SIGGRAPH 2025
The Premier Conference & Exhibition on Computer Graphics & Interactive Techniques

MULTI-DIMENSIONAL PROCEDURAL WAVE NOISE

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MOTIVATION

PROCEDURAL NOISE

MOTIVATION

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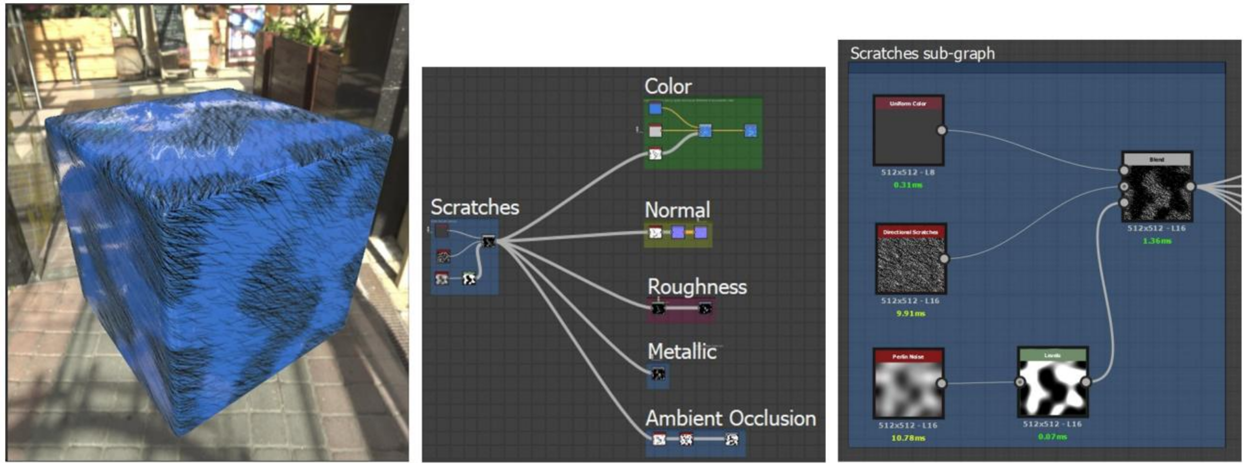
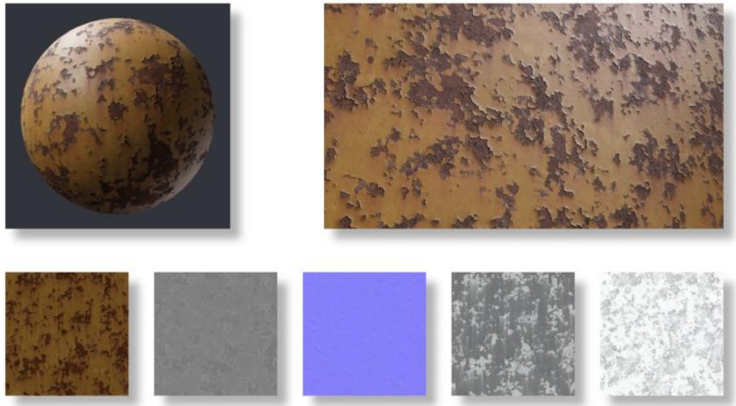


PROCEDURAL NOISE

- Fundamental tool in computer graphics for **texturing** and **modeling** *(e.g. Perlin noise, 1985)*.
- Enhances realism by **adding fine details** and **visual complexity**.
- **Core component** of **procedural** texture/material **tools** (e.g. Substance Designer, Mari).



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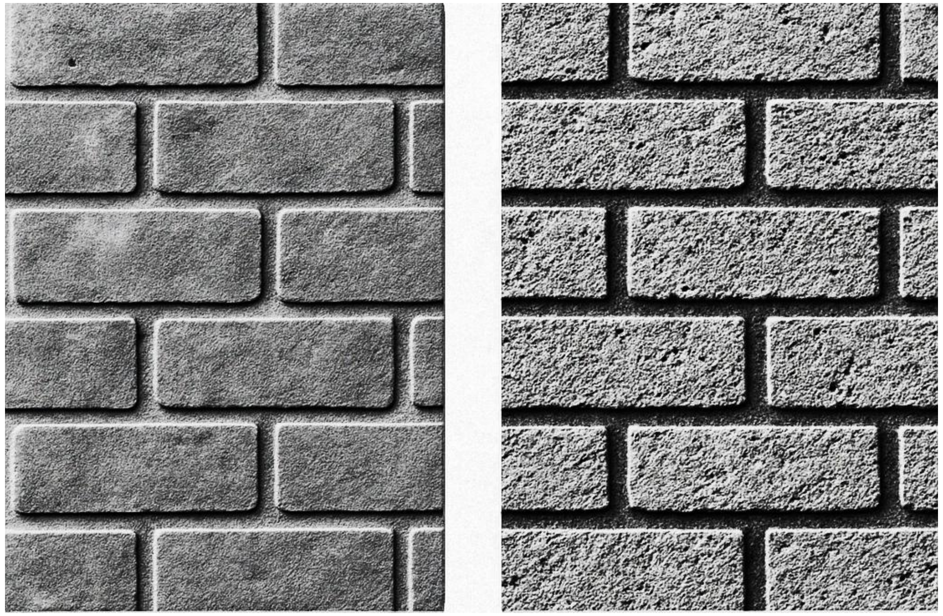
Example of spectral control



LIMITATIONS OF CURRENT NOISE MODELS

- **Spectral control** *(i.e. shaping frequency content)* is a key feature of noise.
- T**oo expensive** in **higher dimensions**, especially for **real-time graphics**.
- **Difficult to animate volumetric noise while keeping spectral control**.

Need for a more efficient, compact, and flexible model.

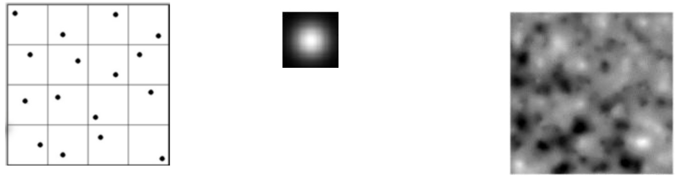
CONTEXT

RELATED WORK

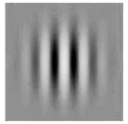
CONTEXT
RELATED WORK

Sparse convolution
J-P. Lewis
1984, 1989

Point Process Kernel Noise



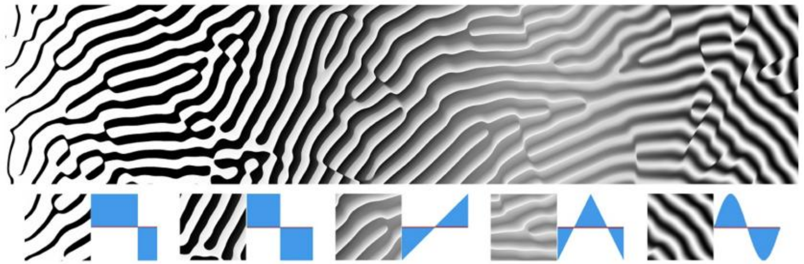
Gabor noise
Lagae et al.
2009



Kernel

SPARSE CONVOLUTION

- **Introduced by Lewis** (1984, 1989)**: convolution** of a **point process** with a **kernel.**
- **Strength**: **spectral control** when using Gabor kernels (Gabor noise, Phasor noise).
- **Weakness**: **high computational cost** because of required high sampling in spatial *(nb points)* and frequency domains *(frequency range)*.



