

BRDF Reconstruction Using Compressive Sensing

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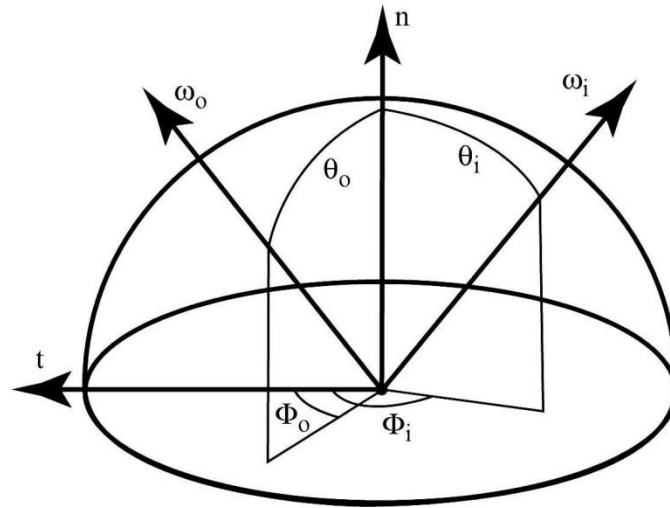
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BRDF Reconstruction Using Compressive Sensing

- Bidirectional Reflectance Distribution Function (BRDF)
- BRDF Measurements
- Problems with BRDF Measurements
- Handling Measurement Problems
- Compressive Sensing
- Reconstruction of BRDF Data
- Results
- Conclusion and Future Work

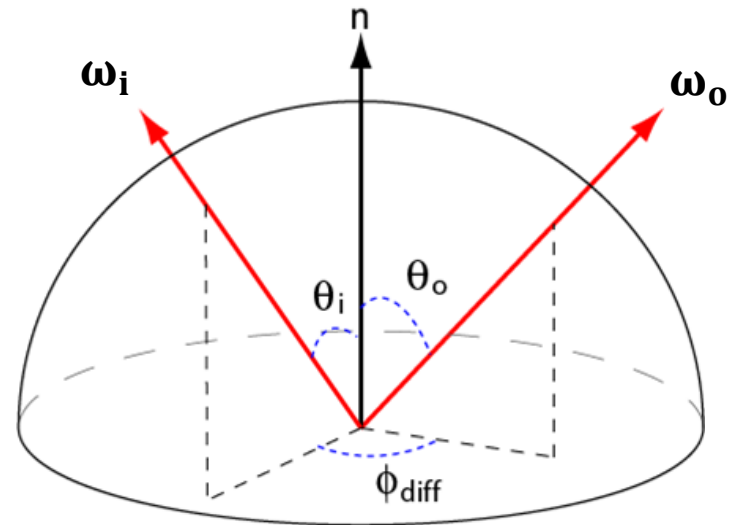
Bidirectional Reflectance Distribution Function (BRDF)



The Bidirectional Reflectance Distribution Function (BRDF) describes the appearance of a material by its interaction with light at a surface point. (Ngan et. al., 2005)

Bidirectional Reflectance Distribution Function (BRDF)

- Bidirectional Reflectance Distribution Function
 - $\rho(\theta_i, \phi_i; \theta_o, \phi_o)$
- Isotropic material
 - Invariant when material is rotated
 - Isotropic BRDF is 3D



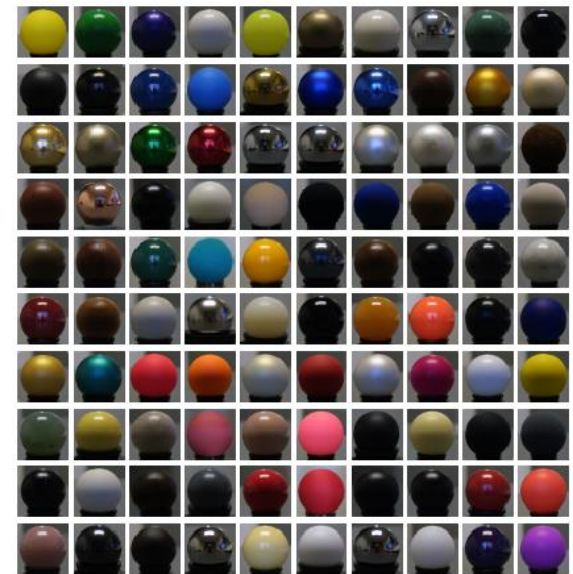
Ngan, et. al., 2005

BRDF Measurements

- CURET: Columbia-Utrecht Reflectance and Texture Database: ~60 materials, 205 samples per BRDF
- Cornell's Reflectance Data: ~10 materials, 1439 samples per BRDF
- Bonn BTF Database: 6 materials, 6561 view/light combinations
- Matusik's image-based measurements: 100 materials, $\sim 10^6$ samples per BRDF

BRDF Measurements

- BRDF's can be measured by devices called Gonioreflectometer.
- They consist of a light source illuminating the material and a sensor that captures light reflected from that material.
- Matusik et. al., designed such a device to measure BRDFs.



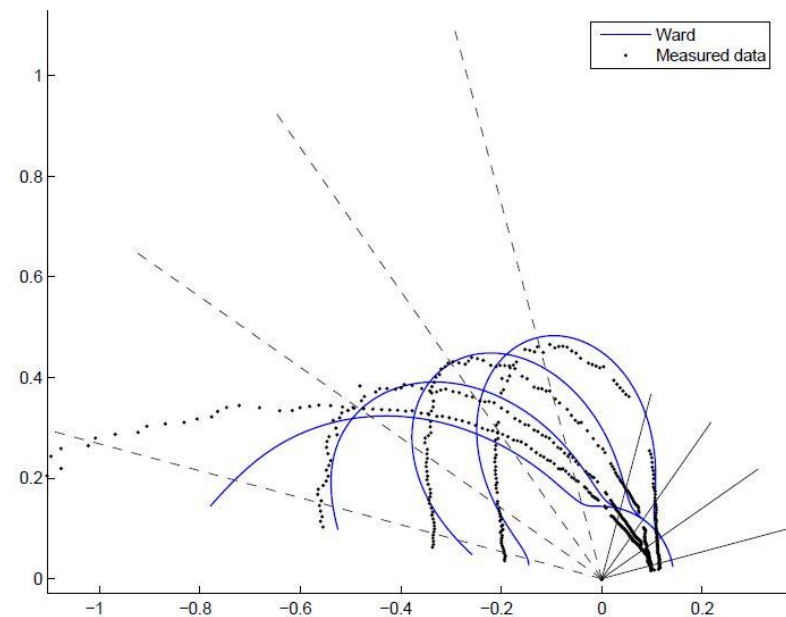
Matusik et. al., 2003

Problems with BRDF Measurements

- BRDF data acquisition can be,
 - Noisy
 - Difficult to obtain samples from grazing angles. (Ngan et. al., 2005)
 - Lens flare artifacts can be observed in measurements. (Romerio et. al., 2008)
 - Incomplete
 - Optical elements of the system do not allow measurements from certain angles. (Matusik et. al., 2003)
 - Time consuming
 - Matusik et. al. stated that data acquisition for a single material can take up to 12 hours.

