Combining model- and deep learning-based approaches for thermal NDE[1]

Péter Kovács

Department of Numerical Analysis,
Eötvös Loránd University, Budapest, Hungary

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Outline

1. Introduction
2. Model based approach
3. ML based approach
4. Hybrid approach
5. Results

Participants

Institute of Signal Processing, JKU Linz

- Univ.-Prof. Dr. Mario Huemer
- Dr. Péter Kovács

Silicon Austria Labs, Linz

- Dr. Bernhard Lehner

Josef Ressel Centre for Thermal NDE of Composites, FH Wels

- Dr. Günther Mayr
- Gregor Thummerer

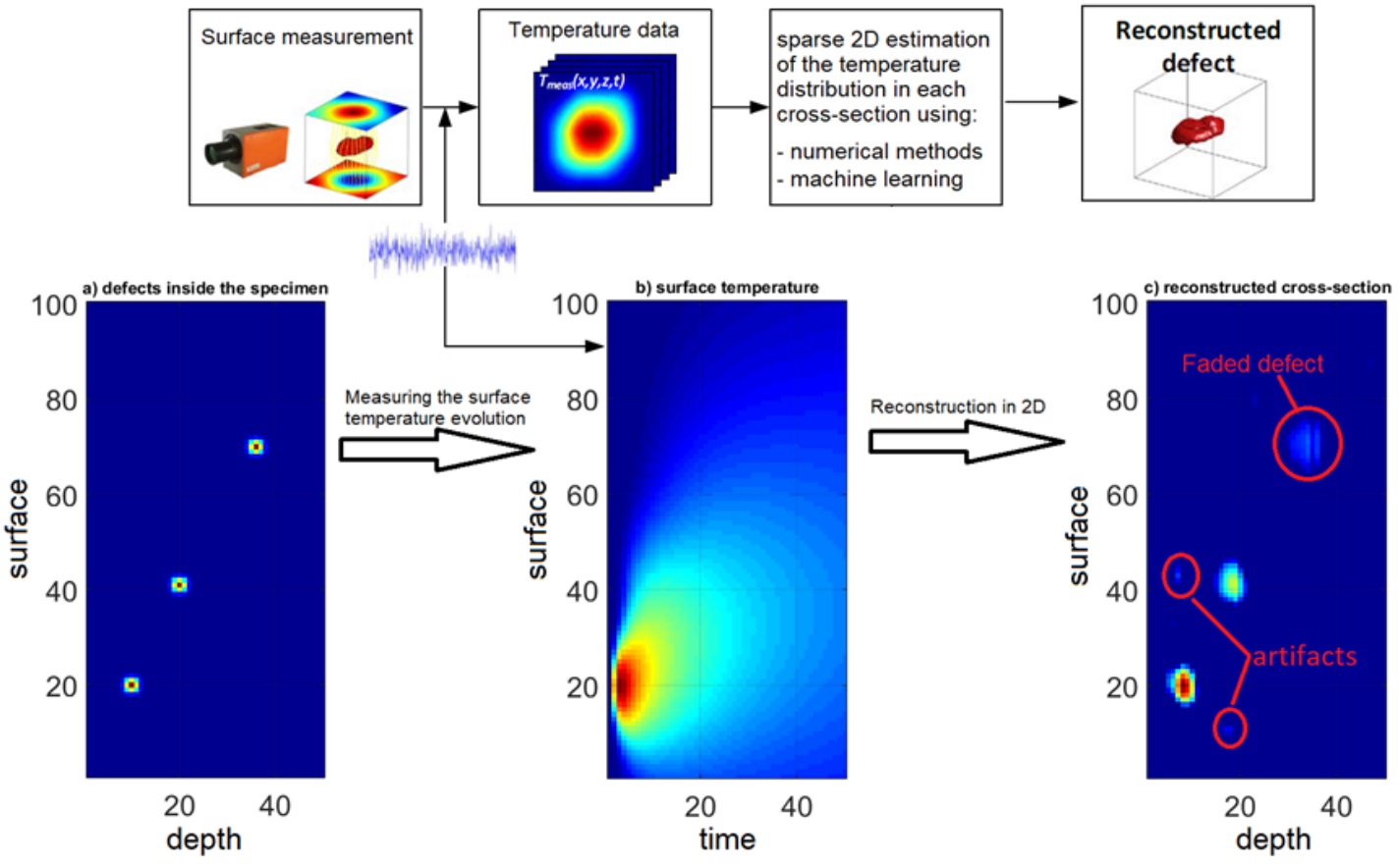
Research Center for Non Destructive Testing GmbH, Linz

- Dr. Peter Burgholzer

Problem description

Goal

Analysis, detection of structural imperfections of materials.



Problem description

Linear model

- T_{meas}: noisy surface temperature measurements after heating.
- x_{init}: initial temperature distribution inside the material.
- $\mathbf{\Phi}$: forward mapping that models the heat conduction.
- The corresponding discrete linear inverse problem:

$$\mathbf{\Phi} x_{init} = T_{meas}.$$

Heuristics

- Non-negativity: entries of x_{init} represents temperature data.
- Sparsity: locations of nonzeros in x_{init} are either defects or noise.
- Group sparsity: nonzero groups in x_{init} are most probably defects.

Challenges in thermographic imaging

- Numerical: it is a discrete ill-posed inverse problem.
- Computational: it is a large-scale problem.
- Modeling: how to derive $\mathbf{\Phi}$?

Virtual wave concept

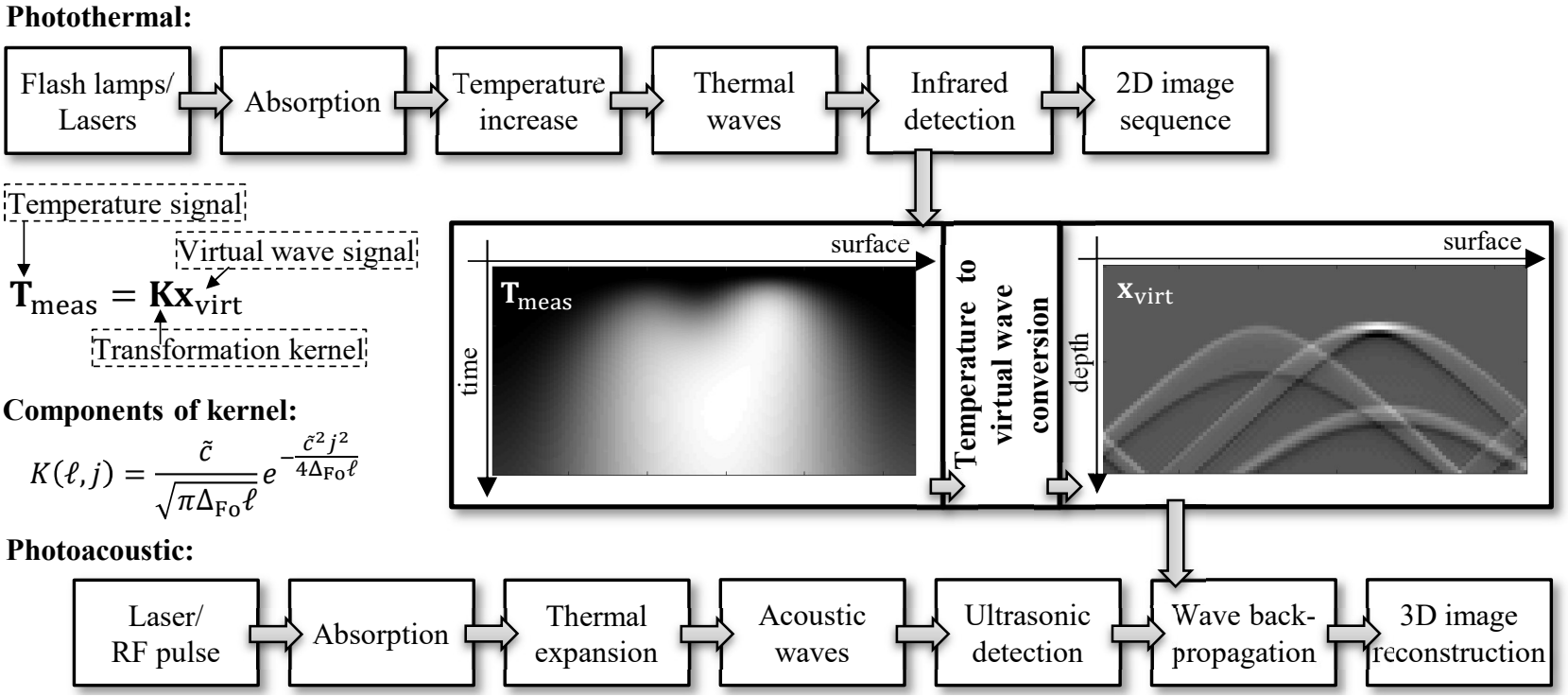


Figure: Conversion from surface temperature to virtual wave signal takes into account both lateral and axial heat flows and therefore allows multidimensional reconstruction at improved spatial resolution.[1]

[1] P. Burgholzer, M. Thor, J. Gruber, and G. Mayr. Three-dimensional thermographic imaging using a virtual wave concept. Journal of Applied Physics, 121(10):105102 1–11, 2017.

Two-stage reconstruction process

Challenges

Stage 1: solving $\mathbf{K}\mathbf{x}_{\text{virt}} = \mathbf{T}_{\text{meas}}$

- The virtual wave conversion is ill-posed, thus numerical regularization is needed.
- Estimating the right amount of regularization is not straightforward.
- Formalizing and including domain knowledge into the reconstruction process is difficult.

Stage 2: solving $\mathbf{M}\mathbf{x}_{\text{init}} = \mathbf{x}_{\text{virt}}$

- In addition to ill-posedness, it is a large-scale inverse problem.
- Standard numerical regularization methods cannot be applied, since
  - M is either too large (T-SAFT),
  - or not explicitly formed (Stolt's f-k migration).

