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Deep Learning–Based Image Reconstruction in Electromagnetic Tomography: Recent Progress and Perspectives

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Abstract: Electromagnetic Tomography (EMT) is a non-destructive imaging modality that reconstructs internal conductivity or permittivity distributions by solving an ill-posed inverse problem. Traditional reconstruction methods, such as Linear Back Projection (LBP) and Conjugate Gradient (CG), often suffer from low accuracy, strong artifacts, and poor edge preservation due to ill-conditioned sensitivity matrices and noise amplification. In recent years, deep learning has provided new solutions for EMT image reconstruction through its strong nonlinear fitting ability and multi-scale feature extraction capability. With the development of encoder–decoder structures, skip-connection strategies, and attention mechanisms, a series of neural-enhanced EMT reconstruction models have emerged, effectively improving artifact suppression, multi-target discrimination, and real-time performance. Among them, U-Net-based frameworks and attention-augmented variants, such as CBAM-U-Net, demonstrate significant advantages in boundary restoration, feature refinement, and noise robustness. This review summarizes the major research progress of deep learning in EMT image reconstruction, outlines the evolution from hybrid shallow models to specialized deep architectures, and discusses future directions for multimodal fusion and advanced neural frameworks.

Keywords: Deep learning; Image processing; Electromagnetic Tomography (EMT)

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1. Introduction

Electromagnetic Tomography (EMT) is a non-destructive imaging technique based on electromagnetic induction principles, enabling contactless characterization of material properties [1]. Its advantages include non-invasiveness, safety, and real-time imaging capability. EMT processes detection signals through excitation, sensing, data transmission, and tomographic reconstruction, where the reconstructed field distributions quantitatively reflect internal electromagnetic parameters. Traditional reconstruction algorithms—including LBP, Tikhonov regularization, Landweber iteration, and Conjugate Gradient—face inherent limitations [2]. Ill-conditioned sensitivity matrices cause noise amplification, while iterative methods incur heavy computational cost and spatial ambiguity in multi-object scenarios. For example, LBP reconstructions exhibit severe boundary localization errors, and CG approaches often require hundreds of iterations to converge. These limitations motivate the incorporation of data-driven priors and nonlinear mapping techniques [3].

Deep learning offers strong nonlinear approximation capabilities and can obtain sufficient prior information through large-scale sample training [4]. By learning mappings between low-quality inputs (e.g., LBP/CG results) and high-fidelity ground truth images, neural networks bypass explicit inversion and automatically suppress artifacts. Encoder–decoder architectures with skip connections enable fusion of shallow edges and deep semantic features. When enhanced with attention mechanisms such as CBAM, networks achieve adaptive feature refinement and improved multi-target discrimination [5].

The purpose of this review is to provide a systematic summary of current deep learning–based EMT reconstruction methods, clarify their development trajectory, and highlight their advantages and limitations from both theoretical and practical perspectives. By reorganizing representative progress and identifying key methodological trends, this review aims to offer a coherent reference for researchers entering the field and to support future work toward more robust and generalizable EMT imaging frameworks.

2. Definition of EMT image reconstruction

In EMT, reconstruction aims to map measured boundary voltages to internal conductivity or permittivity distributions [6]. According to the principle of electromagnetic induction, the EMT system satisfies the Maxwell differential equation

$$\begin{aligned}
&\nabla \times \overrightarrow{H} = \overrightarrow{J} + \frac{\partial D}{\partial t} \\
&\nabla \times \overrightarrow{E} = -\frac{\partial B}{\partial \mathrm{t}} \\
&\nabla \cdot \overrightarrow{B} = 0 \\
&\nabla \cdot \overrightarrow{D} = \rho
\end{aligned} \tag{1}$$

The EMT object field is considered a “stable field”, which satisfies the condition:

$\varepsilon\omega \ll \sigma$

And the measured medium is linear and isotropic

$$\overrightarrow{D} = \varepsilon \overrightarrow{E}, \quad \overrightarrow{B} = \mu \overrightarrow{H}, \overrightarrow{J} = \sigma \overrightarrow{E} \tag{2}$$