Handling Measurement Problems

- Ignore the missing or highly noisy data and fit an analytical model to the remaining part of the data.
 - Increased degree of the lack-of-fit of the model.
 - Does not improve measurement times.



Ngan et. al., 2005

Handling Measurement Problems

- Sample less and reconstruct BRDF data using Compressive Sensing.
 - Tolerant to noise
 - Can recover incomplete data
 - Faster than sampling all the data

Compressive Sensing (CS)

The theory of Compressive Sensing states that if a signal is sparse in a transform domain, then under certain conditions it can be reconstructed exactly from a small set of linear measurements using tractable optimization algorithms. (Sen & Darabi, 2009)

Key Idea Behind CS

- Higher-dimensional data is processed by vectorizing it into a long one-dimensional vector. ($N \times 1$ column vector)
- This signal is called sparse if it can be represented as a linear combination of smaller number of some basis vectors.
- The key idea behind compressive sensing technique is that sparse signals can be reconstructed efficiently.

Sparse Signals

- A vector \mathbf{x} can be transformed into another $N \times 1$ vector \mathbf{s} through an $N \times N$ orthogonal basis matrix Ψ as

$$\mathbf{x} = \Psi \mathbf{s} \quad (1)$$

- If \mathbf{s} is known or can be estimated from the sample data then \mathbf{x} can be reconstructed easily from the above equation.
- If the signal \mathbf{x} is K -sparse in Ψ domain; only K of the s_i coefficients in (1) are nonzero and $(N - K)$ are zero, where $K \ll N$.

Sampling in CS

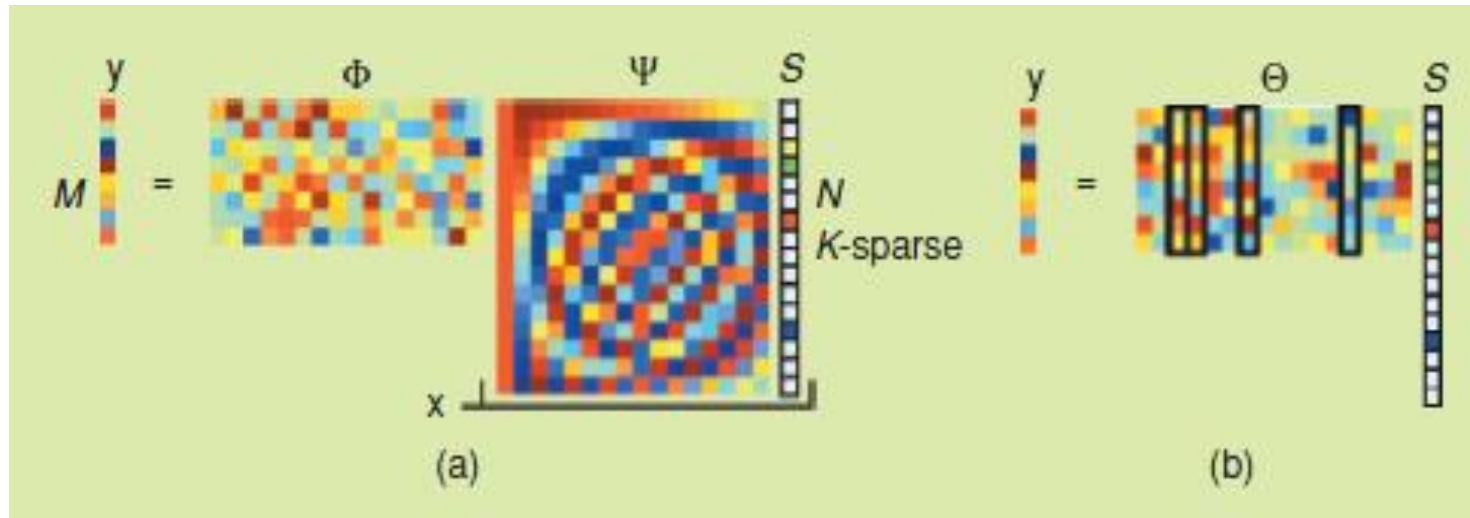
M measurements y_j in an $M \times 1$ vector \mathbf{y} are calculated using measurement vectors as rows in an $M \times N$ matrix $\boldsymbol{\varphi}$ (Sampling matrix).

Then, by substituting \mathbf{x} from (1), \mathbf{y} can be written as:

$$\mathbf{y} = \boldsymbol{\varphi}\mathbf{x} = \boldsymbol{\varphi}\boldsymbol{\Psi}\mathbf{s} = \boldsymbol{\Theta}\mathbf{s} \quad (2)$$

where $\boldsymbol{\Theta} = \boldsymbol{\varphi}\boldsymbol{\Psi}$ is an $M \times N$ matrix.

Sample Illustration



(a) The vector of coefficients s is sparse with $K = 4$.

(b) Measurement process with $\Theta = \varphi\Psi$. There are four columns that correspond to nonzero s_j coefficients; the measurement vector y is a linear combination of these columns. (Baraniuk, 2007)

Conditions Required for CS

- The sampling matrix Φ must allow the reconstruction of the length- N signal \mathbf{x} from $M < N$ samplings (the vector \mathbf{y}).
- Since $M < N$, this problem appears to be ill-conditioned.
- If, however, \mathbf{x} is K -sparse and the K locations of the nonzero coefficients in \mathbf{s} are known, then the problem can be solved and \mathbf{x} can be reconstructed,
- Provided that $M \geq 2K$ and the Restricted Isometry Property (*RIP*) condition is met. (Baraniuk, 2007)

RIP Condition

- The RIP states that a measurement matrix will be valid if every possible set of K columns of Θ forms an approximate orthogonal set.
- The sampling matrix Φ must be as incoherent to the compression basis Ψ as possible.
- Examples of matrices that have been proven to meet RIP include Gaussian matrices, Bernoulli matrices and partial Fourier matrices. (Sen & Darabi, 2009)

ℓ_1 -Minimization

ℓ_1 -minimization can exactly recover K -sparse signals and closely approximate compressible signals with high probability. (Sen & Darabi, 2009)

$$\min \|\mathbf{s}\|_1 \quad s.t. \quad \mathbf{y} = \mathbf{\Theta}\mathbf{s} \quad (4)$$

Reconstruction Algorithm

The reconstruction algorithm then consists of the following steps:

- Determine an $M \times N$ sampling matrix $\boldsymbol{\varphi}$
- Obtain the $M \times 1$ measurement vector as $\mathbf{y} = \boldsymbol{\varphi}\mathbf{x}$
- Determine an $N \times N$ orthogonal basis matrix $\boldsymbol{\Psi}$
- Find the coefficient vector \mathbf{s} using ℓ_1 -minimization
- Reconstruct \mathbf{x} using Eq. (1).

Reconstruction of BRDF Data

- In this work, the compressive sensing technique is applied on isotropic BRDF data which is assumed to have some missing measurements.
- The three dimensional BRDF data is divided into sub-sample blocks.
- Random samples were generated from these sub-sample blocks at a predefined sampling rate.
- Finally, the resulting uniform random samples were used to reconstruct the underlying blocks employing the CS technique.