Numerical regularization in stage 1

Mathematical formulations

Synthesis model:

$$\tilde{c}_\lambda = \arg\min_{0\leq c}\{\left\|T_{meas} - K\overbrace{Sc}^{x_{virt}}\right\|_2^2 + \lambda^2 \cdot \|c\|_1\} \quad (1)$$

Analysis model:

$$\tilde{x}_\lambda = \arg\min_{x}\{\left\|T_{meas} - Kx_{virt}\right\|_2^2 + \lambda^2 \cdot \|Fx_{virt}\|_1\} \quad (2)$$

Advantages

- K is well defined and small compared to the image dimension.
- The first stage can be applied in parallel on each cross-section.
- The optimal value of λ can be estimated by L-curve, cross-validation, normalized cumulative periodogram, etc.

Numerical regularization in stage 1

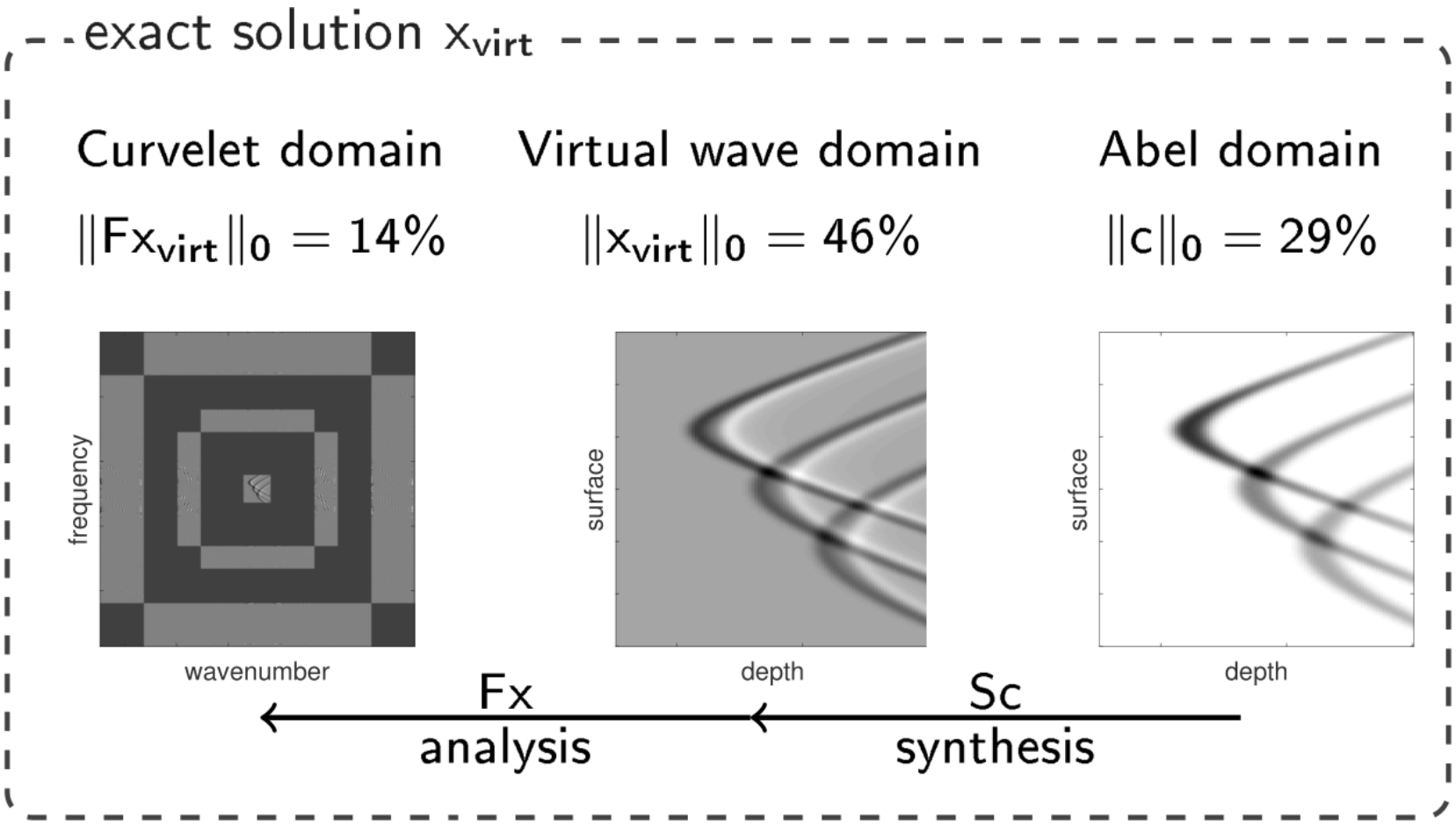
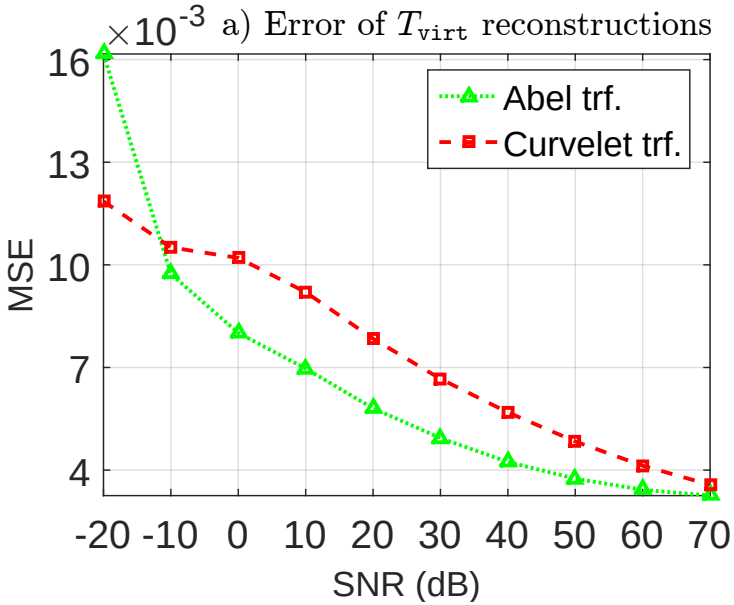
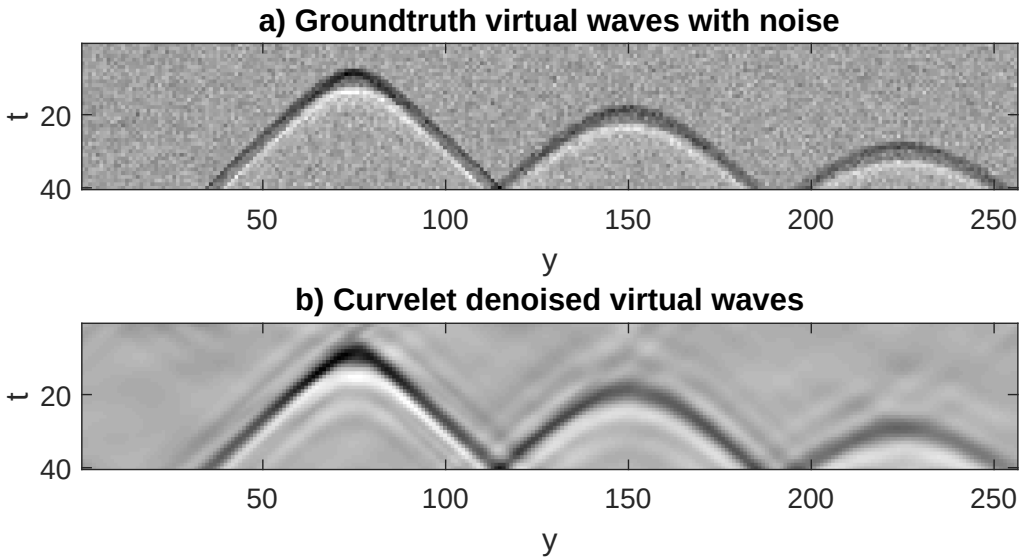


Figure: Sparsity of the virtual waves in different domains.

Numerical regularization in stage 1

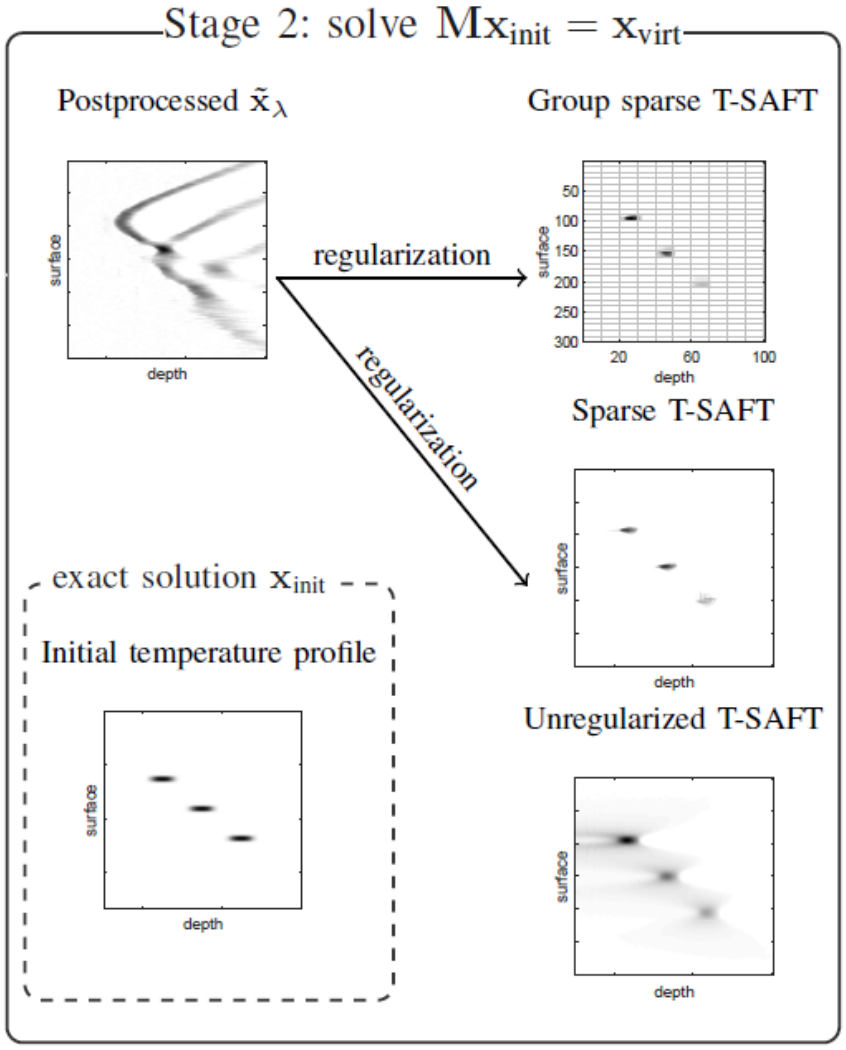




Error of the virtual wave reconstruction methods: *a)* Simulated virtual waves with additive white Gaussian noise; *b)* virtual waves approximated by keeping less than 1% of the curvelet coefficients.[2]

[2] P. Kovács, B. Lehner, G. Thummerer, G. Mayr, M. Huemer, and P. Burgholzer, Deep Learning Approaches for Thermographic Imaging, *Journal of Applied Physics*, vol. 128, no. 15, pp. 155103-1-16, 2020.

