Deep Neural Network as an Optimizer for FMCW THz Image Deblurring

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Abstract. *A stable estimation of the THz model parameters for low SNR configurations is essential to achieve acquisition times required for applications in, e.g., quality control. The deep optimization prior approach was introduced with application to the estimation of material-related model parameters from THz data, which is acquired by a FMCW THz scanning system. Conceptually, this approach estimates the desired THz model parameters by optimizing for the weights of a 3D spatially coupled deep neural network. This approach was verified numerically on various THz parameter estimation problems for synthetic and real data. In this paper, we propose to combine the deep optimization prior approach to the modern 2D blind deblurring method for the FMCW THz image resolution enhancement. The experimental results show that this approach improves the lateral resolution enhancement robustly under low SNR noise condition in comparison to the per-pixel curve fitting method.*

Keywords. Terahertz (THz), Frequency Modulated Continuous Wave (FMCW), parameter estimation, deep learning, non-convex optimization, 3D model based autoencoder, deep optimization prior, deblurring, deconvolution

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1 Motivation

In Frequency Modulated Continuous Wave (FMCW) THz imaging, the THz 3D image can be modelled as a formation model A in depth direction z, by repeating this process for each position (per-pixel) in lateral xy domain [1].

$$A(u;z) = \hat{e}\,\mathrm{sinc}\left(\sigma(z-\mu)\right)\exp\left(-i(\omega z-\phi)\right) \tag{1}$$

where the THz model parameters $u = (\hat{e}, \mu, \sigma, \phi)$ relate to the electric field amplitude, the z-position of the surface, the width of the reflected pulse, and the phase of the spatial signal $g(x, y, z)$, respectively. The resulting complex valued spatial 3D THz signal $g(x, y, z) \in \mathbb{C}^{n_x \times n_y \times n_z}$, where n_x, n_y, n_z is the number of vertical, horizontal and depth samples.

Hence, the objective of THz model parameter estimation is to extract the parameters $u \in \mathbb{R}^4$ of the THz model (1) at each pixel location (x, y) such that it corresponds to the given FMCW THz measurements $G(x, y) \in \mathbb{R}^{n_z \times 2}$ by solving this non-convex optimization problem:

$$\min_u \sum_{x,y} \|A(u_{x,y}) - G_{x,y}\|_2^2, \tag{2}$$

As A is nonlinear and this problem is highly non-convex, (2) is often solved locally with classical first-order gradient descent methods.

Due to the low signal strength of the widely used THz sources, it takes up to hours to acquire high Signal-to-Noise Ratio (SNR) THz image data for robust parameter estimations, and the parameter estimation for high SNR data already requires significant optimization efforts and fine tuned parameter initialization.

Therefore, to improve the robustness of the parameter estimation process for lower SNR THz data, *deep optimization priors* [2] was proposed as a novel unsupervised deep learning approach to solve highly non-linear optimization problems. This approach extended deep image prior [3] to *non-convex* optimization problems and shows that not only the quality of the solution increases, but also the ability to find *lower energy minima*: By reparameterizing the originally *spatially uncoupled* variables u as the output of a U-net [4] acting on the data, a gradient descent algorithm is able to avoid undesirable local minima when the same algorithm on the original variables gets stuck in. Most strikingly, the quality of a classical approach (2) has a severe dependency on a good initialization with physical knowledge, while the common *random initialization* of network weights seems to be sufficient for consistently finding good local minima.

In this paper, we propose the combination of the deep optimization prior approach [2] and the THz image deblurring et al. [1] and investigate the impact of combining both methods to the resolution improvement for FMCW THz imaging. More precisely, we apply modern blind deconvolution method, such as Xu et al. [5], [6] to the result of the THz parameter estimation achieved by the 3D deep optimization prior technique [2].

Section 2 gives a brief overview of the deep optimization prior approach. The details of the deblurring and experimental result are described in Section 3.