Determine a Sampling Matrix

- Gaussian Matrix?

$$\mathbf{y} = \boldsymbol{\Phi}\mathbf{x}$$

$$\mathbf{y} = \begin{bmatrix} 0.26 & 0.15 & 1.78 & 0.36 \\ 0.91 & -0.65 & 1.38 & -0.03 \\ -1.12 & -0.21 & -0.67 & 0.35 \end{bmatrix} \begin{bmatrix} 1.3 \\ ? \\ 2.5 \\ 0.7 \end{bmatrix}$$

$$\mathbf{y} = \begin{bmatrix} ? \\ ? \\ ? \end{bmatrix}$$

Determine a Sampling Matrix

- Permutation Matrix (Point sampling)?

$$\mathbf{y} = \boldsymbol{\varphi}\mathbf{x}$$

$$\mathbf{y} = \begin{bmatrix} 1 & \mathbf{0} & 0 & 0 \\ 0 & \mathbf{0} & 0 & 1 \\ 0 & \mathbf{0} & 1 & 0 \end{bmatrix} \begin{bmatrix} 1.3 \\ ? \\ 2.5 \\ 0.7 \end{bmatrix}$$

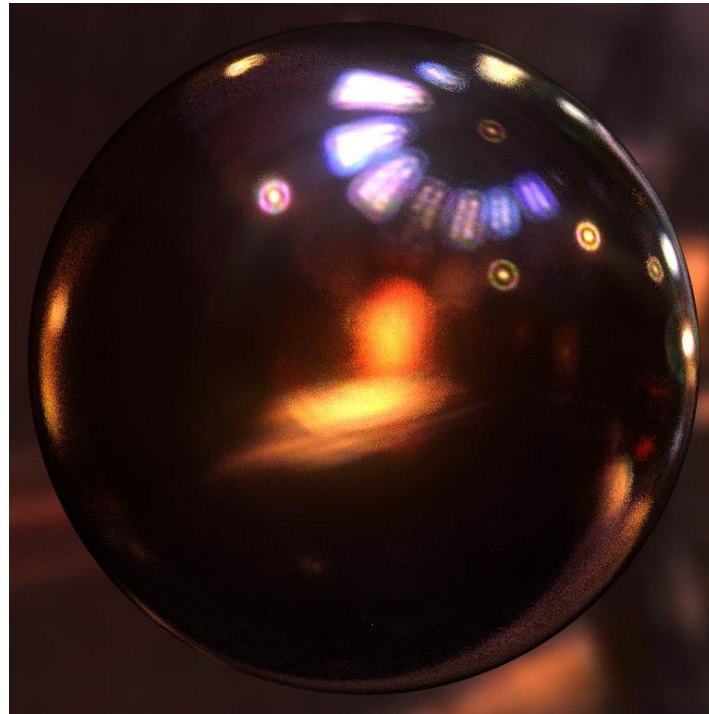
$$\mathbf{y} = \begin{bmatrix} 1.3 \\ 0.7 \\ 2.5 \end{bmatrix}$$

Determine a Basis

- Wavelet Transform?
 - Good sparsity but coherent with point sampling. (Sen & Darabi, 2011)
- Fourier Transform?
 - Acceptable sparsity and incoherent with point sampling.

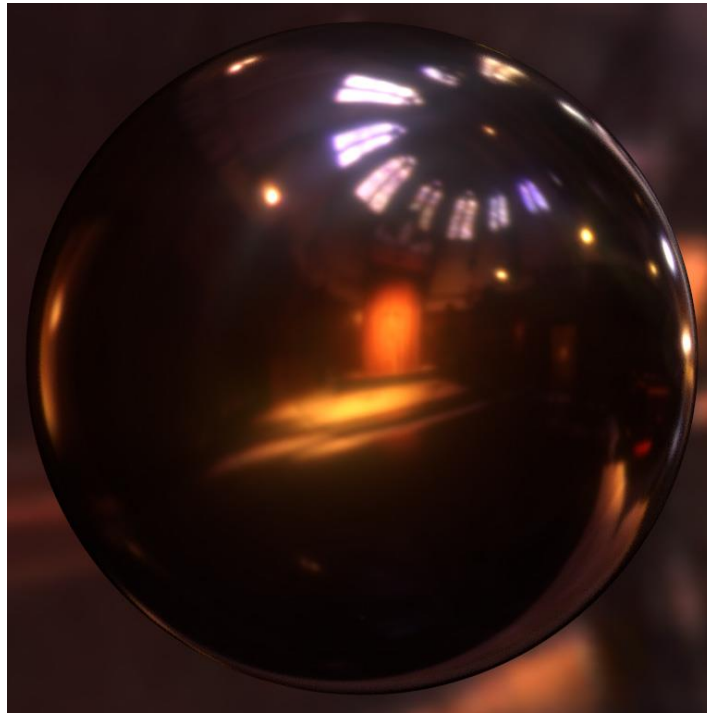
Determine a Basis

- Fourier transform might result in oscillations, which might result in negative values for BRDF.



Determine a Basis

- Take the logarithm of the sampled BRDF and exponentiate it after reconstruction.



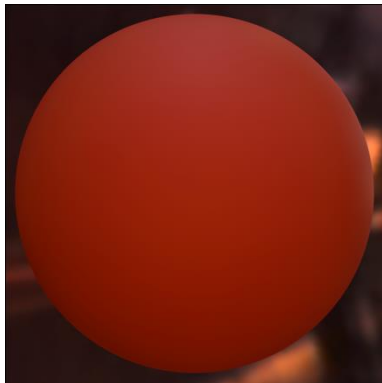
Proposed Approach

- Measure BRDF using few random samples.
- Take the logarithm of the measurements.
- Reconstruct missing data using CS.
- Exponentiate results.

Results

- 6 different materials were reconstructed using different sampling rates.
- Sample scenes are rendered using the fully measured and reconstructed BRDF data.
- Peak-Signal-to-Noise Ratio (PSNR) plots are generated for different sampling rates.

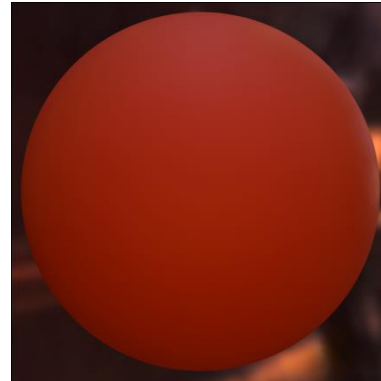
Results (cont.'d)



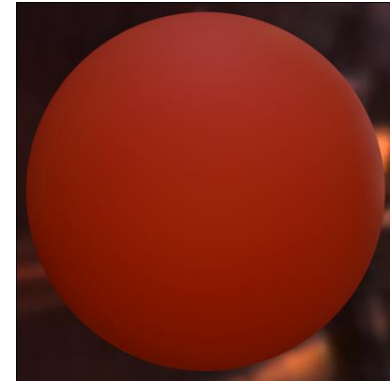
Dark-red-paint
(original)