Phasor noise
Tricard et al.
2019

CONTEXT
RELATED WORK

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LRP noise
Gilet et al.
2014

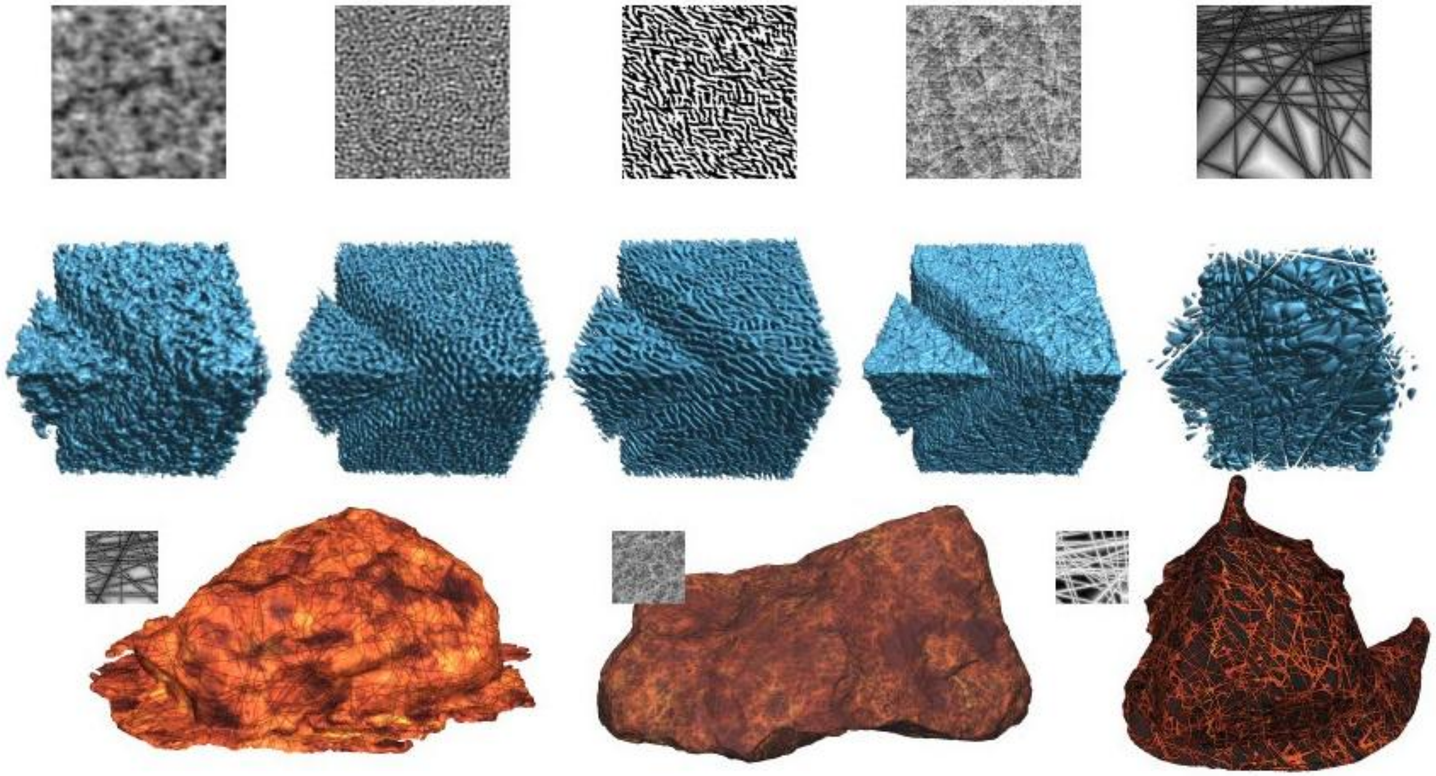
FOURIER SERIES

- **LRP noise** (Gilet et al. 2014)
- **Strength**: better phase control.
- **Weakness**: same as sparse convolution noises, and only 2D.

None of these noises **propose animation keeping the spectral properties**.

CONTRIBUTION

CONTRIBUTION



OUR PROCEDURAL WAVE NOISE MODEL

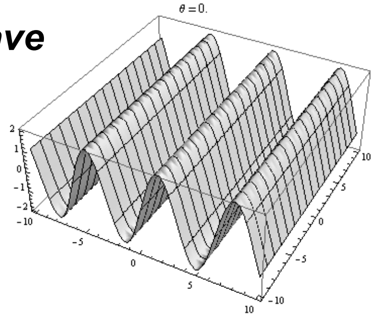
- **Spectral control**
- **Very fast GPU implementation**.
- **Better scaling** in **higher dimensions** (3D+t).
- **Supports animation.**
- **New non-Gaussian patterns**.

CORE FEATURES

GAUSSIAN NOISES

Artistic image from Leopard (Adobe Stock | ID #1262080227)

Plane wave



INSPIRATION

- **White noise** is **inspired** by **white light**
- **Superpositions** of **randomly oriented waves** of **all frequency contents, defined** as a **continuous sum** in the ***frequency*** and ***orientation*** domains.

$$\mathcal{N}(\mathbf{x}, t) = \frac{1}{F} \int_{\mathbb{R}^n} A(\xi) e^{i(2\pi\, \xi \cdot \mathbf{x} + \phi(\xi) - ct)}\, d\xi$$

$$= \frac{1}{F} \int_{\Omega} \int_{0}^{\infty} A(f\omega) e^{i(2\pi f \mathbf{x} \cdot \omega - ct + \phi(f\omega))}\, |\mathcal{J}(f\omega)|\, df\, d\omega,$$

$$|\mathcal{J}(f\omega)| = \mathcal{J}_f(f)\, \mathcal{J}_\omega(\omega)$$

Our key strategy: ***fast*** *separable computation* => mix **precomputation** and **sampling!**

CORE FEATURES
GAUSSIAN NOISES

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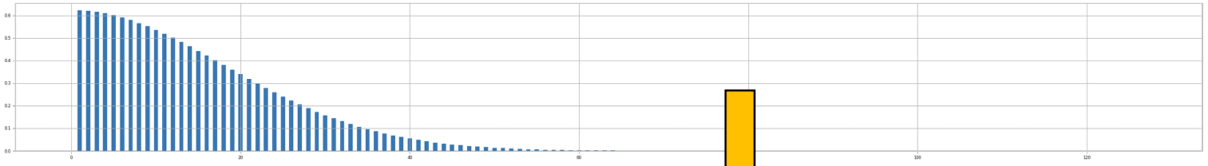
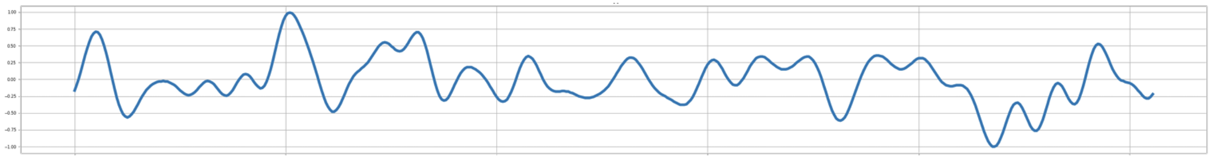
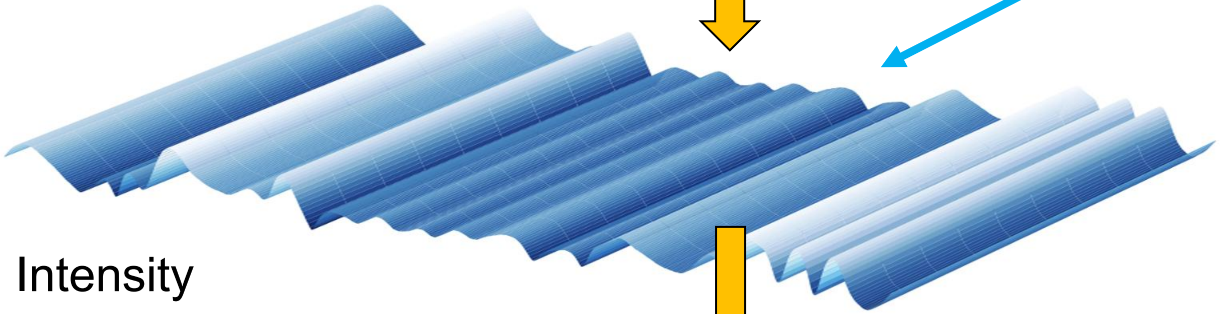
Amplitudes distribution *(per frequency)*



1D profile *(wave)*



Oriented wave *(3D)*



Intensity

WAVE-BASED MODEL

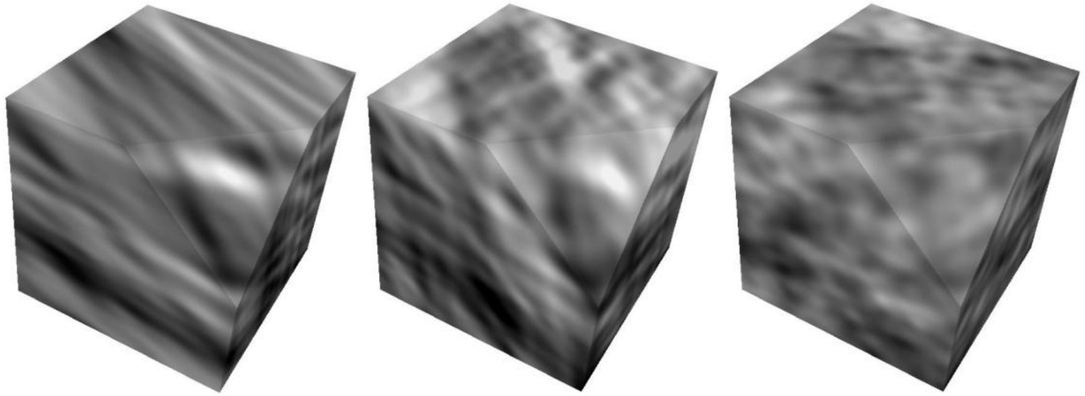
Frequency domain : precomputation!

$$\int_\Omega \int_0^\infty A(f\omega)\, e^{i(2\pi f \mathbf{x}\cdot\omega - ct + \phi(f\omega))}\, |\mathcal{J}(f\omega)|\, df\, d\omega,$$

