

Wide-band Butterfly Network: An architecture for multifrequency sub-wavelength imaging

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GRADUATE STUDENT IN COMPUTATIONAL SCIENCE AND ENGINEERING

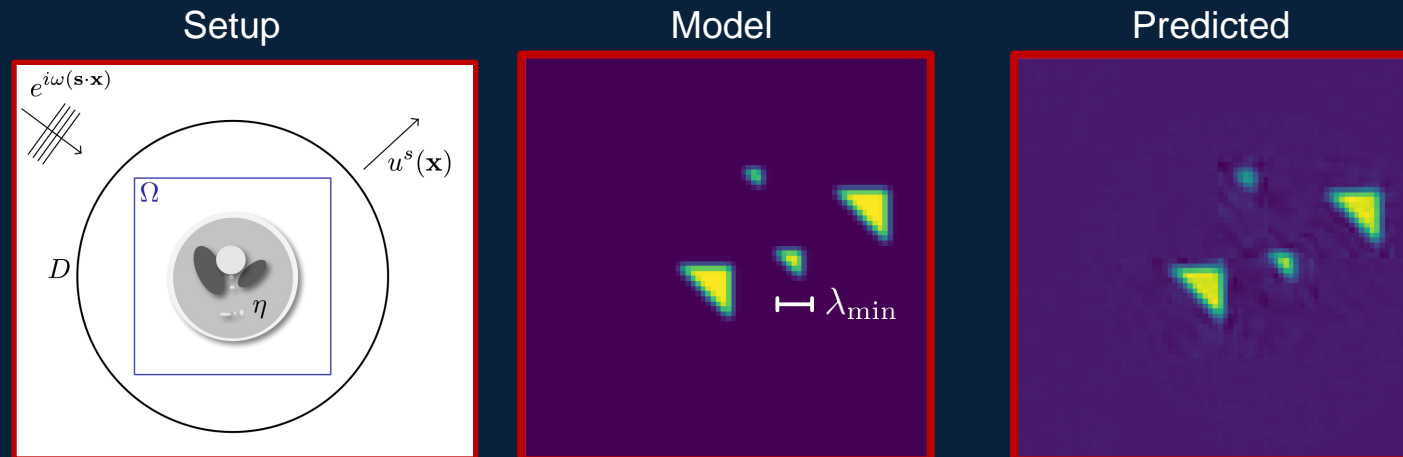
In collaboration with Leonardo Zepeda-Núñez (UW Madison) and Laurent Demanet (MIT)

Acknowledgements



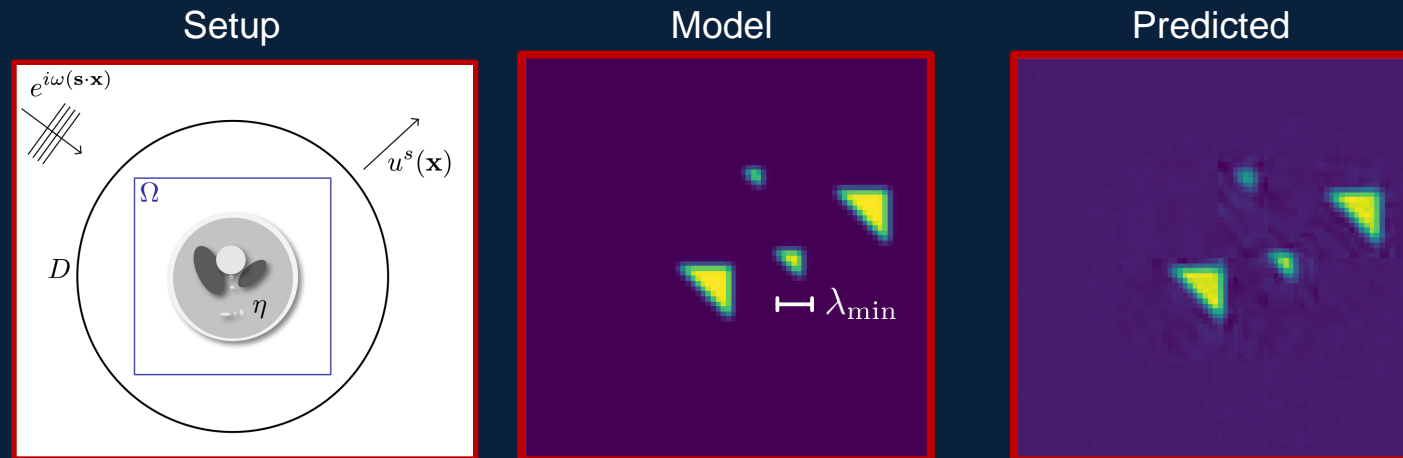
Outline / Contributions

- 1) we introduce a neural network for **seismic inversion below the diffraction limit**



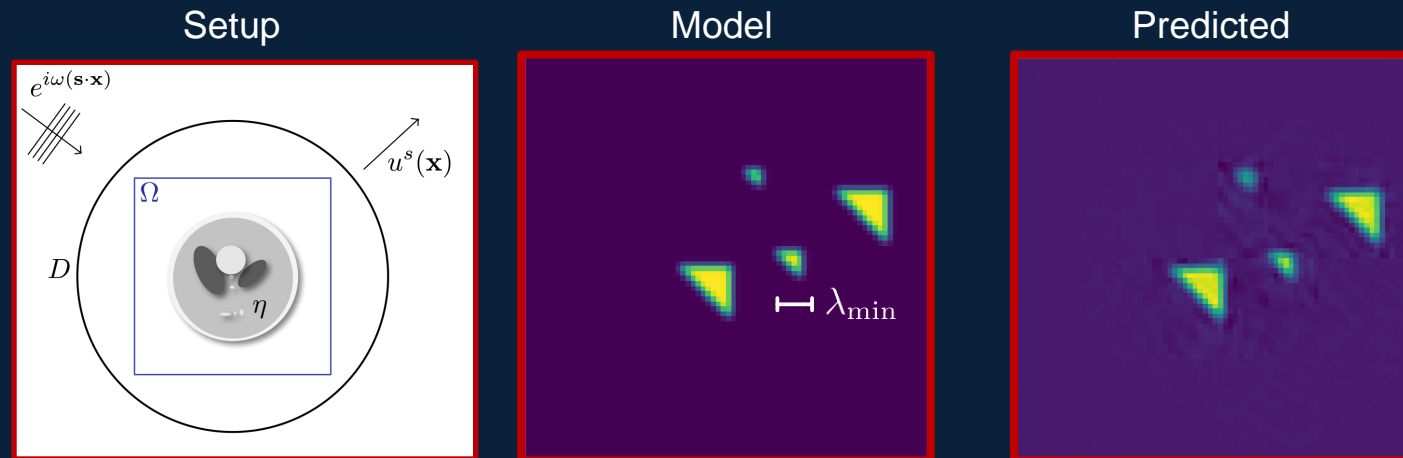
Outline / Contributions

- 1) we introduce a neural network for **seismic inversion below the diffraction limit**
- 2) our architecture **incorporates the physics of wave propagation**



Outline / Contributions

- 1) we introduce a neural network for **seismic inversion below the diffraction limit**
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... but why machine learning?:

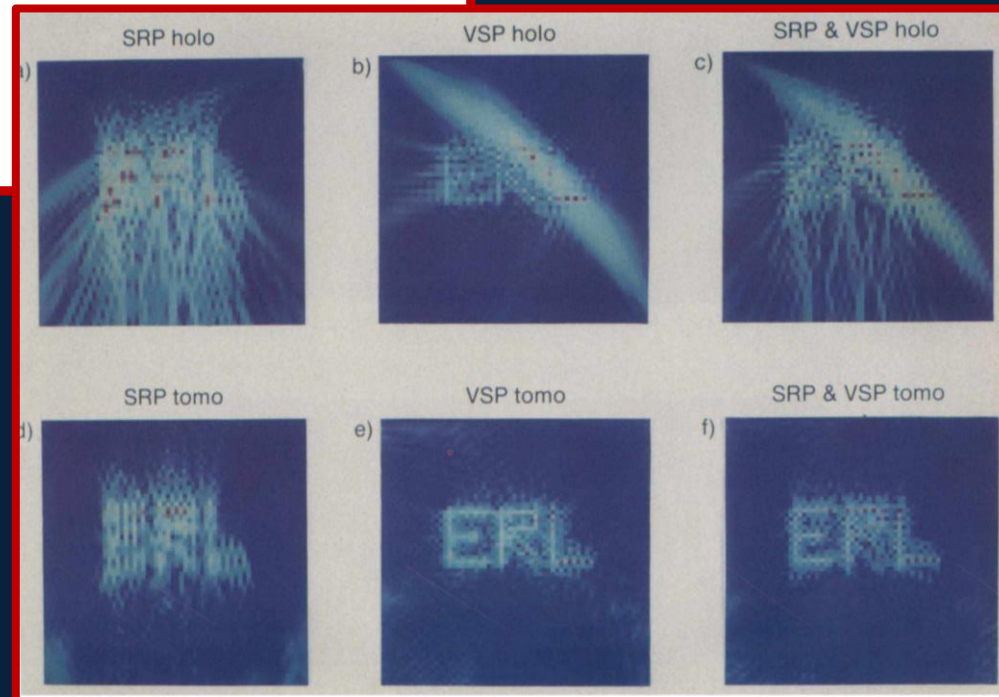
- *as a signal processing problem this is genuinely difficult*
- *it's unclear what are the resolution limits to FWI* [Fichtner & Trampert 2011]
- *machine learning provides evidence of whether this task is even possible!*

Geophysical Relevance

Diffraction tomography and multisource holography applied to seismic imaging

Ru-Shan Wu* and M. Nafi Toksöz*

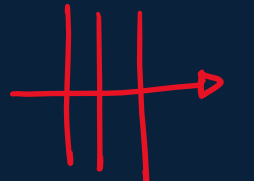
Thanks @Nori Nakata for this reference!

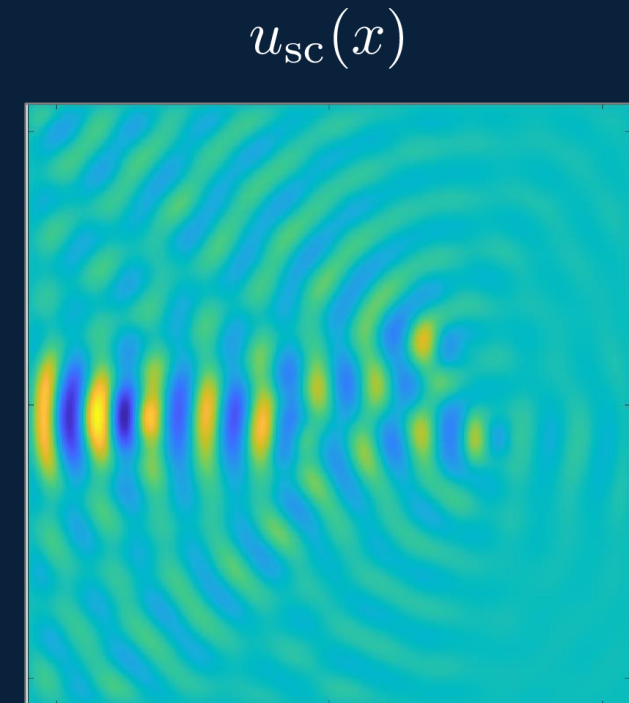
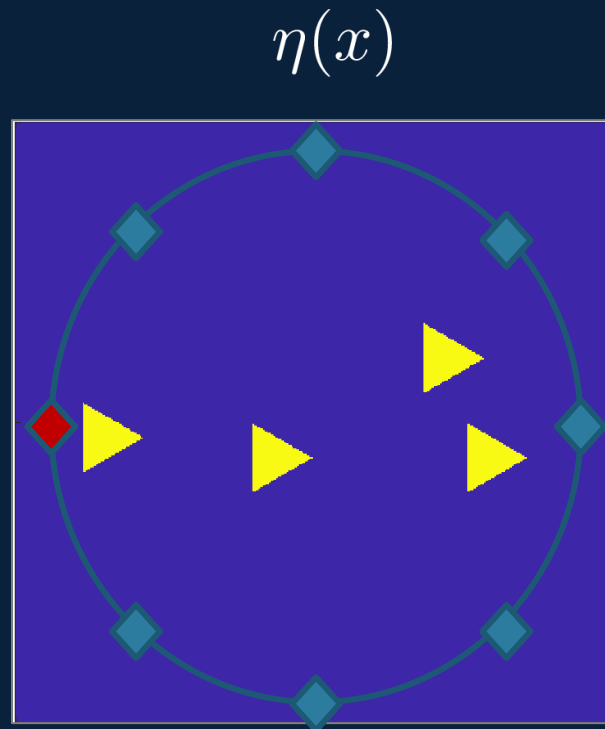


Imaging Setup

ASSUMPTIONS:

- full aperture
- far field
- noiseless
- known background velocity

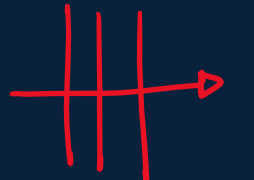

$$e^{i\omega s \cdot x}$$

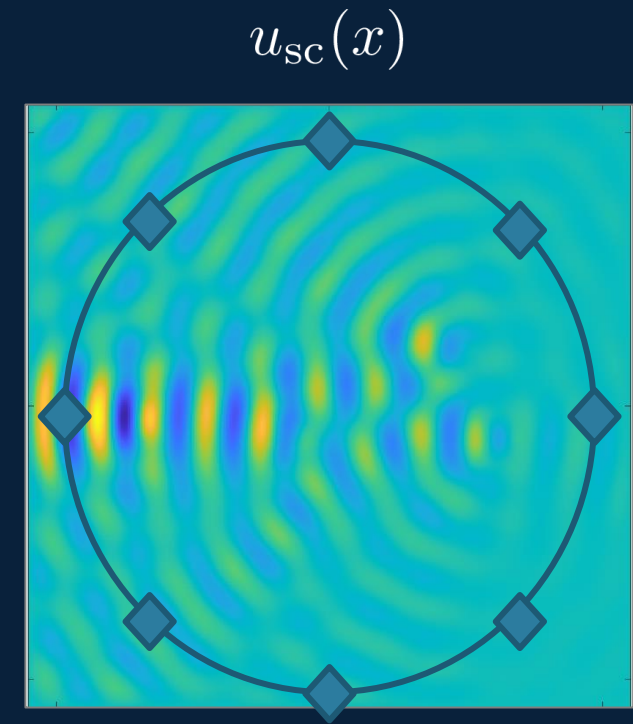


Imaging Setup

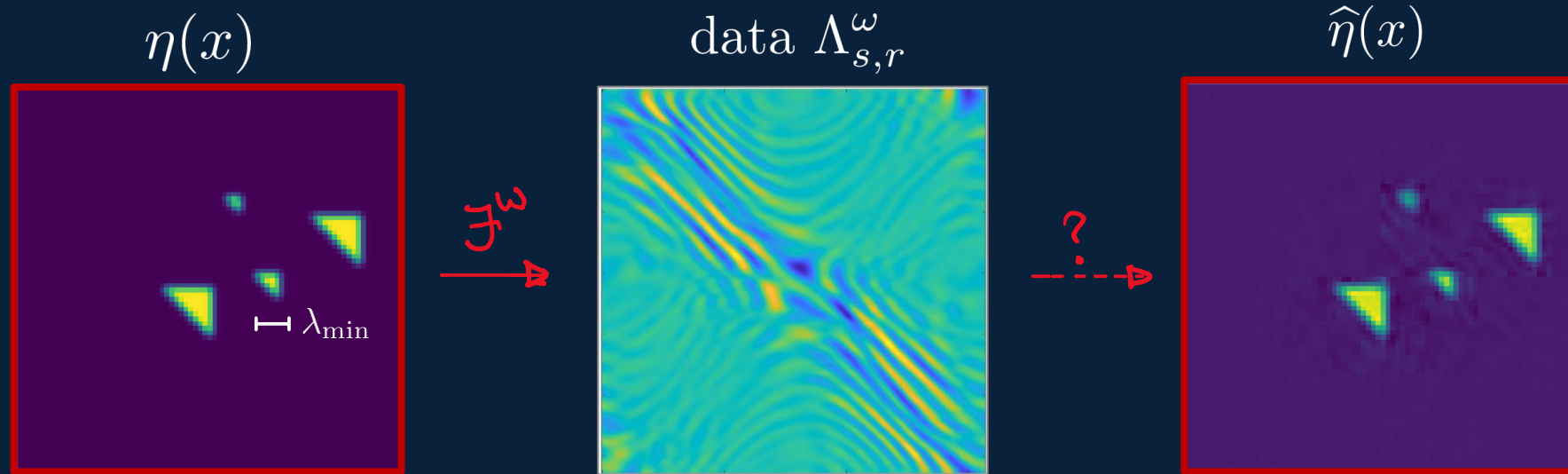
ASSUMPTIONS:

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$$e^{i\omega s_1 \cdot x}$$



Inverse Problem

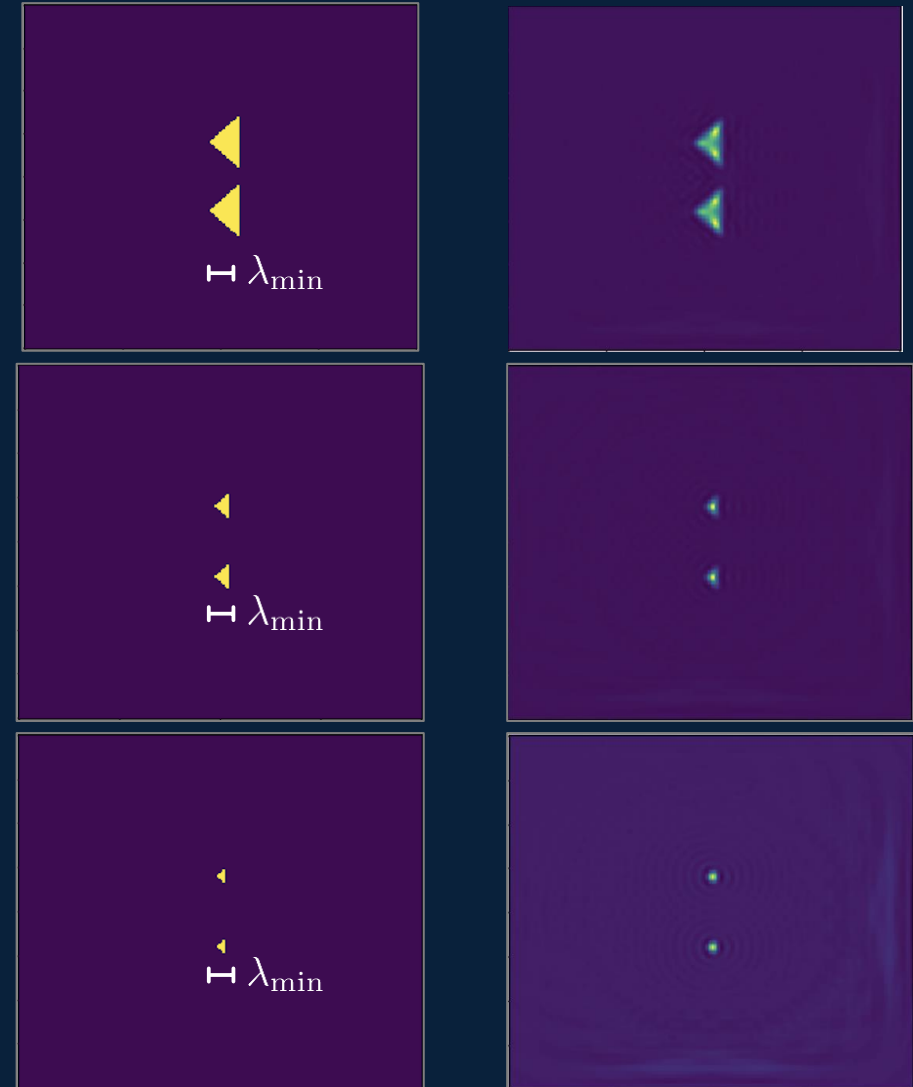


$$\hat{\eta} = \arg \min_{\mu} \left| \sum_{\omega} \left\| \mathcal{F}^{\omega}[\mu] - \Lambda_{s,r}^{\omega} \right\|^2 \right|$$

nonlinear wave (Helmholtz) equation

Super Resolution

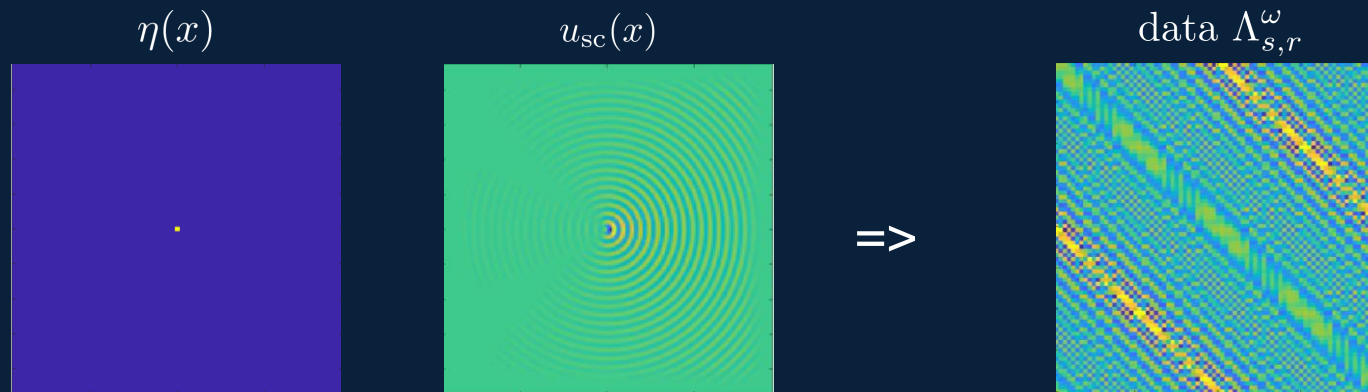
- in the **linearized setup** we are limited to $\frac{1}{2}$ wavelength by the Rayleigh resolution
- in the **nonlinear setup (FWI)** it is less clear what resolution limits are
 - *but sharp images are still possible if you properly regularize*
 - *... consult our resident expert Zhilong Fang to learn more!*
- Donoho (1992) proves **super resolution of point scatterers** is possible:
 - *1. you need multiple frequencies*
 - *2. algorithm must be non-linear*



Architectural Design

QUESTION: Why do we need a custom neural network architecture for this problem?