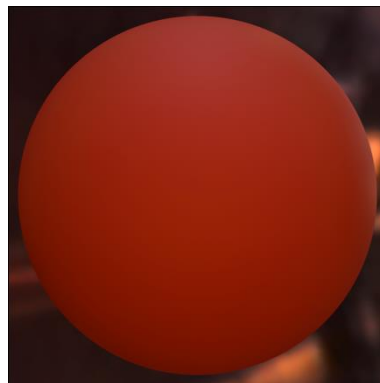
Ratio : 1%
PSNR : 45.04 dB



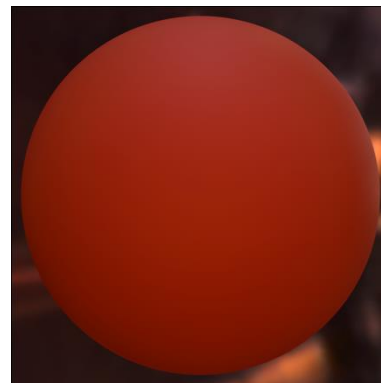
Ratio : 2.5%
PSNR : 49.54 dB



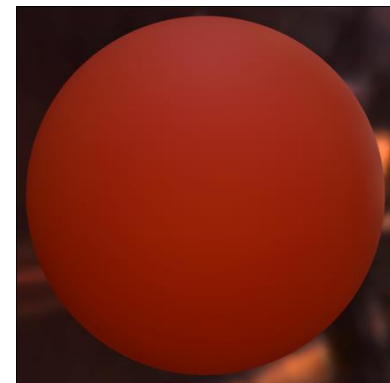
Ratio : 5%
PSNR : 51.46 dB



Ratio : 10%
PSNR : 52.33 dB

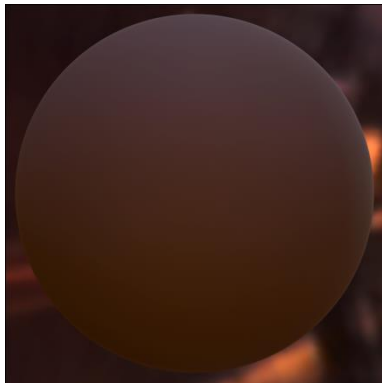


Ratio : 25%
PSNR : 52.48 dB

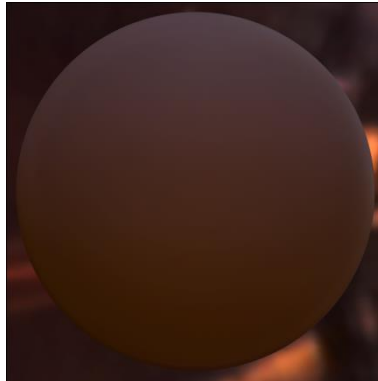


Ratio : 50%
PSNR : 52.91 dB

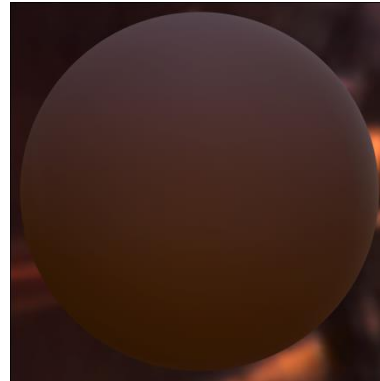
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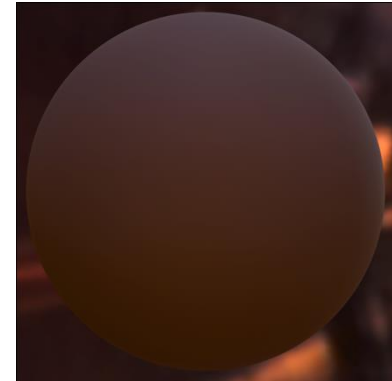
Green-fabric
(original)



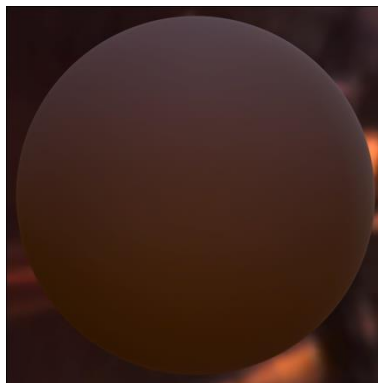
Ratio : 1%
PSNR : 45.72 dB



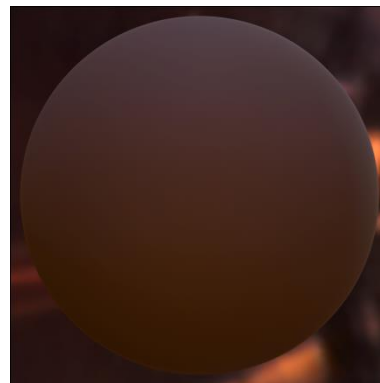
Ratio : 2.5%
PSNR : 50.62 dB



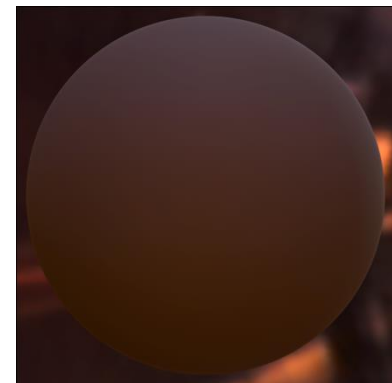
Ratio : 5%
PSNR : 51.83 dB



Ratio : 10%
PSNR : 52.49 dB

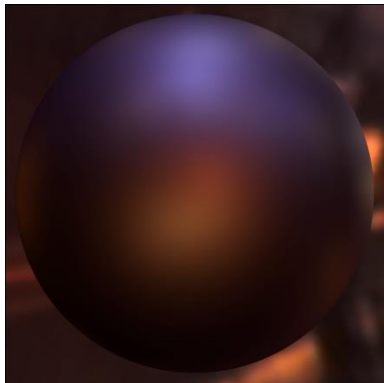


Ratio : 25%
PSNR : 52.72 dB

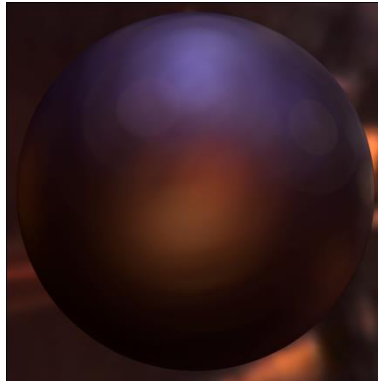


Ratio : 50%
PSNR : 52.76 dB

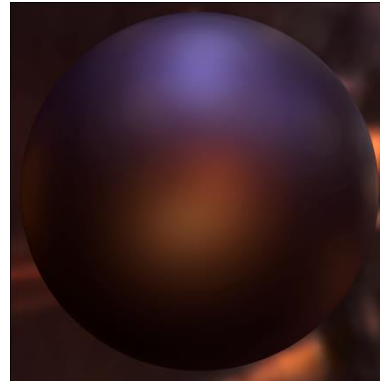
Results (cont.'d)



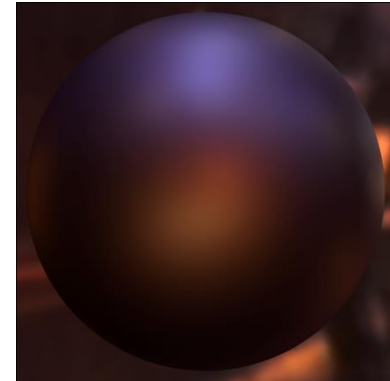
Blue-metallic-paint
(original)