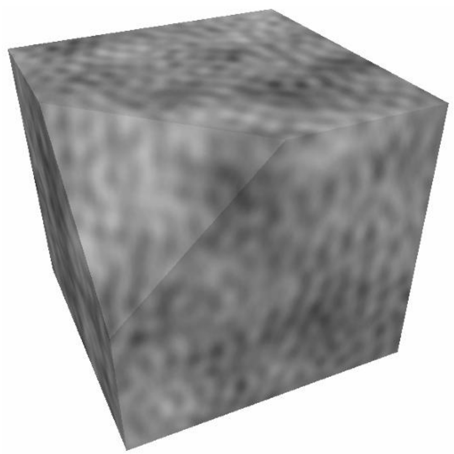
$$|\mathcal{J}(f\omega)| = \mathcal{J}_f(f)\, \mathcal{J}_\omega(\omega)$$

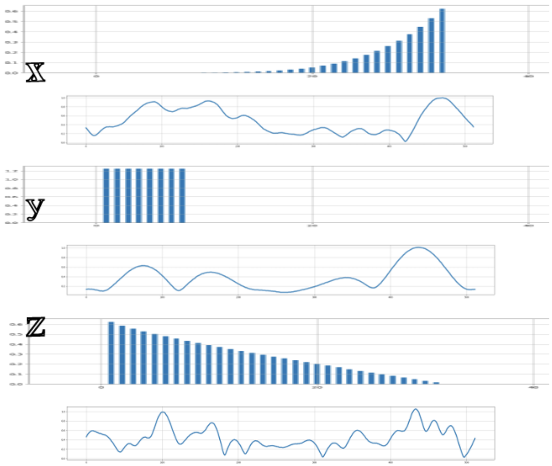
- Managing **amplitude distributions** $A(\xi)$ *(similar to Gabor kernels)*.
- **Random phases** (ϕ) imitates Gaussian processes.
- **Lower cost**: **Precomputed 1D wave profile** *(compact data on GPU)*.

CORE FEATURES
GAUSSIAN NOISES



Nb directions: 4, 30, 60





Orientation domain: Monte-Carlo sampling

$$\int_{\Omega}\int_{0}^{\infty} A(f\omega)e^{i(2\pi f \mathbf{x}\cdot\omega - ct + \phi(f\omega))}\,|\mathcal{J}(f\omega)|\,df\,d\omega,$$

$$|\mathcal{J}(f\omega)| = \mathcal{J}_f(f)\,\mathcal{J}_\omega(\omega)$$

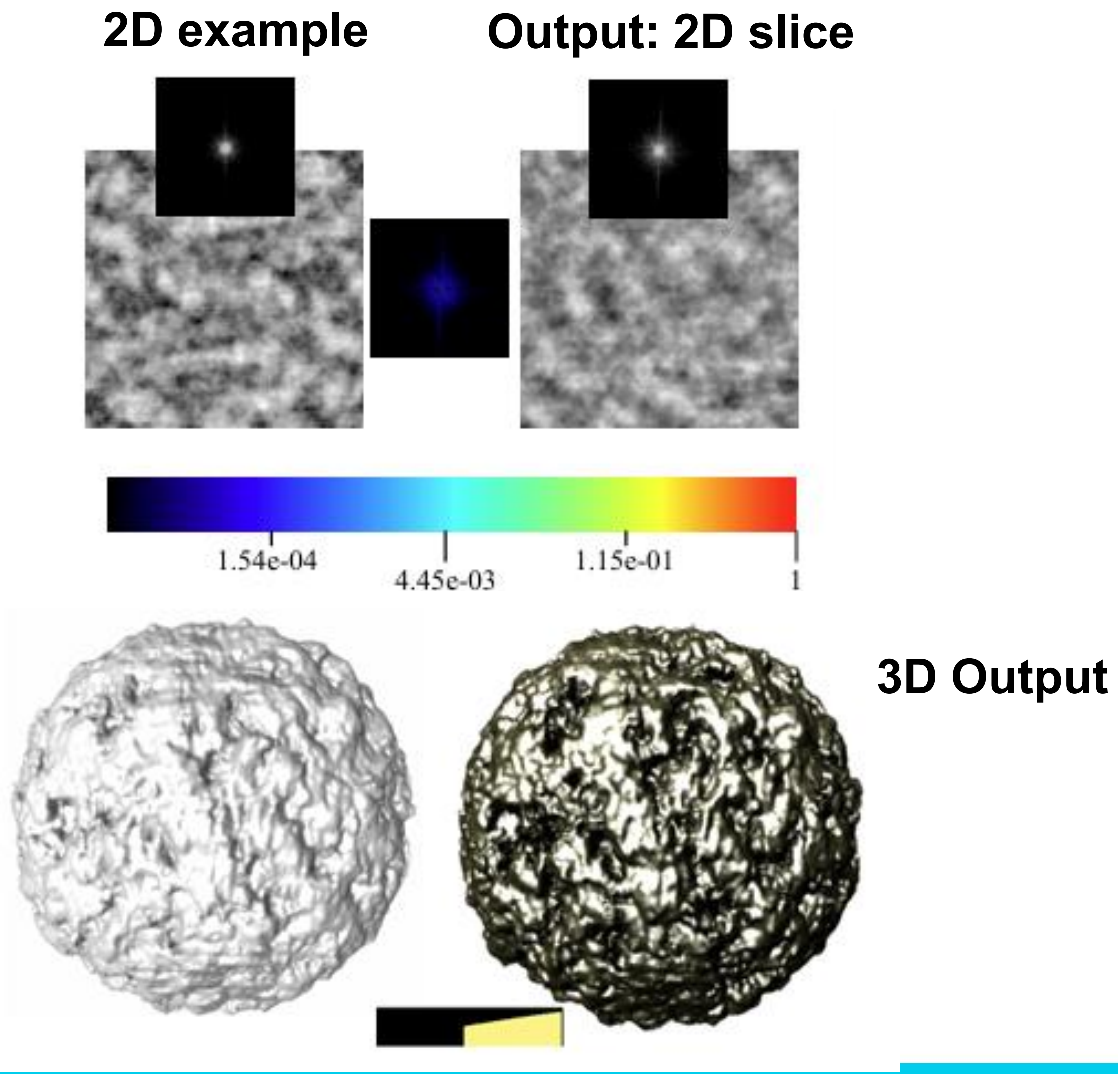
ISOTROPY

- **Sample** direction space Ω **uniformly** in **N directions** *(one 1D proflle, but randomly oriented and shifted waves)*.

ANISOTROPY

- Use **different amplitudes** *(hence waves)* for **different directions** *(storing more 1D profiles)*.