Numerical regularization in stage 2



Challenges

Large-scale ill-posed inverse problem.

Size/shape of the groups must be known a priori.

M is not known explicitly.

Besides measurement noise, nonlinear distortions of stage 1 regularization must be treated.

ML based sparse estimation

Motivation

- Existing iterative algorithms can converge to bad solutions.
- The convergence can be slow, and the solution have to be recalculated for every new image.
- Incorporating problem-specific information into an algorithm.

Sparse estimation via ML techniques

We want to learn an algorithm for solving

$$\widetilde{\mathrm{x}} = \arg\min_{\mathrm{x}} f_{\boldsymbol{\theta}}(\mathrm{x}) = \arg\min_{\mathrm{x}} \{ \|\mathrm{T}_{\mathrm{meas}} - \boldsymbol{\Phi}\mathrm{x}\|_2^2 + \tau^2 \cdot \|\mathrm{x}\|_1 \}.$$

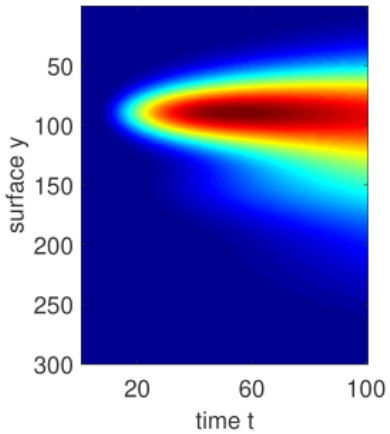
Potential benefits

- Efficiency, i.e. less computation time.
- More accurate final solution, i.e., better local optimum.

ML approches for thermography

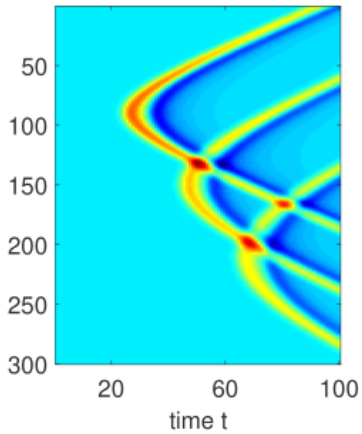
Two-stage reconstruction by the hybrid ML approach.

a) surf. temp. $\mathsf{T}_{\mathbf{meas}}$ $(\alpha = 4)$



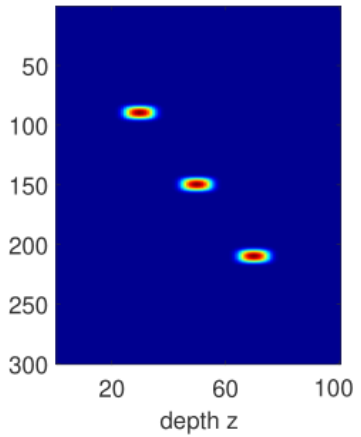
$\Longrightarrow$ solve $\mathsf{T}_{\mathbf{meas}} = \mathsf{K}\mathsf{x}_{\mathbf{init}}$

b) virtual waves $\widetilde{\mathsf{x}}_{\mathbf{virt}}$



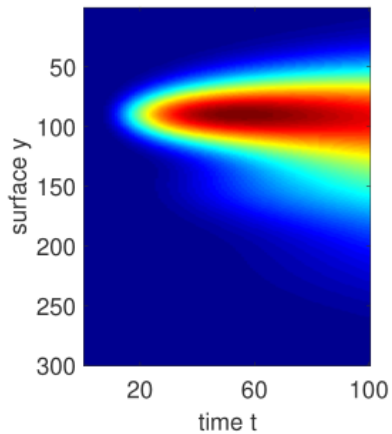
$\Longrightarrow$ learn $\arg\min_{\mathsf{x}} f_{\boldsymbol{\theta}}(\mathsf{x})$ with $\boldsymbol{\theta} = \{\widetilde{\mathsf{x}}_{\mathbf{virt}}, \mathsf{M}\}$

c) init. temp. profile $\widetilde{\mathsf{x}}_{\mathbf{init}}$



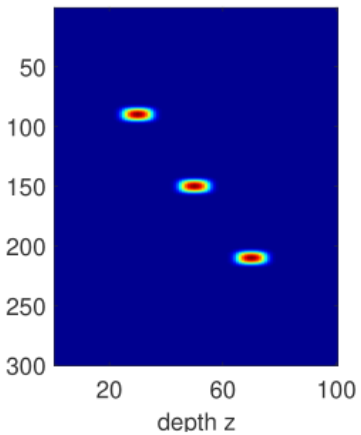
One-stage reconstruction by the end-to-end ML approach.

a) surf. temp. $\mathsf{T}_{\mathbf{meas}}$ $(\alpha = 4)$



$\Longrightarrow$ learn $\arg\min_{\mathsf{x}} f_{\boldsymbol{\theta}}(\mathsf{x})$ with $\boldsymbol{\theta} = \{\mathsf{T}_{\mathbf{meas}}, \boldsymbol{\Phi}\}$

c) init. temp. profile $\widetilde{\mathsf{x}}_{\mathbf{init}}$



Hybrid approach

Reconstruction in 2D

1. Extract the virtual waves $\widetilde{x}_{virt}$ from the measurements T_{meas}.
   - utilize the sparse and non-negative nature of $\widetilde{x}_{virt}$;
2. Estimate temperature distribution $\widetilde{x}_{init}$ by machine learning:
   - input: thermal diffusivity invariant virtual waves $\widetilde{x}_{virt}$
   - output: approximation of $\widetilde{x}_{init}$

Reconstruction in 3D

- Estimate the temperature distribution in each 2D cross-section.
- 3D reconstruction from the sequence of 2D images.

Deep learning by u-net

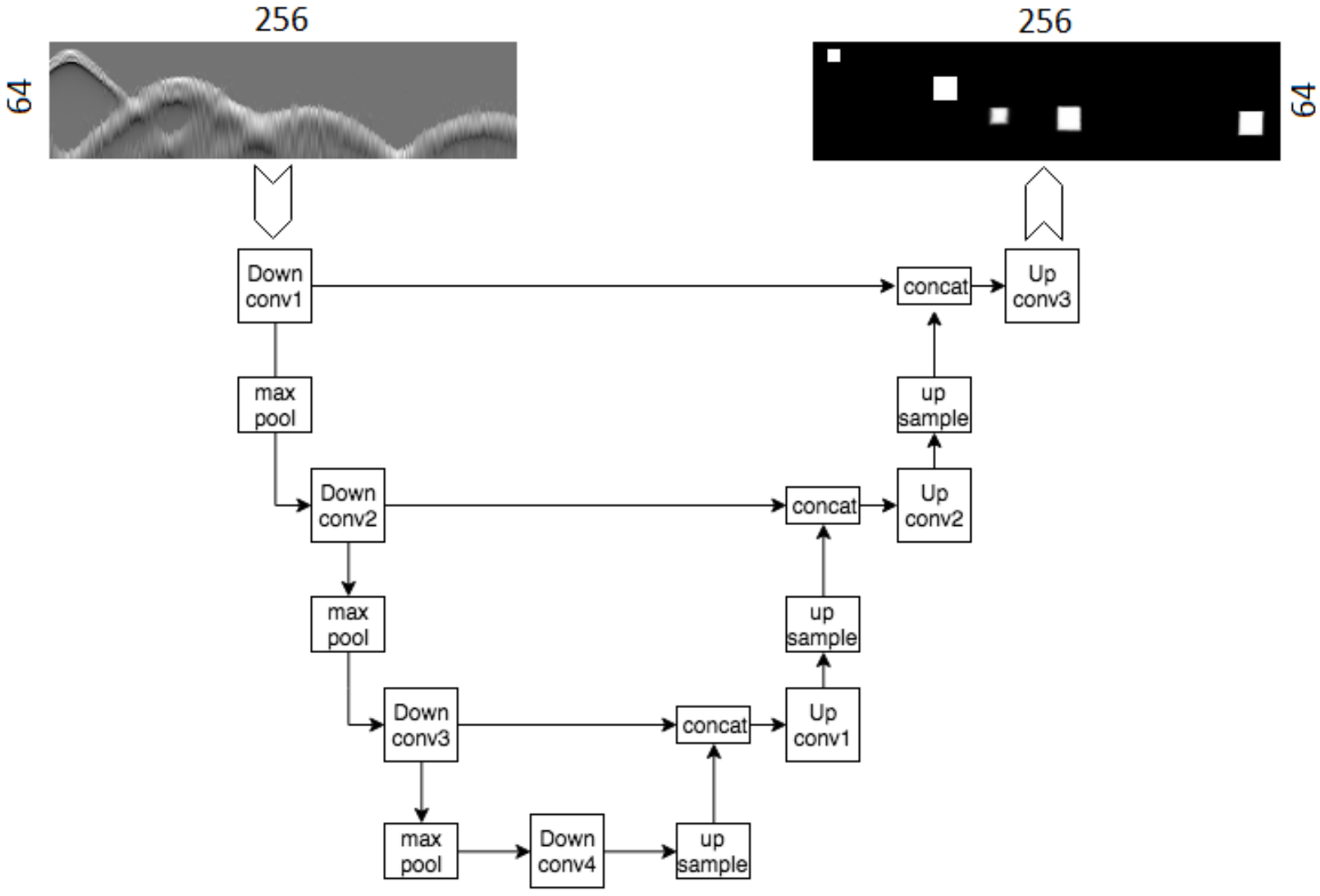


Figure: Architecture of the compact u-net.