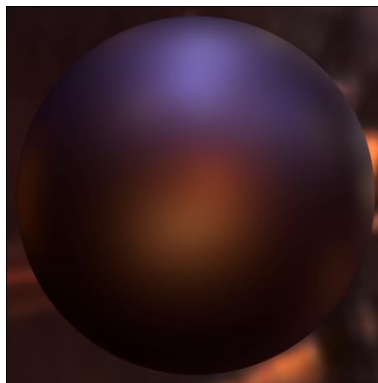
Ratio : 1%
PSNR : 41.58 dB



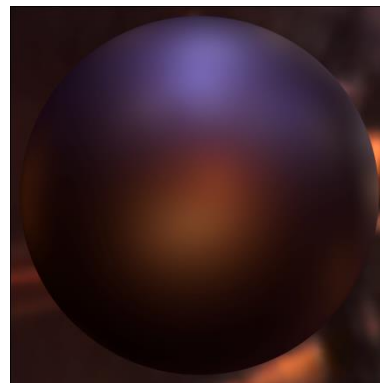
Ratio : 2.5%
PSNR : 47.58 dB



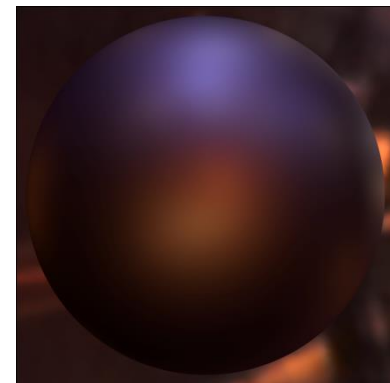
Ratio : 5%
PSNR : 51.71 dB



Ratio : 10%
PSNR : 52.51 dB

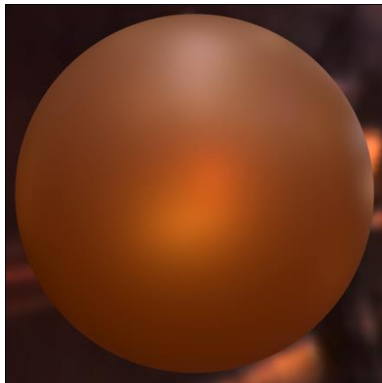


Ratio : 25%
PSNR : 52.62 dB

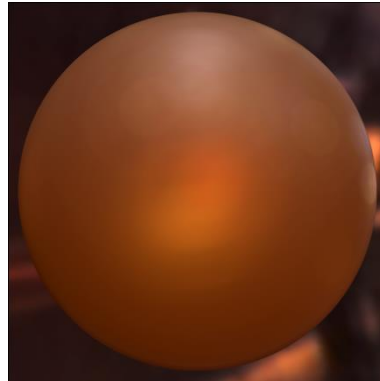


Ratio : 50%
PSNR : 52.64 dB

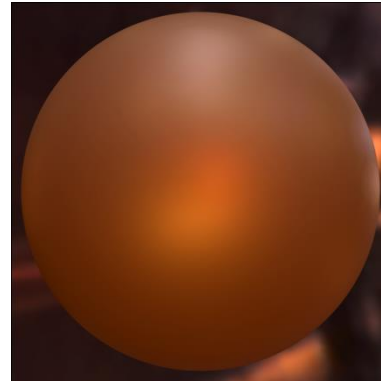
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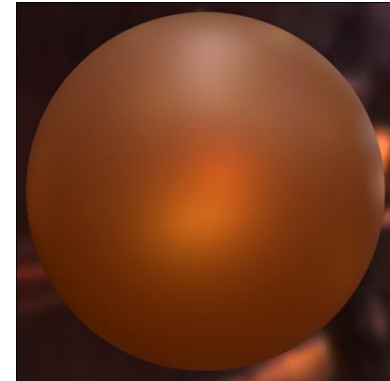
Gold-paint
(original)



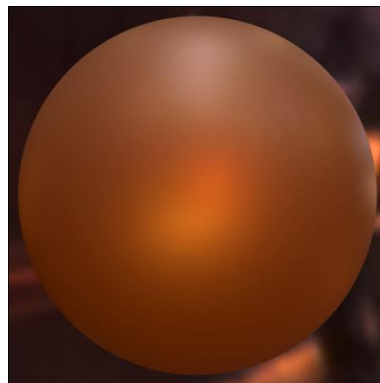
Ratio : 1%
PSNR : 43.01 dB



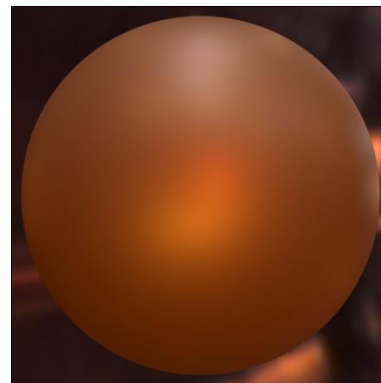
Ratio : 2.5%
PSNR : 48.42 dB



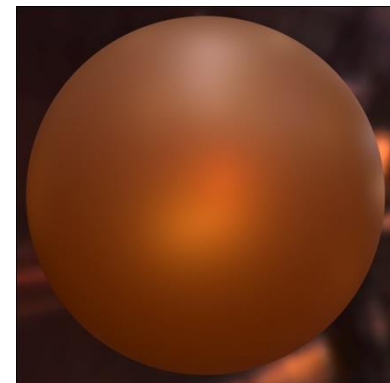
Ratio : 5%
PSNR : 51.22 dB



Ratio : 10%
PSNR : 51.90 dB

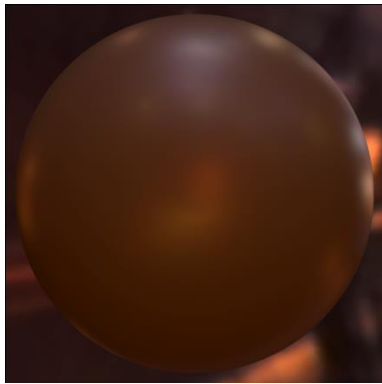


Ratio : 25%
PSNR : 52.01 dB



Ratio : 50%
PSNR : 52.02 dB

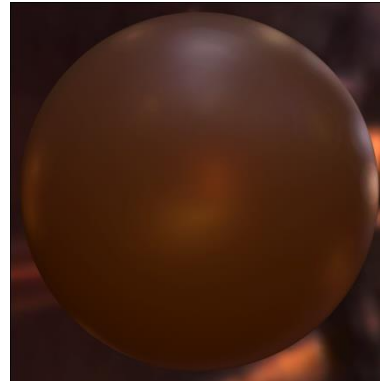
Results (cont.'d)



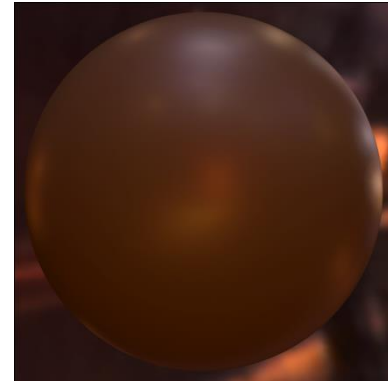
Fruitwood-241
(original)