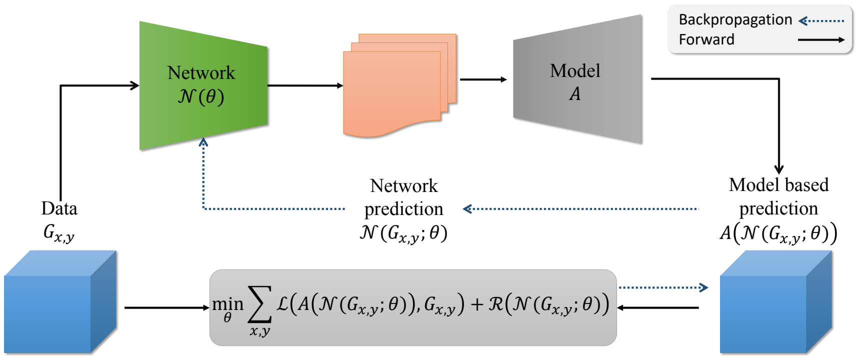

Figure 1. Deep optimization prior approach is reparametrizating $u_{x,y}$ by a network $\mathcal{N}$ in combination with the model-based autoencoder.

2 Deep Optimization Prior

The concept of *deep optimization prior* (DOP) is to reparameterize the unknown (image) variable $u_{x,y}$ in non-convex optimization problems of the form (2) by the prediction of a neural network $\mathcal{N}$ via $u_{x,y} = \mathcal{N}(G_{x,y};\theta)$ for network parameters. Besides from the data term, a regularization term for THz model parameter estimation can be applied, where the regularization improves the THz parameter estimation in the case of individual pixel failure, i.e. shot noise, and yields:

$$\min_{\theta} \sum_{x,y} \|A(\mathcal{N}(G;\theta)_{x,y}) - G_{x,y}\|_2^2 + \lambda \|\nabla \mathcal{N}(G;\theta)_{x,y}\|_1, \tag{3}$$

As illustrated in Fig. 1, this approach is minimizing the loss function $\mathcal{L}$ as an optimizer during the unsupervised *training* procedure, which is different to the unsupervised *training-then-prediction* approach proposed by [7].

The model-based autoencoder [7] allows unsupervised learning of measurement data by resembling an autoencoder with a learnable network based encoder and a physical model-based decoder, and is, therefore, able to deal with measurement-specific distortions. However, during the per-pixel learning phase in [7], the lateral neighborhood information is not considered. Therefore, the 3D model-based autoencoder architecture in Fig. 2 allows unsupervised learning on the THz measurement data using this approach for a lateral spatial coupled optimization. In contrast to the 1D single pixel autoencoder [7], this network-based reparameterization allows spatial coupling even though the THz model (1) is independent in the lateral spatial domain. This U-net network architecture is computational extremely more efficient than CNN architecture, while it couples pixels in large lateral spatial regions, which is an important feature in this application.

The evaluation in [2] showed that this deep optimization prior approach finds a better minima than classical optimizers (Table 1), estimates model parameters in low SNR levels (Fig. 3) and robustly reconstructs parameters in shot noise situations. More details of the experiments can be found in [2].

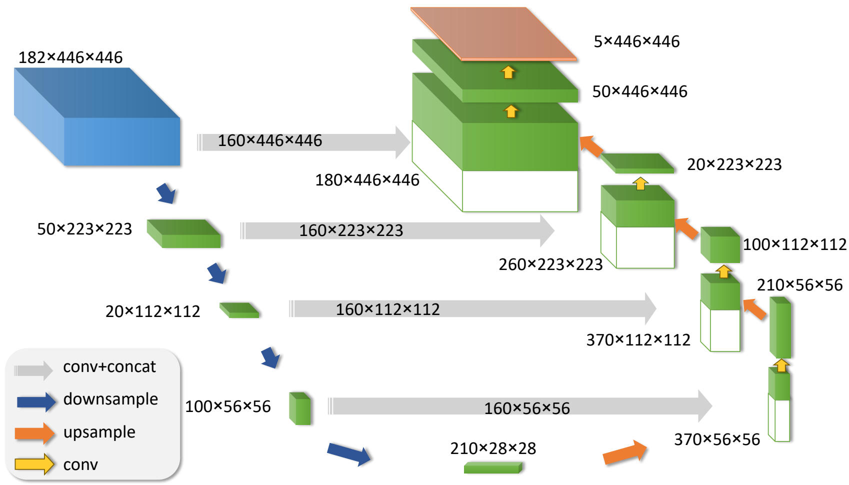

Figure 2. U-net architecture of network $\mathcal{N}$ (example for 182 channels with 446×446 pixels) start from the data tensor $G_{x,y}$ to the desired parameter $u_{x,y} = \mathcal{N}(G_{x,y}; \theta)$.

