

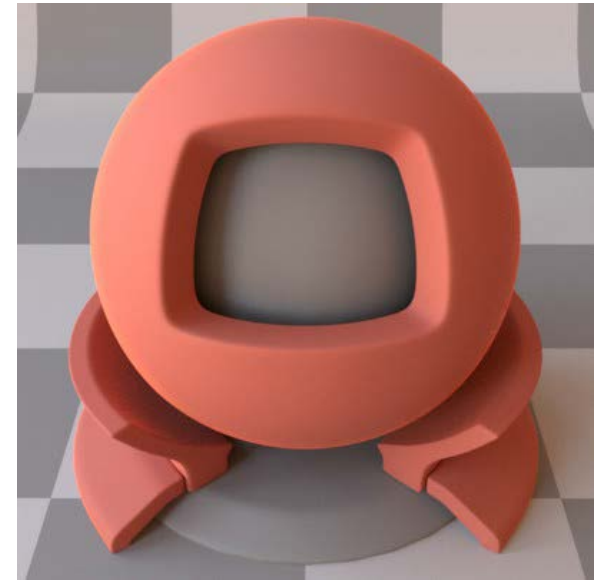
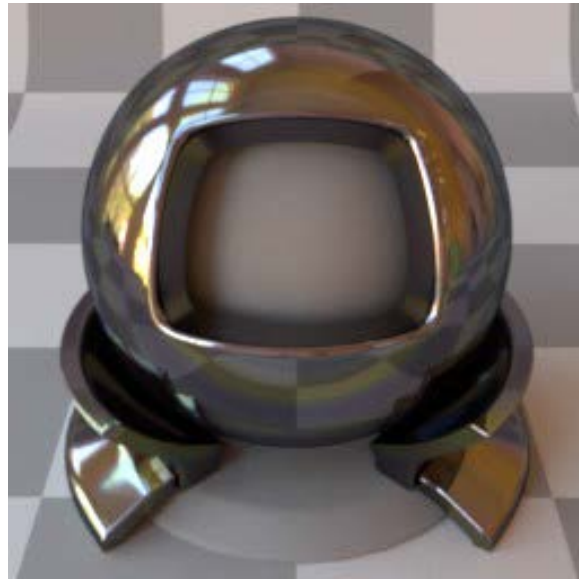
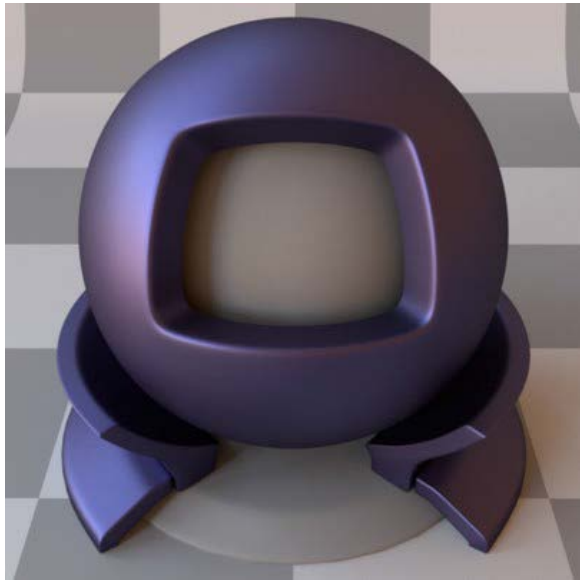
# Microfacet model and Microfacet-based BRDF

2019.05.16

20186413 Murat Gaspard

# Physically based microfacet BRDFs

$$L_o = \int_{\Omega_+} L_i \cdot \mathbf{f}_r \cdot \cos \theta_i \cdot d\omega_i$$

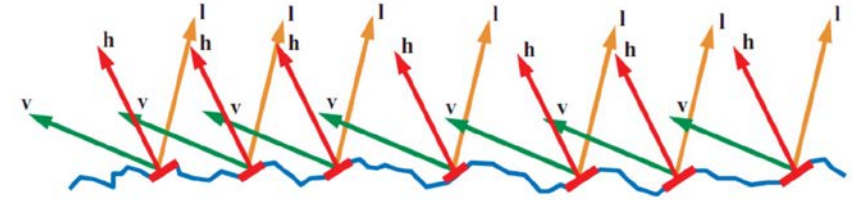


# Microfacet Theory

From Hakyong Kim's talk:

Materials = microsurfaces

Microsurfaces properties can be manipulated



$$f_r = \frac{F \cdot D \cdot G}{4 \cdot \cos \theta_i \cdot \cos \theta_o}$$

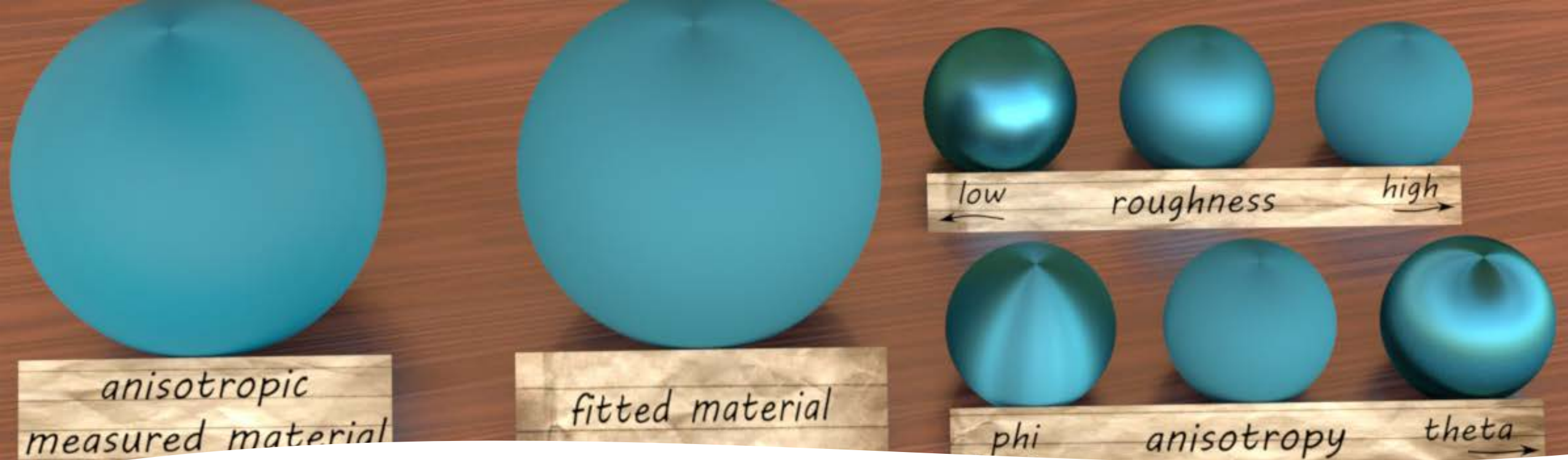
# Papers

- **Extracting Microfacet-based BRDF Parameters from Arbitrary Materials with Power Iterations**

Jonathan Dupuy   Eric Heitz   Pierre Poulin   Victor Ostromoukhov  
Eurographics Symposium on Rendering 2015

- **Fast Global Illumination with Discrete Stochastic Microfacets Using a Filterable Model**

Beibei Wang   Lu Wang   Pierre Poulin   Nicolas Holzschuch  
Pacific Graphics 2018



## Extracting Microfacet-based BRDF Parameters from Arbitrary Materials with Power Iterations

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Eurographics Symposium on Rendering 2015

# Context

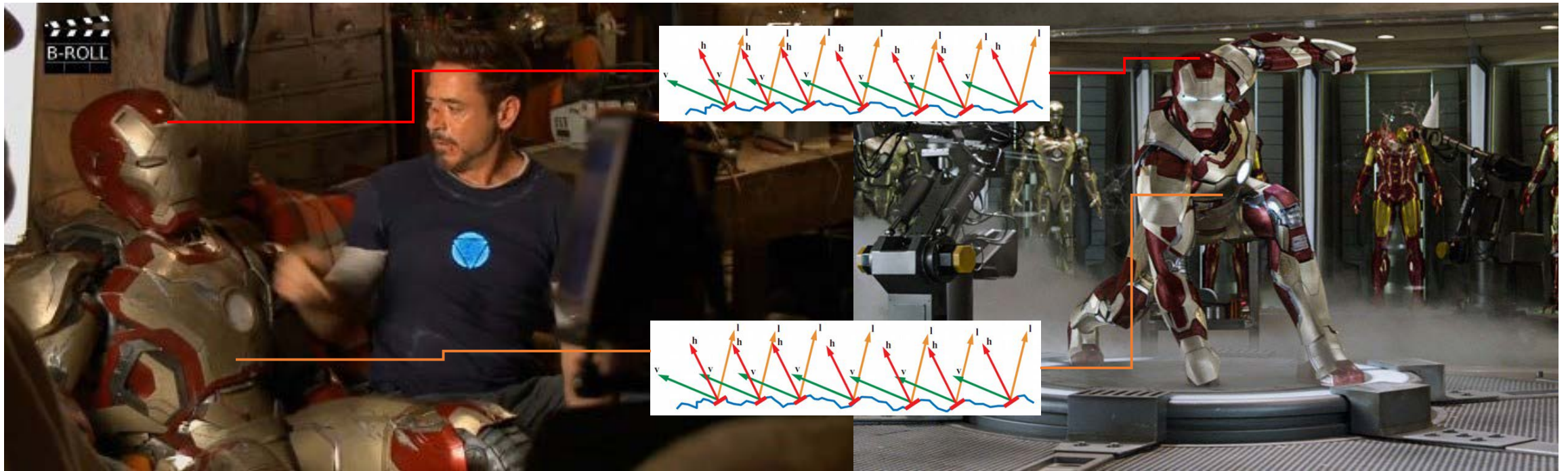


Real  
(real materials)



Digital  
(microfacet BRDFs)

# Context



Real  
(real materials)

Digital  
(microfacet BRDFs)

**How to retrieve the microsurface from real material?**

# Microfacet BRDF Fitting

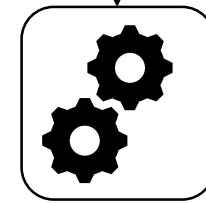
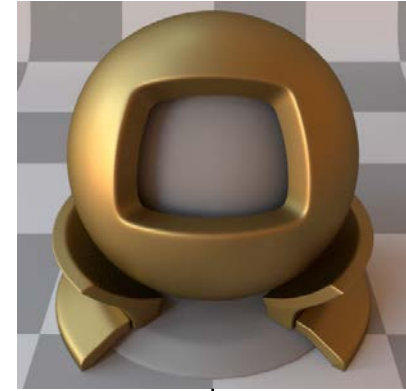
## Approach:

- Fitted microsurface
- Minimize fitting metrics

## Current limitations:

- Robustness / Speed
- Arbitrary metrics
- Reproducibility

Input



Fitting algorithm

output





# Contribution

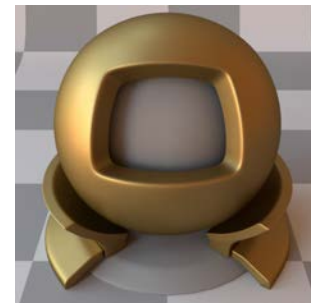
## Idea:

- Find the NDF
- Approximize the Fresnel term

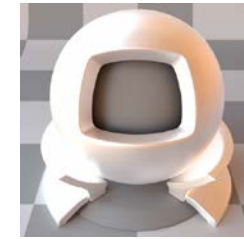
## Properties:

- Robustness
- Simplicity
- Speed
- Reproducibility

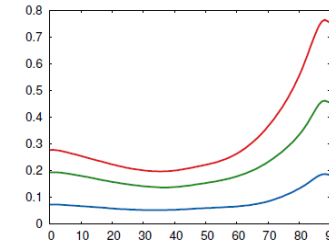
Input



NDF



Fresnel



- Tabulated
- GGX
- Beckmann

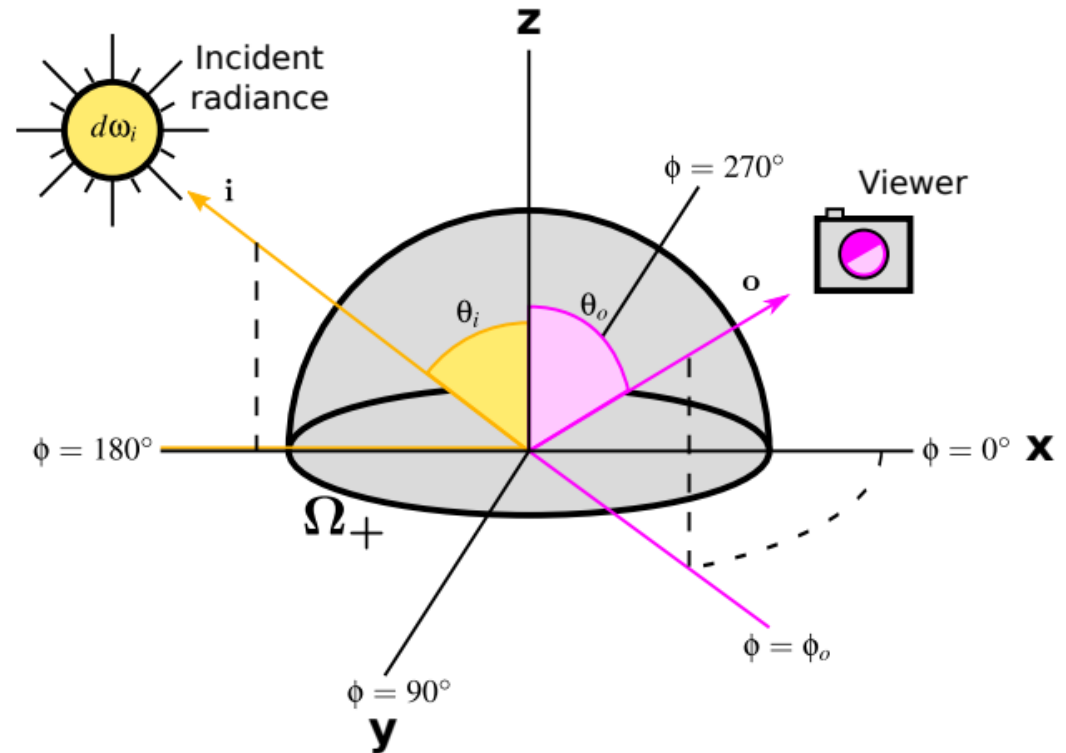


# Microfacet theory

## Assumption:

Single-bounce mirror reflection dominates on the microsurface

$$f_r = \frac{F(\theta_d)D(\mathbf{h})G(\mathbf{i},\mathbf{o})}{4 \cos\theta_i \cos\theta_o}$$



# Microfacet theory

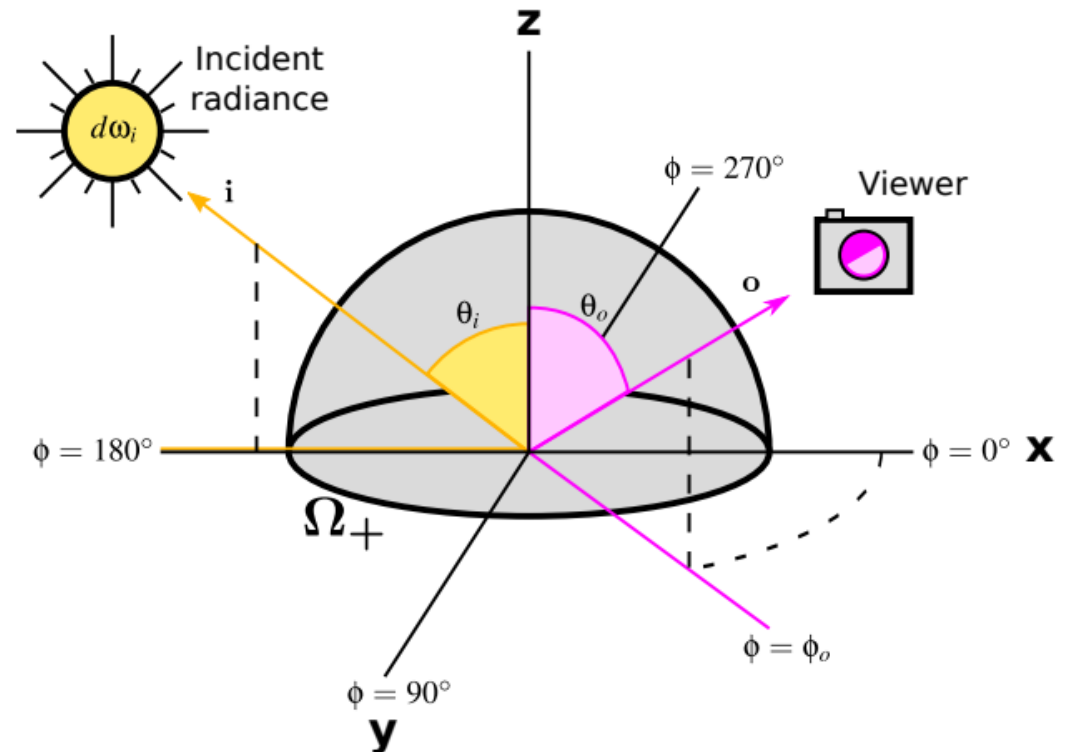
## Assumption:

Single-bounce mirror reflection dominates on the microsurface

$$f_r = \frac{F(\theta_d)D(\mathbf{h})G(\mathbf{i},\mathbf{o})}{4 \cos\theta_i \cos\theta_o}$$

Halfway vector,

$$\mathbf{h} = \frac{\mathbf{i} + \mathbf{o}}{\|\mathbf{i} + \mathbf{o}\|}$$



# Microfacet theory

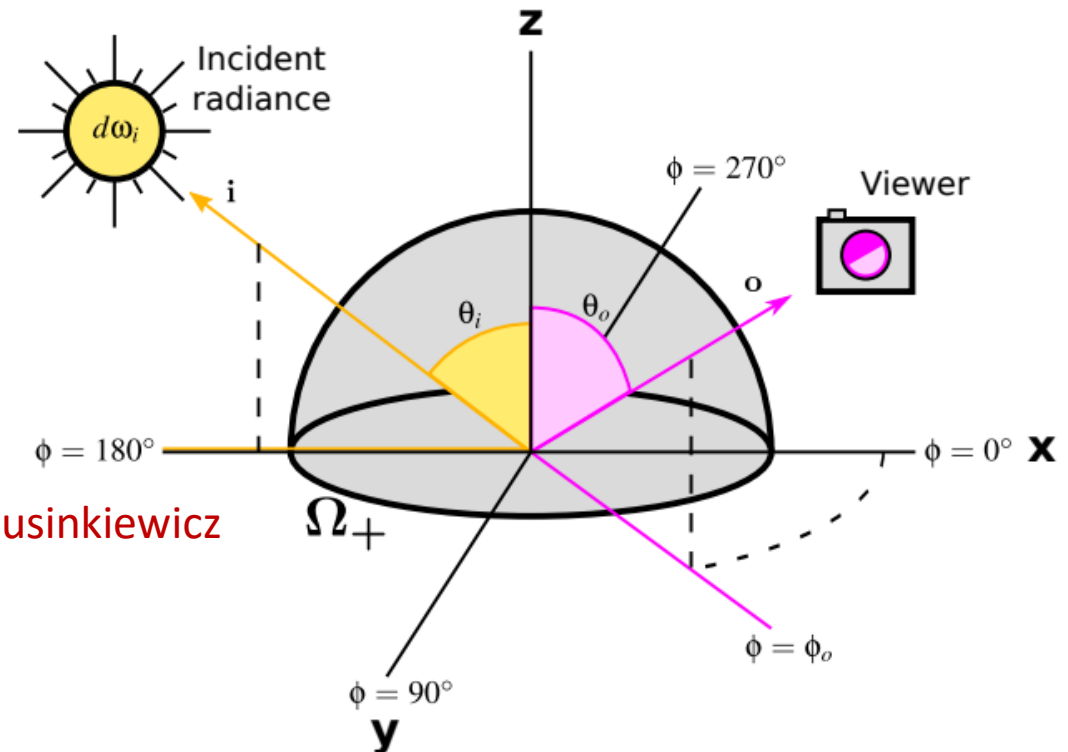
## Assumption:

Single-bounce mirror reflection dominates on the microsurface

$$f_r = \frac{F(\theta_d)D(\mathbf{h})G(\mathbf{i},\mathbf{o})}{4 \cos\theta_i \cos\theta_o}$$

$\theta_d$  = difference angle in the BRDF parameterization of Rusinkiewicz

$$\theta_d = \arccos(\mathbf{i} \cdot \mathbf{h}) \in [0, \pi/2]$$



# Microfacet slopes

Goal:

Simplified the search of the NDF

Normalization constraint on the NDF:

$$\int_{\Omega_+} D(\mathbf{h}) \cos \theta_h d \omega_h$$

# Microfacet slopes

Goal:

Simplified the search of the NDF

Idea:

Instead of searching in the horizontal space ( $\Omega_+$ ), we search into the slopes space ( $\mathbb{R}^2$ )

