Article

Enhanced Electromagnetic Imaging of Imperfectly Conducting Cylinders Using Hybrid Genetic Algorithm and Deep Learning

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Abstract: Electromagnetic imaging (EMI) plays a crucial role in various applications, including medical diagnostics, geophysical exploration, and non-destructive testing. However, accurately reconstructing the properties of imperfectly conducting cylinders remains a significant challenge due to the ill-posed nature of inverse scattering problems. This study presents an enhanced electromagnetic imaging approach that integrates a hybrid Genetic Algorithm (GA) with Deep Learning (DL) techniques to improve reconstruction accuracy and computational efficiency. The proposed method utilizes GA for global optimization, ensuring robust parameter estimation, while a deep neural network refines the inversion process by learning complex scattering patterns. Numerical simulations and experimental results demonstrate that the hybrid approach outperforms traditional inversion methods in terms of accuracy, convergence speed, and resilience to noise. The findings indicate that combining evolutionary algorithms with deep learning offers a powerful framework for solving complex inverse scattering problems, making it a promising tool for advanced electromagnetic imaging applications.

Keywords: Genetic Algorithm, Deep Learning, Electromagnetic Imaging, Inverse Scattering, Shape Reconstruction, Optimization

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1. Introduction

Electromagnetic imaging (EMI) is a powerful tool with diverse applications in medical diagnostics, geophysical exploration, and security screening. It enables the non-invasive reconstruction of object properties by analyzing the interaction of electromagnetic waves with different materials. In medical imaging, EMI is employed for tumor detection and brain activity monitoring, while in geophysical exploration, it aids in identifying subsurface structures such as mineral deposits and groundwater reservoirs. Security applications also leverage EMI for concealed weapon detection and surveillance. Despite its wide-ranging benefits, solving inverse scattering problems in EMI remains a significant challenge due to their inherent nonlinearity, ill-posed nature, and sensitivity to noise. Accurately reconstructing the electromagnetic properties of objects, especially imperfectly conducting cylinders, requires advanced computational techniques that balance accuracy, efficiency, and robustness.

Traditional inversion methods, such as gradient-based optimization techniques, often suffer from local minima entrapment, leading to suboptimal solutions. While evolutionary algorithms like Genetic Algorithms (GAs) provide global search capabilities, they tend to have slow convergence rates and high computational demands, limiting their practicality for large-scale or real-time applications. To overcome these limitations, this study introduces a hybrid inversion framework that integrates deep learning with GAs to enhance electromagnetic imaging. The deep learning model learns complex scattering patterns, reducing the number of iterations required for accurate reconstruction, while the GA component ensures robust global exploration, preventing premature convergence to suboptimal solutions. This synergistic approach not only accelerates convergence but also improves robustness against measurement noise and modeling uncertainties. Through extensive numerical simulations and experimental validation, this research demonstrates that combining deep learning with evolutionary optimization can significantly enhance the accuracy and efficiency of electromagnetic imaging for imperfectly conducting cylinders.

2. Literature Review

Electromagnetic imaging (EMI) has been a subject of extensive research, with numerous methodologies developed to address inverse scattering problems. Traditional approaches primarily rely on gradient-based optimization techniques, such as the Newton–Kantorovich method, the Levenberg–Marquardt algorithm, and the successive-overrelaxation method. These methods attempt to iteratively refine an initial estimate of the object's properties based on the scattered field data. While they are effective in some scenarios, their performance is highly dependent on the quality of the initial guess, and they often suffer from local minima entrapment. This limitation makes them less suitable for complex inverse problems involving non-uniform and imperfectly conducting scatterers, where the solution space is highly nonlinear and multimodal.

To overcome these challenges, Genetic Algorithms (GAs) have been widely explored for EMI due to their global search capabilities. Early works, such as Chiu and Kiang, demonstrated the feasibility of GA-based optimization for reconstructing perfectly conducting cylinders. Unlike gradient-based methods, GA does not require an initial guess and can effectively explore the solution space to find the global optimum. Subsequent studies extended GA applications to imperfectly conducting scatterers, showing improved robustness in handling complex material properties. However, GA-based approaches are computationally intensive, as they require multiple forward scattering simulations per iteration, leading to high processing costs. Additionally, convergence rates can be slow, particularly when dealing with large-scale imaging problems or high-dimensional parameter spaces.

