ROBUST REAL-TIME DETERMINATION OF DIELECTRIC PERMITTIVITY FROM REFLECTION DATA USING A NEURAL NETWORK

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This paper presents a neural network approach for reconstructing dielectric permittivity in the 38 – 52 GHz band. By employing logarithmically compressed time-domain features of the inverse reflection coefficient, the developed convolutional neural network (CNN) model achieves a relative error of 2 – 3 %. The method enables accurate, non-iterative material characterization suitable for rapid analysis.

Keywords: dielectric permittivity, reflection coefficient, neural networks, CNN, non-destructive testing.

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1. Introduction

Experimental determination of the electrodynamic parameters of materials, in particular the dielectric permittivity ε, is a fundamental task in contemporary materials science and applied electromagnetics. To retrieve them, various radio-frequency measurement techniques providing indirect measurements are employed. These techniques require the development of an appropriate mathematical model that links the sought material parameters to directly measured quantities. The resulting relationship is typically nonlinear, so that small perturbations in the experimental data may lead to significant deviations in the reconstructed parameters, rendering the inverse problem inherently unstable and highly sensitive to measurement noise, and thereby necessitating the use of dedicated regularization and robust optimization strategies.

Time-domain approaches based on the separate observation of reflection peaks from the interfaces of a dielectric slab offer a relatively straightforward way to estimate its parameters [1]. For thin plates, however, this strategy becomes ineffective. In [2], the inverse problem is reformulated as an optimal control problem for the Cauchy problem associated with a Riccati-type equation, where the dielectric permittivity profile is treated as the control function; this approach has been successfully validated using experimental data for dielectric layers placed inside a standard rectangular metal waveguide [3]. Another methodology [4] employs the Gelfand–Levitan and Newton–Kantorovich methods; its practical implementation, however, requires extrapolation of the frequency response towards zero frequency using a quasi-duration functional, which substantially complicates the numerical procedure. The quasi-solution method [5] represents a further powerful tool and yields a satisfactory agreement with experimental measurements. Nevertheless, the surveyed results indicate that, even in comparatively simple one-dimensional configurations, the reliable reconstruction of dielectric properties remains algorithmically and computationally demanding.

Motivated by these limitations, recent research has increasingly focused on deep learning techniques, which demonstrate strong potential for addressing nonlinear inverse problems and reconstructing material parameters from indirect measurements. The objective of this study is to enhance the accuracy and robustness of dielectric parameter estimation based on the frequency dependence of the reflection coefficient. In this study, a neural-network-based framework is developed that employs a specially constructed inverted representation of the reflection coefficient, aimed at increasing sensitivity to variations in the material parameters and improving the resolution of the reconstruction under noisy measurement conditions.

2. Analytical model

To address the formulated problem, we employ a well-known analytical expression describing the frequency dependence of the reflection coefficient of a single-layer dielectric structure in free space [6]:

$$R(\omega) = \frac{R - Re^{-j2\frac{\omega}{c}\sqrt{\varepsilon}d}}{1 - R^2 e^{-j2\frac{\omega}{c}\sqrt{\varepsilon}d}} \qquad (1)$$

where R is the Fresnel reflection coefficient at the "air–layer material" interface, ω is the frequency of the probing electromagnetic signal, c is the speed of light in vacuum, and d is the layer thickness.

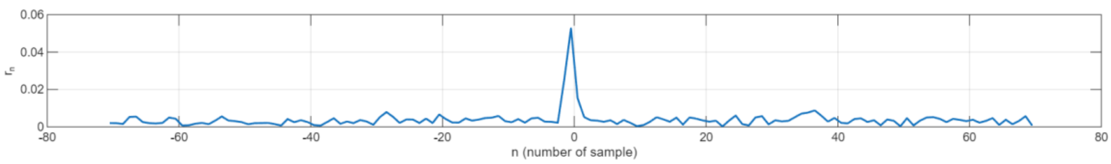
The transformation of the reflection coefficient $R(\omega)$ (1) from the frequency-domain to the time domain $r(t)$ leads to representing the signal as a sum of weighted exponentials whose exponents are determined by the poles of this coefficient. In the case of using the inverted frequency response, the roles of the poles are instead played by the zeros of (1).

On the basis of (1), the corresponding expressions for the poles $\omega_{p,n}$ and $\omega_{z,n}$ zeros take the form:

$$\omega_{p,n} = \frac{2\varphi + 2\pi n - jln|R^2|}{2\frac{1}{c}\sqrt{\varepsilon}d}, \qquad \omega_{z,n} = \frac{2\pi n + jln|1|}{2\frac{1}{c}\sqrt{\varepsilon}d}$$

where φ denotes the phase of the Fresnel reflection coefficient and n is an integer index.