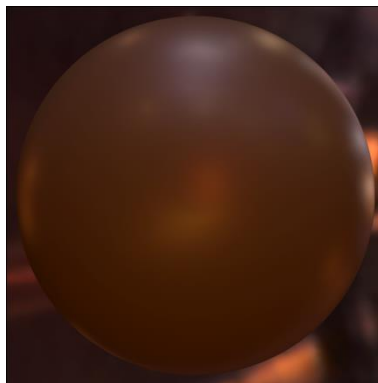
Ratio : 1%
PSNR : 41.68 dB



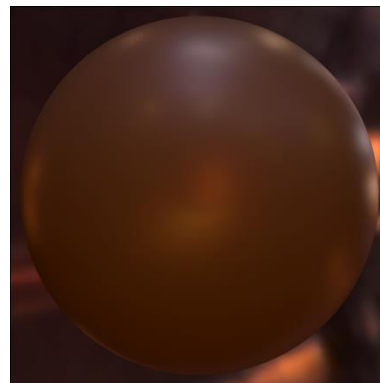
Ratio : 2.5%
PSNR : 44.73 dB



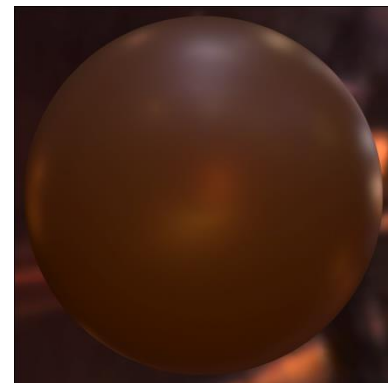
Ratio : 5%
PSNR : 50.26 dB



Ratio : 10%
PSNR : 51.82 dB

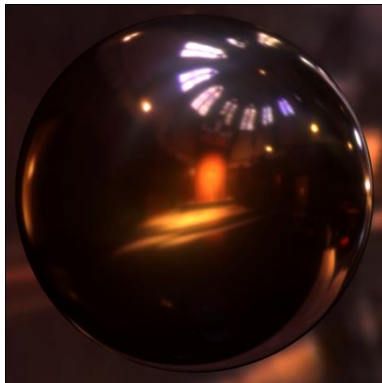


Ratio : 25%
PSNR : 52.11 dB



Ratio : 50%
PSNR : 52.15 dB

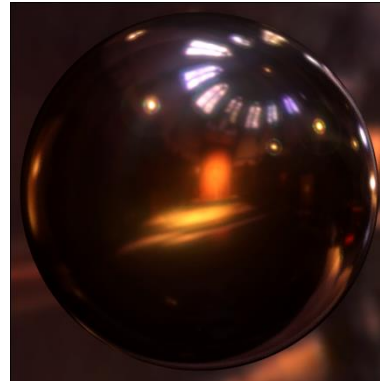
Results (cont.'d)



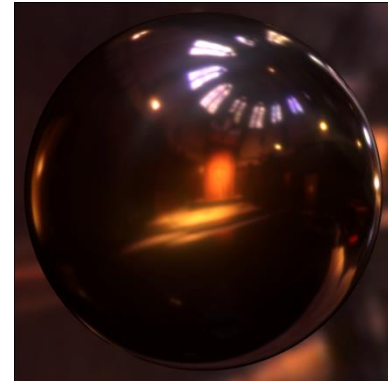
Chrome-steel
(original)



