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RESEARCH ON STRESS DISTRIBUTION NEPHOGRAM OF MOTOR BASED ON GENERATIVE ADVERSARIAL NETWORKS

Technology

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ABSTRACT

In this paper, a research method of generative adversarial network(GAN), which is one of the most active algorithms in deep learning, is used to study the stress nephogram of motor stator. Combining the network with the finite element modeling and simulation calculation, the stator core model of a 4-Pair pole surface mounted permanent magnet synchronous motor is simulated by finite element method, and the stress of electronic stator at different time is obtained by simulation The data set matched with cloud map is used for network training. Two different generation countermeasure networks, pix2pixHD and Cyclegan, are trained. It is found that the two networks can achieve good nonlinear mapping for the stress simulation image of the motor, and can learn the feature mapping of the stator stress nephogram of two different time engraving machines from 0s to 0.05s. By adjusting the parameters and optimizing the loss function, 200 batches of iterations were carried out to keep the stress images generated by the network with high resolution and low resistance loss. It provides a theoretical and practical basis for deep learning in multi physical field modeling and motor optimization.

KEYWORDS

deep learning, generative adversarial network,motor stress analysis,image mapping,motor optimization

INTRODUCTION

At present, there are relatively few studies on applying deep learning neural networks to optimize motor design. This paper proposes to drill holes and add negative magnetostrictive materials to the simulation model to study the influence of negative magnetostrictive effects on the electromagnetic vibration of the motor under the rotating magnetic field, and find the best aperture to suppress the electromagnetic vibration of the motor[1]. And carried out simulations of different positions and different apertures, and obtained multiple sets of simulation experimental data including image data for training two different types of deep learning generative confrontation networks.

Train the convolutional neural network (CNN) in a supervised or unsupervised manner, and build a convolutional neural network with a variety of network architectures to complete various image-to-image mapping tasks[2-5]. By encoding the input image into a hidden representation, then decoding it into an output image. By compensating the difference between the output image and the real image, the best convolutional neural network can be trained to realize the nonlinear mapping from the input image to the transformed image. Literature [6] developed a deep learning model based on convolutional neural network, which is composed of three modules: shape coding, nonlinear mapping and stress decoding. The combination of supervised and unsupervised methods can quickly and accurately predict the results of finite element analysis. For medical research, it can output the stress distribution image of the patient's aortic wall within 1s.

This paper uses a pix2pixHD based on Conditional Generative Adversarial Network (cGAN). This model is an improvement and upgrade of the pix2pix in the basic conditional adversarial network from three aspects: generator, discriminator, and optimization target. The obtained motor stator stress cloud image data set, after adjusting the parameters and training, can well realize the mapping of the data set, and can generate high-resolution and quality images. It has great reference significance for deep learning neural network in the direction of multi-physics modeling and optimization.

Establish A Finite Element Numerical Model To Obtain Training Data

In this paper, a finite element simulation of a stator core model of a 4-pair pole-face mounted permanent magnet synchronous motor is carried out. It is found that in the magnetic density concentration area of the motor stator teeth, the degree of magnetic circuit deflection is large, and the magnetic field distortion at the tip and root of the stator tooth Area, the stress on the stator core is greater. Therefore, the finite element simulation of the scanning traversal calculation of the punching position and the punching radius was performed on the stator core, and the area between the stator teeth where the magnetic density was concentrated and the area between the top and the boundary of the stator teeth where the magnetic density was relatively small were scanned respectively.The scanning simulation results are exported as stress cloud diagrams for later training of two different deep learning neural network models, learning the mapping between the stress cloud diagrams of the electronic stator at different times, and generating stress images similar to the simulation with higher resolution.

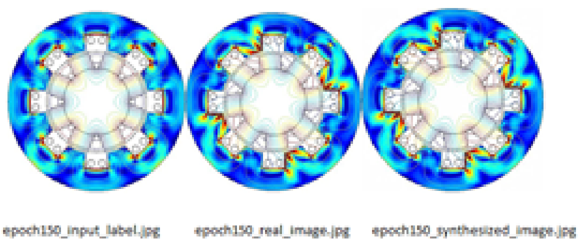

Figure 1: The Train Result Of Eporch150

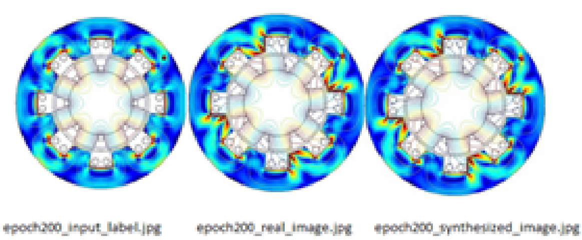

Figure 2: The Train Result Of Eporch200

GAN NETWORK MODEL

Gan Network Structure

GAN network consists of two parts: generator (G) and discriminator (D)[7]. In essence, both are implicit function expressions, implemented by deep neural networks. The generated data is G(z), and its distribution is $p_g(z)$. The goal of GAN is to make $p_g(z)$ similar to the distribution of training samples $p_r(x)$. The input D can be real data x or generated data G(z). The result of D is the probability or scalar that predicts whether the input of D comes from a real distribution.

The generator is G represented by a differential function. G collects random variables z from the prior distribution, and maps the pseudo-sample distribution G(z) through a neural network. This process is up-sampling. The input z usually uses Gaussian noise. Is a random variable or a random variable in the latent space. After the GAN starts training, the parameters of G and D begin to iteratively update. When G is trained, the parameters of D are fixed. The data generated by G is marked as fake data and then input into D. The error is calculated between the output of the discriminator D (G(z)) and the sample label, and the parameters of G are updated by the error back propagation algorithm.

GAN Loss Function

The loss function of GAN is based on a two-person minimax game, which contains two neural networks that compete with each other in a zero-sum game framework. The two participants are represented by two functions, whose input and parameters are different. The discriminator function uses D, its input is x and (D), and its loss function is:

Among them, represents the real data distribution, and represents the generated data distribution. G represents the functional function of the generator.

EXPERIMENTAL RESULTS

What this article uses is a kind of Pix2PixHD in the improved Generative Adversarial Network-Conditional Adversarial Network. The model requires paired data sets for training. The previous work has already obtained the required data sets. By adjusting the parameters, the deep learning framework Pytorch, and improved experimental equipment, using GPU is 12G, NVIDA TITAN XP, and finally can well realize the mapping of the electronic stator stress cloud map from 0s to 0.05s. Our network can visualize the training process of each batch, and can generate HTML files for easy viewing. This article selects two different batches of training results, as shown in Figure 1 and Figure 2. As shown in the figure, the leftmost is the input image, the middle is the image simulated by finite element calculation, and the rightmost is the image trained by the network. We can find that the network can well realize the mapping of motor stress cloud. It can be found that the use of generative adversarial network in this paper can maintain a high resolution, which has guiding significance for deep learning to optimize physical field modeling.

CONCLUSIONS

This article first establishes a numerical model, performs finite element calculations, and finds a relatively optimal position to reduce the stress through simulation calculations, which can reduce the surface stress by 7% when the motor starts to stabilize, and realizes the suppression of a part of electromagnetic vibration and noise the goal of. Then the simulated data was exported, preprocessed to train the deep learning model, and trained to generate the confrontation network Pix2PixHD, which well realized the mapping of the motor stator stress cloud map at different times, and generated a very high-resolution stress cloud map. It has a certain reference role for deep learning in finite element calculation and motor optimization direction.

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