substitution like we did in for the 1 dimensional case, but this time twice, once for each variable separately. The last step, substituting with  $p$  and  $q$  will be useful later in the implementation. The insight should be, that the product of two complex numbers is again a complex number. We will have to compute the absolute value of  $\mathcal{F}^{-1}\{f\}(w_1, w_2)$  which will then be equal  $(p^2 + q^2)^{\frac{1}{2}} |\mathcal{F}^{-1}\{\text{Box}\}(w_1, w_2)|$

### 2.3.4 Final Expression

As the last step of our series of derivations, we plug all our findings together to one big equation in order to compute the colors in the  $CIE_{XYZ}$  colorspace:



For a given heigh-field  $h(x, y)$ , representing a small patch of the nano-structure of our surface, the resulting  $CIE_XYZ$  caused by the effect of dif-fraction can be computed like the following:

$$\begin{pmatrix} X \\ X \\ Z \end{pmatrix} = C(w_i, w_r) \int_{\lambda} \sum_r \sum_s (p(r, s; T)^2 + q(r, s; T)^2)^{\frac{1}{2}} \sum_{n=0}^N \frac{(wk)^n}{n!} \left| F_{fft}^{-1}\{i^n h^n\}(\frac{2\pi u}{\lambda}, \frac{2\pi v}{\lambda}) \right|^2 \phi(u - w_r, v - w_s) \begin{pmatrix} S_x(\lambda) \\ S_y(\lambda) \\ S_z(\lambda) \end{pmatrix} d\lambda \quad (34)$$

where  $(p(r, s; T)^2 + q(r, s; T)^2)^{\frac{1}{2}}$  represents the phaser,  $\phi(x, y) = \pi e^{-\frac{x^2+y^2}{2\sigma_f^2}}$  is the gaussian window,  $\begin{pmatrix} S_x(\lambda) \\ S_y(\lambda) \\ S_z(\lambda) \end{pmatrix}$ .

### 3 Implementation

how to discretize from final derivation to computation? what do we have to precompute, what during runtime? how does the final algorithm look like explain shaders: vertex(geometry, precomp) - and fragment-shader(in local space-tspace) how from  $cie_x yz$  to  $cie_r gb$  how gamma correction how texturing can we do better?

TODO: explain that there is the jrtr and the scene code - what are their responsibilities.

shader

In computergraphics, we are interested in rendering a given scene containing our 3d geometries by using so called shader programs. The purpose of such programs, which run directly on the gpu hardware device, is to compute the colorization and illumination of the objects living in our scene. This computation happens in several stages and depends on the provided input parameters like the camera, light sources, objects material constants and the desired rendering effect one is interested in to model. The shader stages are also modeled as small little programs, the so called vertex-, geometry- and fragment-shaders. Those stages are applied within the rendering pipeline sequentially.

Our shaders are written in GLSL, developed for OpenGL. The decision for using OpenGL has been made since the underlying framework which is responsible for the precomputation of all scene data is based on a framework written in Java using JOGL in order to communicate with the GPU and precompute all the relevant scene data. This framework, the so called jrtr framework has been developed as an exercise during the class computer graphics held by M. Zwicker which I attended in autumn 2012. The framework itself has been extended during this thesis quite a lot. Further, there are also some precomputations involved, performed in matlab. This is basically addressing all the required precomputations for the provided height-fields, referring to computation of the inverse two dimensional Fourier transformations which are further explained within this chapter.

It's noteworthy that all the vertices are processed within the vertex-shader, whereas the fragment shader's responsibility is to perform pixelwise rendering, using the input from the vertex shader. Just remember, fragments are determined by a triple of vertices. hence each pixel has assigned a trilinear interpolated value of all input parameters of its spanning vertices. Usually, all necessary transformations are applied vertex-wise, considering

the vertex-shader as the precomputation stage for the later rendering within the rendering pipeline, in the fragment-shader. In the geometry shader, new vertices around a considered vertex can be created. this is useful for debugging - displaying normals graphically for example.

In this section we are going to explain how to get a fragment-shader from our findings for our BRDF formulation from the last section. this fragment-shader will render the effect of diffraction on our given geometry pixelwise. Therefore, the quality of diffraction depends on the number of pixels we are going to use for the rendering process and this is directly determined by the resolution of the canvas in which the rendered images are being displayed. But, before we can start formulating our fragment-shader we first have to write our vertex shader which does all the precomputations.