Where ε is relative dielectric constant, μ is relative magnetic permeability and σ is conductivity. The vector magnetic potential $\overrightarrow{A}$ is introduced to satisfy

$$B = \nabla \times \overrightarrow{A} \tag{3}$$

Assuming the magnetic permeability is constant, the object field equation of EMT is

$$\nabla^2 A = \mathrm{j}\omega\mu(x,y)\sigma(x,y)\vec{A} \tag{4}$$

Simplify the equation (4) to

$$\vec{A} = \frac{\nabla(\mu(\mathrm{x},\mathrm{y})^{-1}\nabla\vec{A})}{j\varpi\sigma(x,y)} \tag{5}$$

According to the principle of electromagnetic induction, the output voltage U of each detection coil can be expressed as:

$$U = -\frac{d\varphi}{dt} = -n\frac{d(\vec{B}S)}{dt} = -n\frac{d(\vec{A}l)}{dt} = -nj\omega l(\vec{A_1} - \vec{A_2}) \tag{6}$$

Deep learning reframes reconstruction as an image-to-image transformation problem [7]. Low-quality EMT images serve as physical priors, and neural networks perform refinement by extracting multi-scale features, enhancing edges, suppressing noise, and restoring structural details. Thus, deep learning provides a robust alternative definition of EMT reconstruction: physics-guided, data-driven posterior enhancement.

3. Recent research progress

Research on deep learning–based electromagnetic tomography (EMT) image reconstruction has progressed through several evolutionary stages, moving from early hybrid shallow models to specialized deep neural architectures tailored for complex inverse problems. In the early development of learning-assisted EMT methods, researchers attempted to incorporate radial basis function (RBF) neural networks, wavelet-enhanced estimators, and hybrid statistical learning models to compensate for the limitations of traditional algorithms [8]. These approaches demonstrated that introducing data-driven components could effectively improve the stability of conductivity estimation and alleviate the severe artifacts produced by classical iterative solvers. Although the capacity of these shallow models was limited, they laid an important foundation by illustrating that neural representations could embed structural priors absent from purely physics-based solvers.

The emergence of deep learning around 2018–2019 marked a significant shift in EMT research. Deep architectures such as stacked sparse autoencoders (SSAE), fully connected (FC) networks, and multi-scale convolutional sparse coding frameworks began to demonstrate superior reconstruction accuracy compared to classical methods [9]. These models were no longer restricted to simple post-processing; instead, they learned end-to-end mappings from coarse physical reconstructions—typically derived from LBP or CG—to ground-truth conductivity distributions [10]. As a result, they could recover high-frequency structural details and achieve millimeter-level resolution across a broad range of material configurations. Importantly, this stage confirmed that deep networks possess sufficient generalization capability to handle diverse physical fields, dynamic flow conditions, and imperfect measurement environments.

As research continued, the focus gradually shifted from adopting general neural architectures to designing EMT-specific deep models [11]. U-Net became one of the most influential structures due to its encoder–decoder symmetry and skip connections, which effectively combine shallow boundary information with deep semantic representations [12]. This enabled more accurate edge localization and clearer structural depiction than both classical algorithms and earlier learning models. However, the unmodified U-Net still propagated redundant features through its skip pathways, resulting in blurred edges and reduced discrimination in multi-target scenarios. To overcome these limitations, attention mechanisms were introduced, with the Convolutional Block Attention Module (CBAM) emerging as an effective enhancement [13]. By integrating channel and spatial attention, CBAM-U-Net adaptively focuses on conductivity-sensitive regions and suppresses irrelevant background features, producing cleaner boundaries, stronger robustness to noise, and improved performance in complex multiphase and multi-object environments [14]. This attention-driven refinement has allowed EMT reconstruction networks to align more closely with the inherent physical characteristics of electromagnetic induction, thereby marking an important milestone toward high-fidelity, high-speed, and physics-aware deep reconstruction frameworks [15].

4. Conclusion

Deep learning has reshaped EMT image reconstruction by providing data-driven solutions to ill-posed inverse problems. Through nonlinear feature learning, multi-scale fusion, and attention-based refinement, neural-enhanced approaches significantly improve artifact suppression, edge restoration, and multi-target discrimination compared with classical EMT algorithms. U-Net-based models and CBAM-enhanced variants represent important advances, offering high-fidelity imaging with real-time inference capability.

Future research should explore multimodal integration, real-world dataset expansion, and the adoption of advanced architectures such as Transformers and generative adversarial networks. These developments are expected to further improve robustness, generalization, and interpretability in EMT applications.

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Disclosure statement

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