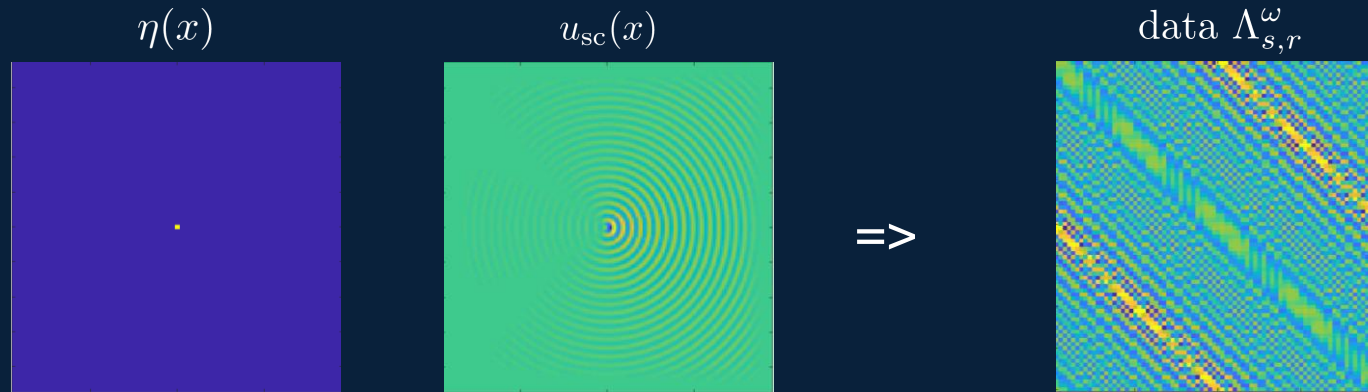
ANSWER: ...because the **physics of wave propagation** makes it challenging



Architectural Design

QUESTION: Why do we need a custom neural network architecture for this problem?

ANSWER: ...because the **physics of wave propagation** makes it challenging



QUESTION: So how should we design our network?

ANSWER: ...to at least perform as well as **linearized Born inversion** (filtered backprojection)

$$\mathcal{F}[\mu] \approx F\mu \quad \hat{\eta} = (F^*F + \epsilon I)^{-1} F^* \Lambda_{s,r}$$

BORN APPROX

Butterfly Network

- Khoo and Ying (2018) – exploit the **analytical properties** of the operators

$$\hat{\eta} = \underbrace{(F^* F + \epsilon I)^{-1}}_{\text{translation invariant convolution operator}} \underbrace{F^*}_{\text{a Fourier Integral Operator (FIO)}}$$

• translation invariant convolution operator
⇒ replace with CNN!

• a Fourier Integral Operator (FIO)
⇒ well approximated by a BUTTERFLY FACTORIZATION

[Hörmander 1985]

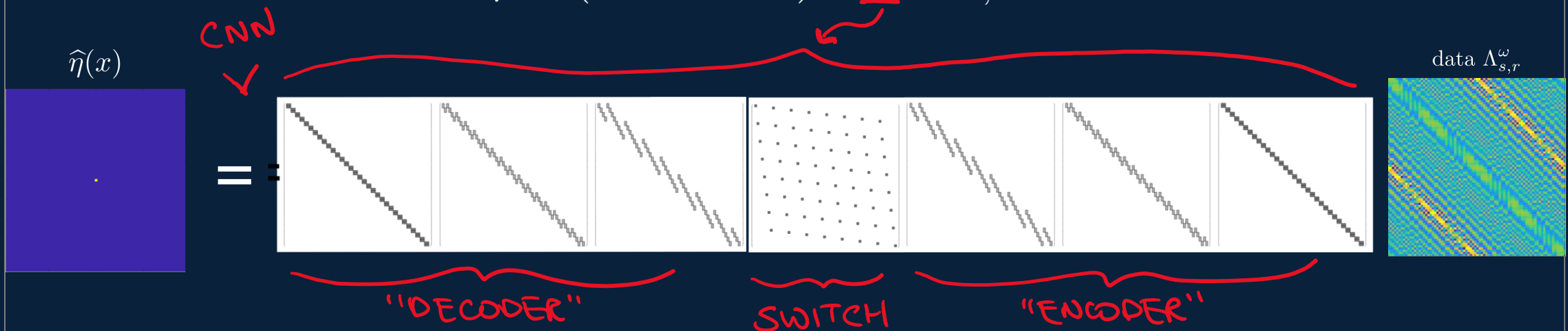
[Michielssen & Boag 1996]

Butterfly Network

THE KEY IDEA

- use the **structure of the matrix factorization** as your architecture

$$\hat{\eta} = (F^* F + \epsilon I)^{-1} F^* \Lambda_{s,r}$$

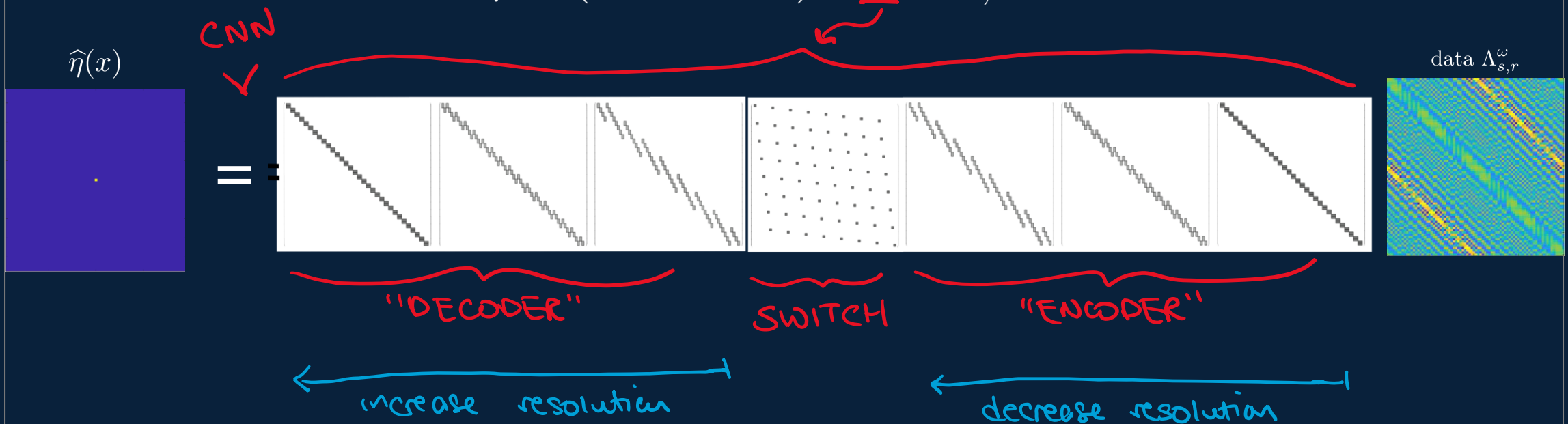


Butterfly Network

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- use the **structure of the matrix factorization** as your architecture

