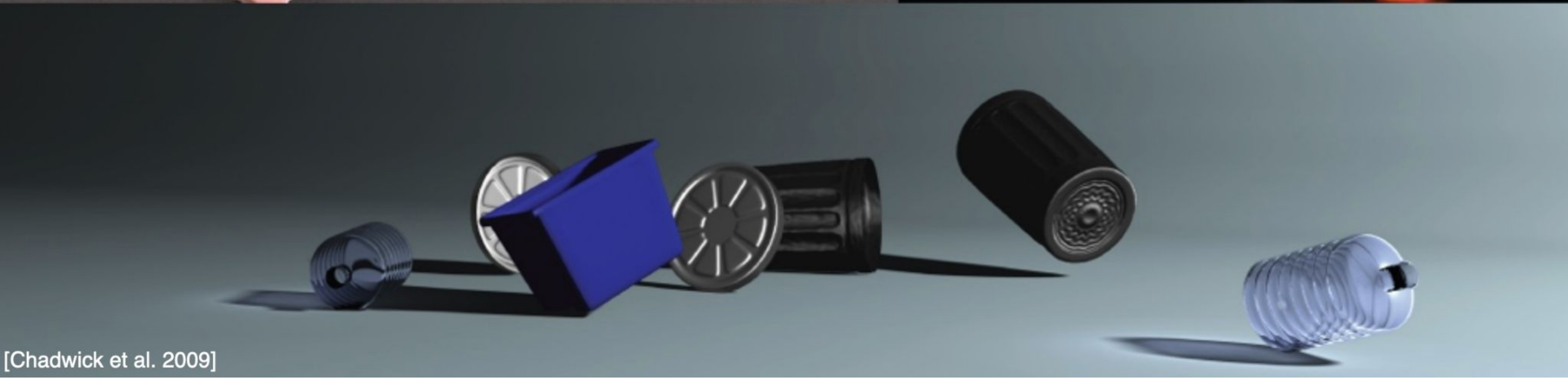


Physical Sound Synthesis

Presenter: Nguyen Minh Hieu, Siripon Sutthiwanna, Ko Wonhyeok

Content

- Motivation
- Related Work
- Our Approach & Limitation
- Role Division

Motivation - Why Physically-based Sound

Motivation (Hieu)

"Easy" Condition

Unbounded Scene, Reflection only on Object

$$(\Delta + k^2)p(x) = 0$$

Motivation (Hieu)

"Easy" Condition

Unbounded Scene, Reflection only on Object

$$(\Delta + k^2)p(x) = 0$$

↓

$$p(\mathbf{x}, t) = p(\mathbf{x})e^{i\omega t}$$

Separation of Variable

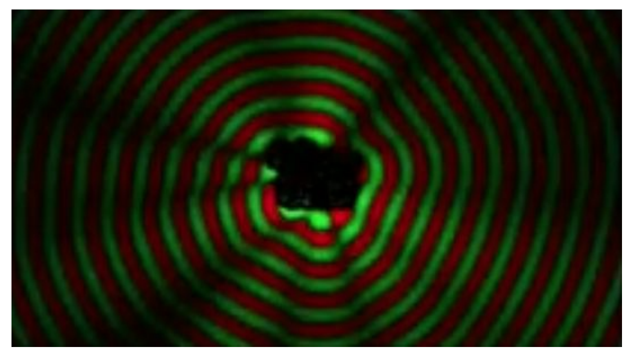
Motivation (Hieu)

“Easy” Condition

Unbounded Scene, Reflection only on Object

$$p(\mathbf{x},t) = |p(\mathbf{x})|q(t)$$

$|p(\mathbf{x})|$



$|p(\mathbf{x})|q(t)$

Motivation (Hieu)

“Easy” Condition

Unbounded Scene, Reflection only on Object

$$p(\mathbf{x}, t) = |p(\mathbf{x})|q(t)$$

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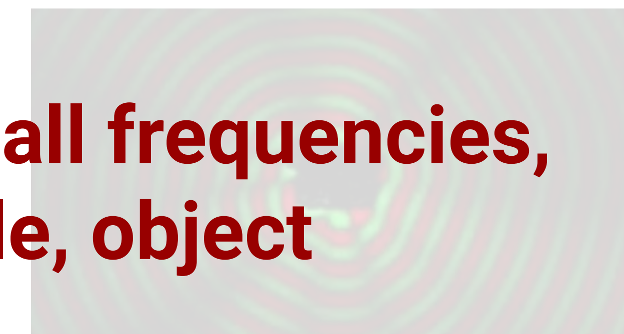


$|p(\mathbf{x})|q(t)$

Need to solve for all frequencies, time sample, object

Motivation (Hieu)