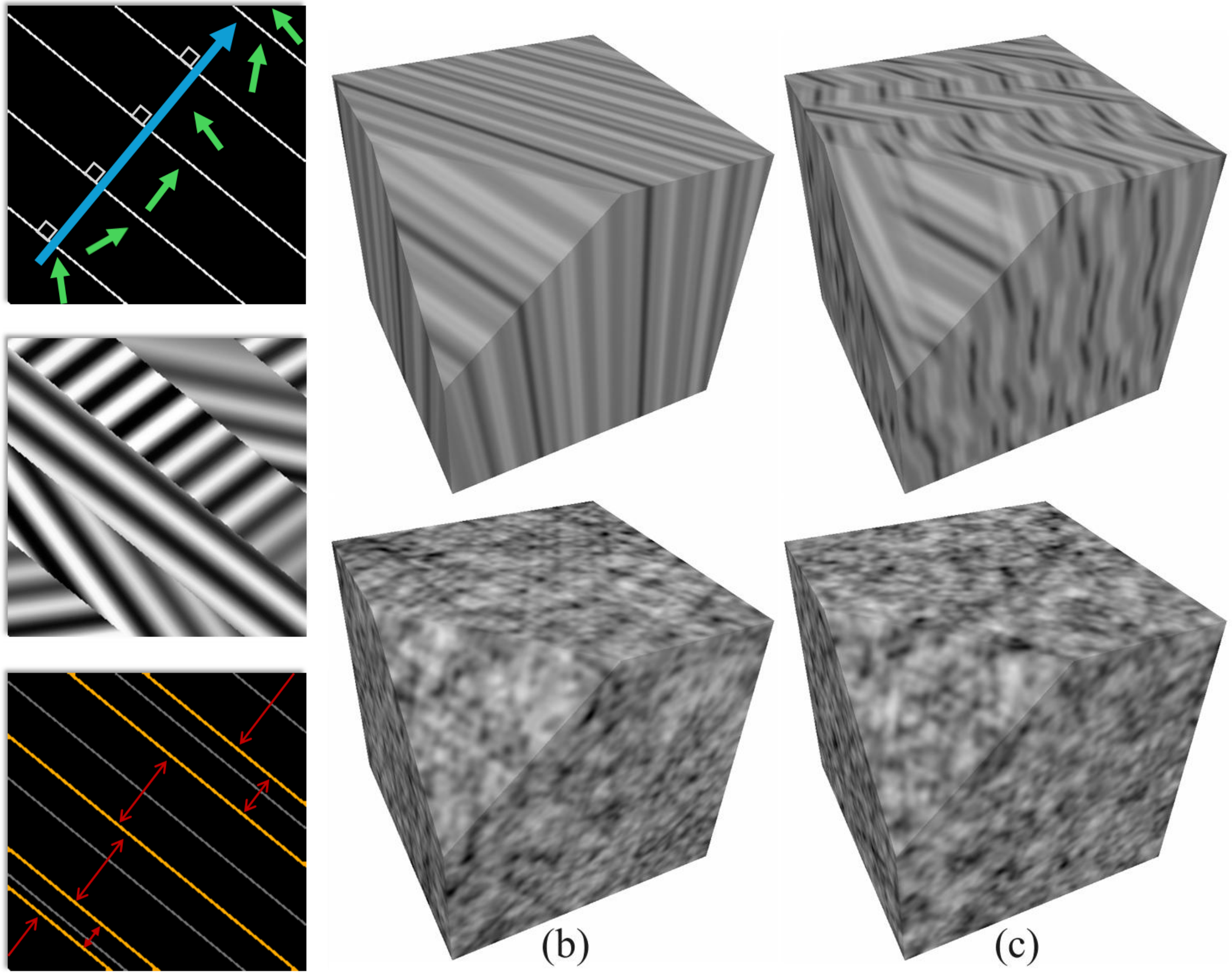
CORE FEATURES
GAUSSIAN NOISES



COMPATIBLE WITH BY-EXAMPLE SYNTHESIS

- **Frequency domain**: difficult to design manually.
- Propose a by-example approach to generate 3D noise using a 2D noise image as input.
- Optimize amplitudes to minimize spectral error of 2D slices.

CORE FEATURES
GAUSSIAN NOISES



ALIGNMENT ARTEFACTS REDUCTION

- **Partition space** into regular slices orthogonal to waves *(and sample random wave orientations around)*.
- **Blending** to smoothly interpolate wave values across slice boundaries: removes visible discontinuities.
- **Jittering** to randomly shift slice positions (irregular slices): adds variability and avoids repetitive patterns.

CORE FEATURES

NON-GAUSSIAN NOISES

CORE FEATURES
NON-GAUSSIAN NOISES

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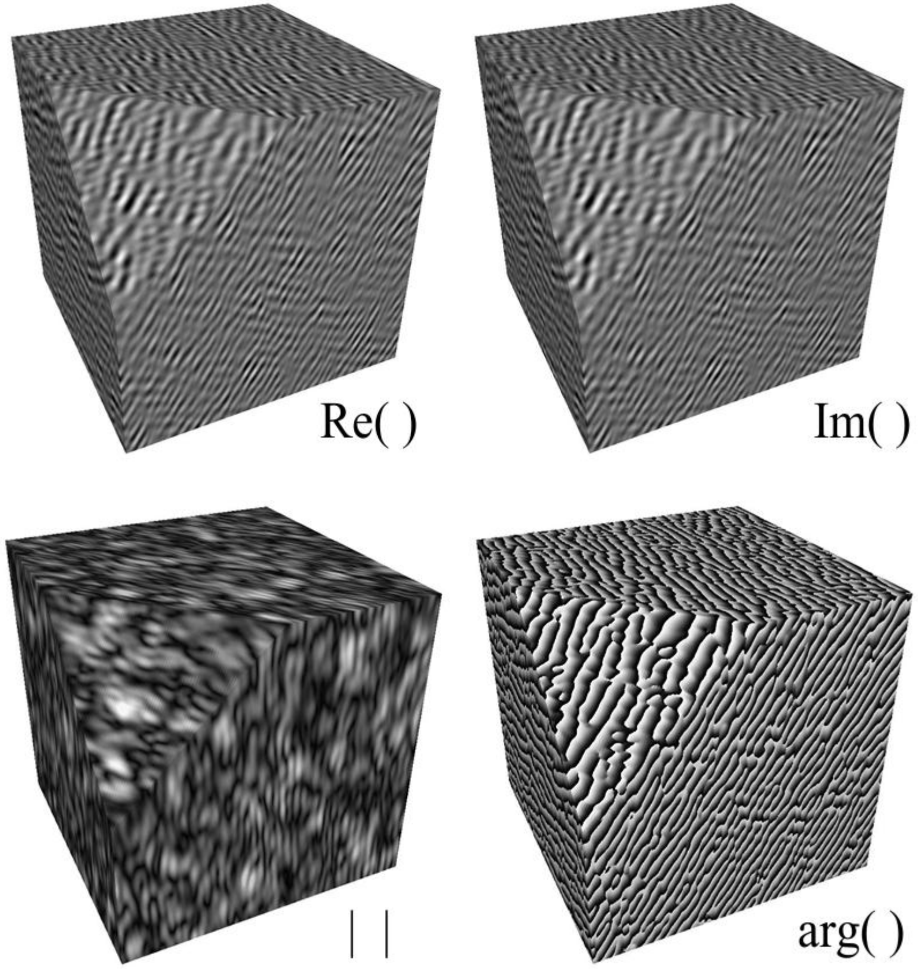

PHASOR AND RIDGED NOISES

- Solid wave noise is **complex valued**.
- Use real, imaginary, modulus or phase.

CORE FEATURES
NON-GAUSSIAN NOISES

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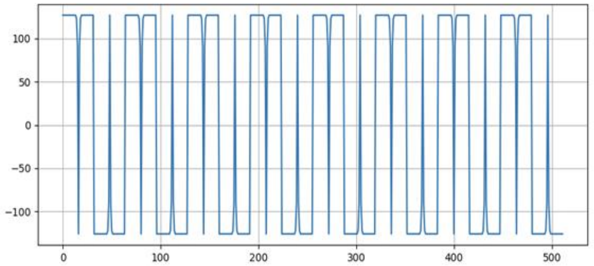
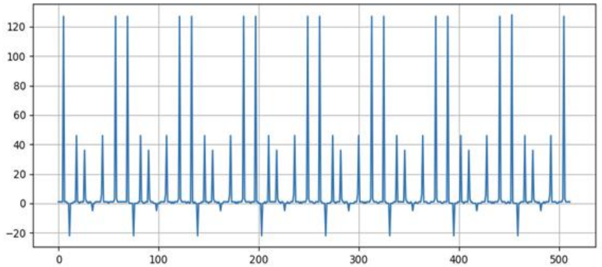
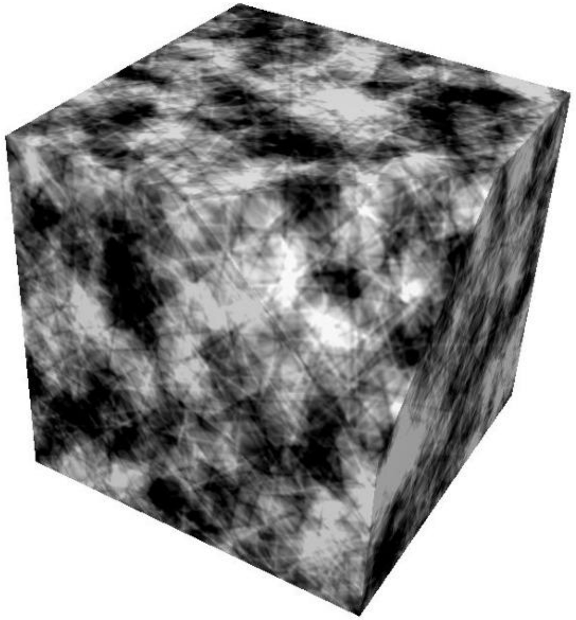
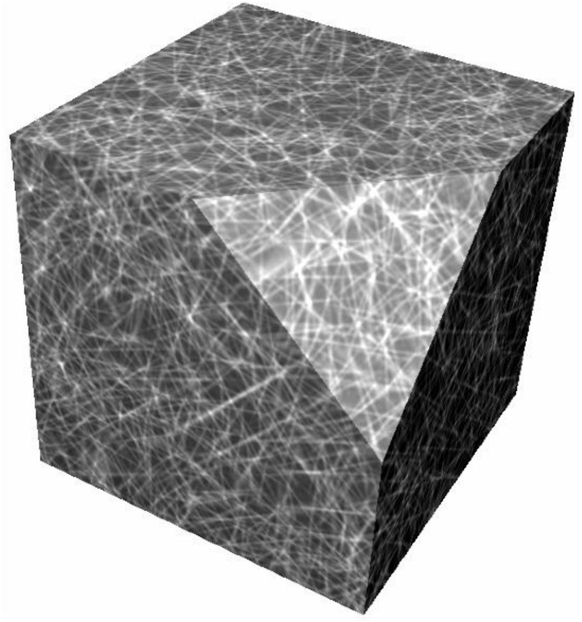