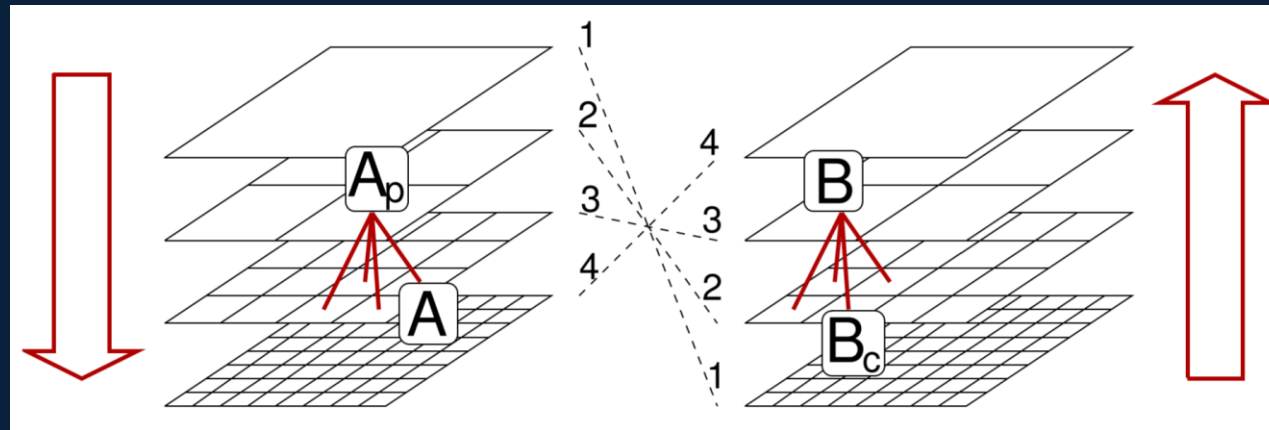
$$\hat{\eta} = (F^* F + \epsilon I)^{-1} F^* \Lambda_{s,r}$$



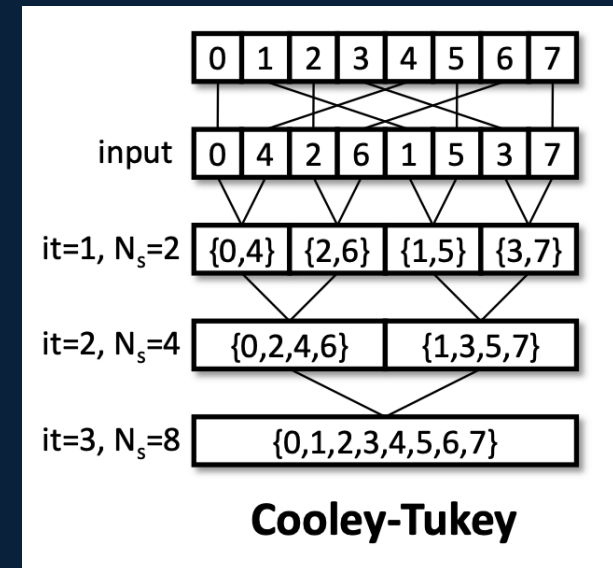
Incorporating Wideband Data

REMEMBER THE REQUIREMENTS FOR SUPER-RESOLUTION

1. need **wideband data to stabilize** inverse problem
2. need **non-linear combination** of frequencies

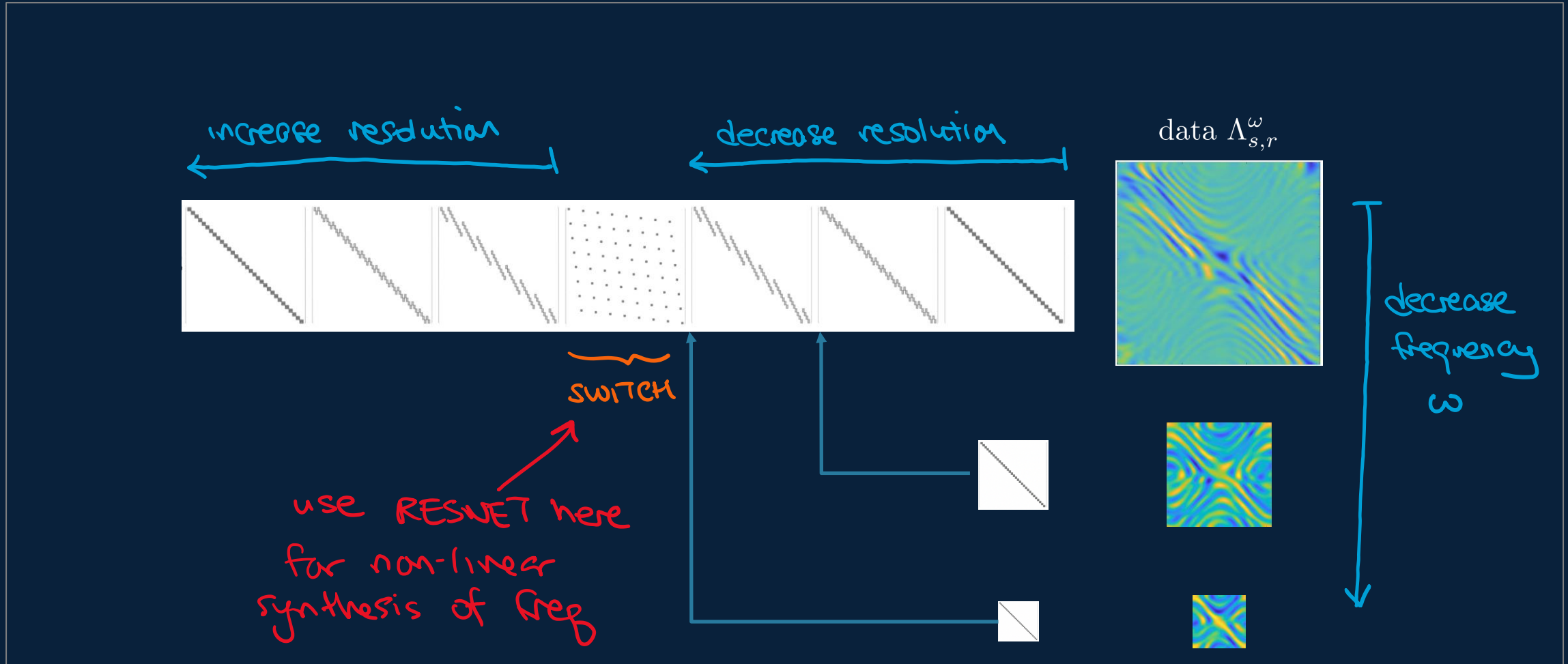


[Candes, Demanet, and Ying, 2008]