Data sets

Mathematical model of the heat diffusion

$$\left(\nabla^2 - \frac{1}{\alpha}\frac{\partial}{\partial t}\right) T(\mathrm{r}, t) = -\frac{1}{\alpha} T_0(\mathrm{r})\delta(t),$$

where

- α stands for the thermal diffusivity,
- T is the temperature as a function of space r and time t,
- T_0 denotes the initial temperature profile at $t = 0$.

Data generation in 2D assuming adiabatic boundary conditions

$$\widehat{T}(k_y, k_z, t) = \widehat{T}_0(k_y, k_z) \cdot \exp(-(k_y^2 + k_z^2) \cdot \alpha t),$$

where

- $\widehat{T}$, $\widehat{T}_0$ are the cosine transforms of T and T_0 in the yz-plane,
- k_y and k_z are the corresponding spatial frequencies.

Data sets

Training data

- 3,000 simulated noise free samples with adiabatic boundary conditions.
- 2-5 square-shaped defects with side lengths between 2 and 6 pixels.
- The resolution of each image is 256×64.
- 10 different versions of each sample were used, representing SNRs from -20 dB to 70 dB in 10 dB steps.
- Overall number of training images: 10×3000

Testing data

- 1,000 simulated samples similar to the training images.
- Overall number of test images: 10×1000
- Real measurement data containing 256 images of size 256×64.

Simulation results

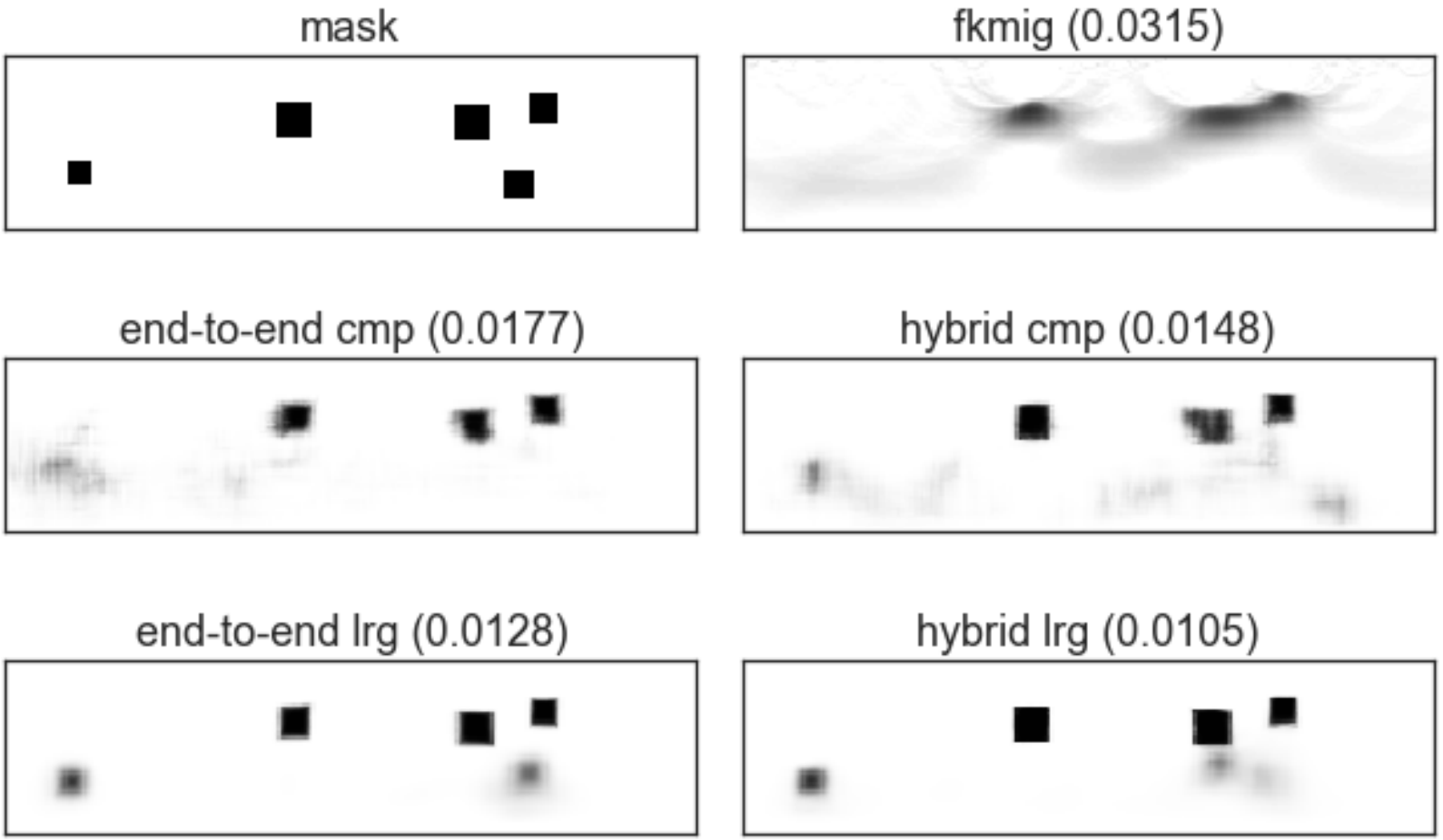


Figure: Reconstructions of a 0 dB SNR example from the test set.

Simulation results

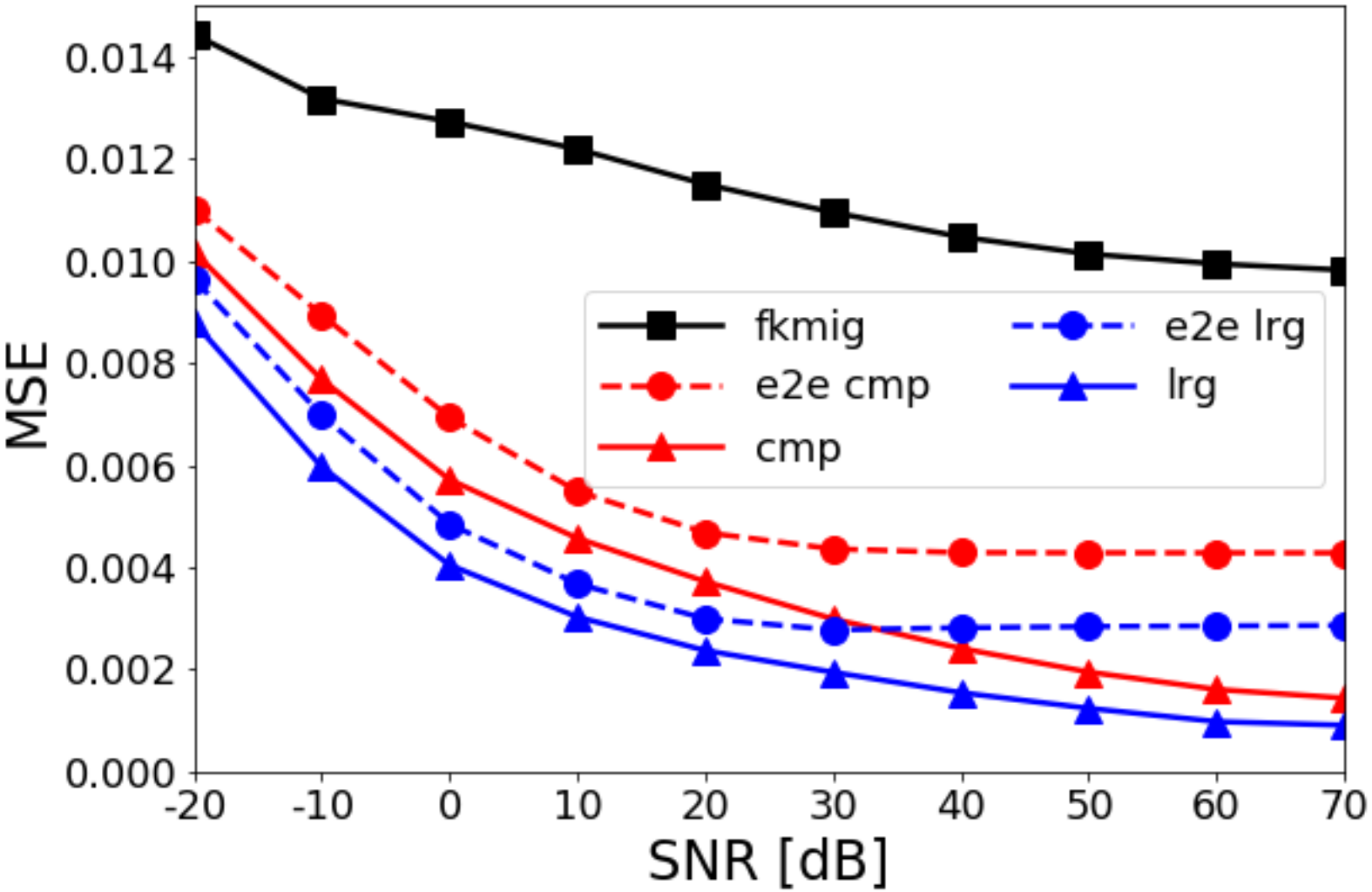
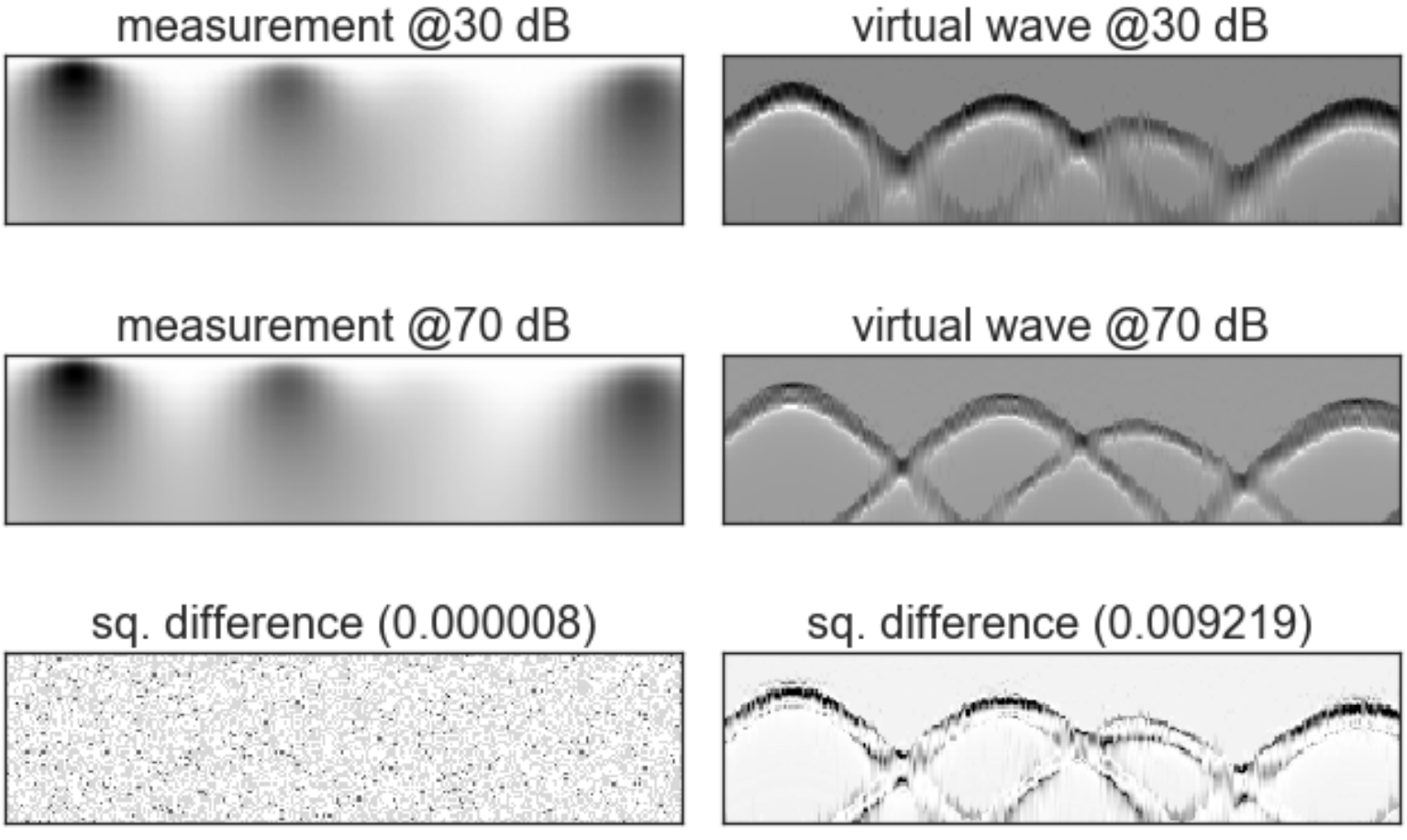


