A Hybrid Approach for Thermographic Imaging with Deep Learning

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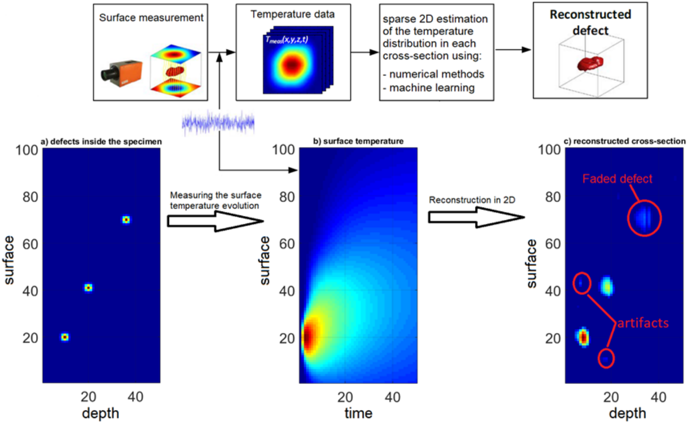
Outline

Problem description

Goal

Analysis, detection of structural imperfections of materials.



Problem description

Linear model

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

$$\mathbf{\Phi u} = \mathbf{d}.$$

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

Two-stage reconstruction process[1]

1. Transformation of the thermographic imaging problem:

$$\tilde{\mathbf{v}} = \arg\min_{\mathbf{v}} \{ \|\mathbf{d} - \mathbf{K}\mathbf{v}\|_2^2 + \lambda^2 \cdot \Omega(\mathbf{v}) \}.$$

2. Applying ultrasonic imaging techniques to the new problem:

$$\tilde{\mathbf{u}} = \arg\min_{\mathbf{u}} \{ \|\tilde{\mathbf{v}} - \mathbf{M}\mathbf{u}\|_2^2 + \mu^2 \cdot \Omega(\mathbf{u}) \}.$$

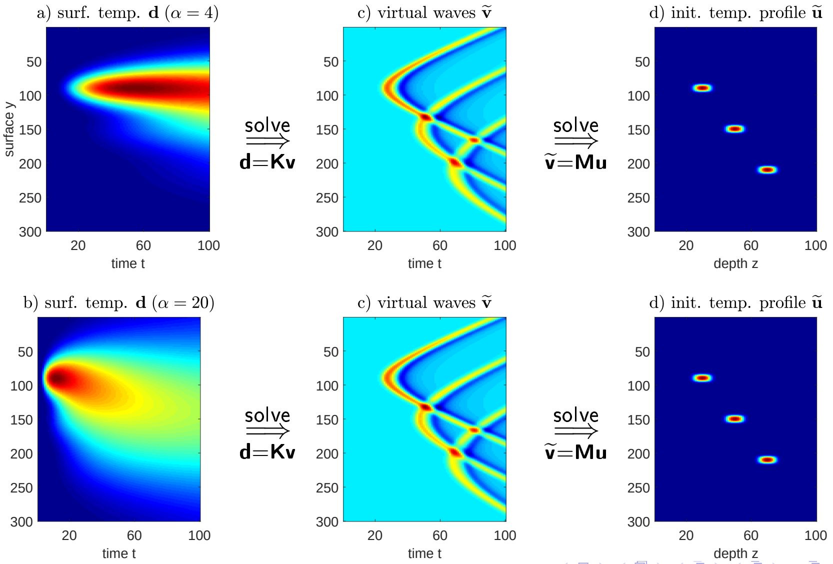
One-stage reconstruction process

By $\mathbf{\Phi} = \mathbf{K}\mathbf{M}$, the full reconstruction can be written as follows:

$$\tilde{\mathbf{u}} = \arg\min_{\mathbf{u}} \{ \|\mathbf{d} - \mathbf{\Phi}\mathbf{u}\|_2^2 + \nu^2 \cdot \Omega(\mathbf{u}) \}.$$

[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



Two-stage reconstruction process

Pros

- The virtual waves are invariant to the thermal diffusivity α.
- $\mathbf{K}$ is well defined and small compared to the image dimension.
- The first stage can be applied independently on each cross-section.

Cons

- It is difficulty to apply sparse numerical solvers in the second stage.
- There is no proper inversion for $\mathbf{M}^+$, just approximations to it.
- The matrix $\mathbf{M}$ is either too large (T-SAFT), or not explicitly formed (Stolt's f-k migration).
- Estimating the optimal regularization parameter μ is challenging.