“Easy” Condition

Unbounded Scene, Reflection only on Object

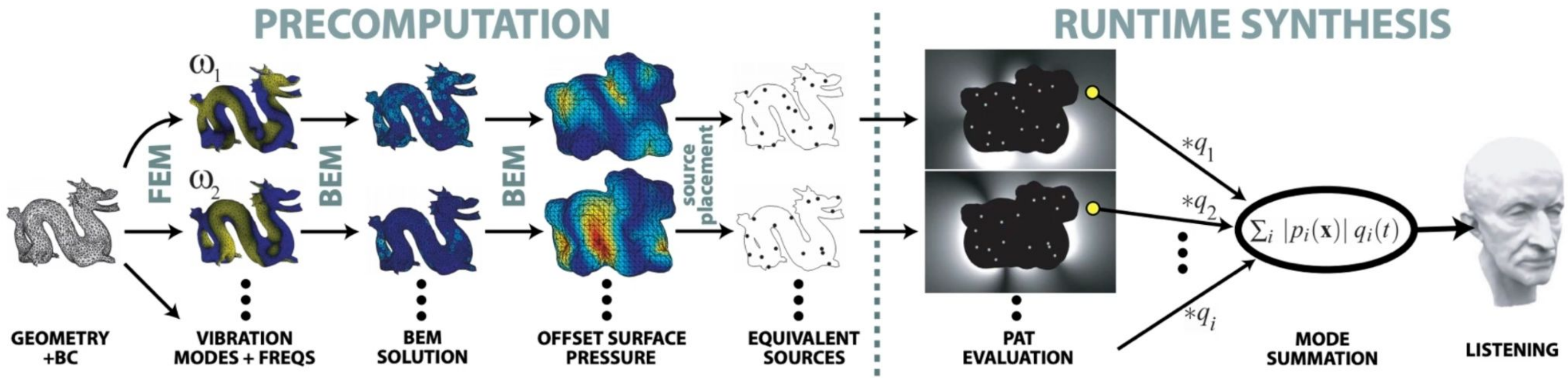


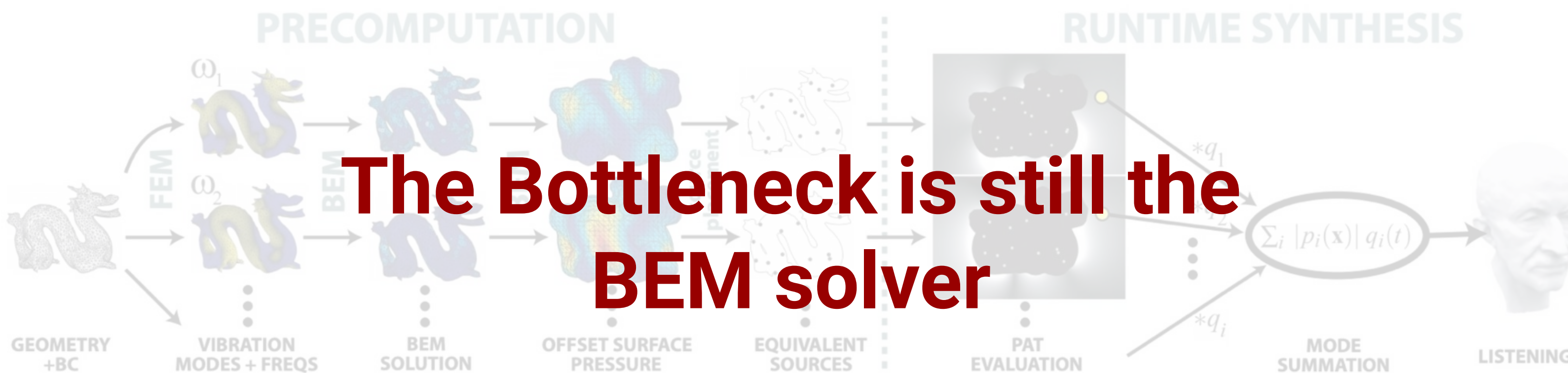
Figure 2: **Overview of Precomputed Acoustic Transfer (PAT)**

Takes DAYS to solve for a scene with a few second

Motivation (Hieu)

"Easy" Condition

Unbounded Scene, Reflection only on Object



The Bottleneck is still the BEM solver

Figure 2: **Overview of Precomputed Acoustic Transfer (PAT)**

Takes DAYS to solve for a scene with a few second

Motivation (Hieu)

Let's solve "Hard" Condition

Bounded Scene, Lots of Reflection

$$p(\mathbf{x}, t) = |p(\mathbf{x})| q(t)$$

Not necessarily true…

Motivation (Hieu)

Let's solve "Hard" Condition

Bounded Scene, Lots of Reflection

Let's tackle the main problem by choosing a different numerical solver.

"Harder Condition"...

Motivation (Hieu)

Let's solve "Hard" Condition

Bounded Scene, Lots of Reflection

Let's tackle the main problem by choosing a different numerical solver.

"Harder Condition"...
but simpler Success Condition

Motivation (Hieu)

Let's solve "Hard" Condition

Bounded Scene, Lots of Reflection

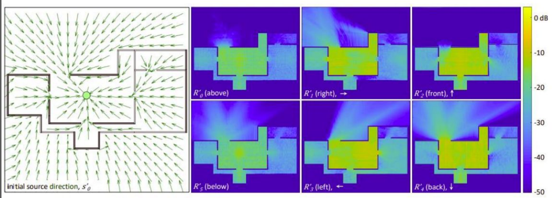
Let's tackle the main problem by choosing a different numerical solver.

"Harder Condition"...
but (MAYBE) simpler Success Condition

Related Work

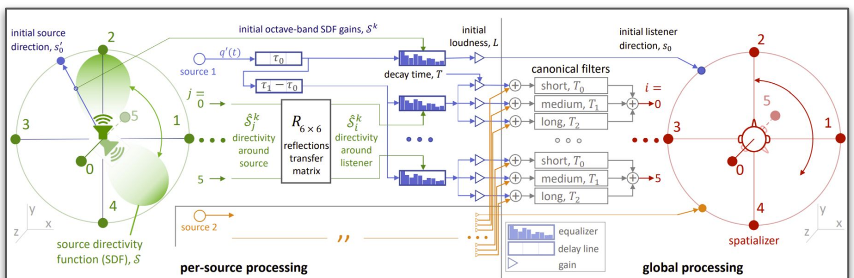
Directional Sources and Listeners in Interactive Sound Propagation using Reciprocal Wave Field Coding

CHAKRAVARTY R. ALLA CHAITANYA*, Microsoft Research and McGill University
NIKUNJ RAGHUVANSHI*, Microsoft Research
KEITH W. GODIN, Microsoft Mixed Reality
ZECHEN ZHANG, Microsoft Research and Cornell University
DEREK NOWROUZEZAHRAI, McGill University
JOHN M. SNYDER, Microsoft Research