Figure: The MSE of the baselines and the proposed method.

Simulation results



Squared differences between virtual waves seems to contain more meaningful information than the squared difference between the measurements, allowing the neural network to produce improved results when fed with virtual waves.

Real measurement data

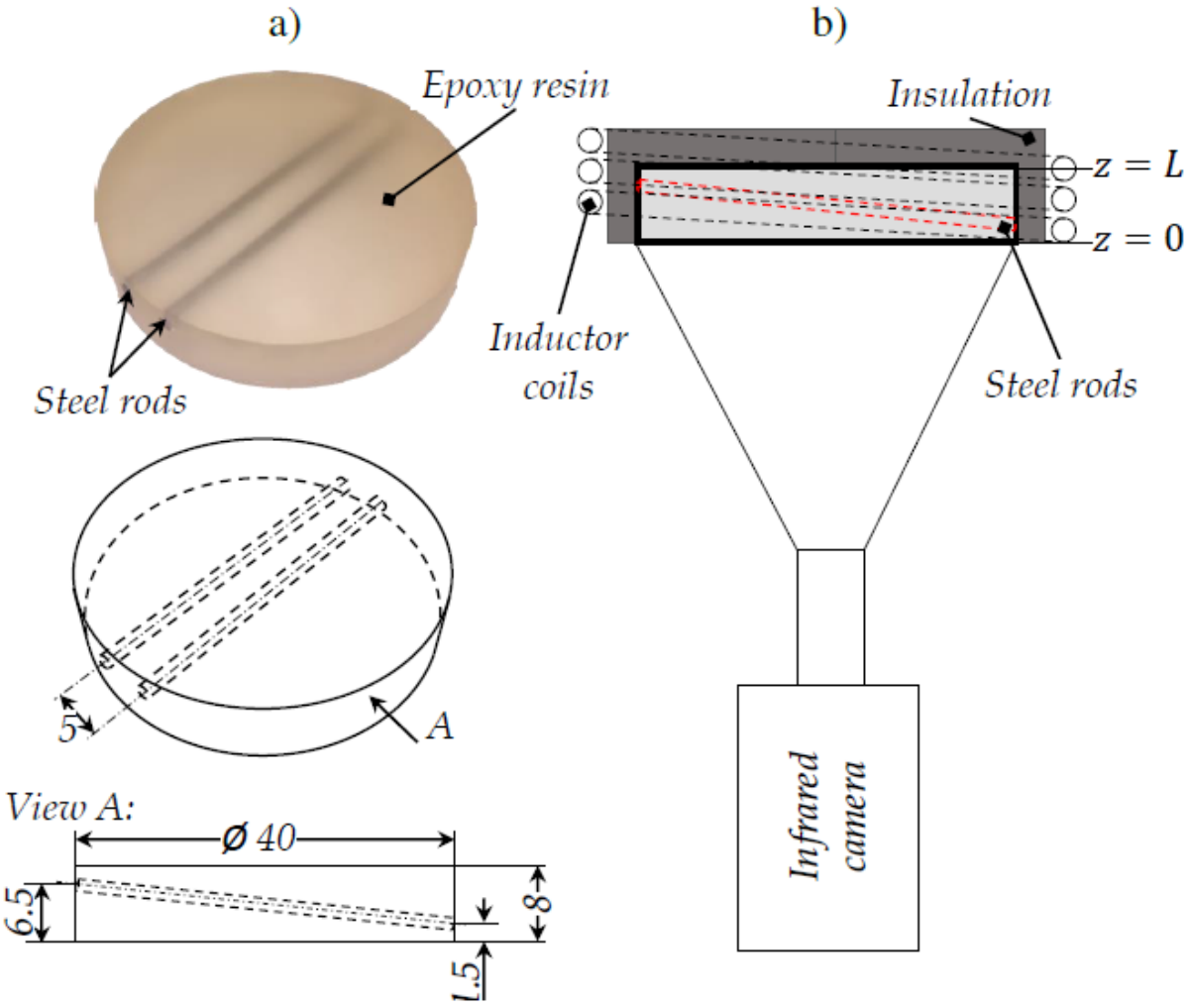


Figure: Parameters of the phantom.

Real measurement data

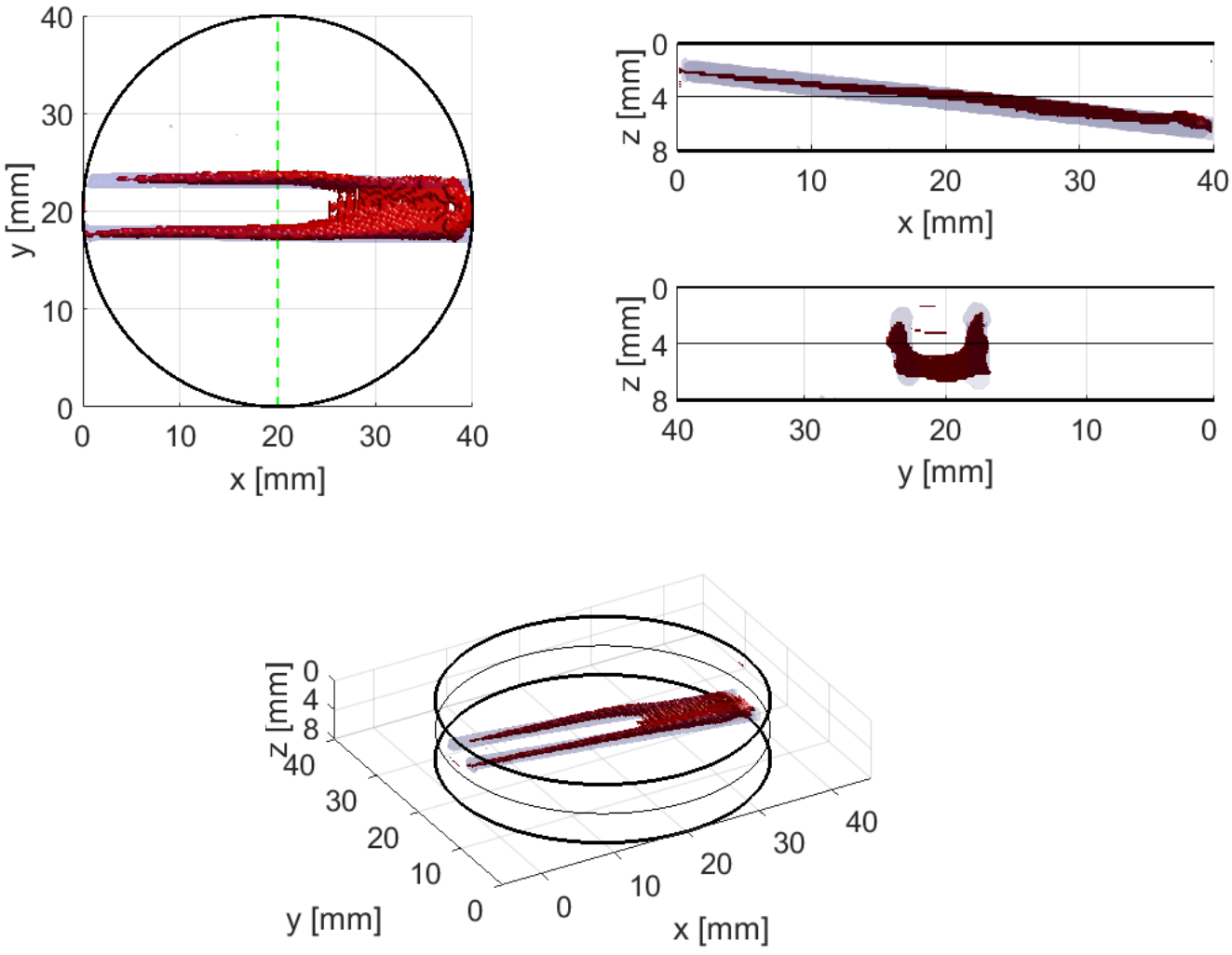


Figure: Using the model-based *fkmig* approach for 3D reconstruction of the specimen without rotation.