For low-contrast materials, the reflection coefficient has poles with large imaginary parts located far from the real axis, so the corresponding time-domain response decays rapidly. This is illustrated in Fig. 1, which shows signals synthesized over 38 – 52 GHz with a 100 MHz step for layers with ε = 1.14, d = 1 mm (Fig. 1a) and ε = 2.10, d = 1 cm (Fig. 1b). In both cases, only a short pulse is observed.



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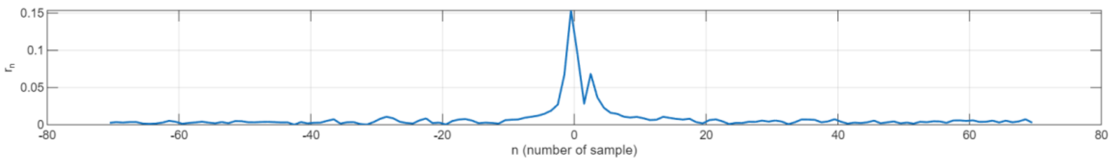
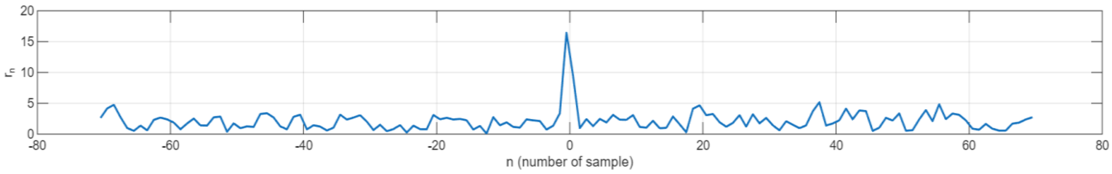


b

Fig. 1. Time-domain representation of the reflection coefficient r_n synthesized over the 38 – 52 GHz band: (a) low-contrast material with permittivity $\varepsilon = 1.14$ and $d = 1$ mm, (b) higher-contrast material with $\varepsilon = 2.10$ and $d = 1$ cm.

Due to the discrete frequency grid and the use of a discrete Fourier transform, the time-domain signal r_n is represented as a function of the sample index n. and, due to the finite discrete frequency grid, has a short duration, which limits subsequent processing. In contrast, when the signal is synthesized from the inverted frequency response, the poles (zeros of the reflection coefficient) lie on the real axis, so the time-domain signal is, in principle, of infinite duration. This is illustrated in Fig. 2 for $\varepsilon = 1.14$ (Fig. 2a) and $\varepsilon = 2.10$ (Fig. 2b) where the signals are significantly prolonged, enabling more accurate parameter estimation.

The inversion of the reflection coefficient in Fig. 2 has several drawbacks: the reciprocals of the coefficient may approach infinity, and measurement noise becomes dominant in the spectrum. To prevent divergence, additional losses should be introduced to enforce a prescribed decay of the time-domain signal, together with dynamic-range compression. In neural-network-based approaches these operations can be incorporated at the stage of generating training signals and therefore do not hinder the procedure, unlike methods that rely on numerical estimation of the zeros.



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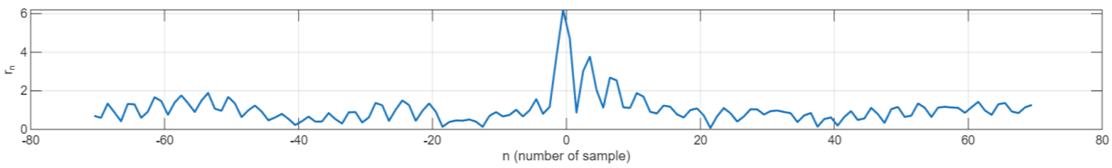

b

Fig. 2. Time-domain signal synthesized from the inverted frequency response $1/R_n$:
(a) low-contrast material with permittivity $\varepsilon = 1.14$ and $d = 1$ mm,
(b) higher-contrast material with $\varepsilon = 2.10$ and $d = 1$ cm.

3. Neural network model for solving the inverse problem

To solve the regression problem of reconstructing the dielectric permittivity (ε) from the time-domain response of the material, a model based on a deep CNN was developed. As input features, we used data obtained from the inverse fast Fourier transform (IFFT) of the function $1/R_n$.