In the  $\Omega_+$  set, normals and slopes are linked through the bijection

$$\tilde{\mathbf{h}} = \begin{bmatrix} -\tan\theta h \cos\phi h = \tilde{\mathbf{x}}_k \\ -\tan\theta h \sin\phi h = \tilde{\mathbf{y}}_k \end{bmatrix}, \quad \tilde{\mathbf{h}} \in \mathbb{R}^2$$

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Normal Distribution fonction

$$f_r = \frac{F(\theta_d) D(\mathbf{h}) G(i, o)}{4 \cos\theta_i \cos\theta_o}$$

$$D(\mathbf{h}) = P(\tilde{\mathbf{h}}) \sec^4\theta_h$$

Probability distribution function P

Normalisatio constraint:

$$\int_{\mathbb{R}^2} P(\tilde{\mathbf{h}}) d\tilde{\mathbf{h}} = 1$$

# Microfacet theory

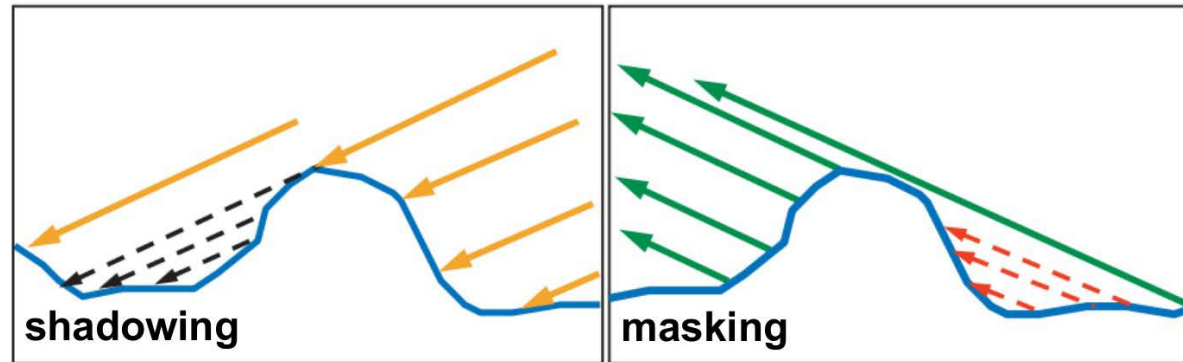
Geometric attenuation factor

$$f_r = \frac{F(\theta_d)D(h)G(i,o)}{4 \cos\theta_i \cos\theta_o}$$

$$G(i, o) = \frac{G_1(i)G_1(o)}{G_1(i)+G_1(o)-G_1(i)G_1(o)} \quad G \in [0,1]$$

Smith monostatic shadowing function:

$$G_1(\mathbf{k}) = \frac{\cos\theta_k}{\int_{\Omega^+} kh D(\mathbf{h}) d\omega_k} \quad G_1 \in [0,1]$$





# Backscattering Equation

Mathematical (previous work)

We focus on backscattering configuration which reduce the dimensionality of the BRDF

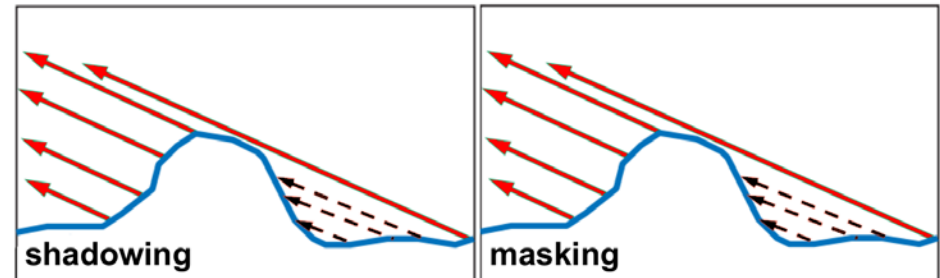
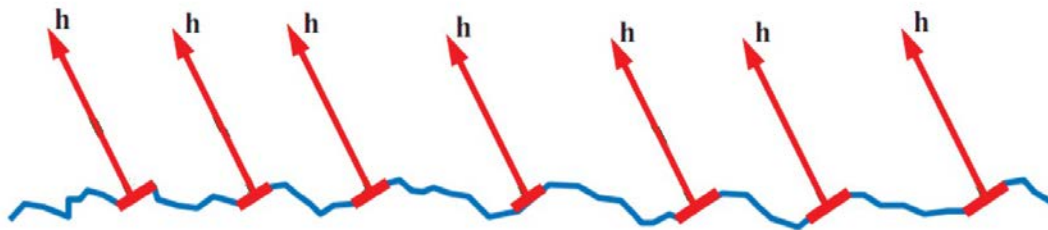
$$\mathbf{l} = \mathbf{o} = \mathbf{h} \quad \theta_d = 0$$

$$f_r = \frac{F_o D(\mathbf{o}) G(\mathbf{o}, \mathbf{o})}{4 \cos^2 \theta_0}$$



$$f_r = \frac{F_o D(\mathbf{o}) G_1(\mathbf{o})}{4 \cos^2 \theta_0}$$

$$G(\mathbf{o}, \mathbf{o}) = G_1(\mathbf{o})$$



# Eigensystem construction

$$f_r = \frac{F_0 D(o) G_1(o)}{4 \cos^2 \theta_0}$$



Inverted equation

$$F_0 P(\tilde{o}) = \int_{\Omega^+} K(o, h) P(\tilde{h}) d\omega_h$$

(Fredholm equation of the second kind)

$$K(o, h) = 4f_r(o, o) \cos^5 \theta_o \mathbf{o}h \sec^4 \theta_h.$$

# Eigensystem construction

$$f_r = \frac{F_0 D(o) G_1(o)}{4 \cos^2 \theta_0}$$



$$F_0 P(\tilde{o}) = \int_{\Omega_+} K(o, h) P(\tilde{h}) d\omega_h$$

Numerically solved by discretizing the equation with a quadrature rule



$$F_0 P(\tilde{o}_i) = \sum_{j=1}^N w_j K(o_i, \mathbf{h}_j) P(\tilde{\mathbf{h}}_j)$$

# Eigensystem construction

$$F_0 P(\tilde{o}_i) = \sum_{j=1}^N w_j K(o_i, \mathbf{h}_j) P(\tilde{\mathbf{h}}_j) \quad \longrightarrow \quad F_0 \mathbf{p} = \mathbf{K} \cdot \mathbf{p}$$

$$\mathbf{p} = (P(\tilde{\mathbf{o}}_1), \dots, P(\tilde{\mathbf{o}}_N))^t$$

$$\mathbf{K} = \begin{bmatrix} w_1 K(\mathbf{o}_1, \mathbf{h}_1) & \cdots & w_N K(\mathbf{o}_1, \mathbf{h}_N) \\ \vdots & \ddots & \vdots \\ w_1 K(\mathbf{o}_N, \mathbf{h}_1) & \cdots & w_N K(\mathbf{o}_N, \mathbf{h}_N) \end{bmatrix}$$

# Eigensystem construction

$$f_r = \frac{F_0 D(\mathbf{o}) G_1(\mathbf{o})}{4 \cos^2 \theta_0}$$



$$F_0 \cdot \mathbf{p}(\tilde{\mathbf{o}}) = K \cdot \mathbf{p}$$

Discretize PDF vector

nonnegative matrix

**Perron-Frobenius theorem**  
the solution is always the eigenvector  
with the largest magnitude

# Backscattering Equation

$$F_0 P(\tilde{\mathbf{o}}) = \int_{\Omega^+} K(\mathbf{o}, \mathbf{h}) P(\tilde{\mathbf{h}}) d\omega_h$$



$$f_r = \frac{F_0 D(\mathbf{o}) G(\mathbf{o}, \mathbf{o})}{4 \cos^2 \theta_0}$$

---

## Algorithm 1 Extract $P$

---

```
function EXTRACT_P( $f_r, N$ )  
  for each  $i, j \in [1, N]$  do      ▷ Build kernel matrix  
     $K_{i,j} \leftarrow w_j 4f_r(\mathbf{o}_i, \mathbf{o}_i) \cos^5 \theta_{o_i} \mathbf{o}_i \mathbf{h}_j \sec^4 \theta_{h_j}$   
  end for  
   $\mathbf{p} \leftarrow (1, \dots, 1)^t$   
  for  $0 \leq i < M$  do      ▷ Power iterations (we set  $M = 4$ )  
     $\mathbf{p} \leftarrow \mathbf{K} \cdot \mathbf{p}$   
  end for  
   $P \leftarrow \text{normalize}(\mathbf{p})$   
end function
```

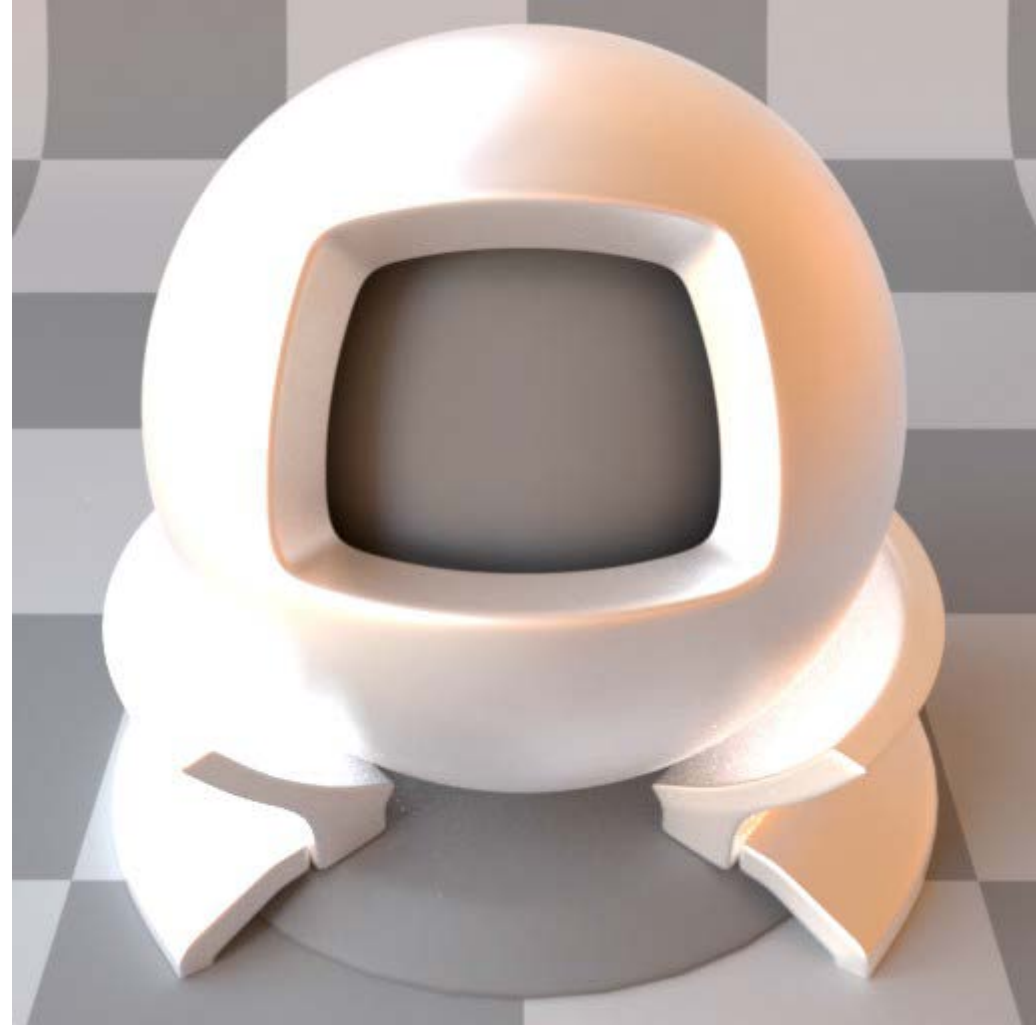
---

# Ideal Mirrors

Special microfacet BRDF:

- Fresnel term is 1
- Independent of wavelength

$$f_{r,id} = \frac{D(\mathbf{o})G_1(\mathbf{o})}{4 \cos\theta_0 \cos\theta_i}$$



# Fresnel Extraction

We compute an average response :

- Fully automatic
- Simple implementation
- Fast evaluation
- Works well in practice

$$F(\theta_d) = \mathbb{E} \left[ \frac{f_r}{f_{r,id}} \mid \mathbf{ih} = \cos\theta_0 \right]$$





# Fresnel Extraction

We compute an average response :

- Fully automatic
- Simple implementation
- Fast evaluation
- Works well in practice

$$F(\theta_d) = \mathbb{E} \left[ \frac{f_r}{f_{r,id}} \mid \mathbf{i}\mathbf{h} = \cos\theta_0 \right]$$

---

## Algorithm 2 Extract $F$

---

```
function EXTRACT_ $F(f_r, f_{r,id})$ 
  for  $\theta_d \in [0, \pi/2]$  do
     $F(\theta_d) \leftarrow 0$ 
     $N \leftarrow 0$ 
    for  $\phi_d, \phi_h \in [0, 2\pi], \theta_h \in [0, \pi/2]$  do
       $\mathbf{i} \leftarrow \text{from\_half\_diff}(\mathbf{h}, \mathbf{d})$ 
       $\mathbf{o} \leftarrow \text{reflect}(\mathbf{i}, \mathbf{h})$ 
       $F(\theta_d) \leftarrow F(\theta_d) + f_r(\mathbf{i}, \mathbf{o}) / f_{r,id}(\mathbf{i}, \mathbf{o})$ 
       $N \leftarrow N + 1$ 
    end for
     $F(\theta_d) \leftarrow F(\theta_d) / N$ 
  end for
end function
```

---

# Validation

29 gold-metallic-paint

Renderings



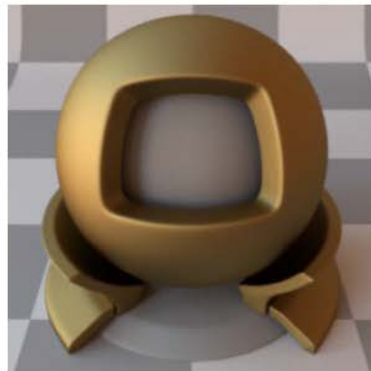
SGD



Reference



Ours: Tabulated



Ours: Gaussian



Reference



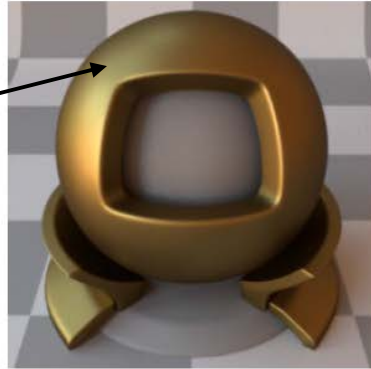
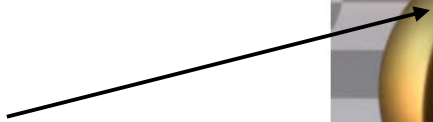
Ours: GGX

# Validation

29 gold-metallic-paint

Renderings

SGD fitting optimization failed  
and resulted in flawed images



SGD



Reference



Ours: Tabulated



Ours: Gaussian

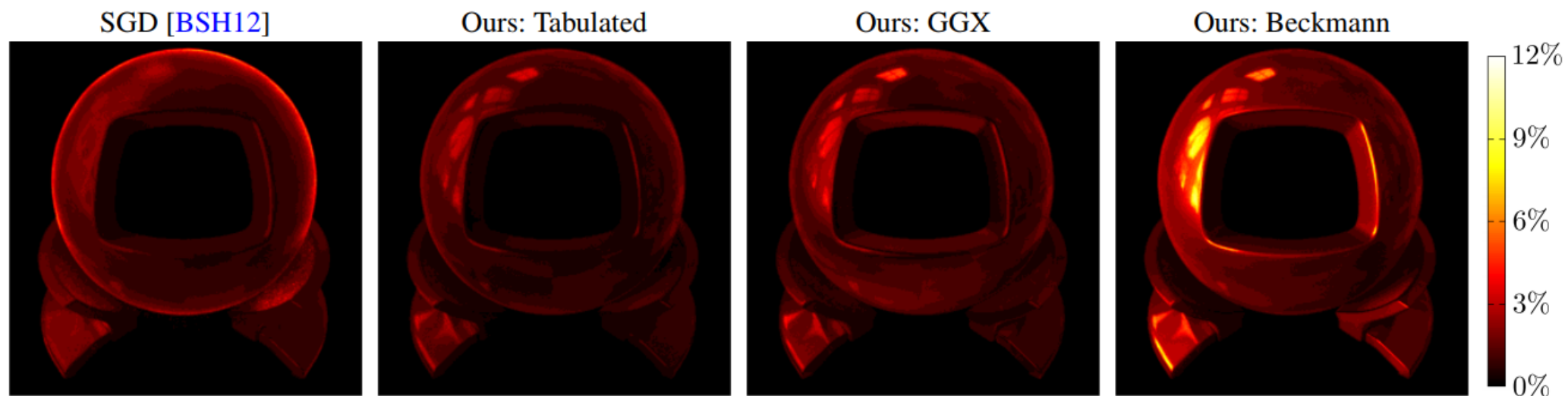


Reference



Ours: GGX

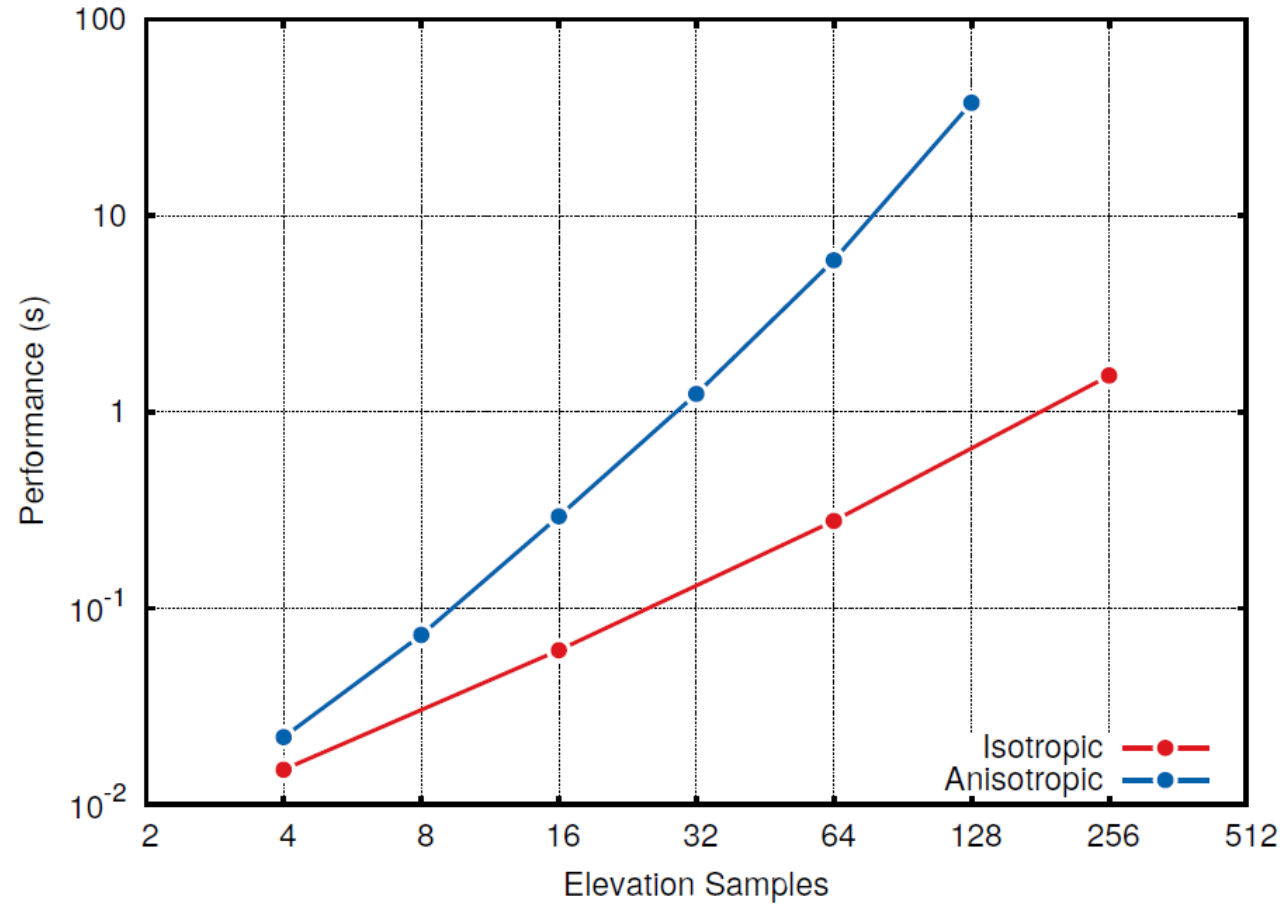
# Accuracy



Mean delta-E difference image on the MERL database

# Speed

(Intel i5-2500 @ 3.30 GHz)