Ratio : 1%
PSNR : 26.92 dB



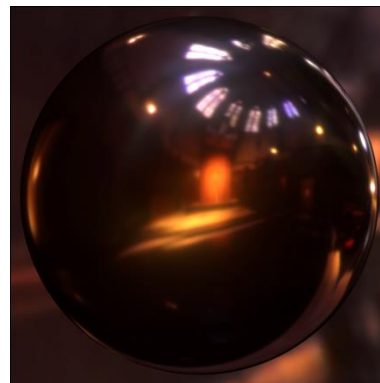
Ratio : 2.5%
PSNR : 35.36 dB



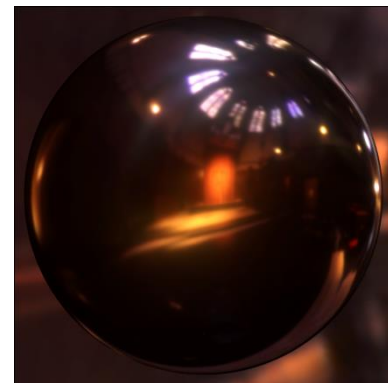
Ratio : 5%
PSNR : 43.20 dB



Ratio : 10%
PSNR : 47.20 dB

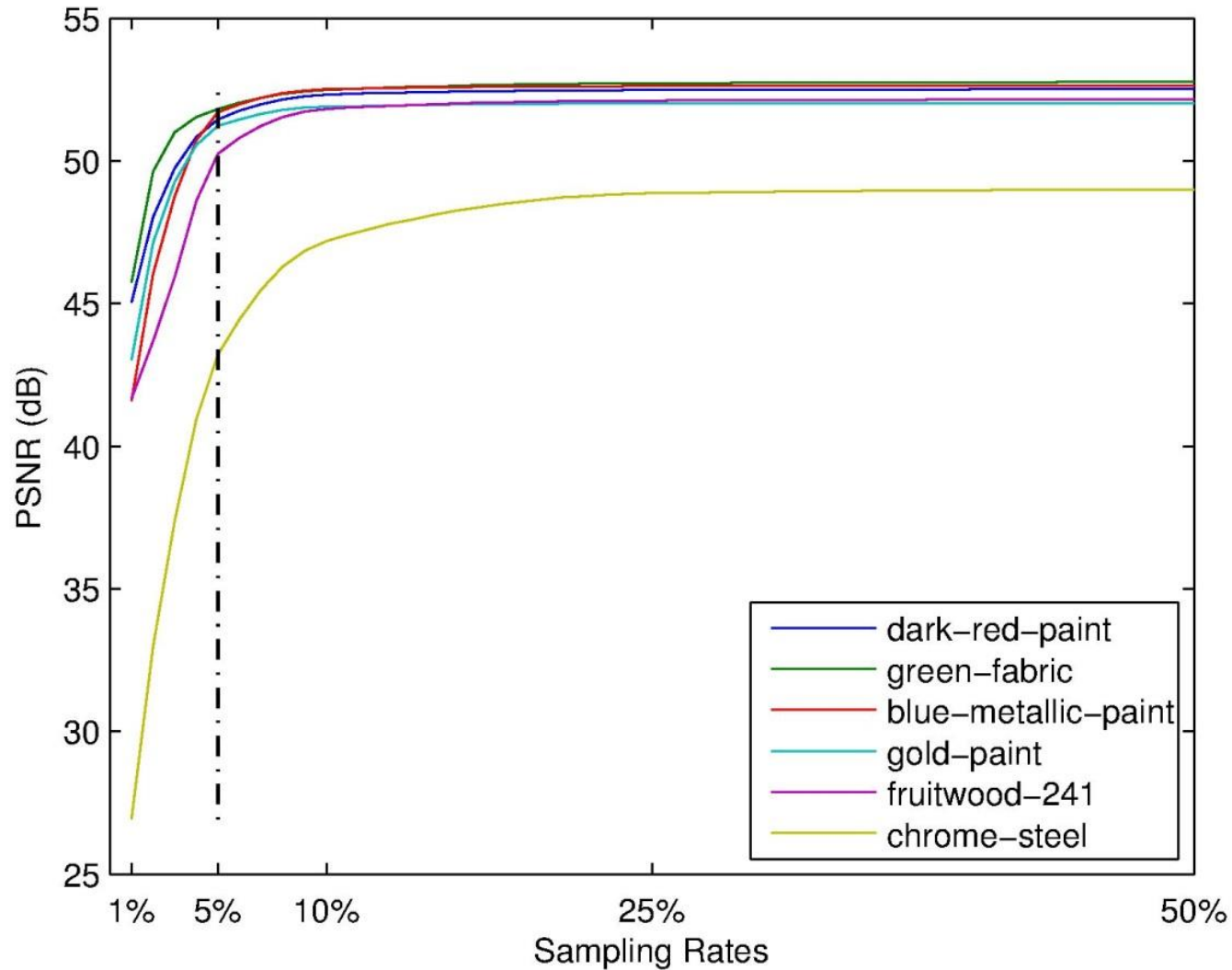


Ratio : 25%
PSNR : 48.86 dB

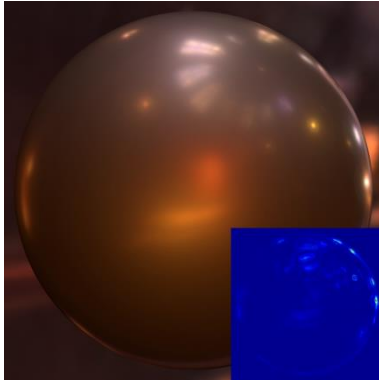


Ratio : 50%
PSNR : 48.99 dB

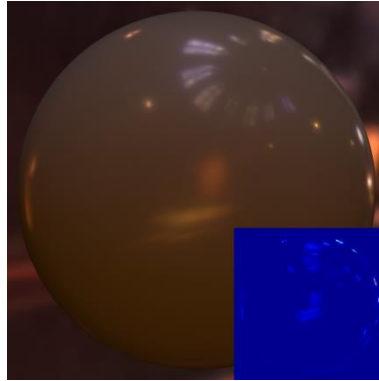
Results (cont.'d)



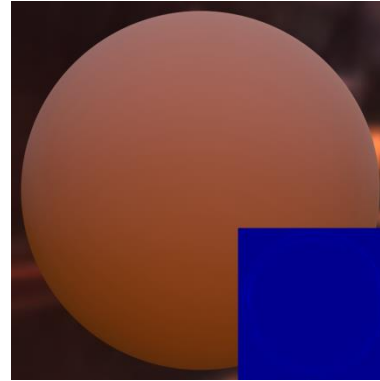
Results (cont.'d)



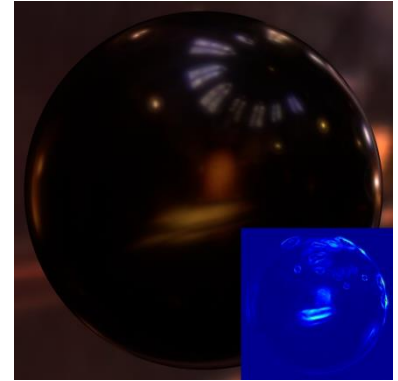
46.54 dB



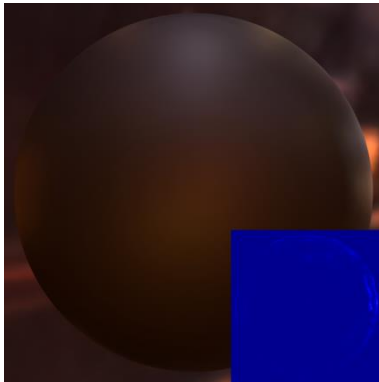
47.52 dB



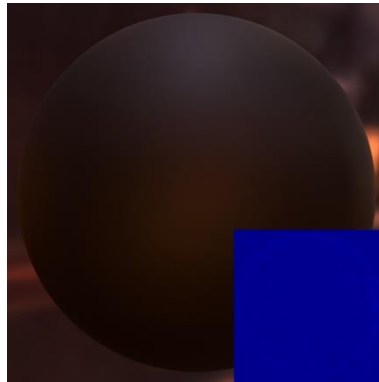
51.96 dB



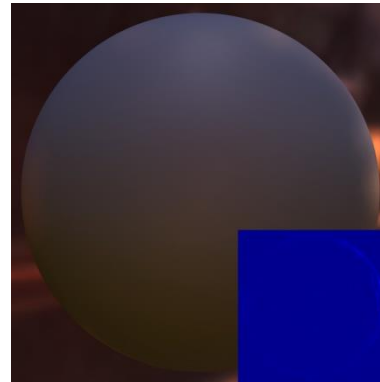
42.75 dB



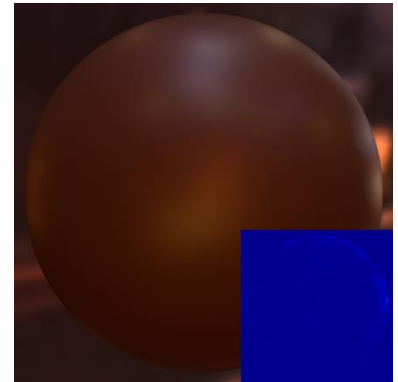
51.02 dB



52.27 dB

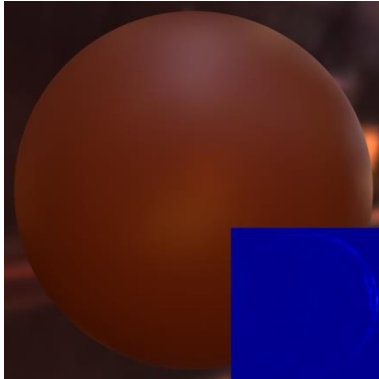


51.34 dB

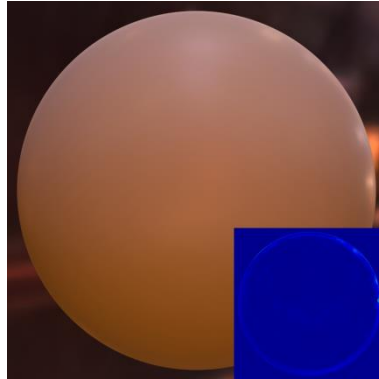


51.14 dB

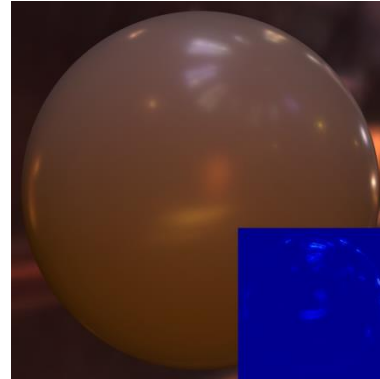
Results (cont.'d)