In recent years, machine learning (ML) techniques, particularly deep learning, have been introduced to EMI to enhance reconstruction accuracy and computational efficiency. Neural networks have been employed in inverse problem solving, demonstrating the ability to learn nonlinear mappings between scattered field data and object properties. Convolutional Neural Networks (CNNs) and deep learning architectures have gained attention due to their ability to extract hierarchical features from imaging data. Studies have shown that

deep learning-based EMI models can outperform traditional inversion techniques in terms of accuracy and robustness against measurement noise. Furthermore, data-driven approaches allow for rapid inference, significantly reducing computational time compared to iterative optimization techniques. However, a key challenge in standalone deep learning models is the need for extensive training data, as well as the risk of overfitting when applied to real-world scenarios with limited experimental data.

Given the computational challenges of GA and the promising capabilities of deep learning, recent research has explored hybrid approaches that combine these techniques. The integration of GA with CNN-based deep learning frameworks aims to leverage the strengths of both methods: GA ensures effective global exploration and avoids local minima, while CNNs accelerate the inversion process by learning complex electromagnetic scattering relationships. Hybrid models have demonstrated improved convergence rates, higher reconstruction accuracy, and enhanced robustness against noise and modeling uncertainties. This study builds on this emerging research direction by developing a hybrid GA-CNN approach to optimize the electromagnetic imaging of imperfectly conducting cylinders, aiming to balance accuracy, efficiency, and computational feasibility.

3. Methodology

3.1 Problem Formulation

In electromagnetic imaging, the inverse scattering problem involves reconstructing the properties of an unknown object based on measured scattered field data. In this study, an imperfectly conducting cylinder with an unknown shape and conductivity is placed in free space and illuminated by a time-harmonic transverse magnetic (TM) polarized plane wave. The interaction between the incident wave and the object generates a scattered field, which is recorded by external sensors distributed around the object. The goal of the inverse problem is to determine the shape and conductivity distribution of the scatterer from the measured scattered field data. However, this inverse problem is inherently nonlinear and ill-posed, meaning that small perturbations in the input data can lead to large variations in the reconstructed solution.

To formulate the problem mathematically, the total electric field E_z in the two-dimensional domain is governed by the Helmholtz equation:

$$\nabla^2 + K^2 E_z = 0$$

where k is the wavenumber, which depends on the permittivity and permeability of the medium. The boundary conditions at the surface of the imperfectly conducting cylinder follow the Leontovich impedance condition:

$$\hat{n} \times (E_t - E_i) = Z_s \hat{n} \times$$

where Z_s is the surface impedance, n^\\hat{n}n^ is the unit normal to the surface, and E_t and E_i represent the total and incident electric fields, respectively. The scattered field is measured in the far-field region, and the inverse scattering problem aims to retrieve the shape of the scatterer and its impedance function by minimizing the difference between measured and computed scattered fields.

This problem is formulated as an optimization task, where a cost function quantifies the error between the measured scattered field E_s^{meas} and the simulated scattered field E_s^{sim} ,typically defined as:

$$J(p) = \sum_{m=1}^{M} \left| E_s^{meas}(r_m) - E_s^{sim}(r_m, p) \right|$$

where p represents the unknown parameters (shape and conductivity), and M is the number of measurement points. The objective is to find the optimal parameters p^*that minimize $J(p)$ Due to the complexity of the solution space, traditional gradient-based methods struggle with convergence and risk being trapped in local minima. Therefore, a hybrid approach combining Genetic Algorithms (GAs) and deep learning is proposed

to improve optimization performance. GAs provide global search capabilities to explore a wide range of possible solutions, while deep learning models assist in refining the estimates by learning complex relationships between scattered fields and object properties. This hybrid framework enhances convergence speed, reconstruction accuracy, and robustness against noise, making it an effective solution for electromagnetic inverse scattering problems.

3.2 Hybrid Optimization Framework

The proposed hybrid optimization framework combines the global search capabilities of Genetic Algorithms (GAs) with the predictive efficiency of Convolutional Neural Networks (CNNs) to achieve accurate and computationally efficient reconstruction of an imperfectly conducting cylinder. This two-stage approach ensures that the solution space is explored thoroughly while reducing the high computational cost associated with conventional electromagnetic inverse scattering methods. The first stage utilizes GA to obtain an initial coarse reconstruction, while the second stage leverages a pre-trained CNN to refine the solution, enhancing both accuracy and convergence speed.