Hybrid approach

Reconstruction in 2D

1. Extract the virtual waves $\widetilde{\mathbf{v}}$ from the measurements $\mathbf{d}$.
   - utilize the sparse and non-negative nature of $\widetilde{\mathbf{v}}$;
2. Estimate the temperature distribution $\widetilde{\mathbf{u}}$ by machine learning:
   - input: thermal diffusivity invariant virtual waves $\widetilde{\mathbf{v}}$
   - output: approximation of $\widetilde{\mathbf{u}}$

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

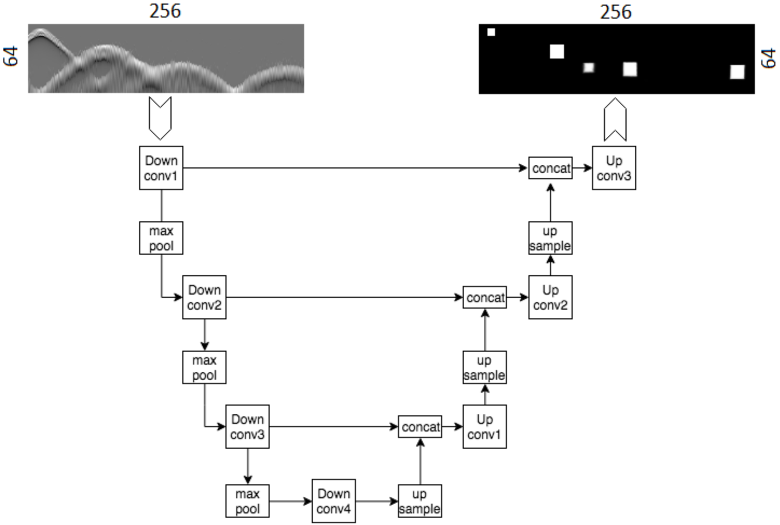


Figure: Architecture of the compact u-net.

Deep learning by u-net

Compact architecture

- 3 layers in the contracting path
- 3 layers in the expansive path
- 16 filters in the first (single channel) layer
- Overall number of weights: **109,000**

Extensive architecture

- 5 layers in the contracting path
- 5 layers in the expansive path
- 16 filters in the first (single channel) layer
- Overall number of weights: **1.8 million**

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.

Training of the u-net

Training and validation

- 24,000 samples were used for training.
- 6,000 samples were kept for validation and model selection.
- Training can be stopped after 20 epochs.

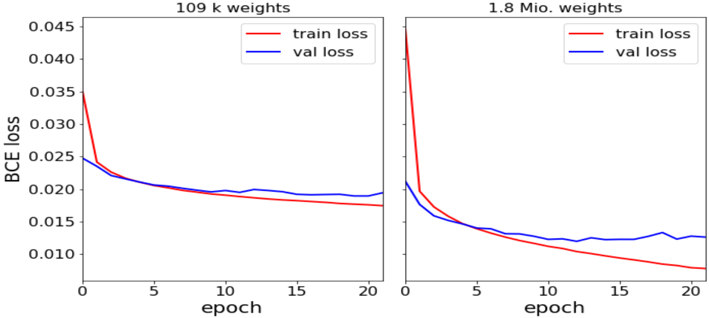


Figure: The loss curves of the proposed u-net variants.

State-of-the-art model based approaches

Numerical solvers for sparse approximation

- SPGL1 is for large-scale one-norm regularized least squares.
- YALL1 is a solver for basic/group sparse reconstruction.
- ASP is for solving several variations of the sparse optimization.
- **ADMM** (alternating direction method of multipliers) is a very general algorithm for solving sparse approximation problems.
- SALSA is a fast ADMM type algorithm for image reconstruction.
- **IRfista** is a recent numerical solver for large-scale problems.

Tested model based approaches

- fkmig: Stolt's f-k migration without sparse regularization.
- tsaft: Synthetic Aperture Focusing Technique in the time domain.
- reg tsaft: same as tsaft, but with sparse regularization.

Simulation results

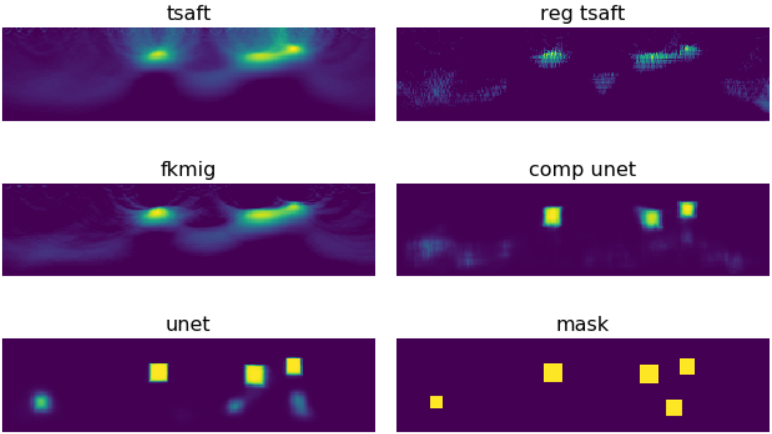


Figure: Reconstructions of a 0 dB SNR example from the test set.