Table 1. Comparison of average ℓ^2-squared loss in (2) using measurement dataset by classical optimizers to the Deep Optimization Prior (DOP) approach. The full details of experiments can be found in [2].

Average Normalized Loss ($\times 10^{-6}$)		
Optimizer	**AdamW**	**DOP**
MetalPCB+AWGN at PSNR Level		
Opt. LR	0.001	0.01
-20dB	36100.08	**30871.59**
-10dB	7380.64	**3271.89**
0dB	965.00	**400.09**
10dB	135.92	**111.22**

3 Deblurring on the THz model parameter image

In this section, we compare the resolution enhancement by the deep optimization prior (DOP) approach to the per-pixel curve fitting approach using the THz image enhancement methodology in [1].

3.1 Experimental Setup

We evaluate the deblurring result on the *MetalPCB+AWGN* datasets from [2], which are based on a measured FMCW THz image datasets using a resolution target. The datasets are synthetically added with an Additive White Gaussian Noise (AWGN) at PSNR noise level from -20dB to 10dB by simulation respectively.

For the comparison of the per-pixel curve fitting optimizer, we choose the AdamW [8] op-

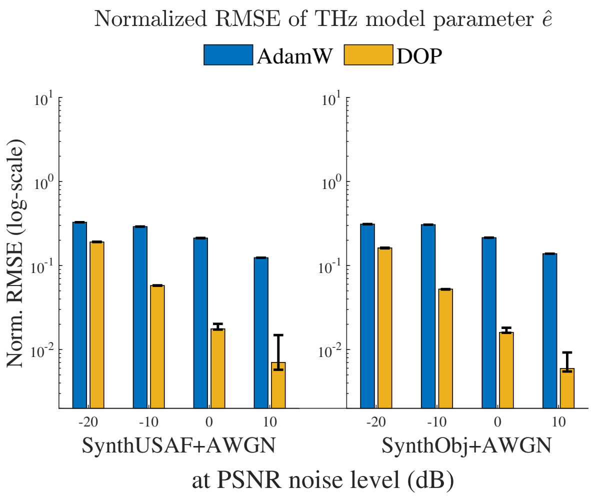

Figure 3. Comparison of RMSE of model parameter $\hat{e}$ using synthetic datasets at AWGN noise level from -20 to 10dB. The full details of the experiments can be found in [2].

timizer adopted in [2] instead of the Trust-Region Algorithm [9] in [1] to be able to properly compare with the DOP approach in [2] by taking the same optimizer and hyperparameters.

For the deconvolution method, we apply one of the modern blind deblurring method by Xu et al. [5], [6], which had the best resolution enhancement performance in the evaluation of [1].

For the evaluation parameter, we reconstruct the intensity image according to the method in [1, Section 7.2.2], while the lateral resolution is defined as the finest dimension that can resolve an target with 3dB intensity difference. In this section, we evaluate the vertical and horizontal intensity difference of each resolution group of the resolution target (from $4000\mu m$ to $280.6\mu m$). The vertical and horizontal resolution is then determined as the first minimum dimension that obtained at 3dB crossing of intensity difference. By repeating to determine the resolution for each noise level, we compare the lateral resolution improvement of the optimization approaches using different AWGN noise level (see Table 2). Note that in practise the intensity difference can decrease non-homogeneously (see example in Fig. 5). Therefore, we additionally determine the range of uncertainty (see Table 2) that indicates the difference between the first and last noise levels obtaining a 3dB crossing intensity difference.

3.2 Evaluation

Fig. 4 shows the intensity images by the original datasets (first row), the AdamW estimation (second row), the DOP estimation (third row), and respective deblurring images (last two rows) using *MetalPCB* datasets at AWGN noise level from -20dB to 10dB. Note, that the original datasets intensity image is extracted by the same methodology in [1, reference intensity in Section 7.2.2], which is the signal intensity of the *MetalPCB+AWGN* datasets