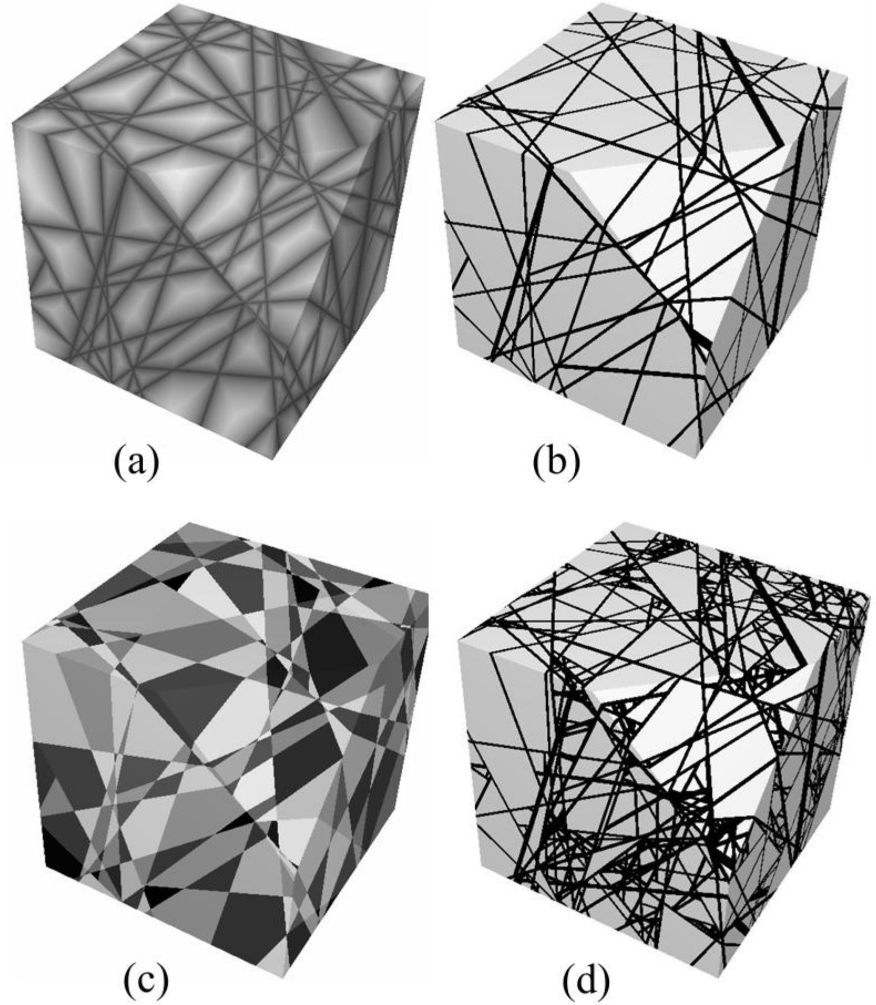




CRYSTAL-LIKE AND WIRED NOISES

- **Arbitrary spatial waves**.
- **Examples:** *using local intensity peaks*.

CORE FEATURES
NON-GAUSSIAN NOISES



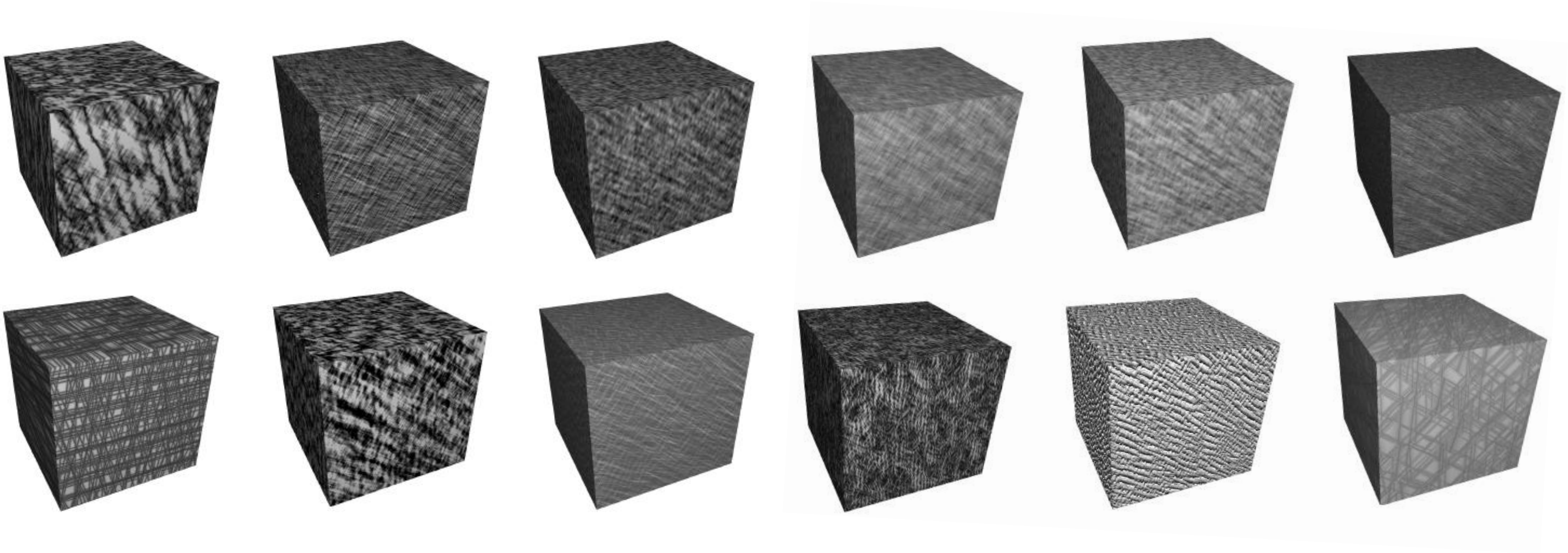
NEW CELLULAR NOISES

- **Substitute the sum** of waves with **another operator** *(different from Worley noise): min, triangular, step, etc.*
- Use stochastic **iterative cell subdivision**, imitating **STIT** patterns *(STable with respect to ITerations of tessellations)*.