Real measurement data

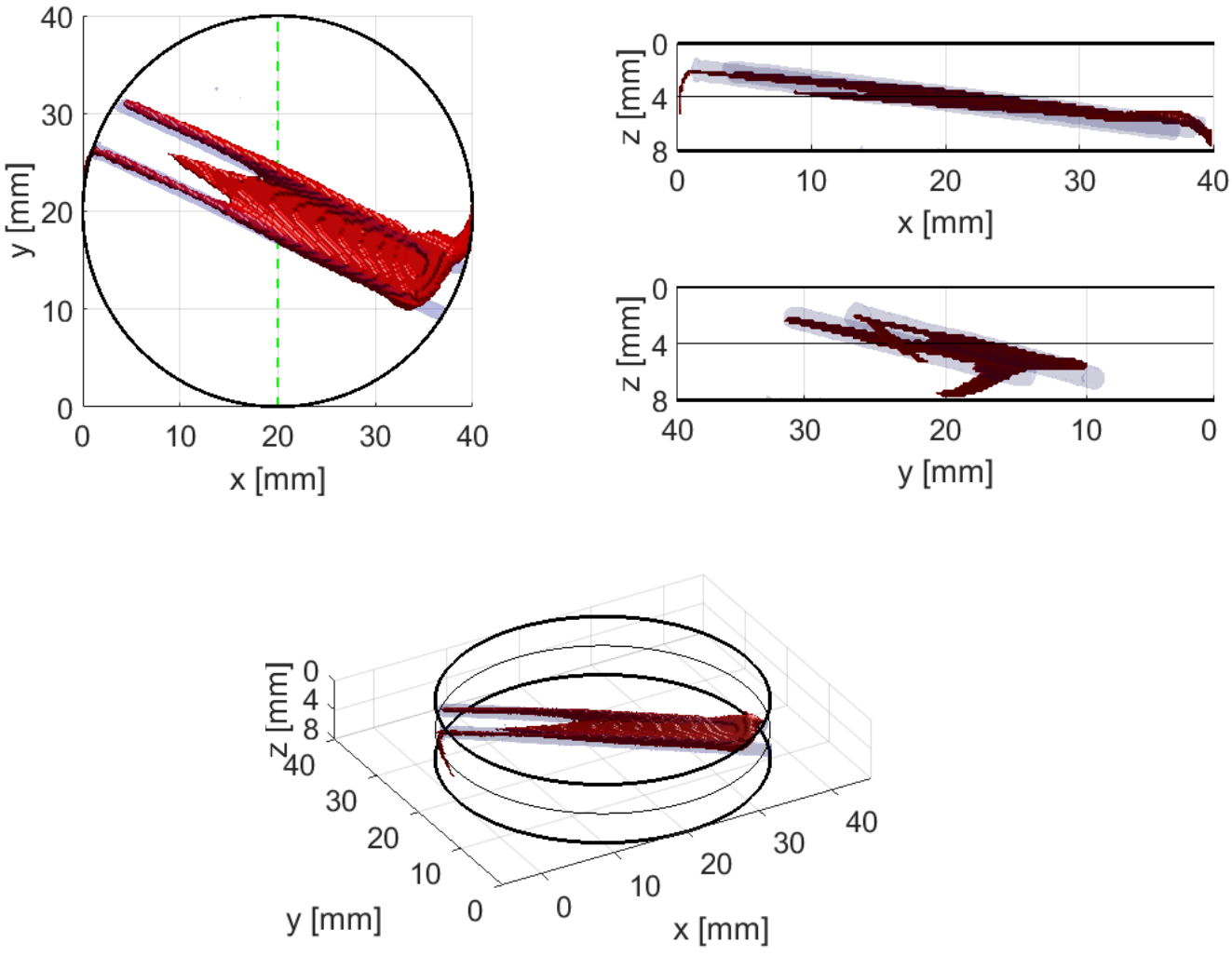


Figure: Using the model-based *fkmig* approach for 3D reconstruction of the specimen a rotation of 25°.

Real measurement data

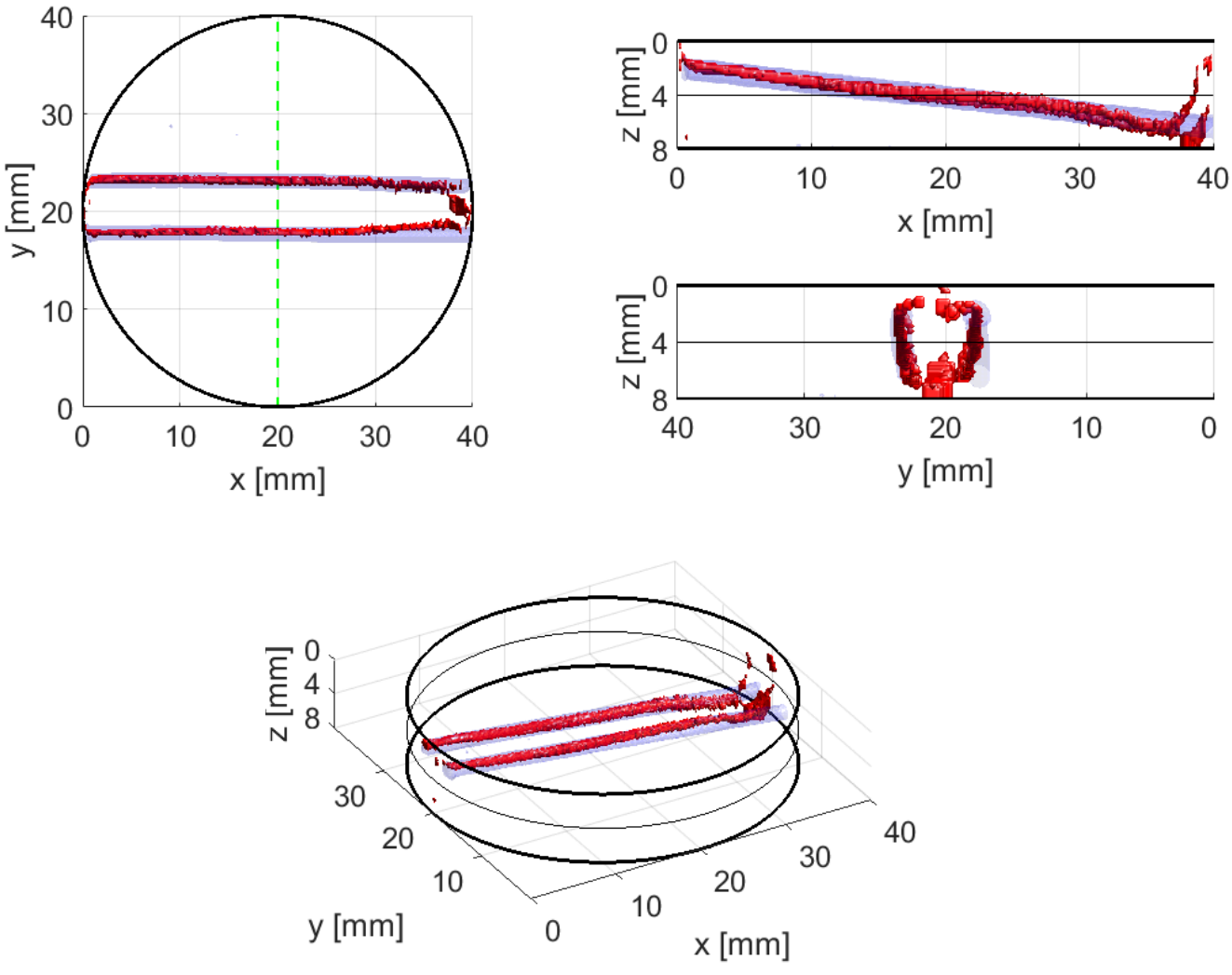


Figure: Using the large end-to-end *e2e lrg* approach for 3D reconstruction of the specimen without rotation.