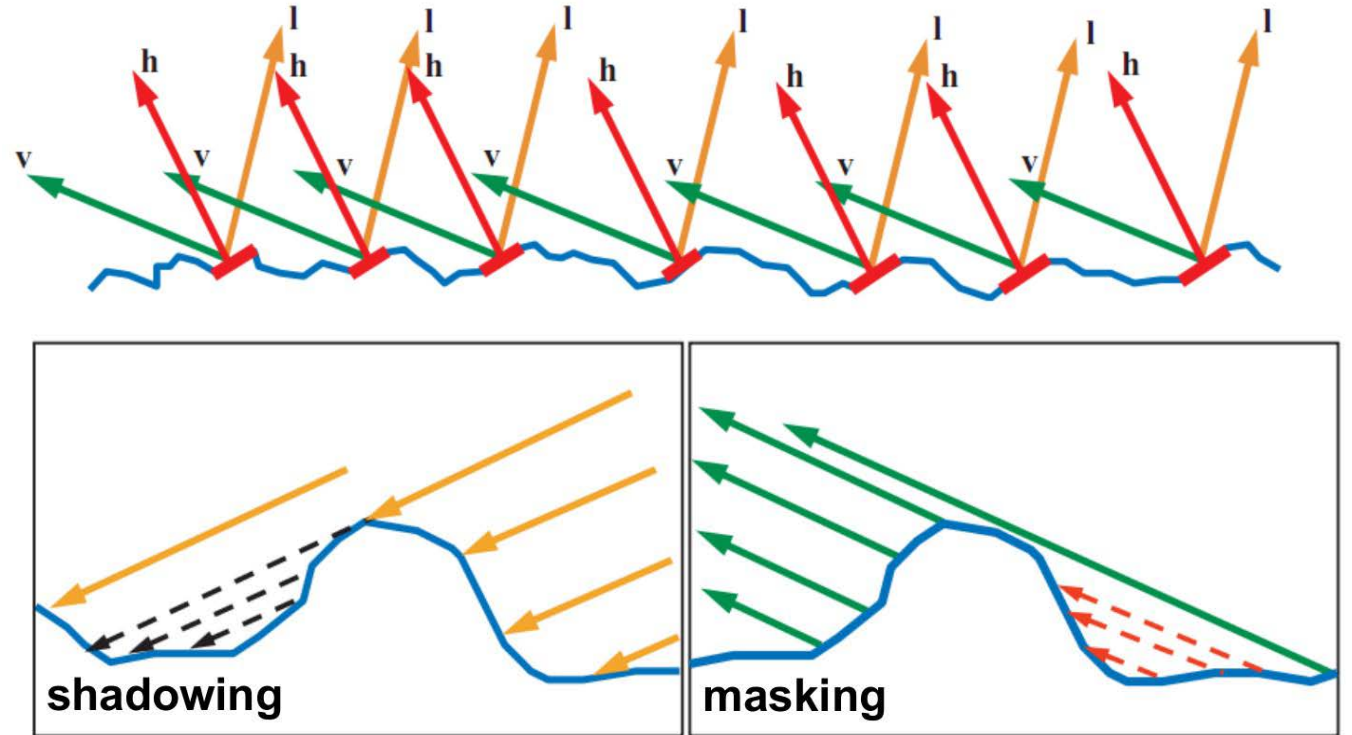


# Microfacet BRDFs

$$f_r = \frac{F \cdot D \cdot G}{4 \cdot \cos \theta_i \cdot \cos \theta_o}$$

Modular components

- Fresnel term  $F$
- Distribution of normals  $D$
- Roughness  $\alpha$
- Geometric factor  $G$



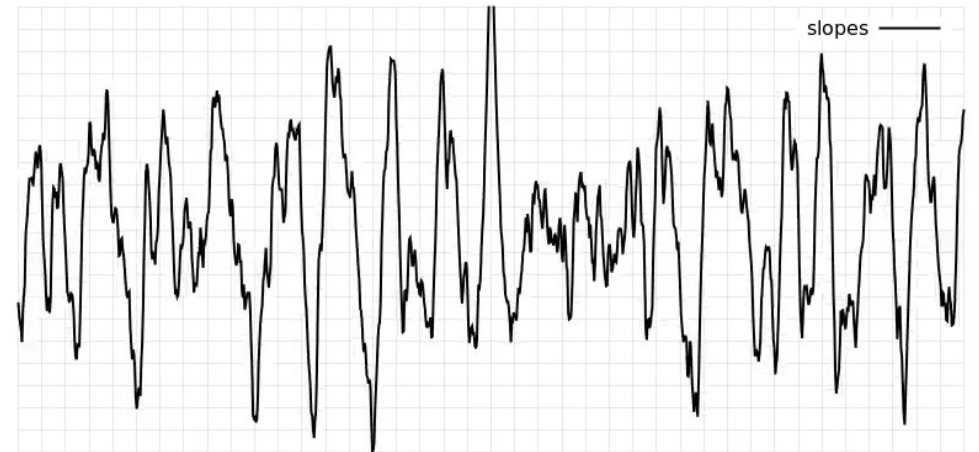
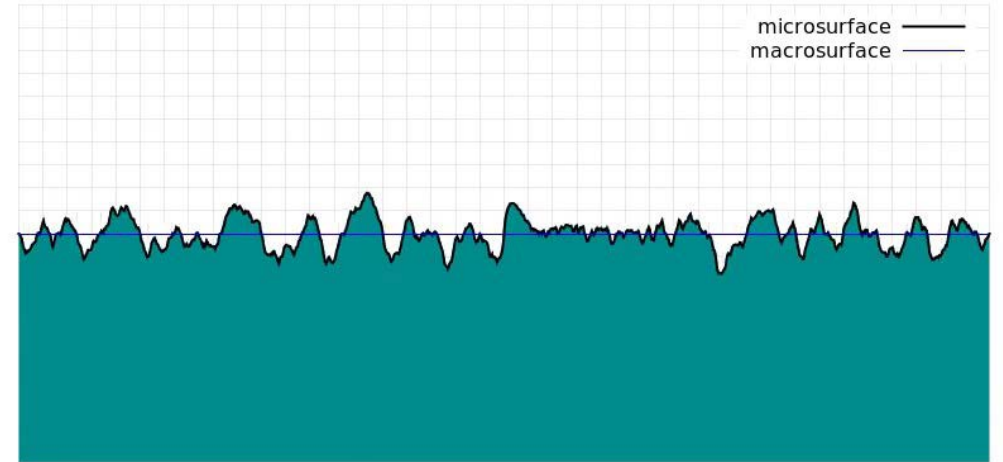
Images from "Real-Time Rendering, 3rd Edition", A K Peters 2008

# Artistic Control

$$D = P \left( \frac{\tilde{x}_h}{\alpha_x}, \frac{\tilde{y}_h}{\alpha_y} \right) \frac{\sec^4 \theta_h}{\alpha_x \alpha_y}$$

Tabulate the slope PDF

- Roughness  $\propto$  stretch<sup>-1</sup>
- Efficient BRDF evaluation
- Efficient BRDF sampling





**Fast Global Illumination with Discrete Stochastic Microfacets Using a Filterable Model**

Beibei Wang Lu Wang Pierre Poulin Nicolas Holzschuch

Pacific Graphics 2018



# Goal



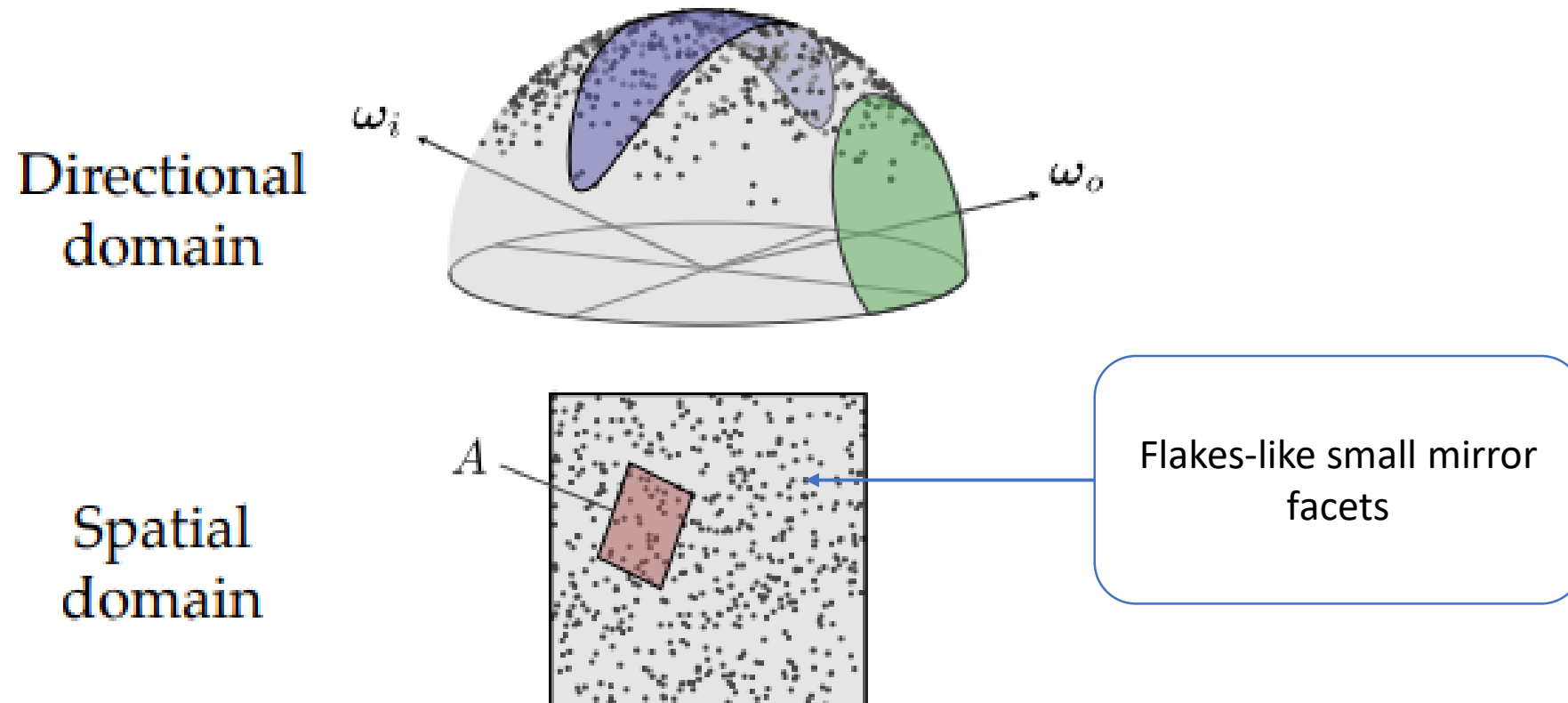
Original

Without Glints

# Previous work

Jakob et al.