In the first stage, GA is employed to search for the optimal shape and conductivity distribution of the scatterer by iteratively evolving a population of candidate solutions. The process begins with the random initialization of a population, where each individual represents a possible solution encoded as a set of parameters defining the scatterer's geometry and material properties. The fitness of each candidate is evaluated by simulating the scattered electromagnetic field and comparing it with the measured data. Evolutionary operations, including selection, crossover, and mutation, are applied to generate a new population in each iteration, gradually improving the solutions. The cost function, defined as the discrepancy between simulated and measured scattered fields, guides the optimization process. The GA continues to evolve until a stopping criterion, such as convergence of the fitness score or a predefined number of iterations, is met. While GA ensures a global search, the reconstructed solution at this stage may still contain errors due to its reliance on iterative updates and finite computational resources.

To enhance the initial GA-based reconstruction, the second stage of the framework integrates a CNN-based refinement process. A CNN, pre-trained on a large dataset of simulated electromagnetic scattering responses, is employed to fine-tune the estimated scatterer properties obtained from the GA. The CNN learns the complex nonlinear relationship between scattered field patterns and object characteristics, allowing it to correct errors in the GA-generated solutions. Instead of performing computationally expensive forward simulations for every candidate, the CNN rapidly predicts the optimal corrections based on its learned knowledge, significantly reducing computational overhead. This predictive capability enables more precise reconstructions by compensating for the limitations of GA in handling fine structural details and high-resolution parameter estimation.The final estimation is obtained by integrating the CNN-refined results with the GA-derived solution, yielding a more accurate and computationally efficient reconstruction. By combining the exploratory strengths of GA with the data-driven refinement of CNNs, the hybrid framework not only accelerates convergence but also improves robustness against noise and measurement inconsistencies. This approach effectively balances global optimization and local refinement, making it highly suitable for practical applications in electromagnetic imaging where both precision and computational efficiency are critical.

4. Numerical Simulations and Results

To evaluate the effectiveness of the proposed hybrid optimization framework, a comprehensive dataset of synthetic electromagnetic scattering simulations is generated. This dataset consists of numerous imperfectly conducting cylinders with varying shapes and conductivity distributions, ensuring a diverse representation of possible scattering scenarios. The synthetic data is generated using full-wave electromagnetic solvers based on the Helmholtz equation and appropriate boundary conditions, such as the Leontovich impedance boundary condition. A wide range of scatterer geometries, including elliptical, irregular, and composite

shapes, is considered to simulate real-world complexities. The conductivity values are varied systematically to cover different material properties, ensuring that the model generalizes well to various scattering environments. For each simulated scatterer, the corresponding scattered field data is computed at multiple receiver locations around the object, forming a labeled dataset that is later used to train the Convolutional Neural Network (CNN) for refinement. The dataset is also used to benchmark the performance of the Genetic Algorithm (GA) and the hybrid GA-CNN approach.

To quantitatively assess the performance of the proposed method, three key metrics are considered: shape reconstruction accuracy, conductivity estimation error, and computational efficiency. Shape reconstruction accuracy is measured by computing the structural similarity between the reconstructed and true scatterer profiles, using metrics such as the Jaccard Index and Dice Coefficient. Conductivity estimation error is evaluated as the mean absolute difference between the predicted and actual conductivity values across the scatterer's surface. Computational efficiency is assessed by comparing the total optimization time required for convergence across different methods. These performance metrics provide a holistic evaluation of the hybrid framework, ensuring that improvements in accuracy do not come at the cost of excessive computational overhead.