Real measurement data

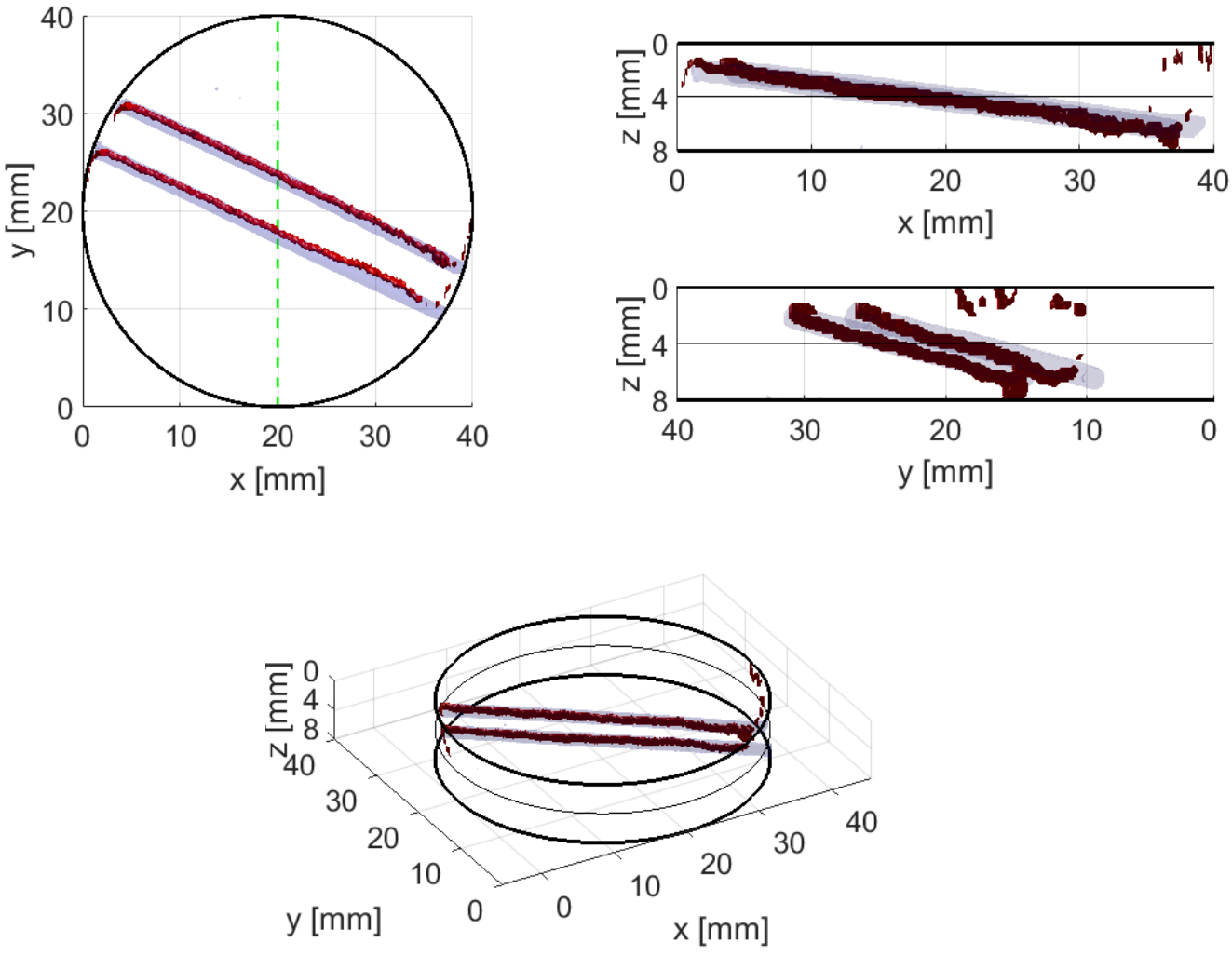


Figure: Using the large end-to-end *e2e lrg* approach for 3D reconstruction of the specimen with a rotation of 25°.

Real measurement data

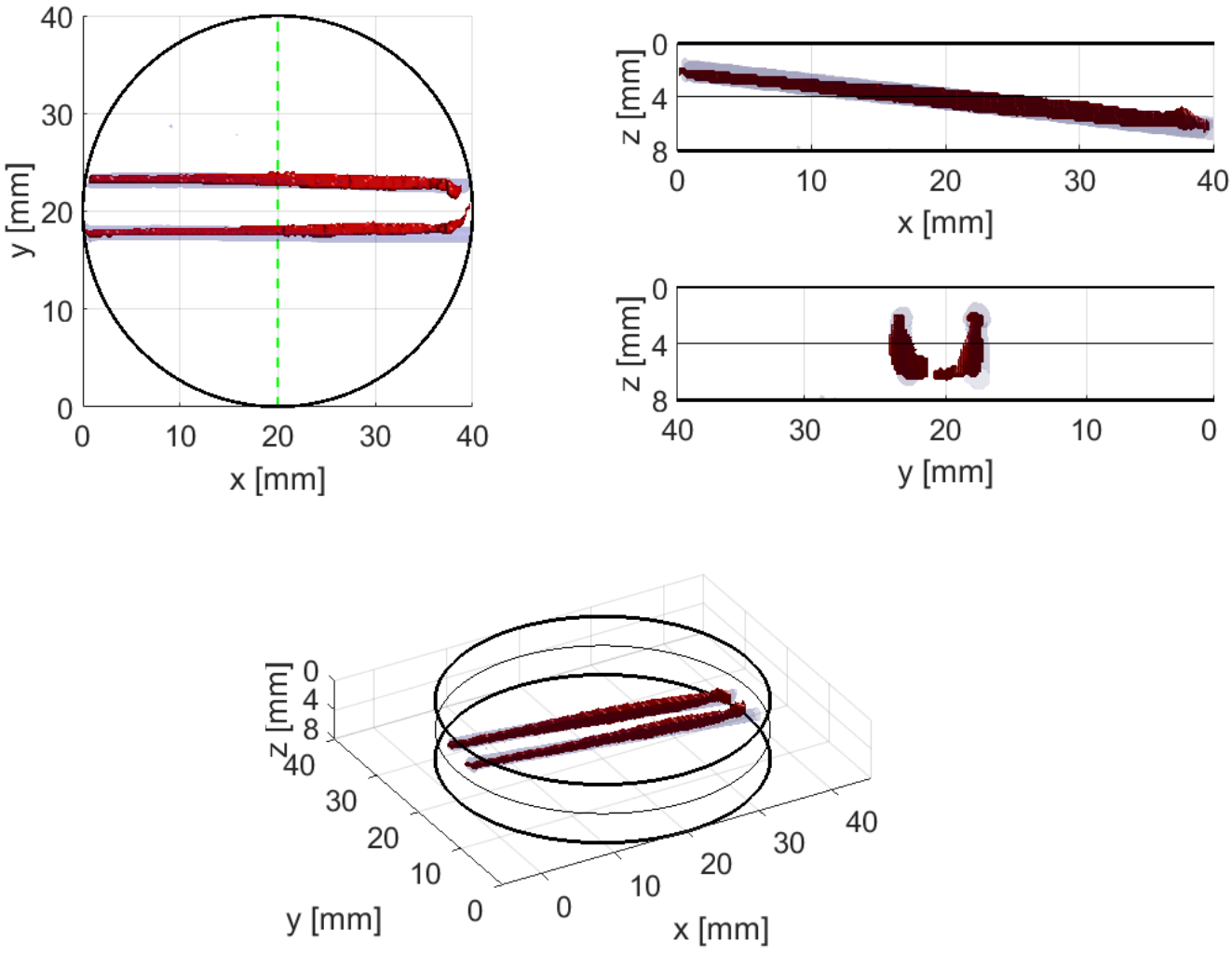


Figure: Using the large hybrid *lrg* approach for 3D reconstruction of the specimen without rotation.

Real measurement data

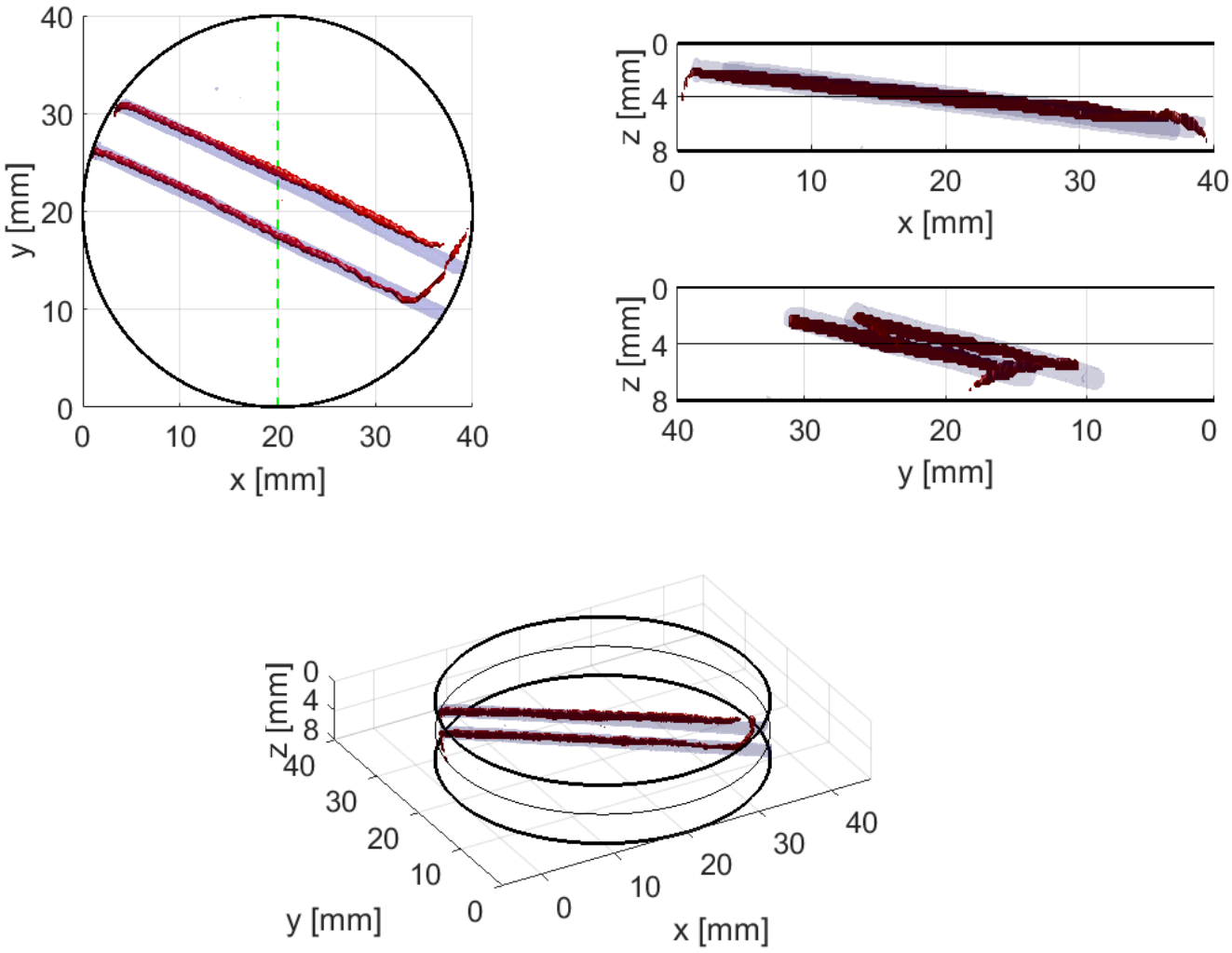


Figure: Using the large hybrid *lrg* approach for 3D reconstruction of the specimen with a rotation of 25°.