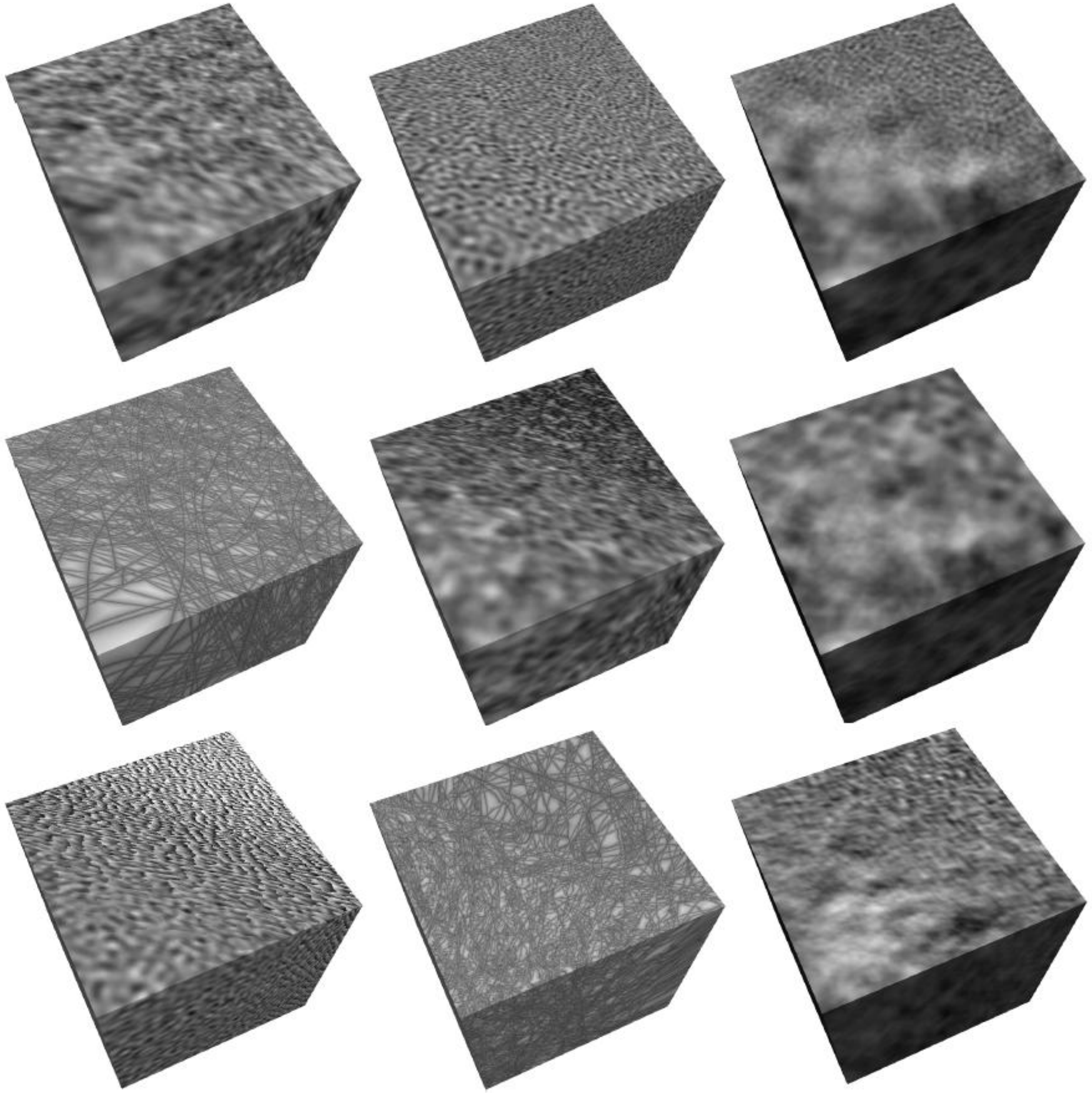
RESULTS

TEXTURING

RESULTS
ANISOTROPY



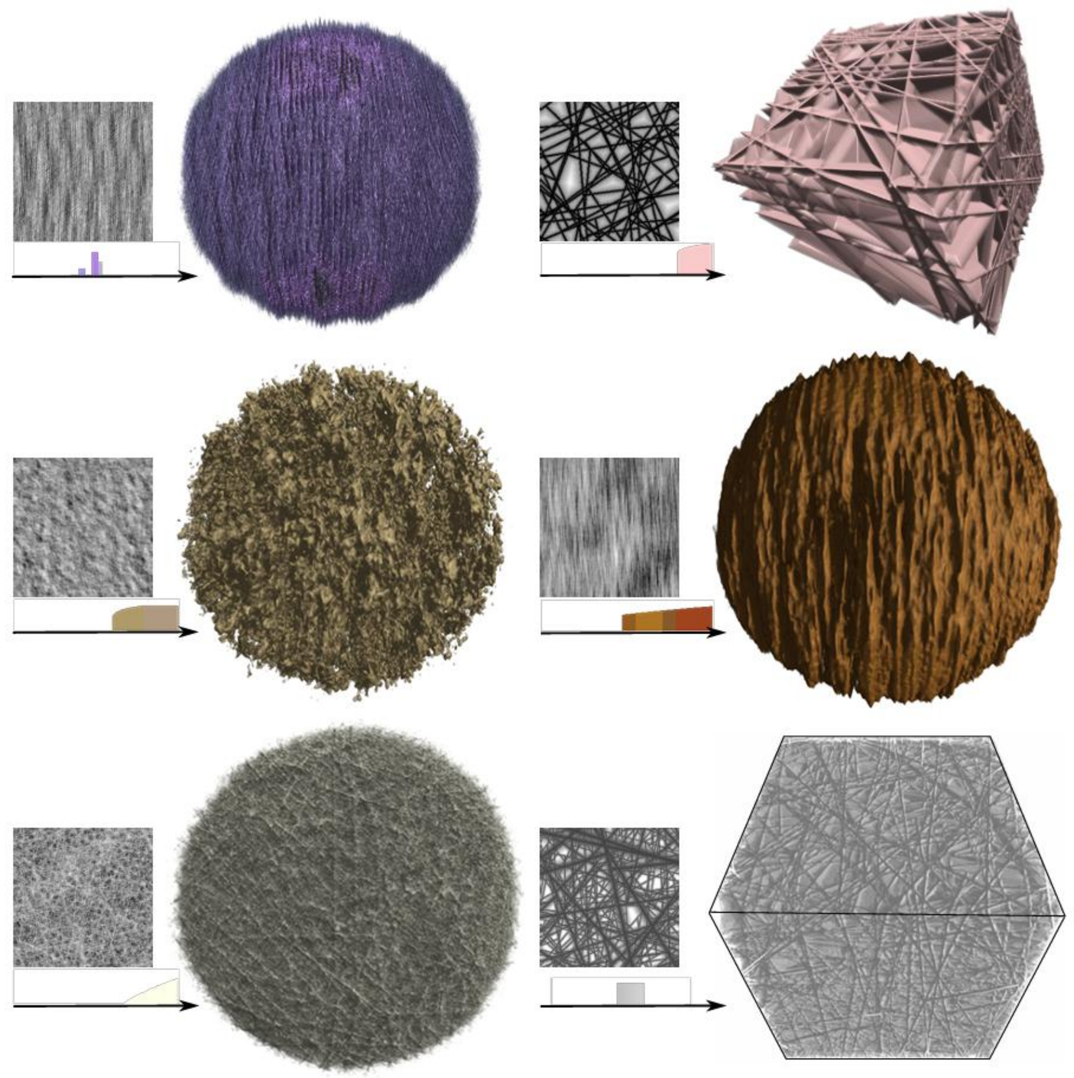
RESULTS



SMOOTH TRANSITIONS

- Linear interpolation.
- Noise smoothly evolves across the volume, from one cube corner to the opposite *(not just across faces).*
- *Examples: variations of frequency range, frequency content and anisotropy, etc.*

RESULTS



GENERATING VOLUMETRIC DATA

- Structured or unstructured micro-material.
- **Transfer functions** for colors and transparency.

RESULTS
MIXING STYLES DRIVEN BY WAVE NOISE

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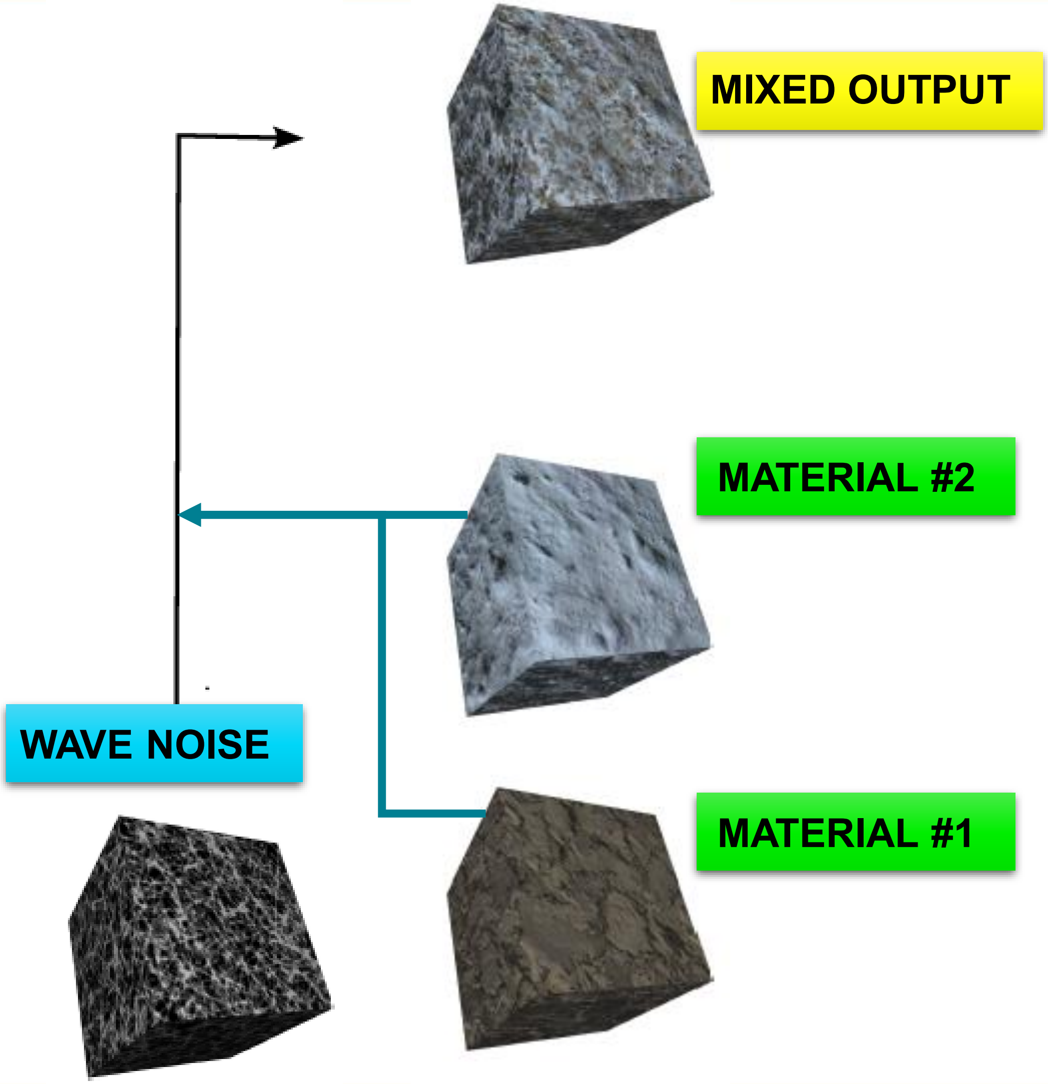

