Electromagnetic Field Estimated by Improved U-net Neural Network

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Abstract

In this paper, the distribution of electromagnetic from the two-dimensional (2-D) finite element analysis of the simplified transformer is estimated by the convolutional neural network (CNN) model U-net improved with ResNet. By changing the geometric dimension, material property and current excitation, the image dataset with different parameters is obtained and additionally expanded by scaling, flipping and rotating. Based on it, the weight parameters of improved U-net model are trained and the optimization for the model is carried out by hyperparameters searching, which improves the estimation precision of the electromagnetic field distribution of the transformer. The estimation results prove the effectiveness of the method.

1 Introduction

Deep learning has become a new method to predict the multi-physical field distribution of the electromagnetic equipment in recent years. Meanwhile, numerical modelling analysis by finite element analysis (FEM) is a widely used method of multi-physics field analysis. Because the numerical analysis is time-consuming, the proxy model is used as an alternative to improve the computation speed under an acceptable accuracy loss. Neural network model has been widely applied in the estimation of electromagnetic field, fluid field, and stress field. U-net architecture is used for the great advantages in small sample sets of restoring images through the skip-connection which extracts the features from the input images and maps them to the output [1]. The estimation of electromagnetic field is essentially a dense regression problem [2].

In this paper, the distribution of electromagnetic field of the simplified model of single-phase dry-type transformer is calculated by FEM. The dataset consisting of electromagnetic simulation images containing the information of dimensions, material properties and current excitations is established. Based on the platform of TensorFlow 2.0, improved U-net models with ResNet blocks and attention respectively are trained to solve the problem of pixel level dense regression. And accurate estimation of electromagnetic field distribution in electrical equipment is realized.

2 Physical model of transformer

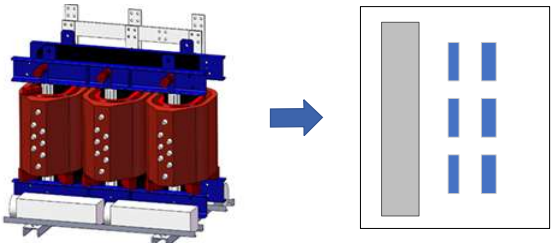
The simplified model of a single-phase transformer is shown in Fig. 1, where the structures of clamps, struts and fans are ignored, and only the key parts are retained, namely the core and winding with important impact on electromagnetic field distribution. The electromagnetic equations of the eddy current region are as follows:

$$\nabla \times (\frac{1}{\mu} \nabla \times \boldsymbol{A}) = -(\boldsymbol{J}_s + \boldsymbol{J}_e) \tag{1}$$

$$\boldsymbol{J}_e = -\sigma_e (\frac{\partial \boldsymbol{A}}{\partial t} + \nabla \varphi) \tag{2}$$

$$\nabla \cdot (\boldsymbol{J}_s + \boldsymbol{J}_e) = 0 \tag{3}$$

Where $\boldsymbol{A}$ is magnetic vector potential, φ is electric scalar potential, $\boldsymbol{\mu}$ is magnetic permeability tensor, $\boldsymbol{J}_s$ is the source current density of the conductor, Je is the eddy current density induced by leakage flux, and $\boldsymbol{\sigma}_e$ is electric conductivity.



(a) (b)

Fig. 1: Physical model. (a) Dry-type transformer (b) Simplified 2-D model

3 Magnetic field estimation

3.1 Deep learning model

The U-net architecture is a full convolutional network consisting of 4 encoder layers, 4 decoder layers and skip-connections [1]. The most prominent characteristic of U-net is that the feature at the down sampling end can skip deep sampling and be splicing to the corresponding up sampling end. The back-propagation algorithm is used to reduce the MSE loss.

When information transmits in deep convolutional networks, performance degradation will be caused by gradient disappearance or gradient explosion, which leads to the failure of effective updating of deep weight parameters. ResNet adds a direct connection channel in ResNet block, directly transferring input information to output through identity skip connection. The difference between input and output becomes easier to be captured, which makes the training process more efficient. Besides, attention mechanism has been widely used in computer vision, which can be regarded as a dynamic weight adjustment process based on the input image features and the ground truth [3]. In this paper, ResNet and attention blocks are all added to improve U-net, which makes training easier and improves prediction accuracy. The overview of improved U-net architecture is shown in Fig. 2.

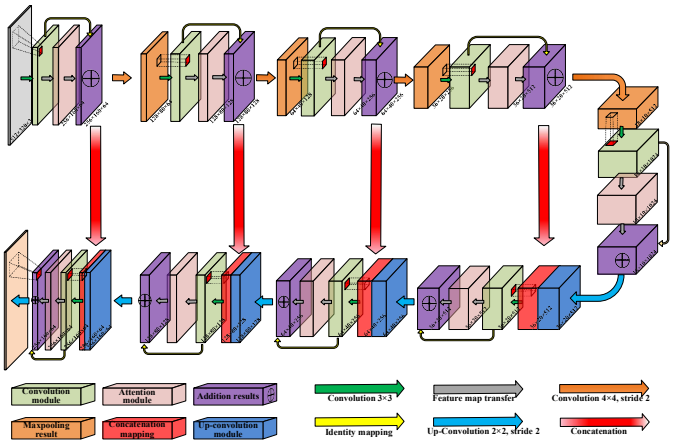
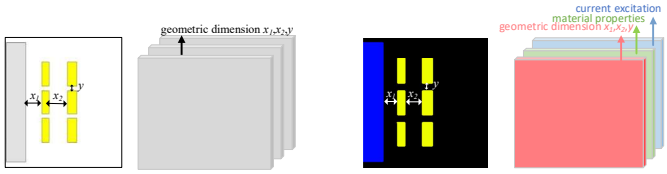


Fig. 2: The overview architecture of Improved U-net.

3.2 Datasets

The quality and scale of dataset have a crucial effect on the training of deep learning network weight parameters. Based on Maxwell's parameterized modelling, a simplified 2-D finite element model of single-phase dry-type transformer is established. The model and the computed magnetic density distribution are recorded as input x and label y.

To explore the influence of different datasets, original RGB images and preprocessing images are trained for comparison. The information in preprocessing images dataset is more explicit. The variation ranges of geometric dimensions between winding, material characteristics and current excitations are considered. To improve the generalization ability, the original training set has been enhanced by the operation of flipping, rotation, and scaling. A new dataset of 3000 images is generated, including 2700 in training set, 270 for validation set and 30 for test set. The process of generating datasets is shown in Fig. 3.



(a) (b)

Fig.3: Two types of datasets. (a) Original RGB images dataset (b)Preprocessing images dataset

3.3 Magnetic field estimation

Trained by the two datasets, the magnetic field estimated results show that the performance of the model trained by three-channel dataset is almost the same with the model trained by the single-channel dataset on the verification set in the early stage. However, when the epoch is greater, three-channel model performs significantly better than single-channel model. Not only that, the addition of ResNet and attention modules have improved the efficiency of training and estimation accuracy.

4 Conclusion

The preprocessing images dataset containing material properties, current excitations and geometric dimensions can more effectively improve the precision than the original RGB images dataset. The U-net with ResNet and attention blocks shows more accurate calculation results. The validity of estimating electromagnetic field distribution through neural network is verified.

Acknowledgements

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