

Magnetic Fields Reconstruction for TEAM Benchmark Problem 35 Using Conditional Variational Autoencoders

Yiying Li¹, Siguang An¹, Guoping Zou¹ and Shiyong Yang²

¹College of Mechanical and Electrical Engineering, China Jiliang University, Hangzhou, 310018, China

²College of Electrical Engineering, Zhejiang University, Hangzhou, 310027, China

Magnetic field reconstruction is a critical task with wide applications in design optimization, inverse problems, and other fields requiring precise electromagnetic field modeling. This paper proposes a novel conditional variational autoencoder-based model that demonstrates significant potential in reconstructing magnetic fields for random radius distributions in the TEAM benchmark problem 35 without relying on prior field conditions. The method utilizes coil distribution images as conditional labels and field distributions as the reconstruction targets, achieving a robust convergence and a low reconstruction error. Experimental results on randomly generated test cases in TEAM problem 35, with arbitrary radius distributions, show that the proposed approach accurately reconstructs fields.

Index Terms—Conditional variational autoencoder, deep learning, magnetic field, reconstruction.

I. INTRODUCTION

ELECTROMAGNETIC optimization problems, particularly in the realm of inverse design, are inherently complex and computationally demanding. These problems typically involve determining the structural configurations that yield a desired electromagnetic response, such as specific scattering patterns or field distributions. The challenge arises from the need for precise numerical simulations to model electromagnetic phenomena, which often require extensive computational resources and significant time investments. Recent advances in deep learning have provided promising alternatives to conventional numerical techniques. Among the various machine learning techniques, the conditional variational autoencoder (CVAE) has shown a considerable promise in solving such inverse problems by learning the complex mappings between input and output data within a probabilistic framework.

Unlike traditional numerical methods, which require solving complex equations for each iteration of the optimization process, the CVAE offers a data-driven approach that can significantly reduce the computational effort and time required for optimization. Kawamata *et al.* used CVAE to optimize an electric machines by generating shapes of magnetic materials that correspond to the intended magnetic energy [1]. Barmada *et al.* employed a CVAE to reconstruct electromagnetic fields and utilized a convolutional neural network for source identification [2]–[3]. In these study, one quarter of the magnetic field distribution map was employed as the conditional label for field reconstruction, yielding satisfactory results for reconstruction across three distinct families of geometries. However, the design variables are often randomly distributed in inverse design rather than following a specific pattern. Furthermore, when the region of interest in the optimization is narrow, the limited amount of contained information presents significant challenges for training the CVAE effectively.

This paper proposes a CVAE-based model for fields reconstruction in the TEAM benchmark problem 35 [4]. Firstly,

in the training of the CVAE, coil distribution images generated from the optimization variables in TEAM benchmark problem 35 are used as conditional labels, with the magnetic field distribution serving as the target for reconstruction. Secondly, in the decoding stage, the latent vector required for decoding is determined by identifying a sample from the training dataset whose optimization variables (e.g., the ten radii in TEAM benchmark problem 35) have the smallest error compared to those of the input sample. Finally, the effectiveness of the proposed method is validated through experimental field reconstruction for TEAM benchmark problem 35.

II. THE PROPOSED METHOD

A. The CVAE

The CVAE is a generative model that extends the standard variational autoencoder by incorporating conditional information to guide the generation process. The architecture of a CVAE consists of three main components: the encoder, the latent space Z , and the decoder, as shown in Fig.1. The encoder (left) takes both the input data X and conditional labels Y to produce a latent representation Z , which captures the data distribution conditioned on Y . The decoder (right) uses both Z and Y to reconstruct the target output X_{pre} , ensuring the generated data aligns with the conditional constraints. The inclusion of the conditional labels in both the encoding and decoding processes allows the CVAE to generate outputs that are closely aligned with the desired characteristics specified by the labels.

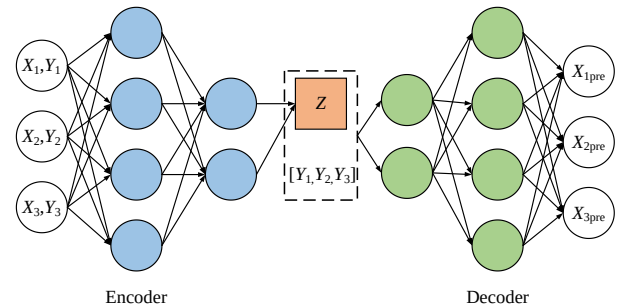


Fig. 1. The architecture of a CVAE.

B. The Proposed CVAE-based Method

TEAM benchmark problem 35 is a standard multi-objective optimization problem designed to evaluate optimization algorithms in electromagnetics [4]. It involves the design of radii of ten coils to achieve specific magnetic field distributions in region Ω , as shown in Fig. 2, making it a widely used test case for validating the effectiveness of field reconstruction and optimization techniques.