ACM Transactions on Graphics, 2020

20210025
Ko Wonhyeok



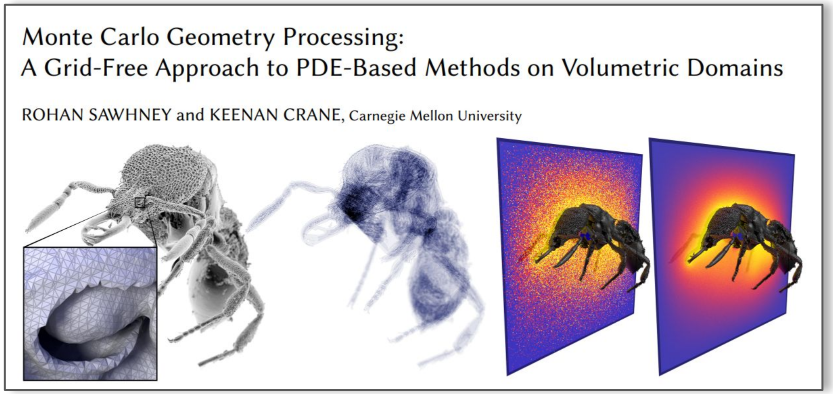
Precomputing initial source and reflections

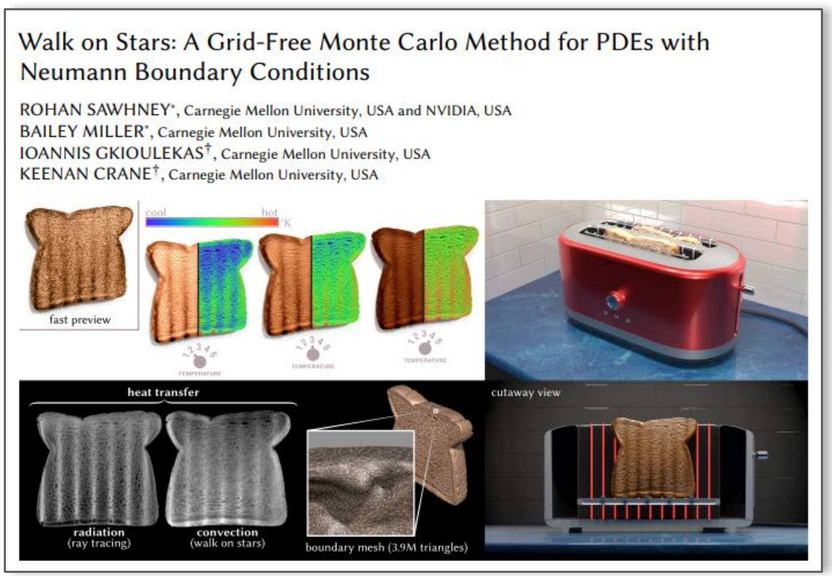
- Fast and effective at Runtime

But,

- memory hungry
- hard to optimize
- limited to small static scenes
- solving propagation, not synthesis