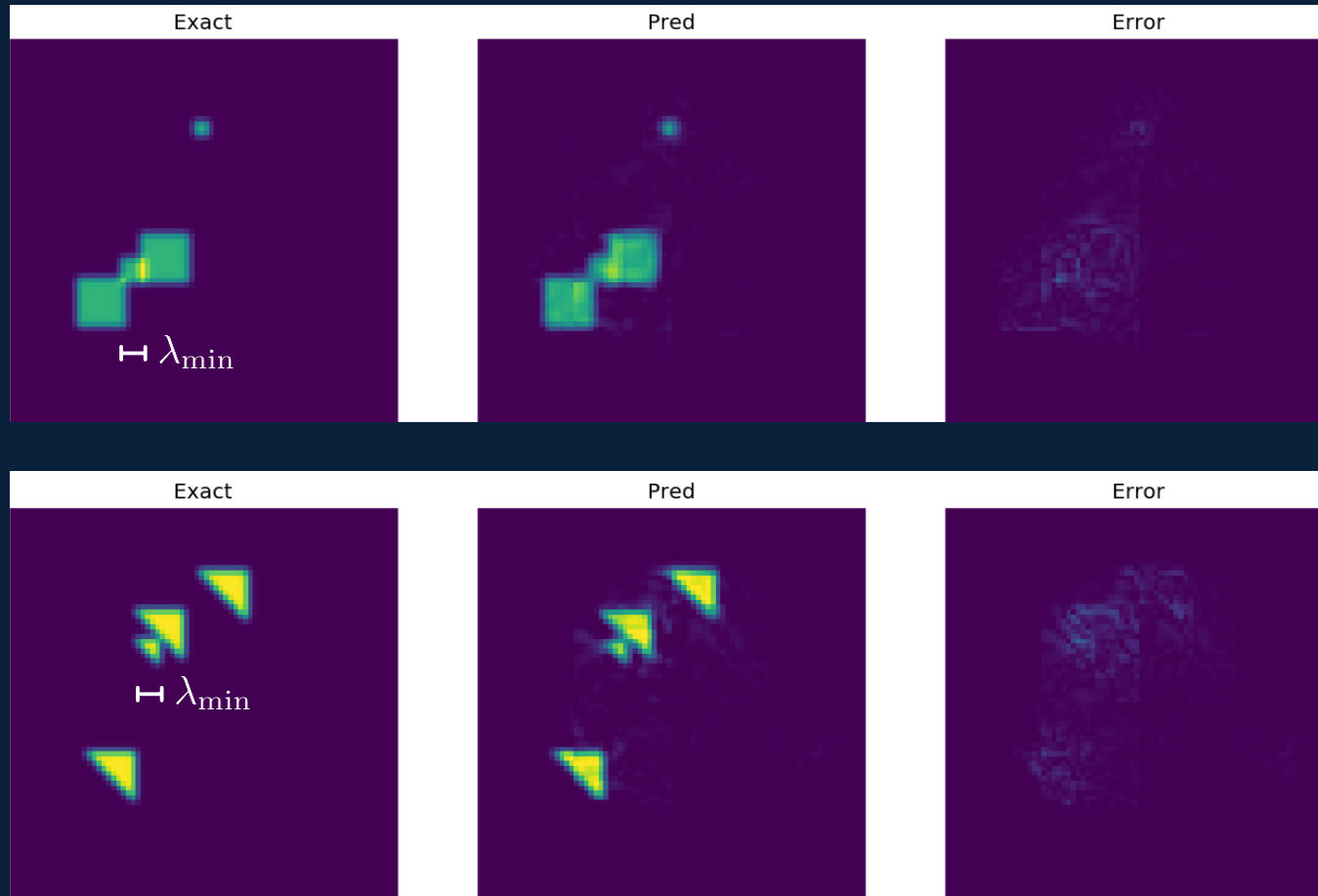
[Cooley & Tukey 1965]