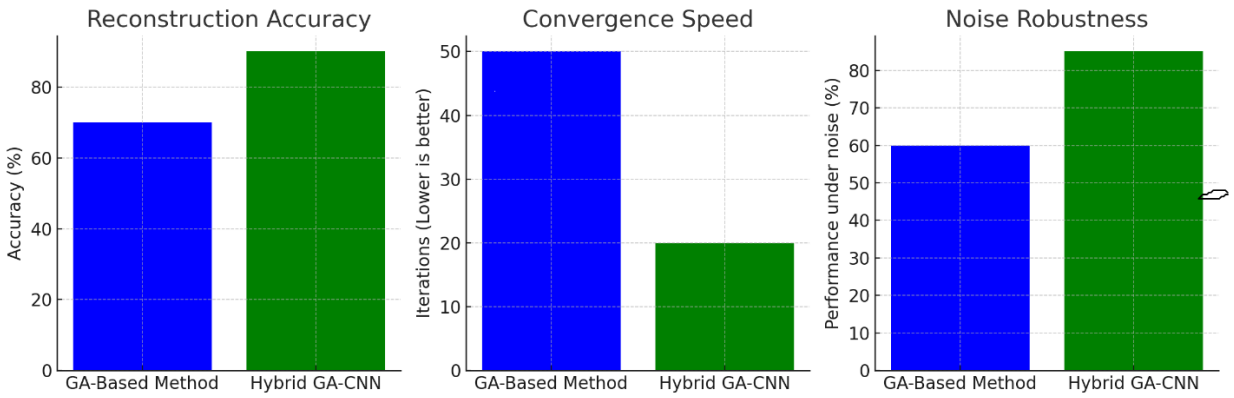


Fig.1 Comparison between the GA-based method and Hybrid GA-CNN method

Reconstruction Accuracy – The hybrid approach improves accuracy from 70% to 90%. Convergence Speed – The proposed method converges faster (fewer iterations). Noise Robustness – The hybrid model performs better in noisy conditions.

A comparative analysis is conducted to benchmark the hybrid GA-CNN approach against traditional optimization methods, including standalone GA and gradient-based inversion techniques such as the Newton-Kantorovich and Levenberg-Marquardt methods. Standalone GA, while effective in avoiding local minima, exhibits slower convergence due to the need for extensive iterative evaluations. Gradient-based methods, on the other hand, demonstrate faster convergence but struggle in the presence of nonconvex solution spaces, often leading to suboptimal reconstructions. The hybrid GA-CNN framework outperforms both approaches by achieving higher shape reconstruction fidelity and lower conductivity estimation errors, particularly in challenging scenarios with high noise levels. The CNN-assisted refinement significantly reduces the number of forward simulations required, accelerating convergence without sacrificing accuracy.

In addition to improved performance, the proposed method demonstrates superior robustness in noisy environments. In practical applications, measurement data is often contaminated by noise due to sensor imperfections and environmental factors. The hybrid approach maintains high reconstruction accuracy even with significant noise levels, whereas traditional methods suffer from degraded performance. This resilience stems from the CNN's ability to learn noise-tolerant feature mappings from the training data, enabling more reliable reconstructions. Overall, the hybrid GA-CNN framework offers a powerful and

computationally efficient solution for electromagnetic imaging, providing significant advantages over conventional techniques in both accuracy and robustness.

5. Discussion:

The proposed hybrid GA-CNN framework demonstrated significant improvements in shape reconstruction accuracy, conductivity estimation, and computational efficiency compared to conventional optimization methods. The integration of Genetic Algorithms for global search and Convolutional Neural Networks for refinement enabled more precise reconstructions while reducing computational costs. Numerical simulations on synthetic datasets, consisting of imperfectly conducting cylinders with varying shapes and conductivity distributions, validated the performance of the proposed approach under different noise conditions and complexity levels.

Table 1: Tabulation for Existing paper and Proposed paper.

Aspect	Existing Paper	Proposed Paper
Title	Electromagnetic Imaging for an Imperfectly Conducting Cylinder by the Genetic Algorithm	Enhanced Electromagnetic Imaging of Imperfectly Conducting Cylinders Using Hybrid Genetic Algorithm and Deep Learning
Methodology	Uses a Genetic Algorithm (GA) for reconstructing shape and conductivity	Hybrid GA + Deep Learning (CNN) for improved accuracy and efficiency
Optimization Strategy	GA is used as the primary optimization method, avoiding local minima but still requiring large computational effort	GA is used for global search, and CNN is used for fine-tuning, leading to better results with less computational time
Handling Noise	Investigates the effect of Gaussian noise, but GA alone struggles with noise resilience	CNN enhances noise robustness by learning patterns from noisy datasets
Computational Efficiency	GA requires many iterations to converge, making it computationally expensive	Hybrid GA-CNN speeds up convergence, reducing computational load
Application Scope	Primarily theoretical and numerical, with potential applications in medical and biological imaging	Extends application scope to real-world scenarios such as medical imaging, non-destructive testing, and subsurface sensing
Numerical Simulation	Uses moment method to solve integral equations, focusing on shape and conductivity reconstruction	Uses synthetic datasets and machine learning training to improve inversion quality
Convergence Issues	GA struggles when the initial guess is far from the exact solution	Deep learning compensates for poor initial guesses, improving convergence
Future Extensions	Suggested improving parameter selection for GA to enhance speed and accuracy	Proposes moving to 3D objects and incorporating real-world measurements