Related Work





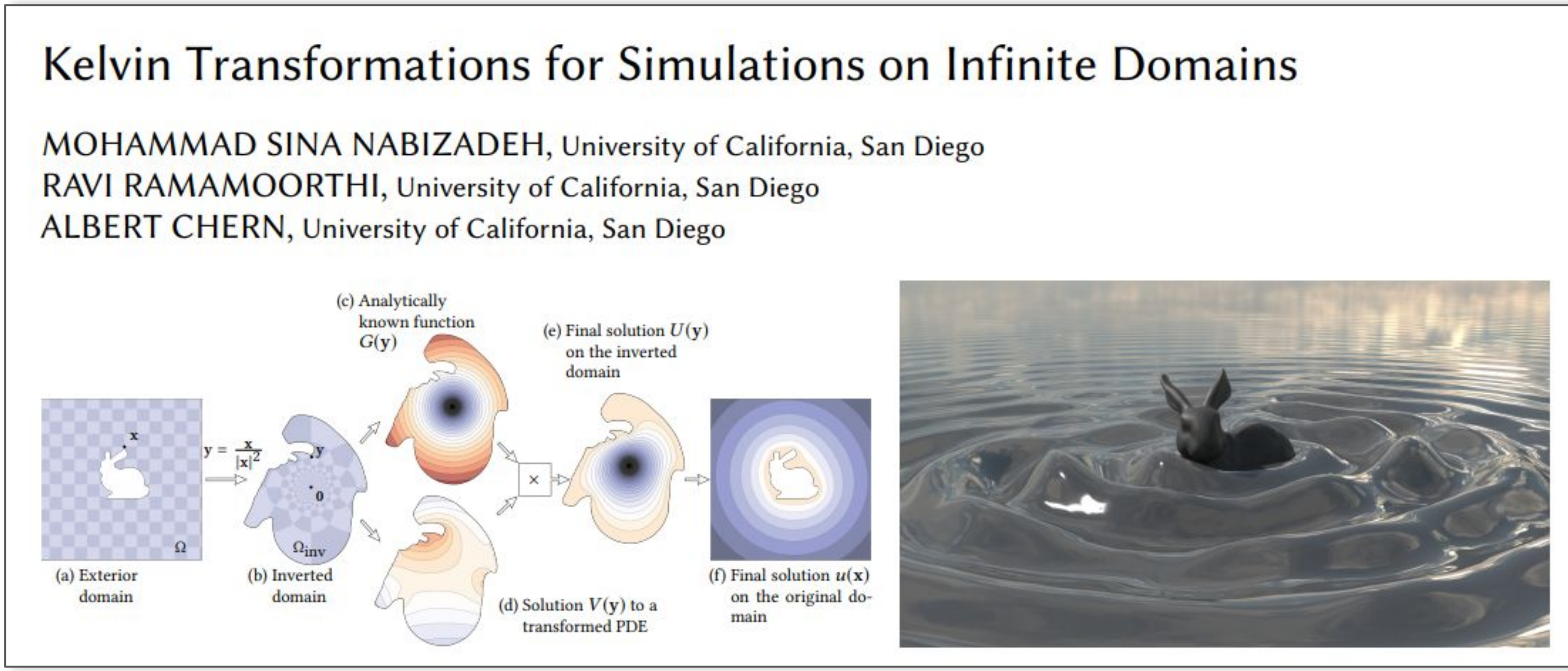
Walk on Sphere & Walk on Stars

- No pre-computation
- Unbiased

But,

- Hard to get effective samples in unbounded domain
- can't solve all PDEs…

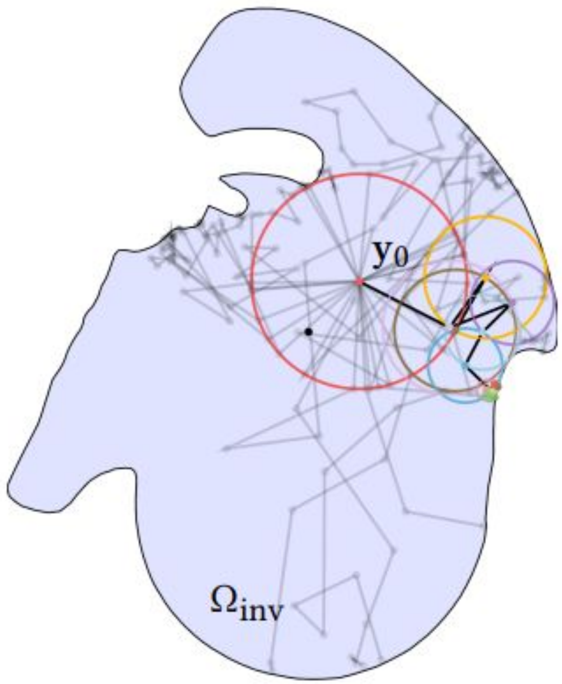
Solving Wave Equation with MCM (1)

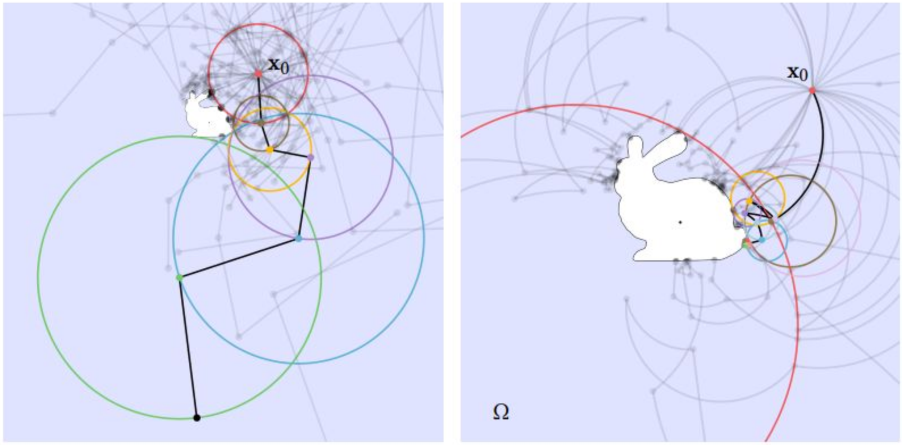

Kelvin Transformations for Simulations on Infinite Domains

MOHAMMAD SINA NABIZADEH, University of California, San Diego
RAVI RAMAMOORTHI, University of California, San Diego
ALBERT CHERN, University of California, San Diego

Physically-based sound rendering should be done on unbounded domain.

Solving Wave Equation with MCM (2)

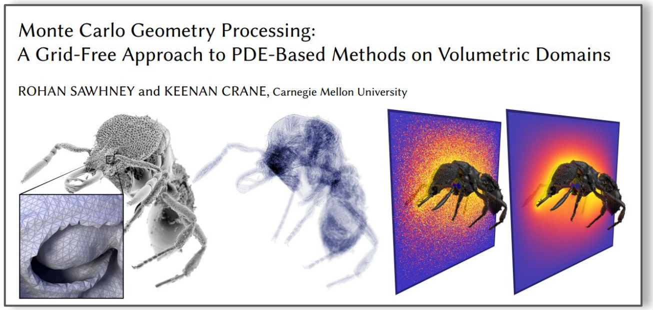


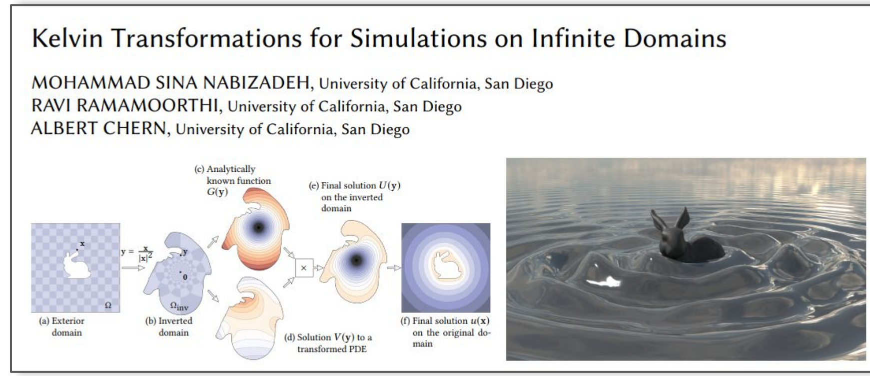


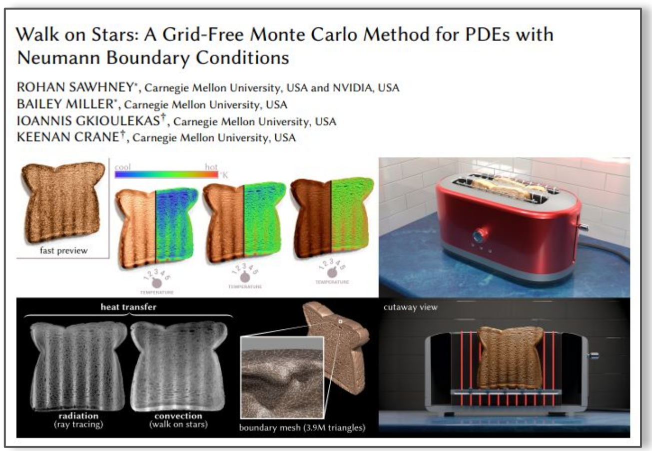
(a) WoS-RR on an infinite domain (b) WoS-KT on the original domain

Main idea: Inverse the domain to make the unbounded infinity to become a singularity in the center.