The input dataset was constructed from the real and imaginary parts of the signal. The dimensionality of the input space for a single sample was $[N_t \times 2]$ where N_t is the number of time samples, and 2 corresponds to the $\Re$ and $\Im$ channels.

To address the high dynamic range of IFFT signals, where primary reflections dominate, a sign-preserving logarithmic compression [7] was applied. This transformation enhances weak features and mitigates gradient saturation. To further stabilize training, outliers were clipped at the 99th percentile, followed by Z-normalization of both input features and target labels to zero mean and unit variance.

The proposed architecture is a specialized one-dimensional convolutional neural network for deep analysis of two-channel time series. It comprises three convolutional blocks that successively increase the abstraction level of extracted features. The first block performs early fusion of the real and imaginary signal components, forming a shared feature vector, while the remaining two blocks model temporal dependencies in this compressed space.

Network weights were optimized using the Adam algorithm with mean squared error (MSE) as the loss function. Training was conducted for 150 epochs with mini batches of 32 samples and random shuffling of the training set. Model performance on the independent test set was evaluated using MSE and the Pearson correlation coefficient, computed after denormalization of the network outputs to assess the accuracy of reconstructing ε

During testing, the model achieved high accuracy in reconstructing the dielectric permittivity: the Pearson correlation coefficient was, $R_{\mathrm{P}} \approx 0.992$, and the mean absolute error (MAE) was 0.032. In the considered range $\varepsilon' \in [1.1, 2.1]$ and $d = 1$ mm, this corresponds to a relative error of about 2 – 3%, which is comparable to the instrumental accuracy of standard free-space measurement techniques. This indicates a nearly linear response without noticeable bias and supports the effectiveness of logarithmic compression for signals with a wide dynamic range.

4. Conclusions

This study proposes and validates a neural-network–based method for reconstructing the dielectric permittivity of materials in the millimeter-wave range (38 – 52 GHz). The developed CNN model demonstrates high prediction accuracy $R_P \approx 0.992, MAE \approx 0.032$. These results confirm the effectiveness of deep learning for rapid material characterization, providing measurement accuracy comparable to instrumental methods while avoiding computationally expensive iterative algorithms.

References

1. **Alekseev, V. V.** Multifrequency Near-Zone Radar of 6-mm Wave Range with Combination of Pulse Synthesis and Transversal Scanning / V. V. Alekseev, M. V. Andreev, O. O. Drobakhin, Ye. V. Kondratyev, D. Yu. Saltykov // Telecommunications and Radio Engineering. – 2007. – Vol. 66, No. 10. – P. 855 – 861.

2. **Brovenko, A. V**. One-dimensional inverse problems of electromagnetic sounding of stratified dielectric media / A. V. Brovenko, A. A. Vertiy, N. P. Melezhik, P. N. Melezhik, A. Y. Poyedinchuk // Telecommunications and Radio Engineering. – 2016. – Vol. 75. – P. 477 – 487.

3. **Vertiy, A. A.** Dielectric Permittivity Profile Reconstruction in Microwave Band for Layered Dielectric Slab Located in the Standard Metal Waveguide / A. A. Vertiy, P. N. Melezhik, A. Y. Poyedinchuk, S. V. Mizrakhy, P. K. Nesterov // 17th International Conference on Mathematical Methods in Electromagnetic Theory (MMET). – Kyiv, Ukraine, 2018. – P. 217 – 220.

4. **Alexin, S. G.** Comparison of the Methods of 1-D Permittivity Profile Reconstruction: Real Measurement Data Processing / S. G. Alexin, O. S. Antropov, O. O. Drobakhin // Telecommunications and Radio Engineering. – 2010. – Vol. 69. – P. 1121 – 1127.

5. **Andreev, M. V.** One-Dimensional Inverse Problem Solution for Multilayered Dielectric Structures Using Least Square Spectral Estimation Method / M. V. Andreev, V. F. Borul'ko, O. O. Drobakhin // Proc. 1995 Int. Symp. on Electromagnetic Theory. – St. Petersburg, 1995. – P. 148–150.

6. **Born, M.** Principles of Optics: Electromagnetic Theory of Propagation, Interference and Diffraction of Light / M. Born, E. Wolf. – 7th expanded ed. – Cambridge: Cambridge University Press, 1999. – 952 p.

7. **Zheng, A.** Feature Engineering for Machine Learning: Principles and Techniques for Data Scientists / A. Zheng, A. Casari. – Sebastopol: O'Reilly Media, 2018. – 218 p.