Simulation results

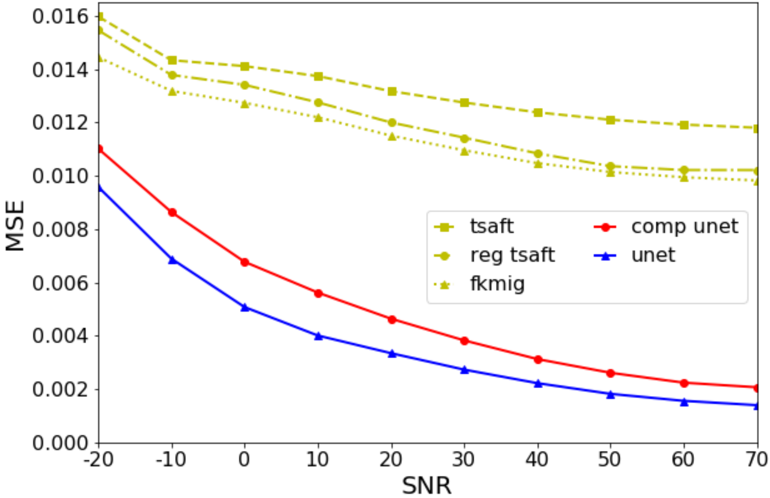


Figure: The MSE of the baselines and the proposed method.

Real measurement data

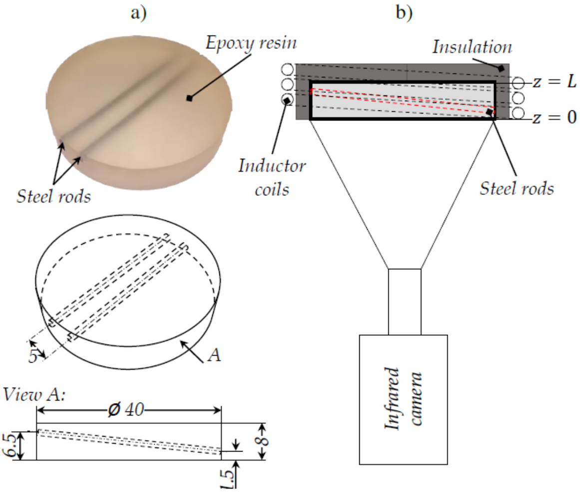


Figure: Parameters of the phantom.

Real measurement data

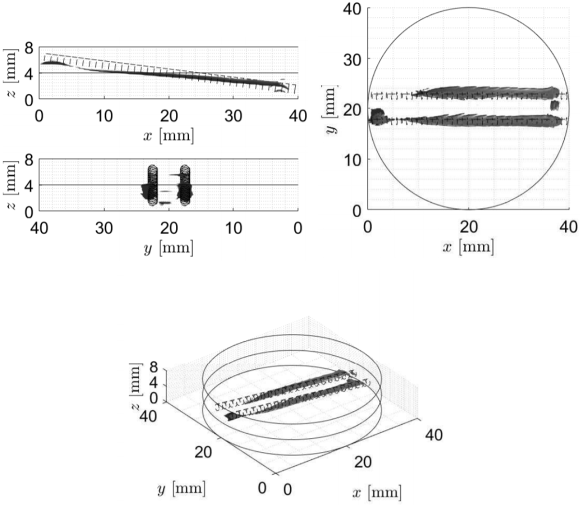


Figure: Model based reconstruction via ADMM and Stolt's f-k migration.

Real measurement data

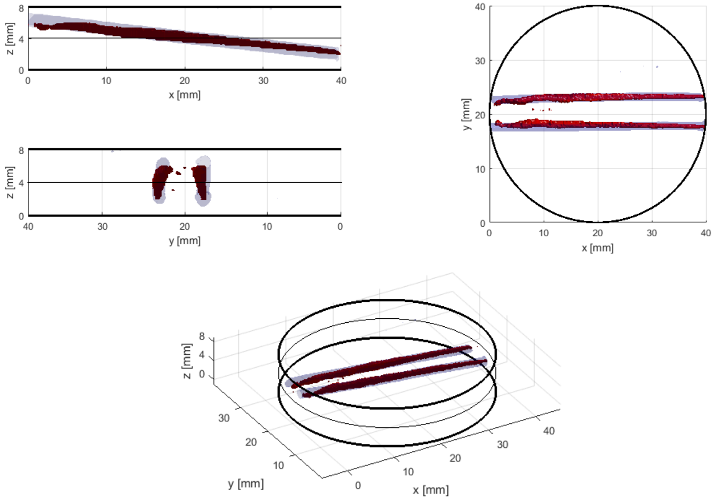


Figure: Hybrid reconstruction (red), groundtruth volume (blue).

References

P. Kovács, B. Lehner, G. Thummerer, G. Mayr, and Huemer M. Burgholzer, P., A hybrid approach for the thermographic imaging with deep learning, 2019, [Online], Available: **https://codeocean.com**.

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.

S. Gazzola, P. C. Hansen, and J. G. Nagy. IR Tools: a MatLab package of iterative regularization methods and large-scale test problems. Numerical Algorithms, pages 1–39, 2018.

O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. International Conference on Medical image computing and computer-assisted intervention, Springer, pp. 234–241, 2015.

J. F. Claerbout, editor. EARTH SOUNDINGS ANALYSIS: Processing versus Inversion. Blackwell Scientific Publications, Cambridge Center, Cambridge, MA, USA, 2004.