Solving Wave Equation with MCM (3)



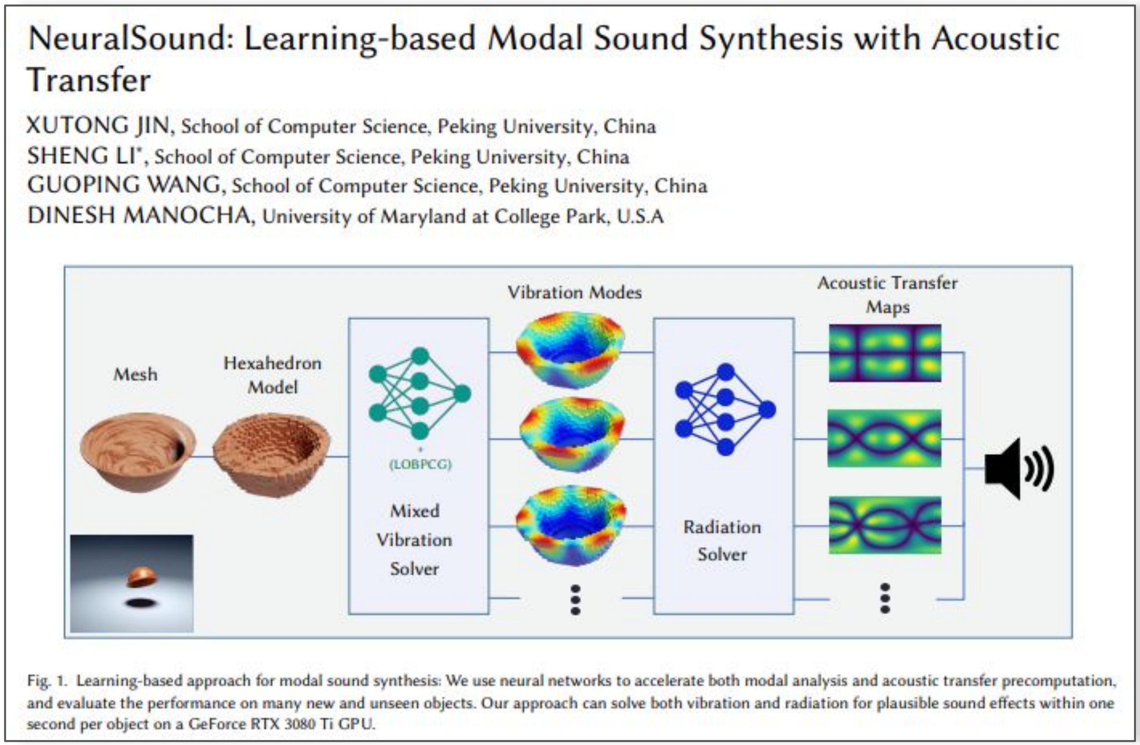




$$\frac{\partial^2 p(\boldsymbol{x},t)}{\partial t^2} = c^2 \nabla^2 p(\boldsymbol{x},t) + c\alpha \nabla^2 \frac{\partial p(\boldsymbol{x},t)}{\partial t}, \quad \boldsymbol{x} \in \Omega,$$

However, there is no stochastic representation of wave equation in general domain.

New Approach: Neural-Network based soln.


NeuralSound: Learning-based Modal Sound Synthesis with Acoustic Transfer

XUTONG JIN, School of Computer Science, Peking University, China
SHENG LI*, School of Computer Science, Peking University, China
GUOPING WANG, School of Computer Science, Peking University, China
DINESH MANOCHA, University of Maryland at College Park, U.S.A

Fig. 1. Learning-based approach for modal sound synthesis: We use neural networks to accelerate both modal analysis and acoustic transfer precomputation, and evaluate the performance on many new and unseen objects. Our approach can solve both vibration and radiation for plausible sound effects within one second per object on a GeForce RTX 3080 Ti GPU.

NeuralSound [SIGGRAPH 2022]