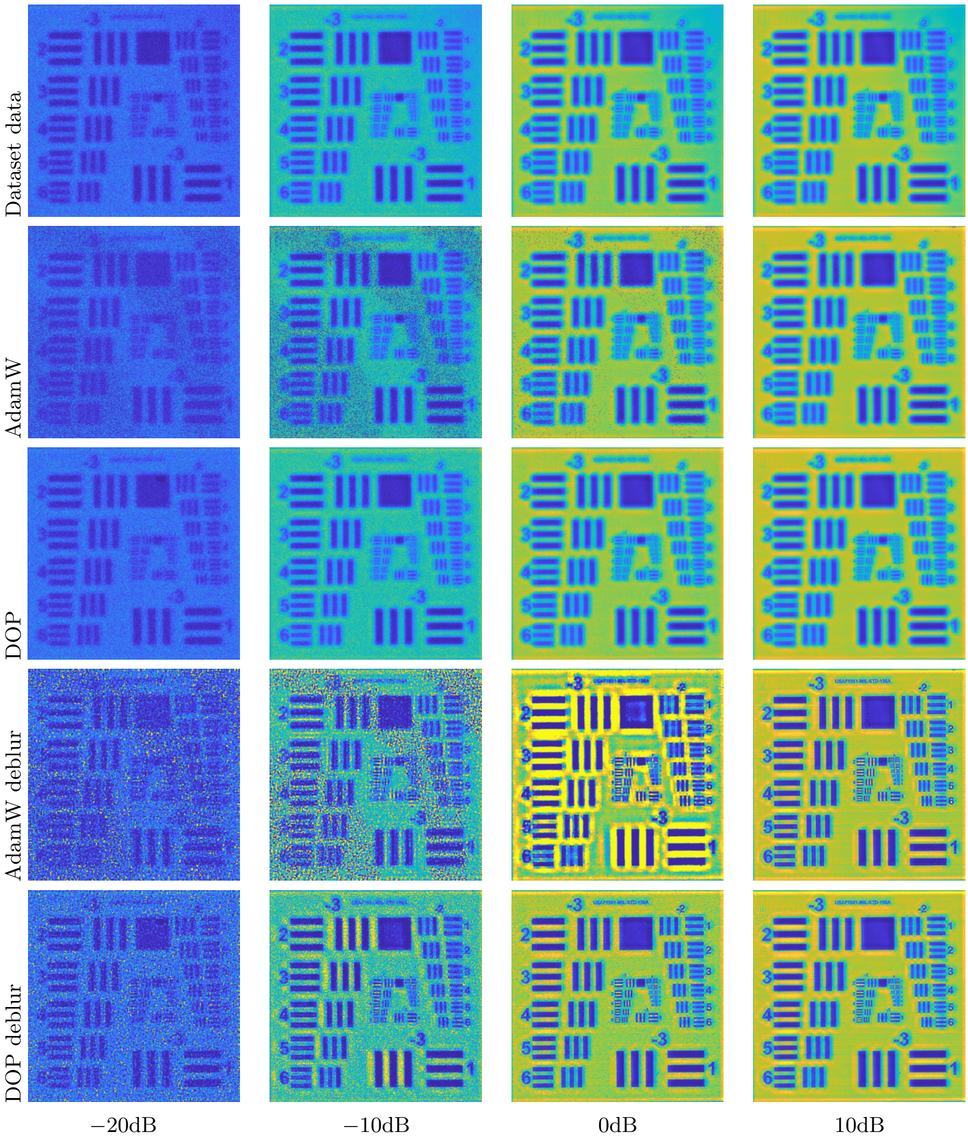

Figure 4. Comparison of THz intensity images by original dataset data (first row), the per pixel AdamW optimizer approach (second row) and the DOP approach (third row) using MetalPCB datasets at AWGN noise level from -20dB to 10dB. Images by AdamW and DOP (last two rows) approaches are deblurred by blind deconvolution method from Xu [5], [6].

data at the center of sampling window.