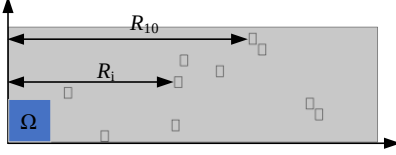


Fig. 2. Coil configurations of TEAM benchmark problem 35.

In the proposed approach, the CVAE is trained using coil distribution images generated from optimization variables as conditional labels, with the whole field distribution serving as the reconstruction target. This enables the CVAE to learn the relationship between the coil configurations and the corresponding field distributions, as shown in Fig. 3.

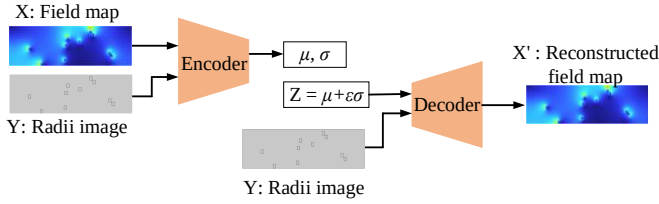


Fig. 3. The CVAE model training.

In the decoding phase, the proposed method selects the sample with the smallest error in the design variable (e.g., the radii of the coils in TEAM benchmark problem 35) from the training data, noted as Y_s , to help the given label Y to obtain the latent space,

$$Y_s = Y_{\min} \|R_i - R_Y\| \quad (1)$$

where Y_s is the chosen label image of coils distribution, R_i is the ten radii vector of the i^{th} radii image from the training data, R_Y is the ten radii vector of the given label Y . The corresponding latent vector, Z_s , generated by the encoder by Y_s , is then used as the input to the decoder to reconstruct the field distribution.

III. EXPERIMENTS AND RESULTS

The CVAE is trained using a total of 1,024 randomly generated solutions, of which 80% (819 solutions) are allocated to the training set, and the remaining 20% (205 solutions) are used for the test set. The architecture of the CVAE follows the design described in [2]. Training is conducted for 2,000 epochs, with a mini-batch size of 220 and a learning rate of 0.001 for the Adam optimizer. All images are resized to 84×30 pixels, consistent with the approach in [2]. In the training process, the loss function is defined as a combination of two components: the reconstruction loss which measures the discrepancy between the original and the decoded field map, and the Kullback-Leibler Divergence (KLD) term [5] which regularizes the latent space,

$$\text{loss} = \text{mse}(X', X) + 0.1\text{KLD} \quad (2)$$

where X is the original field map, X' is the reconstructed magnetic field map. The convergence of the training loss with respect to the number of epochs is shown in Fig. 4. The model exhibits high efficiency in learning complex spatial relationships between coil distributions and the resulting field patterns, with fluctuations in the later stages remaining minimal, confirming its robustness and reliability.

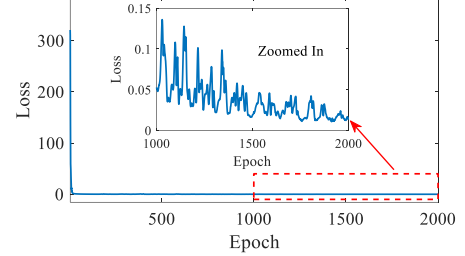


Fig. 4. Training loss with respect to the number of epochs.

In the reconstruction phase, as depicted in Fig. 5, the proposed method accurately reconstructs the field maps for randomly generated radius distributions across four test cases. The reconstructed maps closely align with the original field distributions, preserving critical spatial features and field variations, demonstrating the model's ability to generalize effectively under varying and non-fixed radius distributions. Furthermore, the method's independence from requiring any magnetic field distribution as a condition and its reliance solely on arbitrary radius distributions further highlight its practical flexibility and broader applicability. A more detailed exploration of optimization experiments and an in-depth analysis to further substantiate the proposed method's effectiveness and advantages will be presented in the full paper.

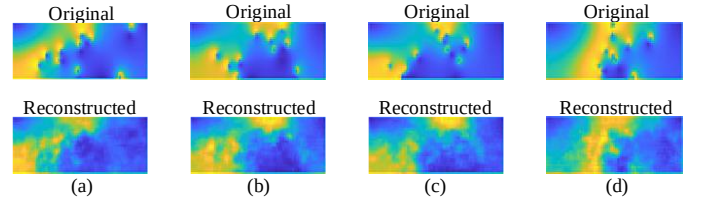


Fig. 5. Comparison of original and reconstructed field map for four random test cases, (a) case 1, (b) case 2, (c) case 3, (d) case 4.

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