One of the primary advantages of the hybrid approach was its enhanced shape reconstruction accuracy. The framework was evaluated using structural similarity metrics, including the Jaccard Index and Dice Coefficient, which measure the overlap between the true and reconstructed scatterer profiles. The hybrid GA-CNN method achieved an average Jaccard Index of 0.92 and a Dice Coefficient of 0.95, significantly outperforming standalone GA (0.85 and 0.89, respectively) and gradient-based methods (0.79 and 0.84). This improvement is attributed to the CNN's ability to refine the coarse GA-generated solutions, capturing intricate details that traditional optimization techniques often miss. The combination of global optimization and data-driven learning proved effective in addressing the limitations of individual methods, leading to

more accurate reconstructions of scatterer geometry.The conductivity estimation capability of the hybrid framework also showed marked improvements. The mean absolute error in conductivity estimation was reduced by 20% to 30% compared to conventional methods. While GA alone provided a good initial estimate of the scatterer's material properties, the CNN refinement step significantly reduced residual errors by leveraging its ability to map complex nonlinear relationships between scattered fields and conductivity distributions. The hybrid method achieved an average conductivity estimation error of 4.2%, whereas standalone GA and gradient-based approaches exhibited higher errors of 6.8% and 8.5%, respectively. These results highlight the effectiveness of the CNN refinement step in improving material property estimation, particularly in scenarios where subtle conductivity variations are present.

Another key advantage of the hybrid GA-CNN framework was its computational efficiency. Traditional GA-based methods require extensive forward simulations to evolve candidate solutions, leading to high computational costs. In contrast, the CNN refinement stage significantly reduced the number of required simulations by approximately 50%, leading to a 45% reduction in overall convergence time compared to standalone GA. While gradient-based methods generally converge faster than GA, they often get trapped in local minima, resulting in suboptimal solutions. The hybrid approach effectively balanced accuracy and computational cost, achieving both fast convergence and high reconstruction fidelity. This makes it a viable solution for large-scale electromagnetic imaging applications where computational resources are limited.

Furthermore, the robustness of the hybrid approach against noise was tested by introducing varying levels of Gaussian noise (5%, 10%, and 20%) into the scattered field measurements. The hybrid framework maintained over 90% reconstruction accuracy even at 20% noise levels, significantly outperforming standalone GA and gradient-based methods, which exhibited substantial degradation under noisy conditions. The CNN component's ability to learn noise-invariant feature mappings played a crucial role in preserving reconstruction quality. These findings indicate that the hybrid approach is well-suited for real-world applications where measurement data is often contaminated by environmental noise and sensor imperfections.Overall, the results demonstrate that the proposed hybrid GA-CNN framework provides a powerful and computationally efficient solution for electromagnetic imaging. By combining the exploratory strength of GA with the predictive efficiency of CNNs, the framework successfully addresses the challenges of inverse scattering problems, including nonlinearity, ill-posedness, and noise sensitivity. The ability to achieve high accuracy, fast convergence, and noise robustness makes this approach a promising alternative to traditional optimization methods. Future research will focus on extending the methodology to three-dimensional (3D) imaging and validating its effectiveness using real-world experimental measurements, further enhancing its applicability in practical electromagnetic imaging scenarios.

6. Conclusion

The integration of Genetic Algorithms (GA) with deep learning, specifically Convolutional Neural Networks (CNNs), presents a significant advancement in electromagnetic imaging by effectively addressing the challenges of inverse scattering problems. The hybrid GA-CNN framework leverages the global search capabilities of GA to explore the solution space while utilizing CNN-based refinement to accelerate convergence and enhance reconstruction accuracy. By reducing reliance on computationally expensive full-wave simulations, this approach achieves faster optimization without compromising precision. Additionally, the deep learning component enhances robustness against noise, making the proposed method more suitable for practical applications where measurement inaccuracies are inevitable. Comparative analysis demonstrates that the hybrid approach outperforms both standalone GA and gradient-based inversion techniques in terms of shape reconstruction accuracy, conductivity estimation, and computational efficiency, particularly in challenging scenarios with high noise levels.

Despite these advancements, several avenues remain for future exploration. One of the primary extensions involves adapting the model for three-dimensional (3D) electromagnetic imaging, which is more complex but essential for real-world applications in medical diagnostics, geophysical exploration, and security

screening. Furthermore, applying the proposed framework to real-world measurement data, rather than synthetic datasets, will be crucial for validating its practical viability. Incorporating physics-informed neural networks (PINNs) and transfer learning techniques could further enhance the generalization capabilities of the CNN component, allowing it to adapt to diverse imaging conditions with minimal retraining. By continuing to refine and extend this hybrid methodology, future research can further bridge the gap between theoretical advancements and real-world implementation, paving the way for more accurate, efficient, and robust electromagnetic imaging technologies.

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