By visual comparison of the intensity images of AdamW and DOP estimation, we observe that DOP approach obtains less outliers for very low SNR level, i.e., −20dB and −10dB. These outliers are more significantly observable after the deblurring procedure, which makes

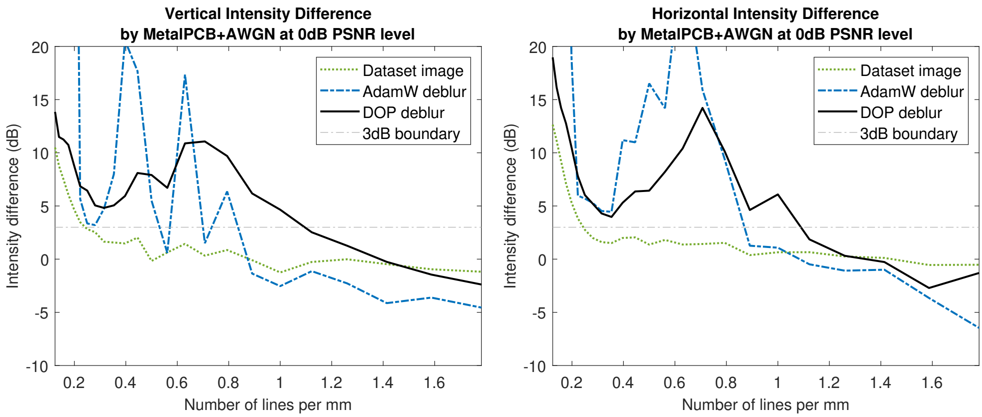

Figure 5. Comparison of the vertical and horizontal intensity difference using *MetalPCB* datasets at 0dB AWGN noise level for each resolution target group from $4000\mu m$ to $280.6\mu m$.

the deblurred DOP intensity image having a better quality than the deblurred AdamW intensity image because of the robustness of DOP estimation.

Fig. 5 plots the vertical and horizontal intensity difference for each resolution target group from $4000\mu m$ to $280.6\mu m$, using the *MetalPCB* datasets at 0dB AWGN noise level as an example.

As a higher intensity difference represents a better ability to resolve a resolution target, both deblurred AdamW and DOP intensity images out-perform the original dataset image, while the deblurred DOP intensity image obtains a more stable intensity difference than the deblurred AdamW image. By comparing the 3dB crossing dimension obtained by both deblurred images, the DOP apporach enhances the performance of deblurring method because of the robustness of model parameter estimation.

Table 2. Comparison of vertical and horizontal resolution using *MetalPCB* datasets at AWGN noise level from -20 to 10dB. The range of uncertainty is shown in parentheses. The best (lower is better) optimizers are highlighted.

Vertical Resolution in μm (range of uncertainty)			
SNR	**Dataset image**	**AdamW deblur**	**DOP deblur**
-20dB	2282.62 (-0.0)	2808.23 (-2027.3)	**2223.05 (-1454.1)**
-10dB	2088.29 (-0.0)	2318.77 (-1712.9)	**585.87 (-0.0)**
0dB	2066.73 (-0.0)	944.45 (-344.4)	**457.60 (-0.0)**
10dB	2022.34 (-0.0)	**535.28 (-0.0)**	568.10 (-99.6)
Horizontal Resolution in μm (range of uncertainty)			
SNR	**Dataset image**	**AdamW deblur**	**DOP deblur**
-20dB	**2208.92 (-0.0)**	2633.74 (-0.0)	**2288.36 (-1539.3)**
-10dB	2099.83 (-0.0)	1808.98 (-1076.7)	**1048.52 (-447.1)**
0dB	2054.55 (-0.0)	575.93 (-0.0)	**460.14 (-0.0)**
10dB	2055.73 (-0.0)	573.10 (-80.8)	**444.31 (-0.0)**

Table 2 compares the vertical and horizontal resolution for the AWGN noise level from −20dB to 10dB respectively, and the range of uncertainty is shown in parentheses.

As we can see from the table, the DOP approach is generally improving the deblurring method with respect to the resolution enhancement ability. The improvement of the DOP approach over the AdamW approach is mainly due to the enhanced robustness of model parameters estimation, which obtains a shorter range of uncertainty except for the vertical resolution at 10dB and the horizontal resolution at −20dB noise level.

4 Summary

In this paper, we propose the combination of the deep optimization prior approach [2] and the THz image deblurring [1], and evaluate the impact of combining both methods to the lateral resolution improvement for FMCW THz imaging. We apply the modern blind deconvolution method such as Xu et al. [5], [6] to the result of the THz parameter estimation by the deep optimization prior approach [2] and the per-pixel curve fitting approach [1], and evaluate the lateral resolution enhancement. Experiments demonstrate that the deep optimization prior approach improves the lateral resolution enhancement because of the robust reconstruction of model parameters in low SNR noise level.

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