Incorporating Wideband Data



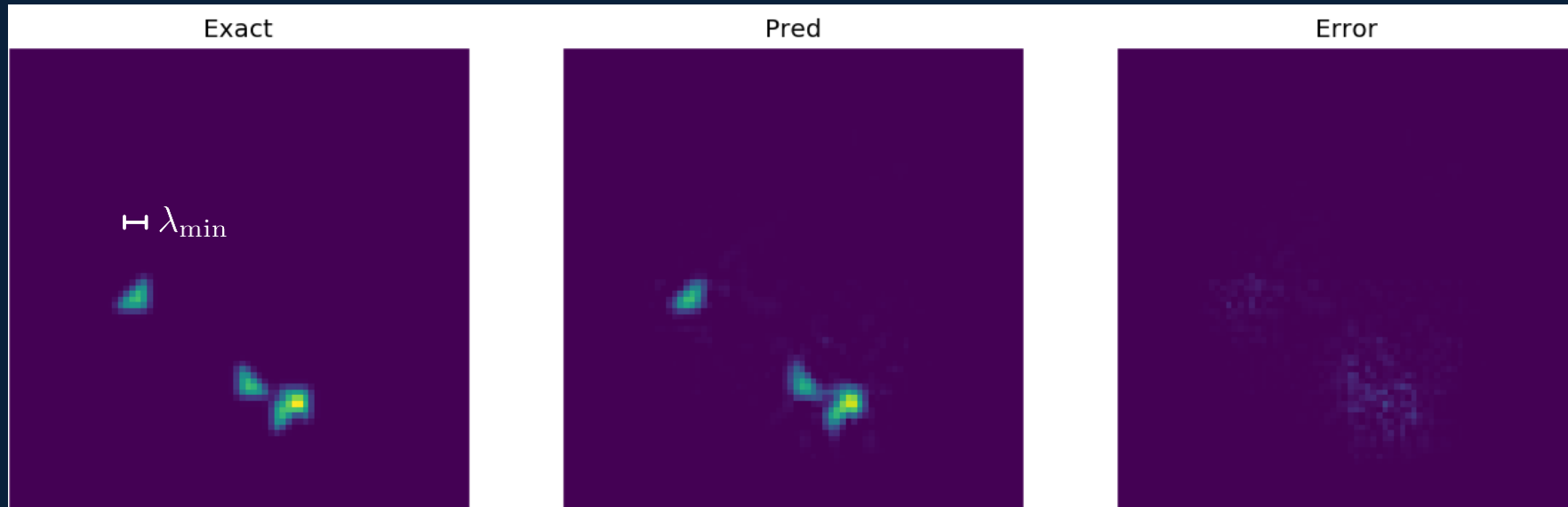
Numerical Results

MIXED RESOLUTION



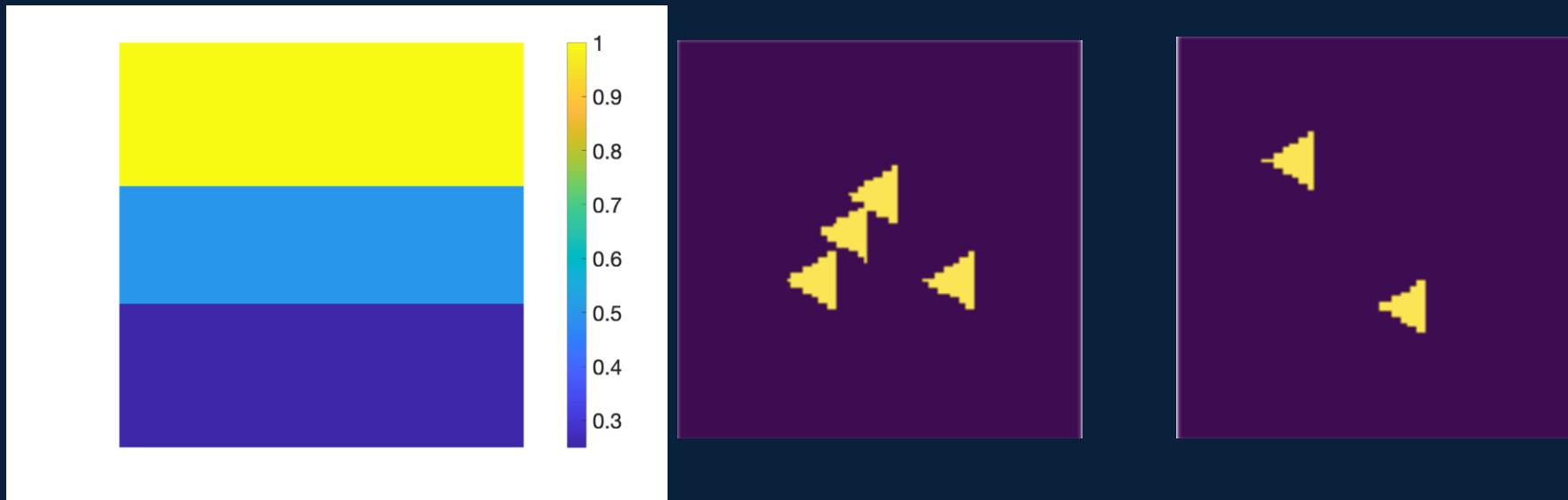
Numerical Results

ROTATIONS



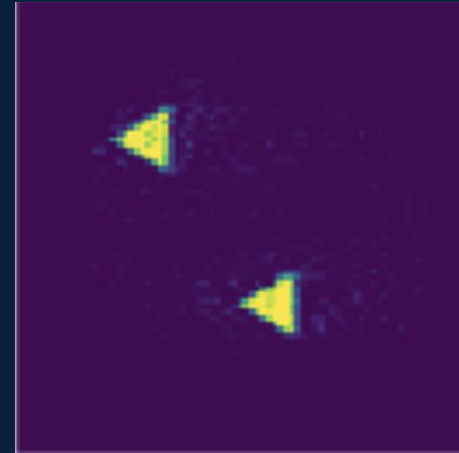
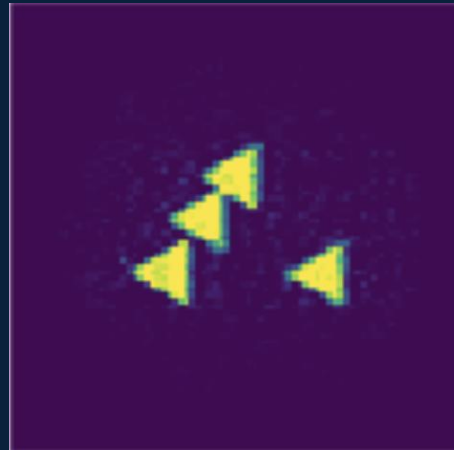
Numerical Results

INHOMOGENEOUS BACKGROUND



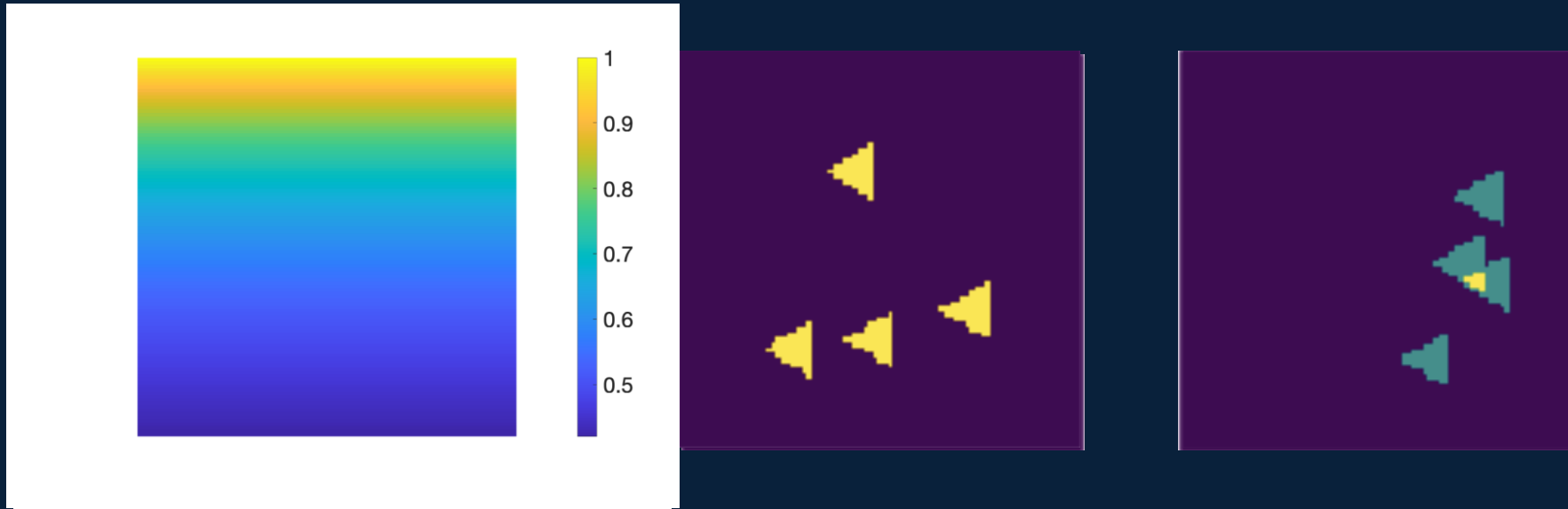
Numerical Results

INHOMOGENEOUS BACKGROUND



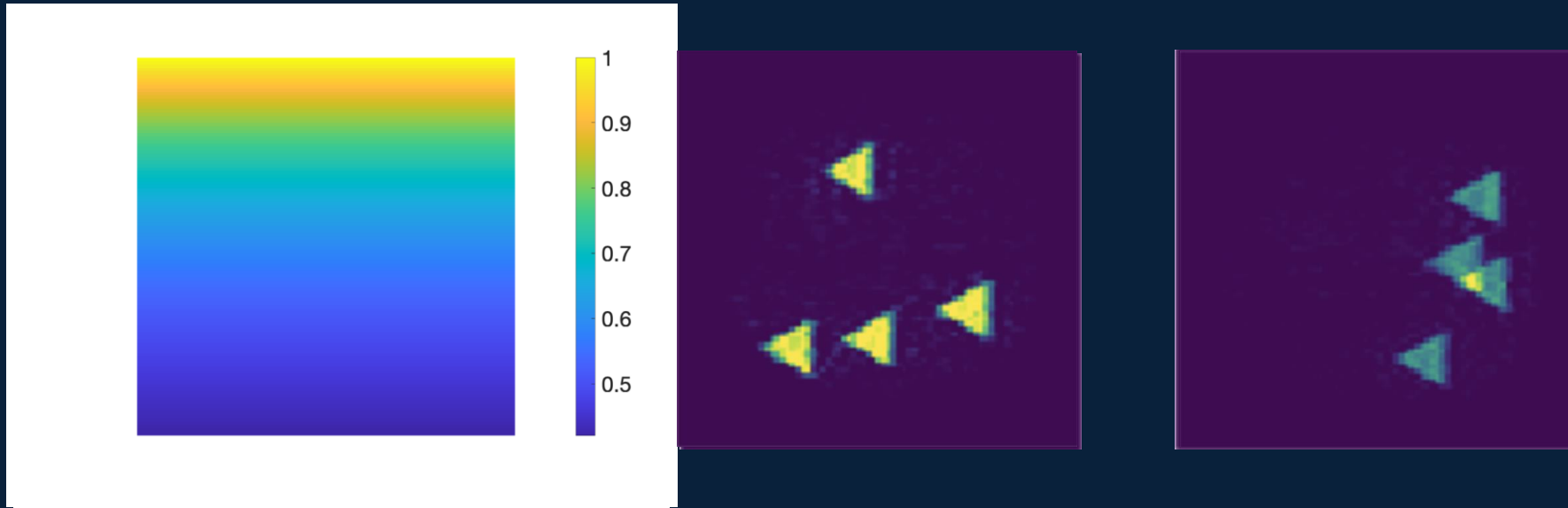
Numerical Results

INHOMOGENEOUS BACKGROUND



Numerical Results

INHOMOGENEOUS BACKGROUND





Thank You! Questions?