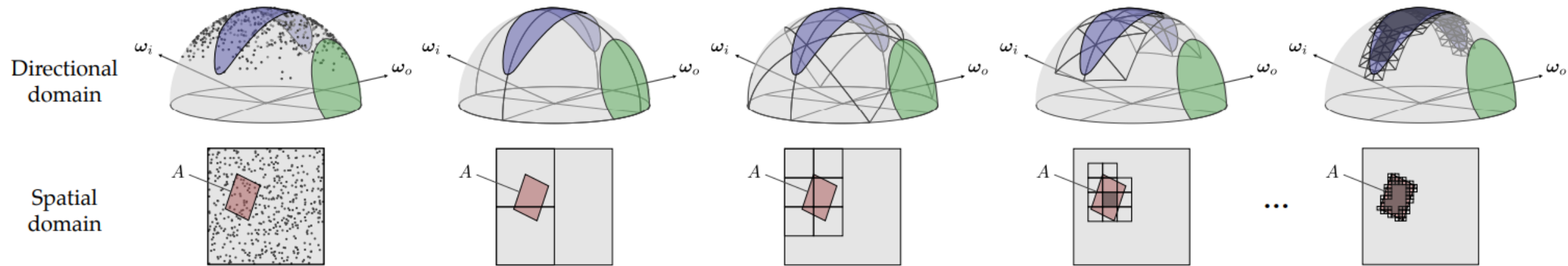
**Discrete Stochastic Microfacet Models**



# Previous work

Jakob et al.

## Discrete Stochastic Microfacet Models



These specular patches are organized in a hierarchy

# Discrete Stochastic Microfacet Model

Extend the microsurface BRDF model to take into account a finite extend in **space** and **angle**

$$\hat{f}_r(A, \omega_i, \Omega_0) = \frac{1}{a(A)\sigma(\Omega_0)} \int_A \int_{\Omega_0} f_r(x, \omega_i, \omega_o) d\omega_o dx$$

A = finite area around x

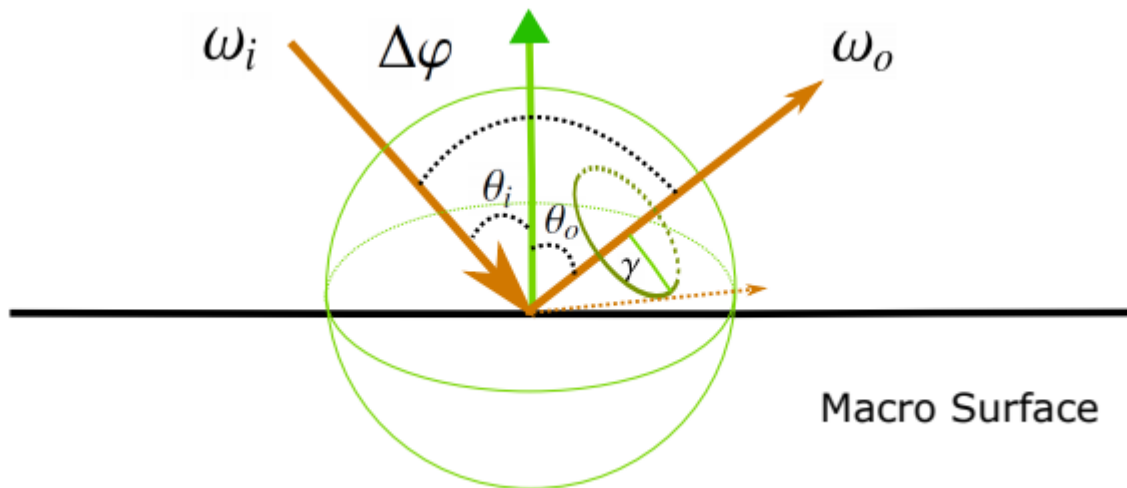
$\Omega_0$  = finite solid angle around outgoing direction  $\omega_o$

$$f_r(x, \omega_i, \omega_o) = \frac{F(\omega_i, \omega_o)D(x, \omega_h)G(\omega_i, \omega_o, \omega_h)}{4 \cos\theta_i \cos\theta_o}$$

# Discrete Stochastic Microfacet Model

We now assume the surface is made of discrete small mirror particles instead of a continuous microfacets

$$\hat{f}_r(A, \omega_i, \Omega_0) = \frac{1}{a(A)\sigma(\Omega_0)} \int_A \int_{\Omega_0} f_r(x, \omega_i, \omega_o) d\omega_o dx \quad \rightarrow \quad \hat{f}_r(A, \omega_i, \Omega_0) = \frac{(\omega_i \cdot \omega_h) F(\omega_i, \omega_o) \hat{D}(x, \omega_h) G(\omega_i, \omega_o, \omega_h)}{a(A)\sigma(\Omega_0)4(\omega_i \cdot n)(\omega_i \cdot n)}$$



$$\hat{D}(x, \Omega_h) = \frac{1}{N} \sum_i^N 1_{\Omega_h}(\omega_h^k) 1_A(x^k)$$

Sum of a finite set of particles

A = pixel footprint

# Discrete Stochastic Microfacet Model

$$\hat{D}(x, \Omega_h) = \frac{1}{N} \sum_i^N 1_{\Omega_h}(\omega_h^k) 1_A(x^k)$$

Sum of a finite set of particles

A = pixel footprint

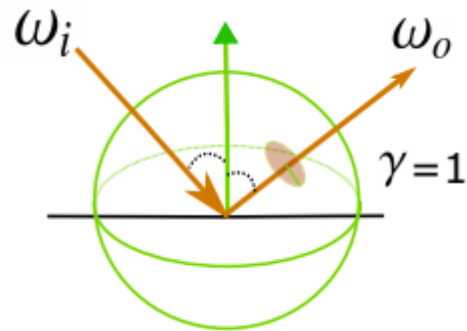
4 dimensional normal distribution

Count the number of particles in the 4 dimensional domain  $A \times \Omega_h$

# Filterable Discrete Stochastic Microfacet Model

Replace the particle count with a particle probability function  
Introduce a **Directional Probability Function** (DPF)

$P(\omega_i, \omega_o, \gamma)$  = probability a particle exist that reflect lights incoming from direction  $\omega_i$  into a coe centered around direction  $\omega_o$  with half angle  $\gamma$



$\omega_i$  and  $\omega_o$  are independent variables

# Filterable Discrete Stochastic Microfacet Model

Replace the particle count with a particle probability function  
Introduce a **Directional Probability Function** (DPF)

$$P(\omega_i, \omega_o, \gamma) \approx \frac{1}{N} \sum_{k=1}^N \mathbf{1}_{\Omega_h}(\omega_h^k)$$

$$\hat{D}(A, \omega_i, \omega_o) = \left( \frac{1}{N} \sum_{k=1}^N \mathbf{1}_A(\mathbf{x}^k) \right) P(\omega_i, \omega_o, \gamma)$$

$\mathbf{x}$  and  $(\omega_i, \omega_o)$  are independent variables

$$\hat{D}(A, \omega_i, \omega_o) = \frac{1}{N} \sum_{k=1}^N \mathbf{1}_A(\mathbf{x}^k) H(\lambda(\mathbf{x}) - P(\omega_i, \omega_o, \gamma))$$

$$H(u) = \begin{cases} 1, & \text{if } u > 0, \\ 0, & \text{otherwise.} \end{cases}$$



# Filterable Discrete Stochastic Microfacet Model

$$\hat{D}(A, \omega_i, \omega_o) = \frac{1}{N} \sum_{k=1}^N \mathbf{1}_A(\mathbf{x}^k) H(\lambda(\mathbf{x}) - P(\omega_i, \omega_o, \gamma))$$

$$H(u) = \begin{cases} 1, & \text{if } u > 0, \\ 0, & \text{otherwise.} \end{cases}$$

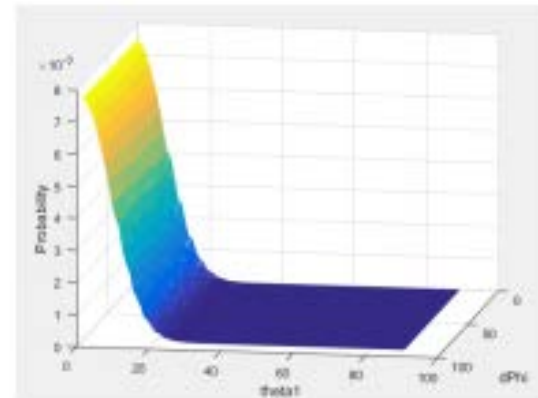
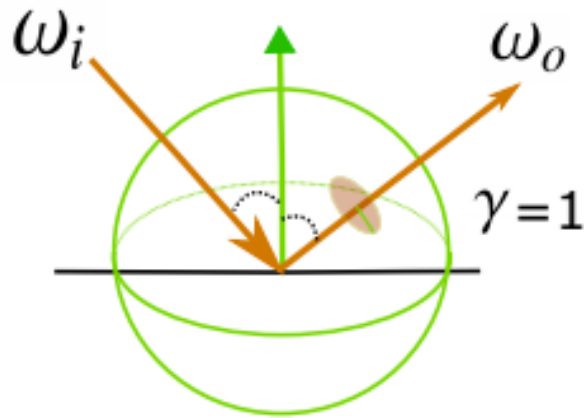
$\lambda(\mathbf{x})$  = uniformly Distributed random value from Tiny Encryption Algorithm

$\lambda(\mathbf{x})$  is used to assign a random value between 0 and 1 to each position  $\mathbf{x}$

# Filterable Discrete Stochastic Microfacet Model

## Preprocess

compute and store  $P$  for  $\gamma = 1^\circ$ , by sampling regularly in each dimension, computing and storing the value for  $P$ .