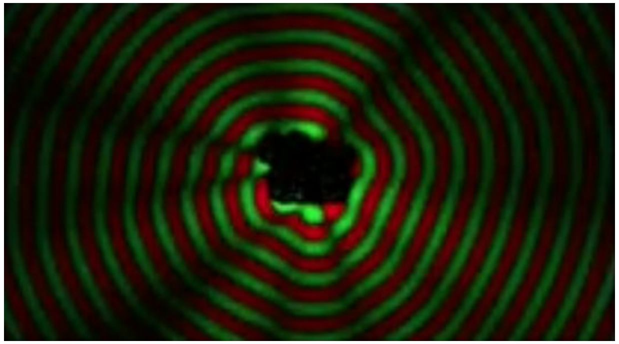
Review

"Easy" Condition

Unbounded Scene, Reflection only on Object

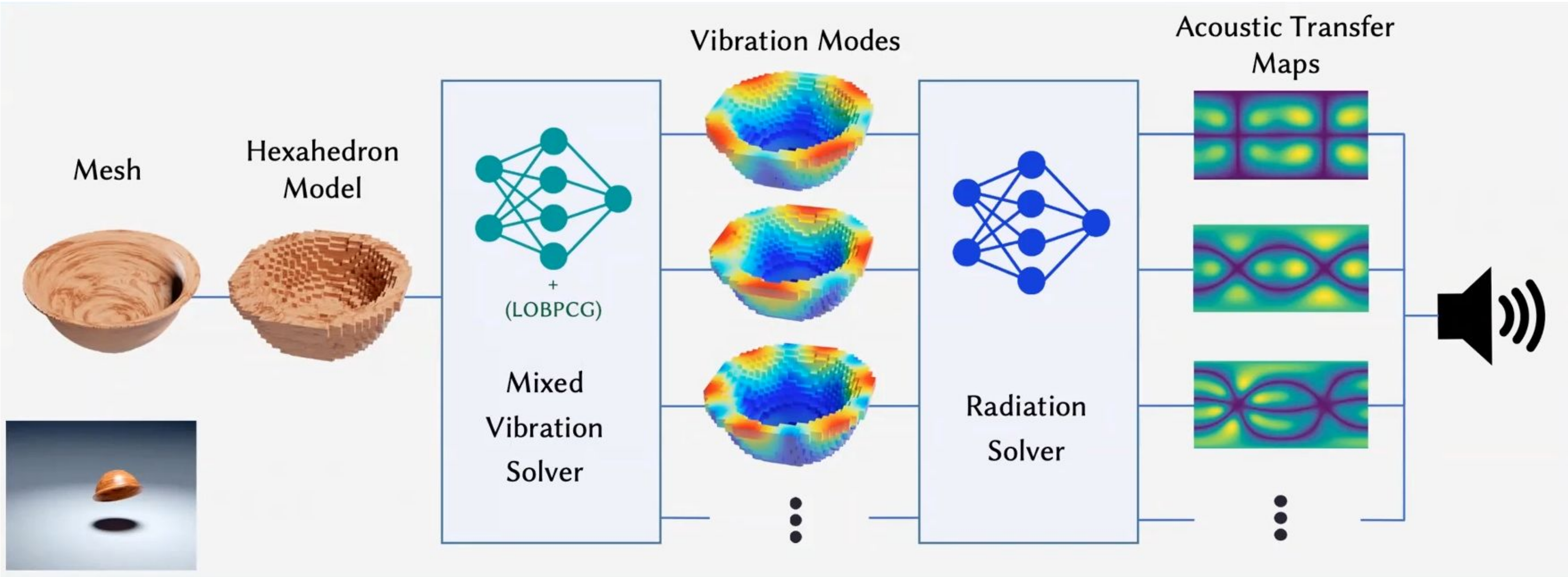
$$p(\mathbf{x},t) = |p(\mathbf{x})|q(t)$$

$|p(\mathbf{x})|$



$|p(\mathbf{x})|q(t)$

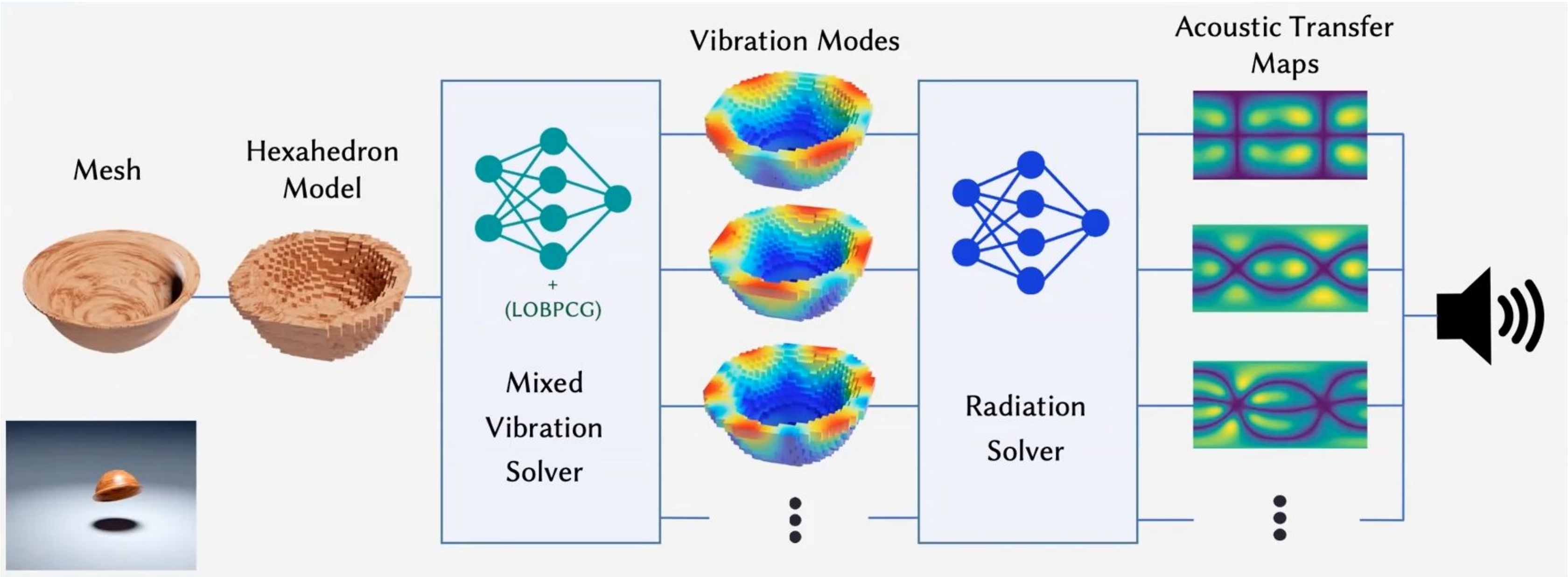
Architecture of Neural Sound



The architecture consist of 2 parts:

- Mixed Vibration Solver: Obtain the modes of vibration of the object.
- Radiation Solve: Determine the sound pressure generated by each modes