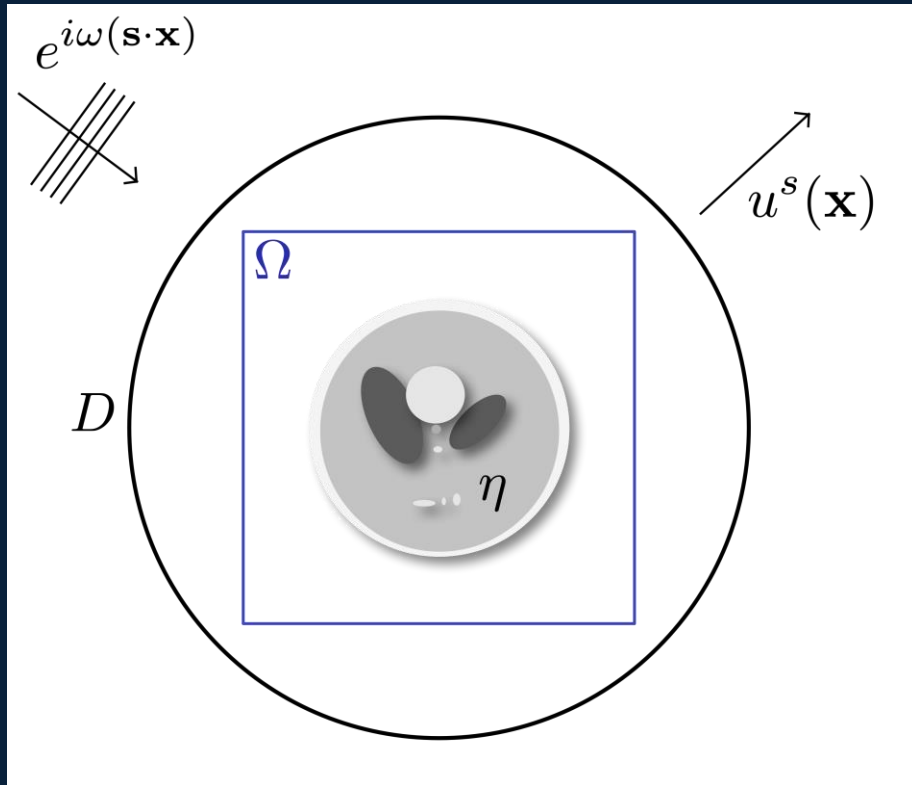
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Bonus Slides

Mathematical Setup



$$(\Delta + \omega^2 m(x))u_{\text{tot}}(x) = 0$$

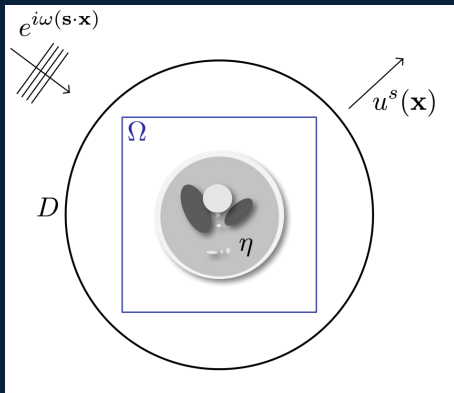
$$m(x) = 1 + \eta(x)$$

$$u_{\text{tot}}(x) = e^{i\omega\mathbf{x}\cdot\mathbf{s}} + u_{\text{sc}}(x)$$

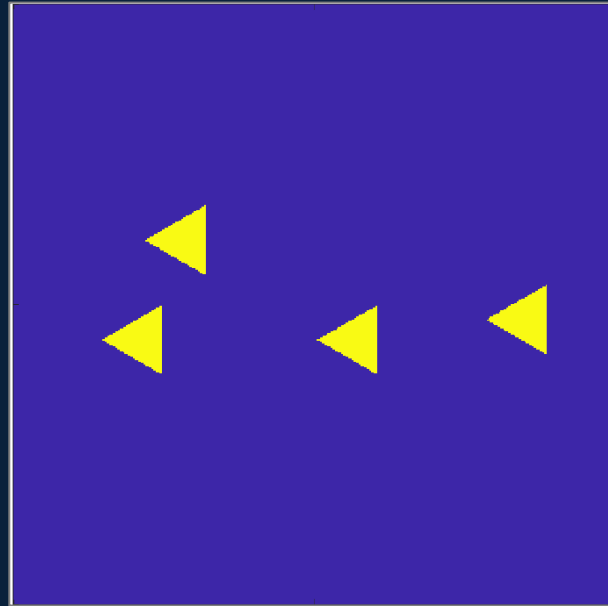
$$(\Delta + \omega^2 m)u_{\text{sc}} = -\omega^2 \eta e^{i\omega\mathbf{x}\cdot\mathbf{s}}$$

$$\left(\frac{\partial}{\partial|x|} - ik\right)u_{\text{sc}} = o(|x|^{-1})$$

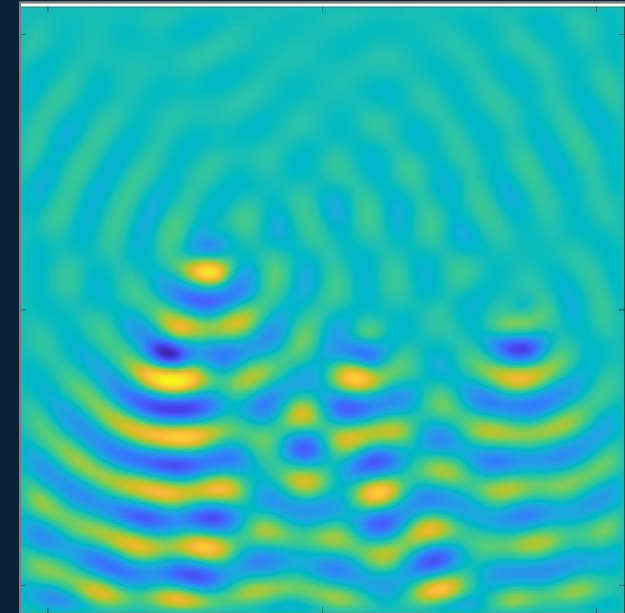
Imaging Setup



$\eta(x)$



$u_{sc}(x)$



$$(\Delta + \omega^2 m(x))u_{\text{tot}}(x) = 0$$

$$m(x) = 1 + \eta(x)$$

$$u_{\text{tot}}(x) = e^{i\omega \mathbf{x} \cdot \mathbf{s}} + u_{\text{sc}}(x)$$

$$(\Delta + \omega^2 m)u_{\text{sc}} = -\omega^2 \eta e^{i\omega \mathbf{x} \cdot \mathbf{s}}$$

$$\left(\frac{\partial}{\partial |x|} - ik\right)u_{\text{sc}} = o(|x|^{-1})$$

Geophysical Relevance

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Diffraction imaging by focusing-defocusing: An outlook on seismic superresolution

reconstruct the geometry of strong and smooth reflectors—most often with success. At the same time, however, correct identification of geological discontinuities, such as faults, pinch-outs, and small-size scattering objects, is an important problem in interpretation of seismic data. Local structural and lithological elements in the subsurface of a size comparable to the wavelength are usually ignored during processing and identified only during interpretation. Unfortunately, the reliability of such identification is generally low. It is precisely the seismic

dynamical behavior can be analyzed and exploited in more refined algorithms. The phase content of the diffraction image can be analyzed to extract more information on fault edges, their orientation, and their relation to reflectors. In three dimensions, diffractions differentiate between edges and tips (Klem-Musatov, 1994). In 4D (time-lapse) studies, diffractions can help to monitor the displacement of the oil/gas–water contact during production.

In any case, we have shown that diffraction imaging is feasi-