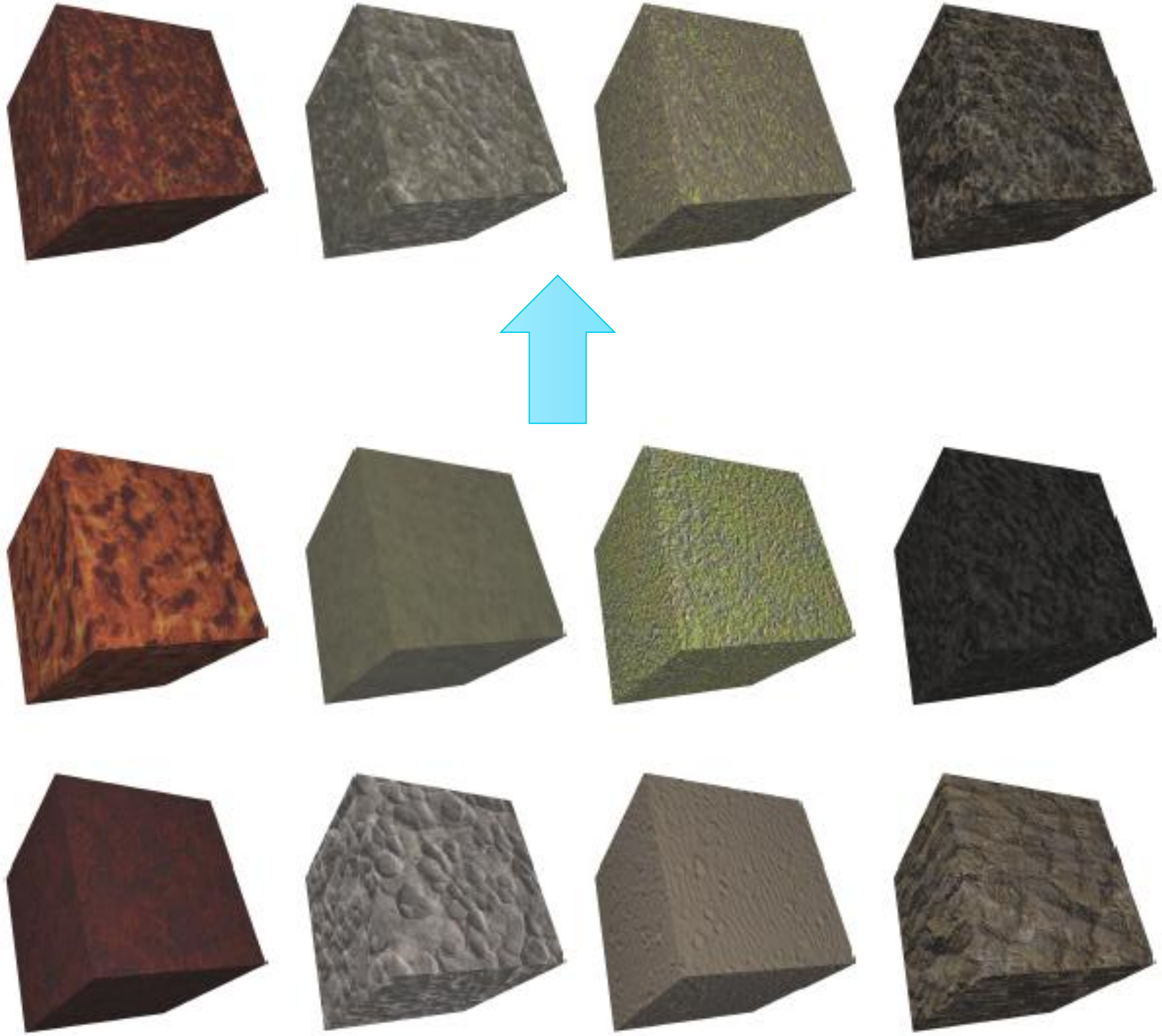

RESULTS
PBR MATERIALS GENERATION

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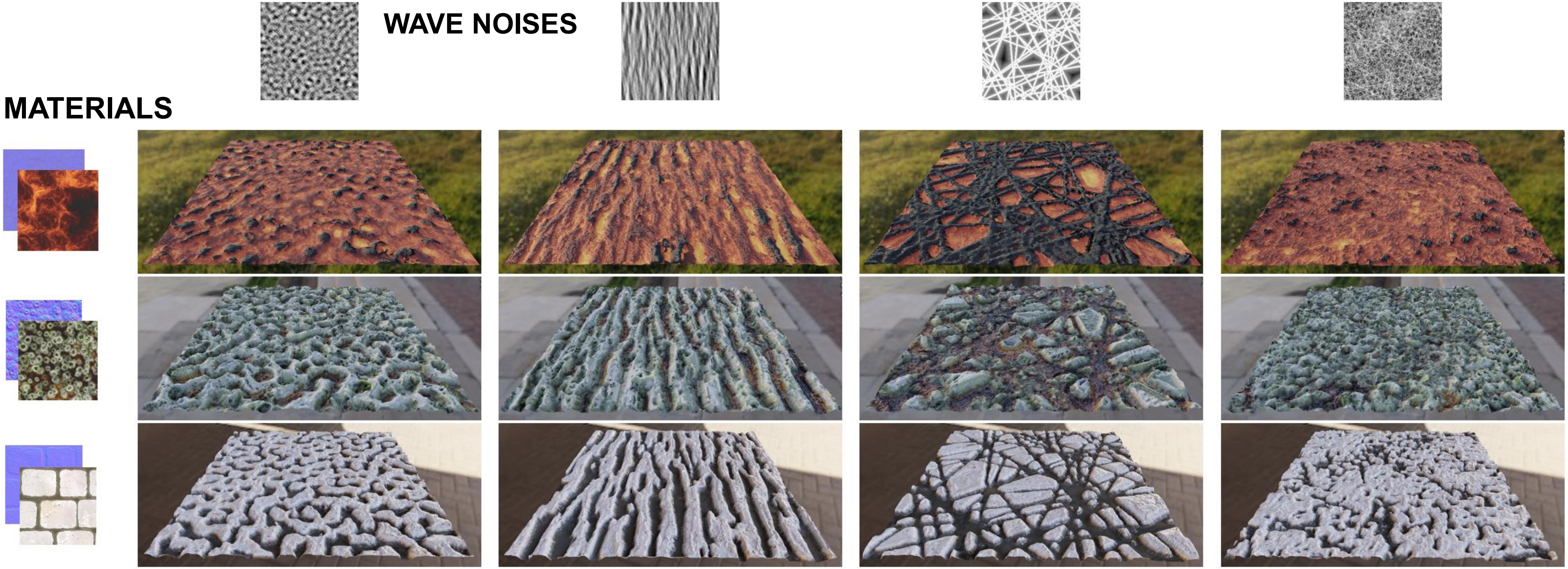
SEMI-PROCEDURAL TEXTURES

GUEHL ET AL. 2020

- to guide color/material *details* by our wave noise *structure*.