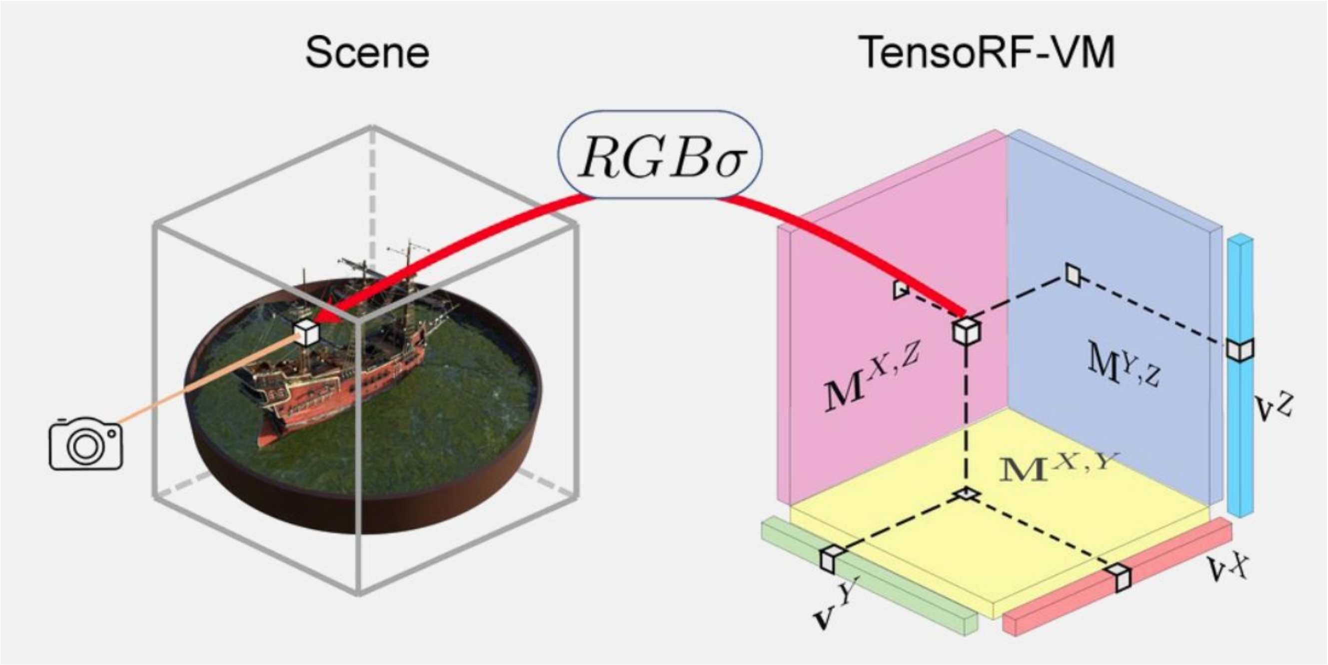
Architecture of Neural Sound



Main Limitation

voxel-base has low-resolution, requires lots of computation

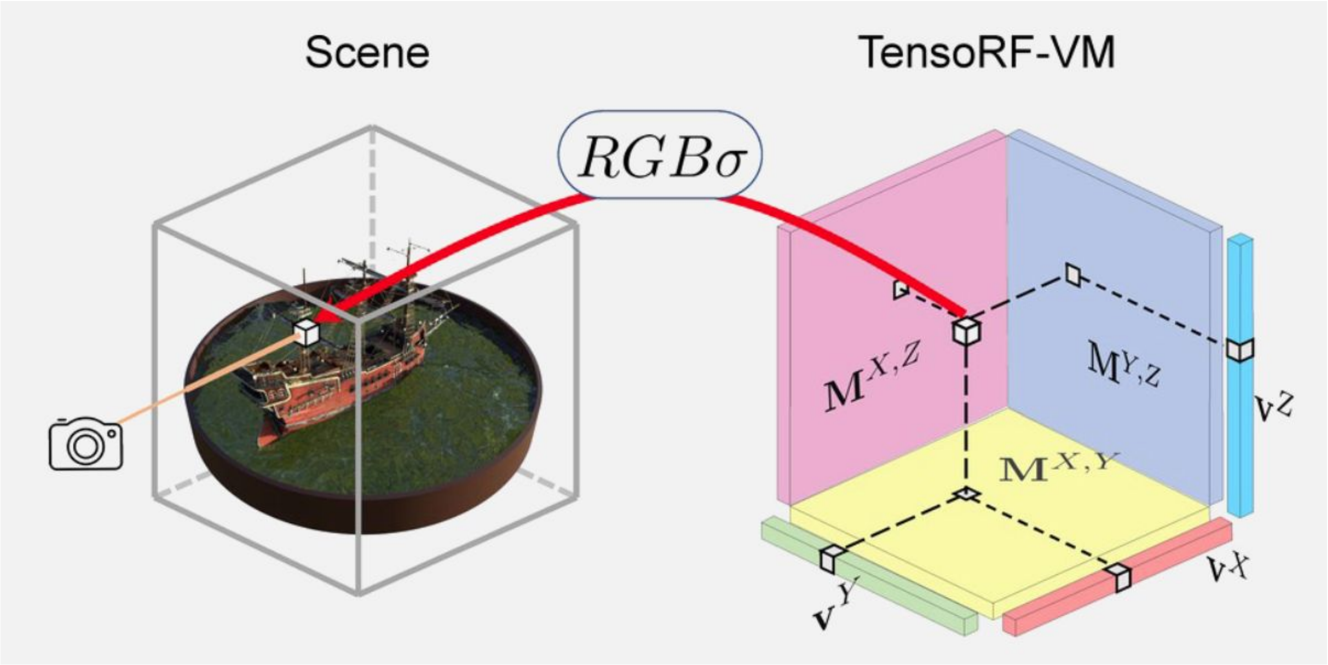
Inspiration from Neural Rendering



Main Limitation

voxel-base has low-resolution, requires lots of computation

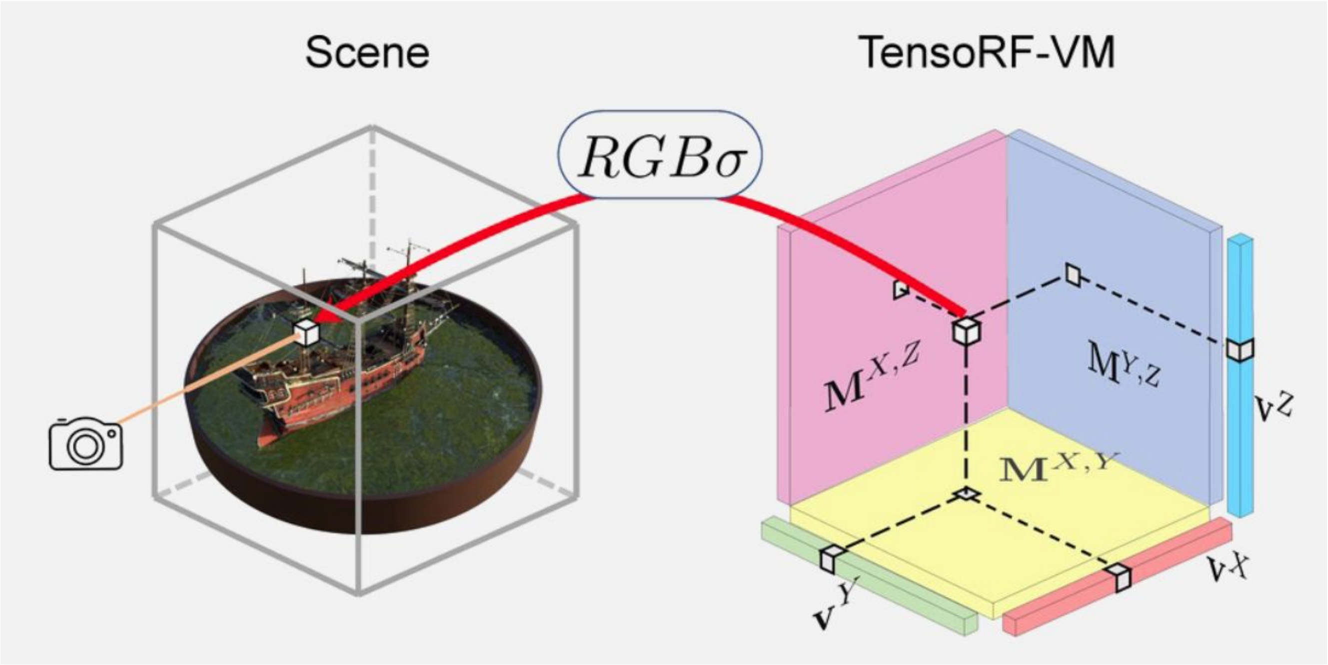
Inspiration from Neural Rendering



Hybrid Neural-Explicit Representation

efficient representation → high quality, low memory, fast training