# Filterable Discrete Stochastic Microfacet Model

## Preprocess

- Build a hierarchical representation of the Directional Probability Function, using Gaussian blur
- Each level is generated by blurring the finest level
- 9 hierarchical levels, for  $1^\circ$  ,  $2^\circ$  ,  $5^\circ$  ,  $10^\circ$  ,  $20^\circ$  ,  $30^\circ$  ,  $45^\circ$  ,  $60^\circ$  and  $90^\circ$

# Filterable Discrete Stochastic Microfacet Model

## 2 steps hierachical traversal

- Angle
- Space

Look up in the precomputed table;  
Select the appropriate hierachical level;  
Extract the prcomputed value for P

---

### Algorithm 1 Spatial Traversal

---

```
function  $\hat{D}_s(A, \omega_i, \omega_o)$ 
  query  $\leftarrow A$ 
  queue  $\leftarrow \text{node}(N_{\text{start}})$ 
  count  $\leftarrow 0$ 
   $p \leftarrow P(\omega_i, \omega_o)$ 
  while queue  $\neq \emptyset$  do
    node  $\leftarrow$  queue.pop()
    if node  $\cap$  query ==  $\emptyset$  or |node| = 0 then pass
    else if node  $\subseteq$  query then  $n_k \leftarrow$  |node|
      for  $i < n_k$  do  $\psi \leftarrow \lambda(k)$ 
        if  $\psi > p$  then count  $\leftarrow$  count + 1
      end if
    end for
    else if error criterion satisfied then
      overlap  $\leftarrow$  (node  $\cap$  query).vol()/node.vol()
       $n_k \leftarrow$  |node|
      for  $i < n_k$  do  $\psi \leftarrow \lambda(k)$ 
        if  $\psi > p$  then count  $\leftarrow$  count + overlap
      end if
    end for
    else
      for c in node.split() do queue.push(c)
    end for
    end if
  end while
  return count
end function
```

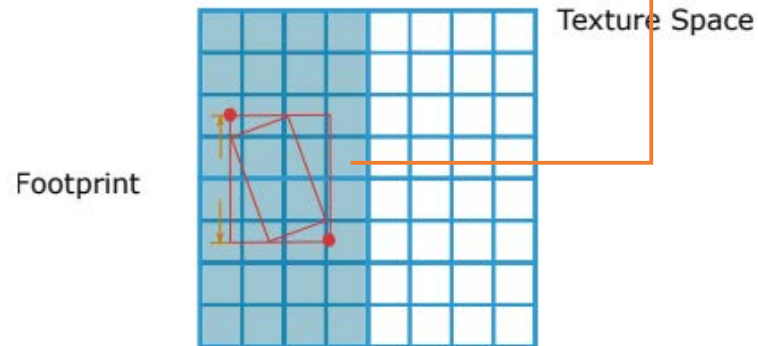
---

# Filterable Discrete Stochastic Microfacet Model

## 2 steps hierachical traversal

- Angle
- Space

Traversal in texture space;  
Assume flakes are uniformly distributed in space;



---

### Algorithm 1 Spatial Traversal

---

```
function  $\hat{D}_s(A, \omega_i, \omega_o)$ 
  query  $\leftarrow A$ 
  queue  $\leftarrow \text{node}(N_{\text{start}})$ 
  count  $\leftarrow 0$ 
   $p \leftarrow P(\omega_i, \omega_o)$ 
  while queue  $\neq \emptyset$  do
    node  $\leftarrow$  queue.pop()
    if node  $\cap$  query ==  $\emptyset$  or |node| = 0 then pass
    else if node  $\subseteq$  query then  $n_k \leftarrow$  |node|
      for  $i < n_k$  do  $\psi \leftarrow \lambda(k)$ 
        if  $\psi > p$  then count  $\leftarrow$  count + 1
        end if
      end for
    else if error criterion satisfied then
      overlap  $\leftarrow$  (node  $\cap$  query).vol()/node.vol()
       $n_k \leftarrow$  |node|
      for  $i < n_k$  do  $\psi \leftarrow \lambda(k)$ 
        if  $\psi > p$  then count  $\leftarrow$  count + overlap
        end if
      end for
    else
      for c in node.split() do queue.push(c)
      end for
    end if
  end while
  return count
end function
```

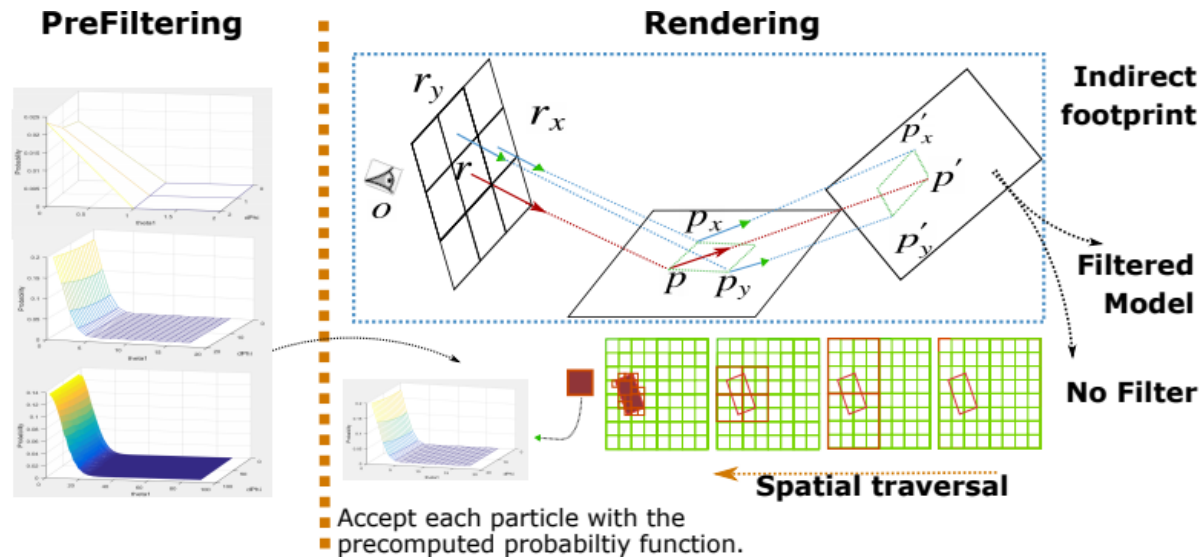
---

# Filterable Glint Computation

- For each path, compute the path footprint at each light bounce
- Compute the average glint contribution at this footprint

$$\hat{D}(A, \omega_i, \omega_o) = a(A) \times P(\omega_i, \omega_o, \gamma),$$

- If the glint count is larger than a given threshold, use the average contribution.
- Otherwise, use the separable model described



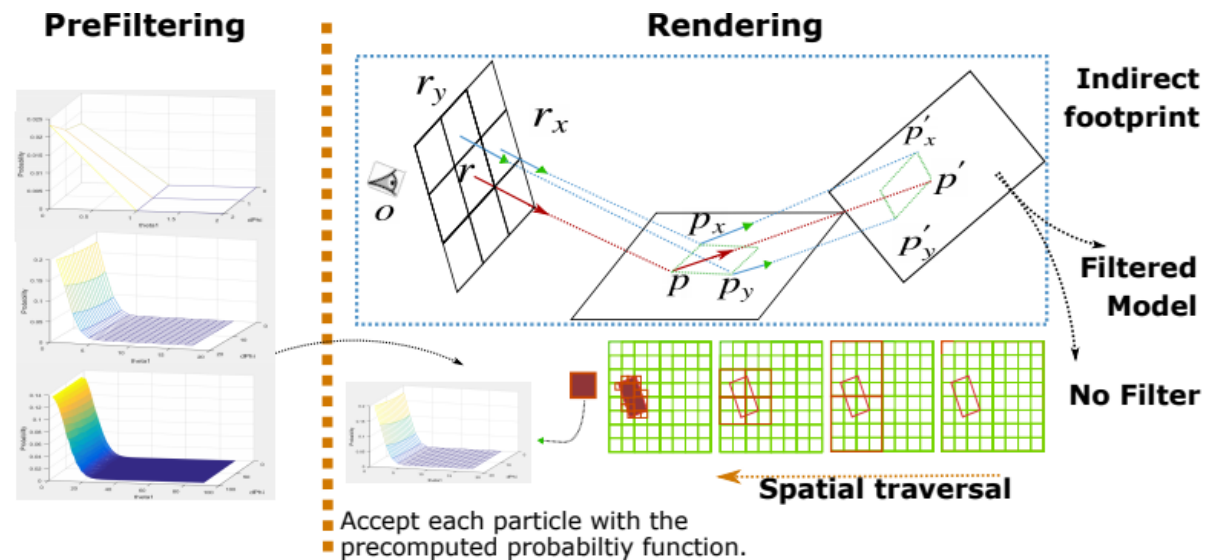
# Discrete Stochastic Microfacets Using a Filterable Model

## Idea:

- If a footprint cover a large surface,
- individual glint are not noticeable;
  - average contribution

## In practice:

- Filterable model preffer for
- material far from camera;
  - Several bounce in global illumination



# Validation



*Our model (with filtering)*  
Total: 4.6 min, Cost: +21%

*Our model (no filter)*  
Total: 7.4 min, Cost: +95%

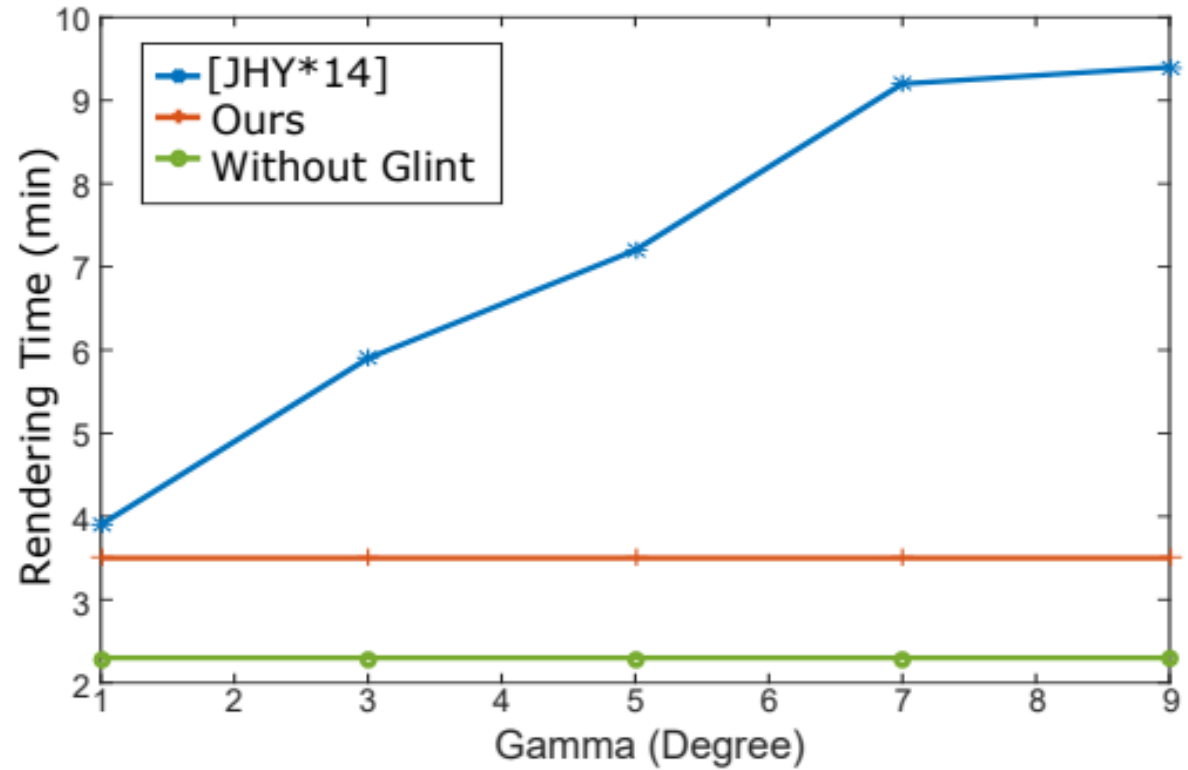
*Original [JHY\*14],*  
Total: 24.4 min, Cost: +542%