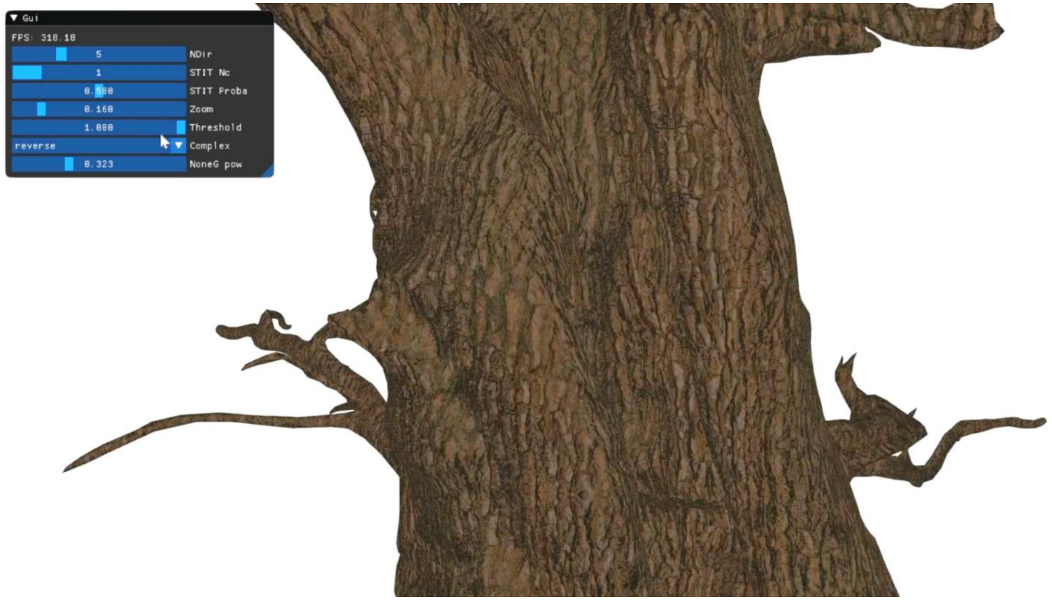
RESULTS
TEXTURING

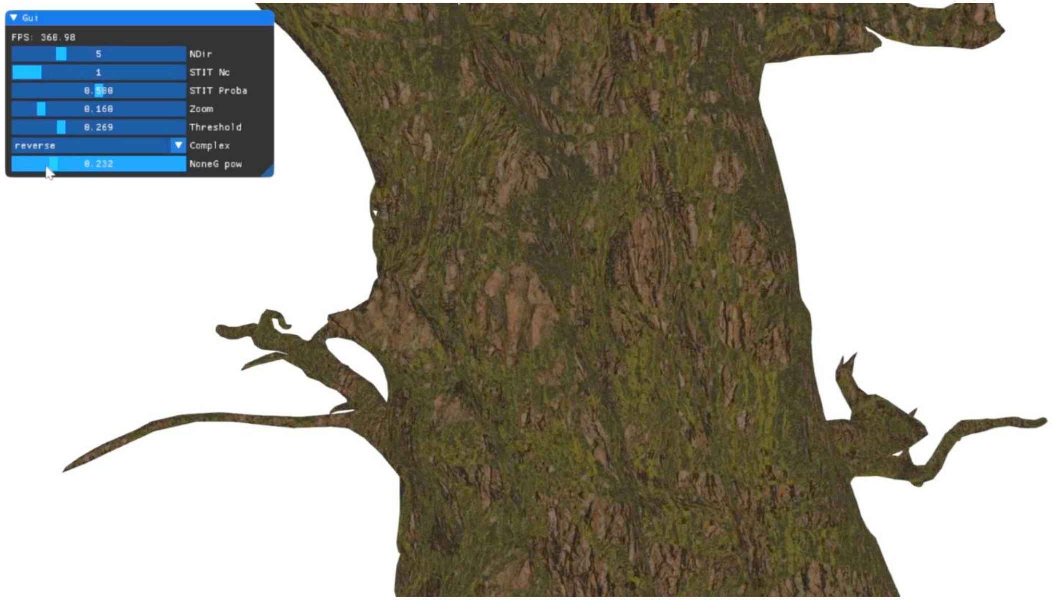
3D TEXTURING

- **Style Transfer Functions**.
- **No need for UV coordinates** *(rasterization)*.

RESULTS
TEXTURING

VIDEO

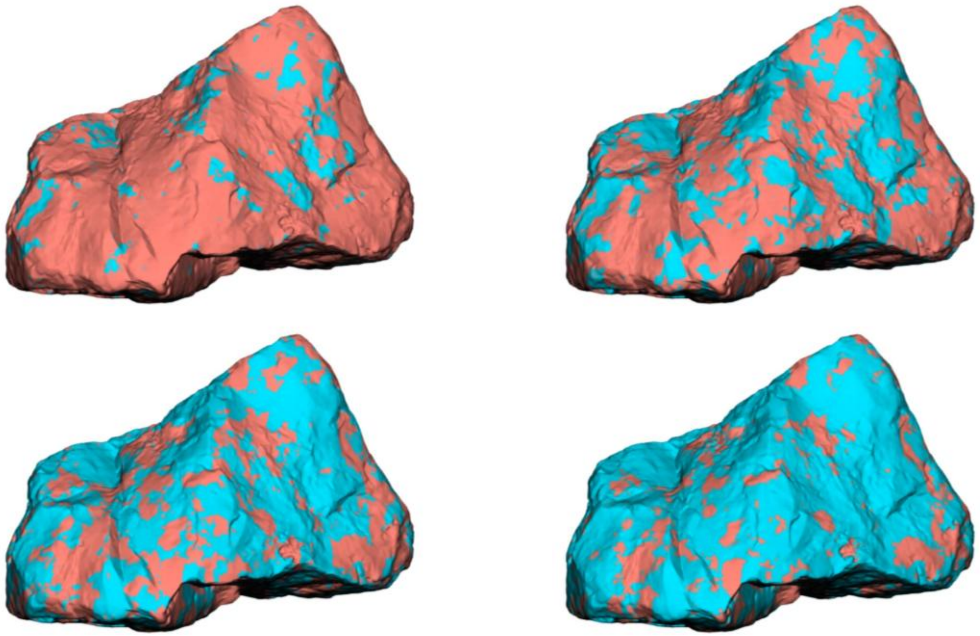




RESULTS
ANIMATION

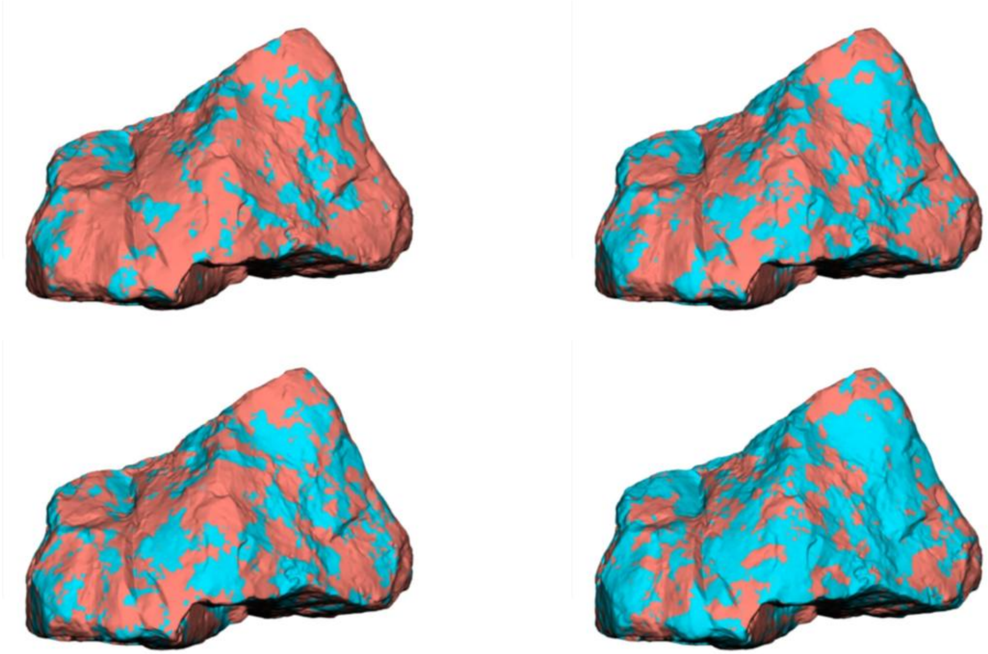
GENERATION OF ANIMATED MATERIAL (3D+T)

Keyframe animations: lack realism since features merely fade in and out without undergoing any structural changes.



VIDEO

3D+t ***(time)*** **noise**: introduce **local temporal variations**, enabling features to not only fade in and out but also evolve dynamically.



RESULTS
PERFORMANCE

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3D Textures	Perlin Noise (fractal)	Worley Noise (fractal)	Gabor Noise			Wave Noise 3D/3D+t/4D		
			10 Kernels	50 Kernels	90 Kernels	10 Dir	50 Dir	100 Dir
25[illegible]	5.6	15.15	40.86	175.86	315.2	2.6/2.74/7.45	11/11.7/25.8	22/23.3/44.6
51[illegible]	44	131	311.3	1 438	2 584	20.8/22/53.1	88.1/93.2/206.6	175/185.6/361.3
10[illegible]	346	1 047	2 552	116 000	206 000	167/176.4/429	706/749.6/1 719	1 410/1 502/2 970
2D Te[illegible]res								
10[illegible]	0.328	0.94	2.23	11.0	22.12	0.14	0.62	1.28
20[illegible]	0.92	2.75	6.37	32.9	61.9	0.39	1.82	3.72

- **Competitive** with **Perlin fractal** noise **but better spectral control**.
- **Significantly faster** than **Gabor** noise **at equivalent spectral quality**.
- **Better scaling** in **higher dimensions** (animation and 4D).

CONCLUSION

CONCLUSION

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MULTI-DIMENSIONAL PROCEDURAL WAVE NOISE

- **New procedural noise model**: **superposition** of **randomly oriented hyperplanar waves** with **random phases**.
- **Spectral control**.
- **Reproduces existing gaussian noises**, while **preserving essential procedural properties** *(infinite extent, resolution independence, and **fast GPU implementation**)*, with both **isotropy** and **anisotropy**.
- **Better scales** to **3D, 3D+T**, and even **higher dimensions** — all with **minimal data** and **low memory usage**.
- Supports **animation** *(local temporal variations)*.
- **More general**: variety of **non-Gaussian noises** with **new recursive cellular patterns** — but spectral control difficult *(future work!)*

MULTI-DIMENSIONAL PROCEDURAL WAVE NOISE

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PASCAL GUEHL

RESEARCH ENGINEER (PHD)

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