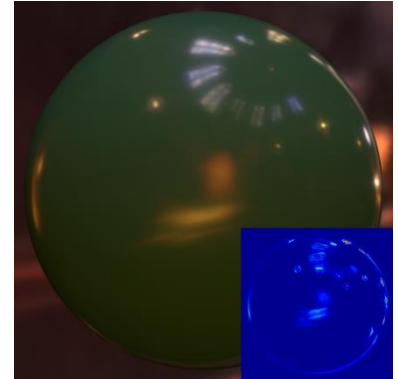
51.10 dB



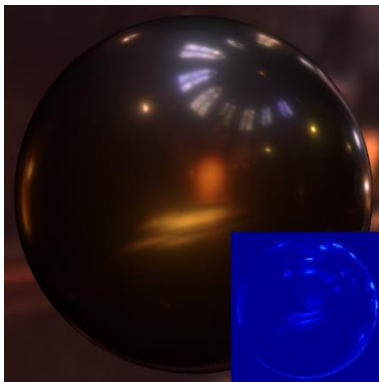
48.63 dB



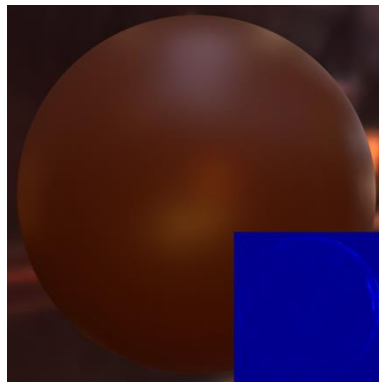
48.75 dB



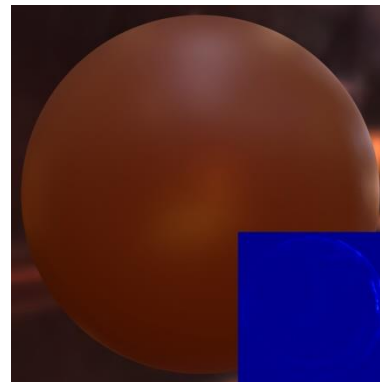
41.83 dB



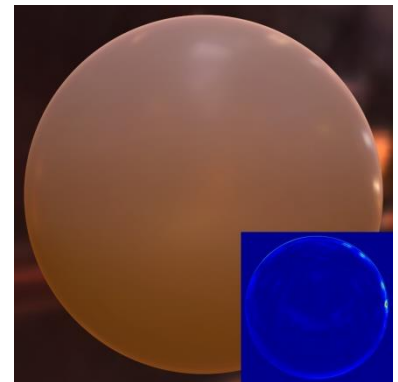
45.51 dB



50.65 dB

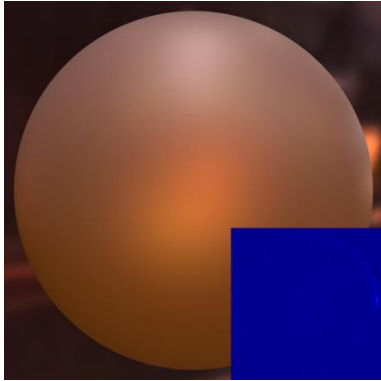


49.78 dB

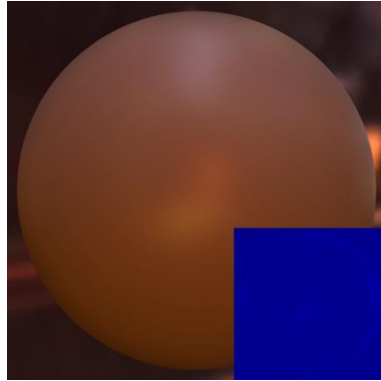


45.06 dB

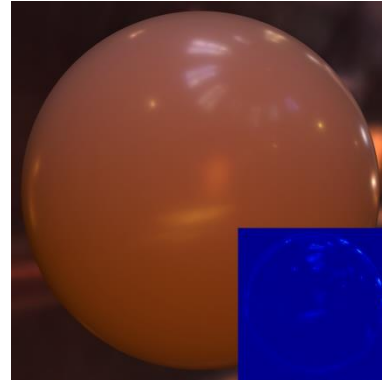
Results (cont.'d)



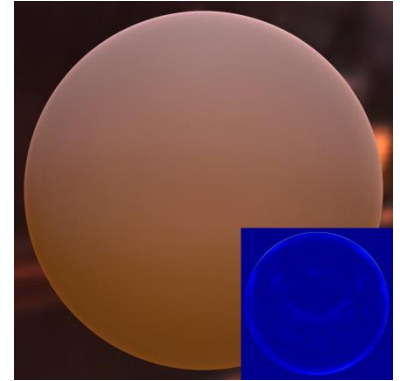
51.51 dB



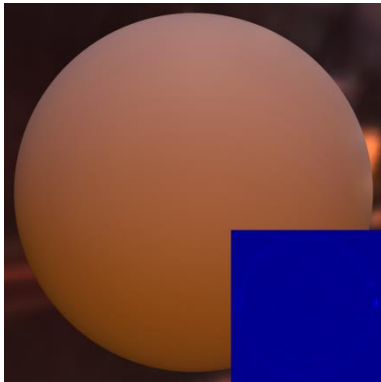
51.58 dB



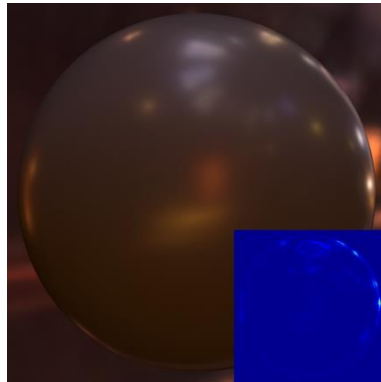
48.90 dB



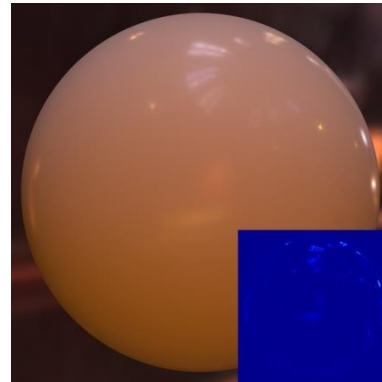
46.31 dB



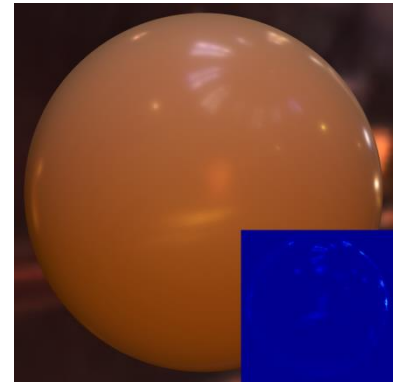
51.95 dB



48.60 dB



49.04 dB



49.76 dB

Conclusion and Future Work



- CS approach produces visually acceptable quality for all material types by sampling only 5% of the original data.
- It is demonstrated that the proposed technique can also be used for the data sets having missing or unreliable measurements.
- This approach can also be extended to higher dimensional data like anisotropic materials.

Thanks!

Questions?

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