By the end of the day we will end up with two different shaders, one which basically samples the whole lambda space using a gaussian window. This shader will be modeling the effect of diffraction completely but will also be rather slow. The other shader will use a gaussian window too but will just use a few wavenumber for the sampling process. Furthermore, this shader will thread specularly seperatly as a special case which will be more like an approximation.

tell how we are going to sample - uniformly along lambda - explain drawback of this approach - explain possible solutions for this issue. maybe refer to reference shader or leave this for the disscusion part.

### **3.1 Setup**

explain geometry computation explain light(source) setup explain factories explain camera setup explain how materials are stored explain how assigned to jrtr explain how passed to glsl shader - see computer graphics slides maybe show schematically the architecture

### **3.2 Precomputations in Matlab**

explain matlab code explain shifts explain what will be outputed

### **3.3 jrtr Framework**

explain how this will work

### 3.4 GLSL Diffraction Shader

start using the final findings from chapter 2 and substitute explain how all the components are computed and why they are computed like this.

---

**Algorithm 1** Vertex diffraction shader

---

**foreach** *Vertex*  $v \in Shape$  **do**  
**end for**

---

---

**Algorithm 2** Fragment diffraction shader

---

```
foreach Pixel  $p \in \text{Fragment}$  do
   $BRDF_{XYZ}, BRDF_{RGB} = \text{vec4}(0.0)$ 
   $(u, v, w) = \hat{\mathbf{k}}_1 - \hat{\mathbf{k}}_2$ 
  for  $(\lambda = \lambda_{min}; \lambda \leq \lambda_{max}; \lambda = \lambda + \lambda_{step})$  do
     $k = \frac{2\pi}{\lambda}$ 
     $(w_u, w_v) = (ku, kv)$ 
     $w_{color} = (S_x(\lambda), S_y(\lambda), S_z(\lambda))$ 
    for  $(r)$  do
      for  $(s)$  do
         $coords = \text{getLookUpCoord}(r, s)$ 
         $P = \text{taylorApprox}(coords, k, w)$ 
         $w_{r,s} = \text{gaussianWeight}(dist)$ 
         $scale_{pq} = pqFactor(w_u, w_v)$ 
         $P* = scale_{pq}$ 
         $P_{abs} = |P|^2$ 
         $P_{abs}* = w_{r,s}$ 
         $BRDF_{XYZ}+ = \text{vec4}(P_{abs} * w_{color}, 0.0)$ 
      end for
    end for
  end for
   $BRDF_{XYZ} = BRDF_{XYZ} * C(\hat{\mathbf{k}}_1, \hat{\mathbf{k}}_2) * shadowF$ 
   $BRDF_{XYZ}.xyz = D_{65} * M_{XYZ-RGB} * BRDF_{XYZ}.xyz$ 
   $BRDF_{RGB}.xyz = D_{65} * M_{XYZ-RGB} * BRDF_{XYZ}.xyz$ 
   $BRDF_{RGB} = \text{gammaCorrect}(BRDF_{RGB})$ 
end for
```

---

## 4 Data Acquisition and Evaluation

what is this chapter about how is evaluation performed our shader

### 4.1 Diffraction Grating

list def from wiki

$$d\sin(\theta_m) = m\lambda$$

$$d(\sin(\theta_i) + \sin(\theta_m)) = m\lambda$$

$$\sin(\theta_m) = \left( \frac{m\lambda}{d} - \sin(\theta_i) \right)$$

$$\forall \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3 : \exists r \in [0, \infty) \exists \phi \in [0, 2\pi] \exists \theta \in [0, \pi] \text{ s.t.}$$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} r\sin(\theta)\cos(\phi) \\ r\sin(\theta)\sin(\phi) \\ r\cos(\theta) \end{pmatrix}$$

### 4.2 Snake Skin Parameters

## 5 Results

differece of this shader compared to evaluation shader

## 6 Conclusion

explain why we did our derivations explain why our approach is a good idea explain how the straight foreward approach would behave compared to our approach, computing the fourier transformations straight away. explain what we achieved, summary say something about draw-backs and about limitations of current apporach say something about the ongoing paper

### 6.1 Further Work