*Without Glints,*  
Total: 3.8 min



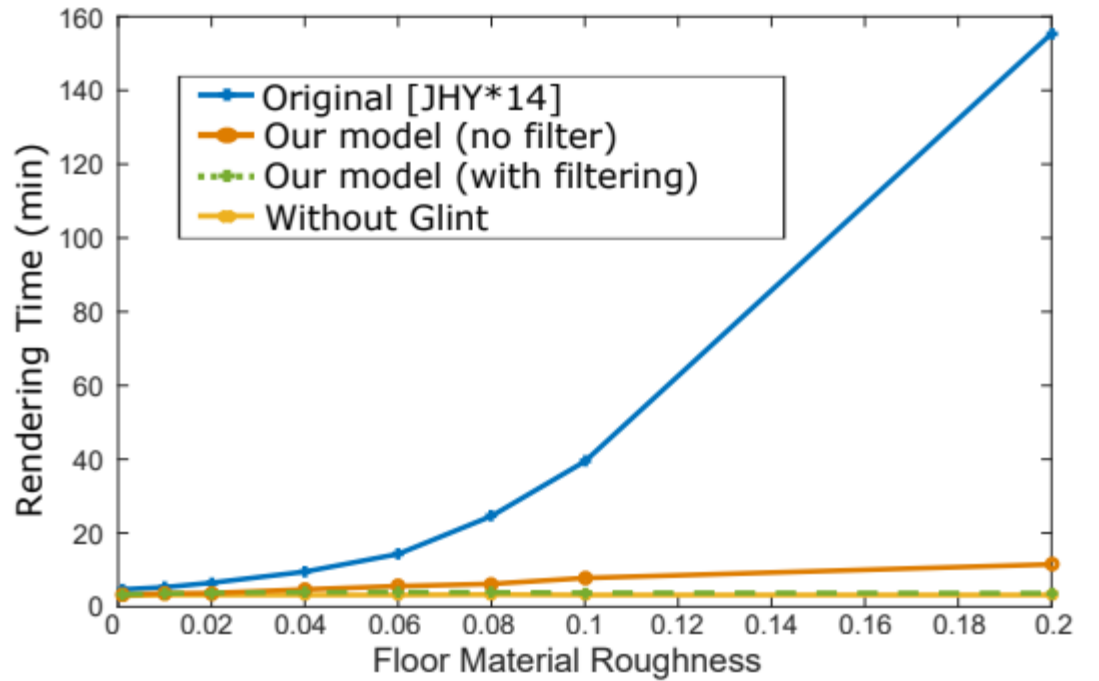
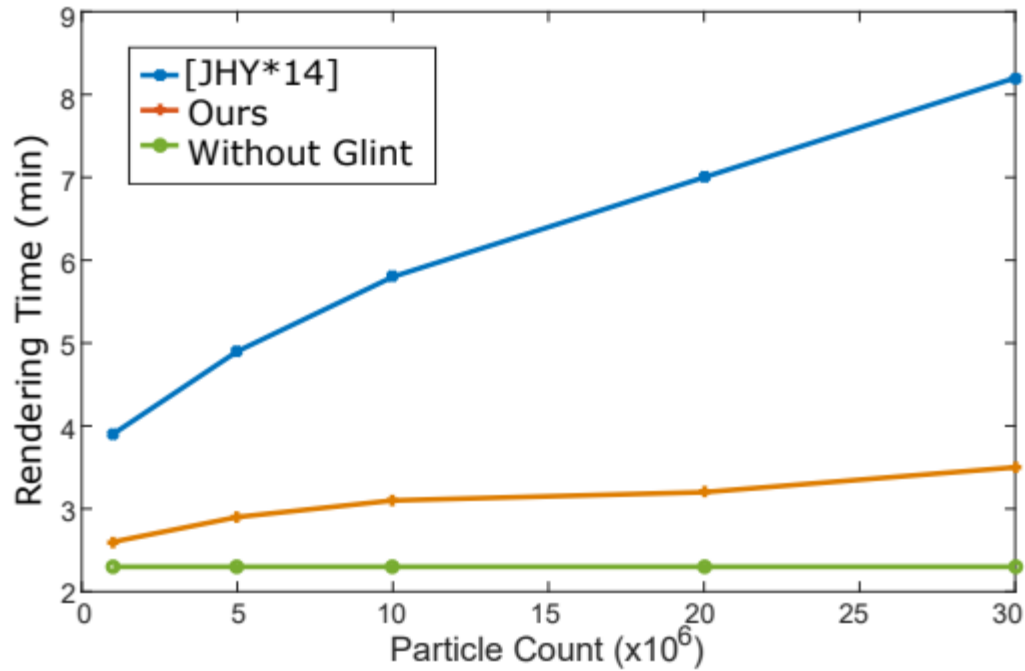
# Speed

(Intel i7 (40 cores) with 32 GB of main memory @ a 2.20GHz)



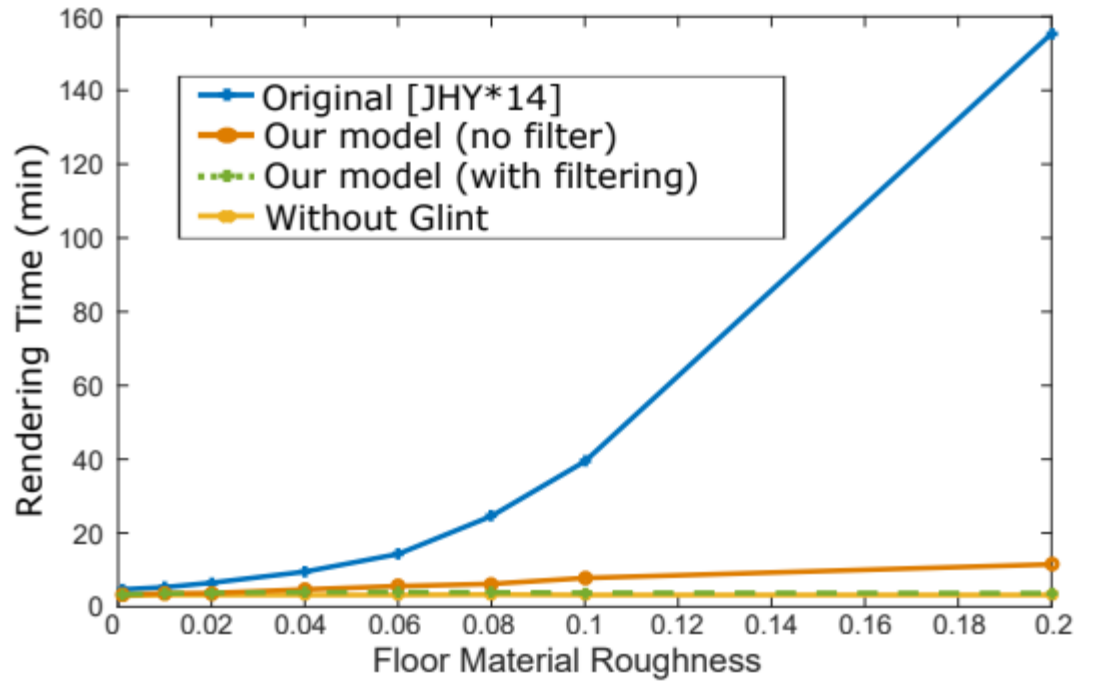
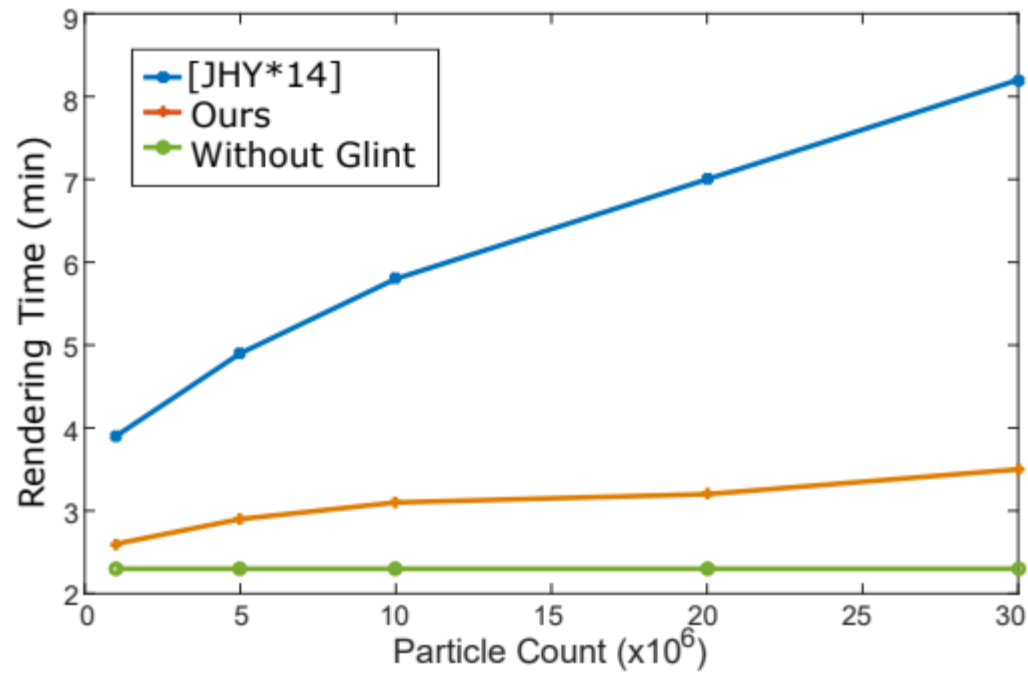
# Speed

(Intel i7 (40 cores) with 32 GB of main memory @ a 2.20GHz)



# Speed

(Intel i7 (40 cores) with 32 GB of main memory @ a 2.20GHz)



# Quiz

- In ‘Extracting Microfacet-based BRDF Parameters from Arbitrary Materials with Power Iterations’ , a bijection is used to link ( ) space and the slopes space ( ) .

a.  $\Omega_d$  and  $\mathbb{R}^4$

c.  $\mathbb{R}^2$  and  $\Omega_+$

b.  $\Omega_+$  and  $\mathbb{R}^2$

d.  $\mathbb{R}^2$  and  $\Omega_d$

- In ‘Fast Global Illumination with Discrete Stochastic Microfacets Using a Filterable Model’, which variables do we consider for indépendance?

a.  $x$  and  $(\omega_i, \omega_o)$

c.  $\gamma$  and  $(\omega_i, \omega_o)$

b.  $x$  and  $\gamma$

d.  $\omega_h$  and  $\gamma$