Inspiration from Neural Rendering

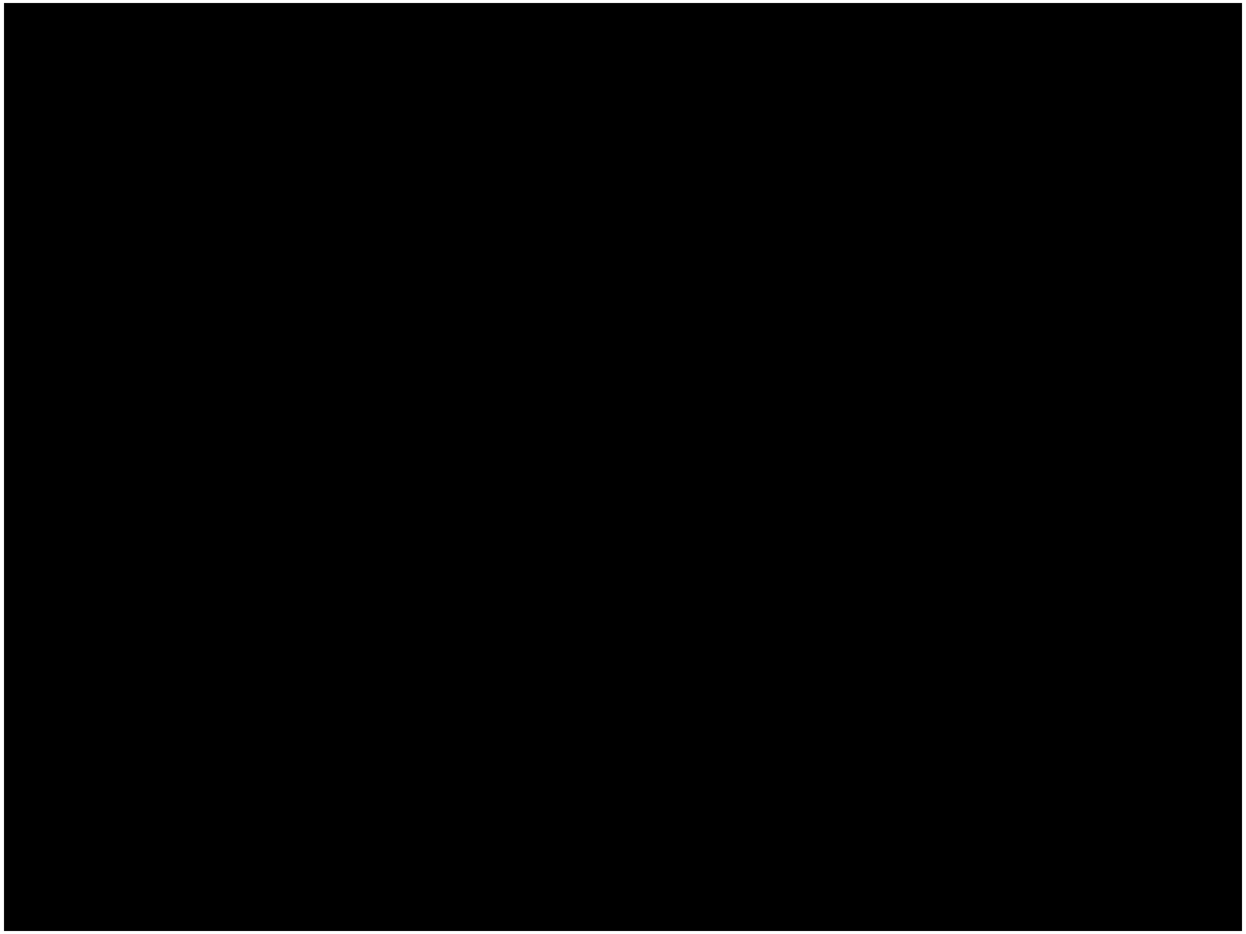


Hybrid Neural-Explicit Representation

efficient representation → high quality, low memory, fast training

“explicit” representation → compatible with existing pipeline

Result of Neural Sound



Role Division

Nguyen Minh Hieu

- **Coordinator, Model Design, Training**

Siripon Sutthiwanna

- **Dataset, Training**

Ko Wonhyeok

- **Dataset, Training**