Future plans

Improving the reconstruction in each stage

Stage 1: **Gergő Galiger** – replace model-based sparse solvers by

- deep neural networks (DNN),
- unfold iterative solvers into NNs (e.g., FISTA-Net)

Stage 2: **István Sagyebó** – extending the training set by

- non-uniform defects,
- non-square defects,
- samples with Poisson noise.

Other research directions

- Training for true 3D models.
- Modeling anisotropic materials.
- Considering non-adiabatic boundary conditions.

Future plans

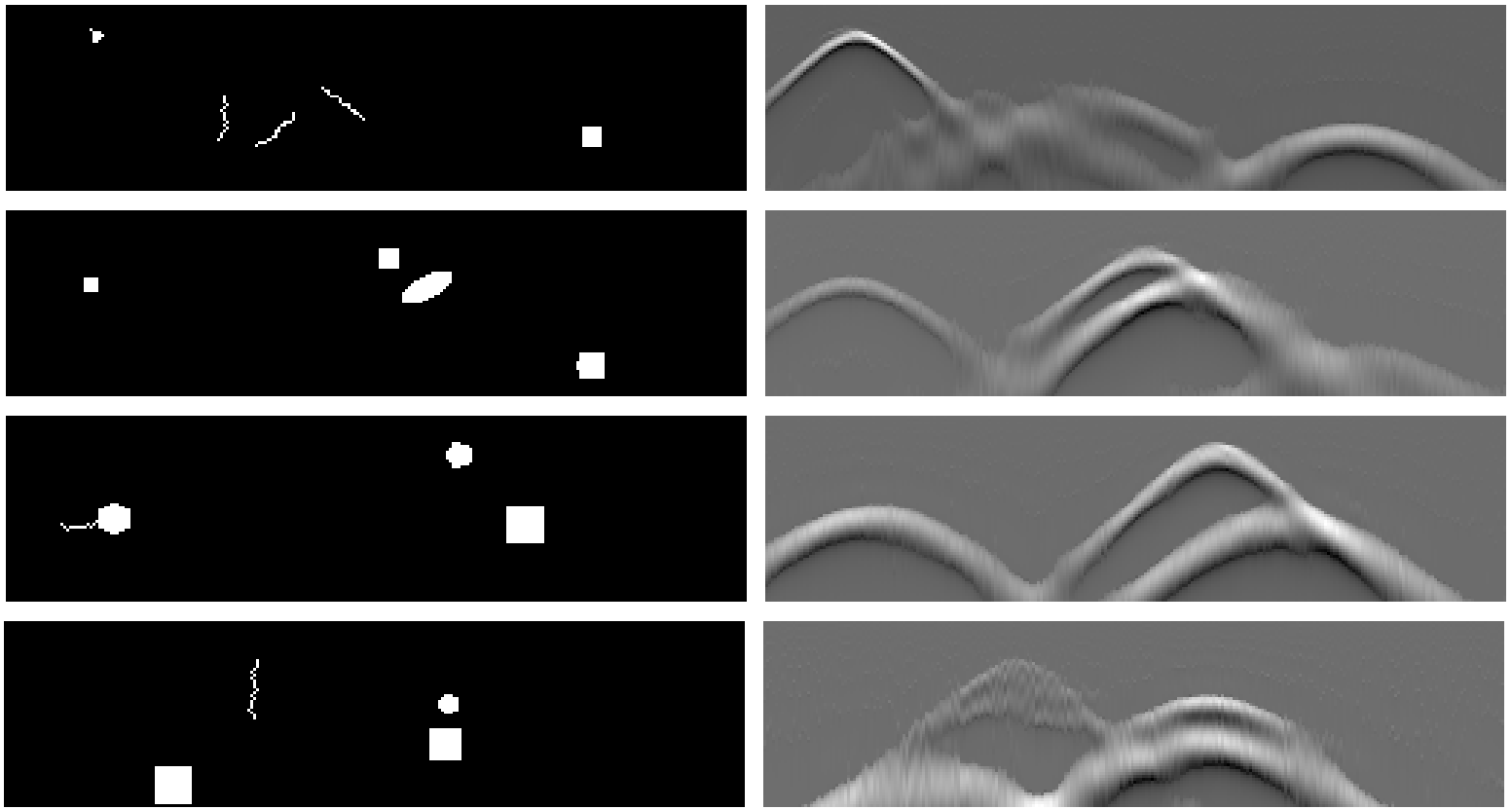


Figure: New target images and the corresponding virtual waves.

Future plans

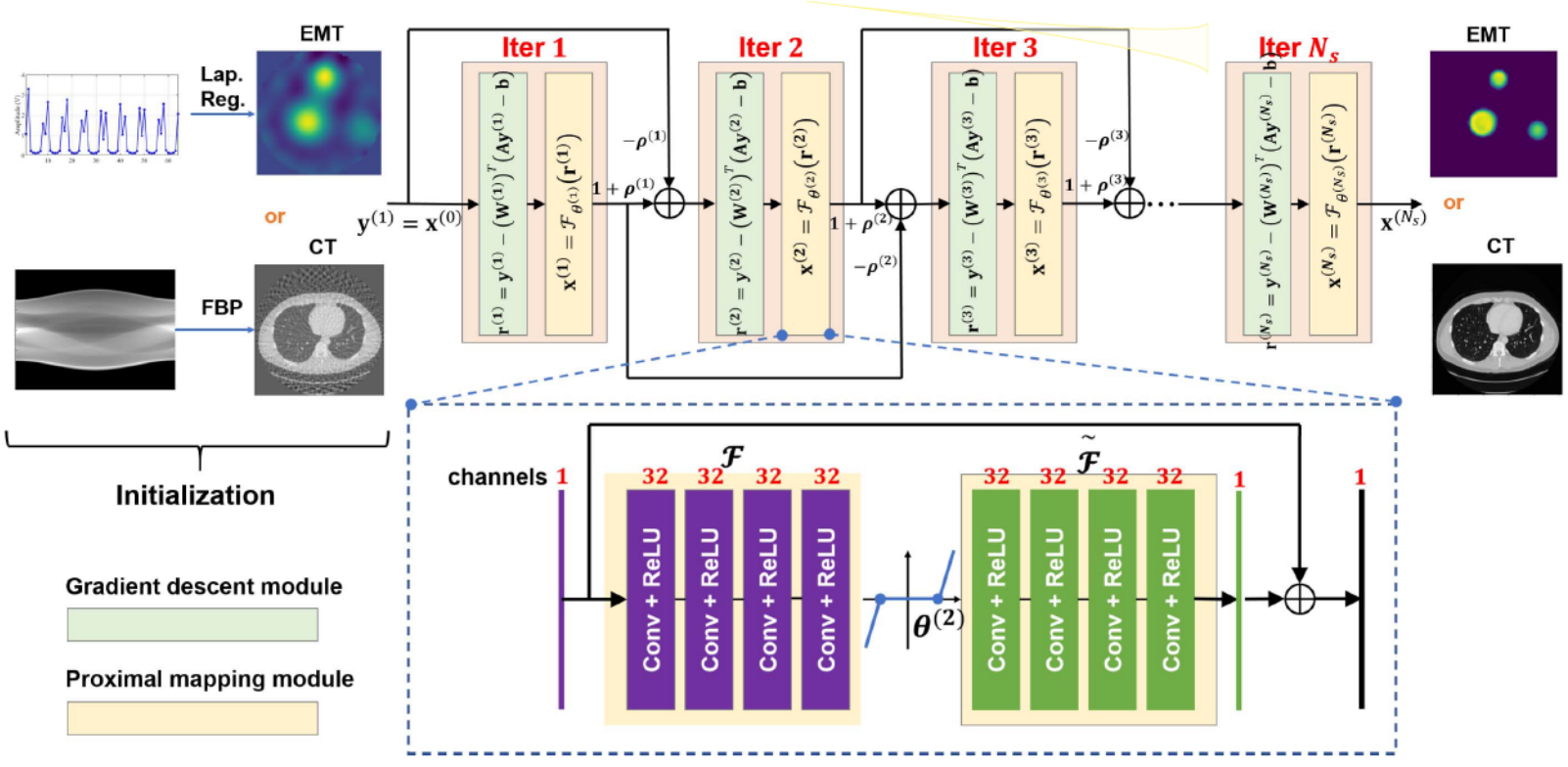


Figure: The overall architecture of the FISTA-Net for solving sparse approximation problems.[4]

[4] J. Xiang, Y. Dong, and Y. Yang. FISTA-Net: Learning a Fast Iterative Shrinkage Thresholding Network for Inverse Problems in Imaging. IEEE Transactions on Medical Imaging, 40(5):1329–1339, 2021.

Publications

Conferences

- P. Kovács, B. Lehner, G. Thummerer, G. Mayr, M. Huemer, and P. Burgholzer. A hybrid approach for the thermographic imaging with deep learning, **ICASSP 2020**, pp. 4277-4281.
- P. Burgholzer, G. Thummerer, G. Mayr, P. Kovács, and M. Haltmeier. Iterative methods for thermographic reconstruction using the virtual wave concept, **Quantitative InfraRed Thermography Conference**, 2019.
- B. Lehner, T. Gallien. Uncertainty Estimation for Non-destructive Detection of Material Defects with U-nets, **International Conference on Advances in Signal Processing and Artificial Intelligence**, 2020.

Journals

- P. Kovács, B. Lehner, G. Thummerer, G. Mayr, M. Huemer, and P. Burgholzer, Deep Learning Approaches for Thermographic Imaging, **Journal of Applied Physics**, vol. 128, no. 15, pp. 155103-1-16, 2020.
- B. Lehner, T. Gallien, P. Kovács, G. Thummerer, G. Mayr, P. Burgholzer, and M. Huemer, Uncertainty Estimation for Deep Learning-based Thermographic Imaging, **Sensors & Transducers**, vol. 249, no. 2, pp. 25–35, 2021.
- P. Kovács, B. Lehner, G. Thummerer, G. Mayr, P. Burgholzer, and M. Huemer, Surfing Virtual Waves to Thermal Tomography: From model- to deep learning-based reconstructions, **IEEE Signal Processing Magazine**, vol. 39, no. 11, pp. 55–67, 2022.