Implementation of Convolutional Neural Networks for Predicting Vortical Flow Field

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1. Introduction

Multi-objective optimization should be conducted in a design process given that airfoil design entails a number of aerodynamic requirements, such as high lift, low drag, and stall characteristics [1]. These aerodynamic requirements can be obtained through flow field analysis using computational fluid dynamics (CFD) simulations. However, CFD simulations require a lot of time and expensive computation in the air foil design process.

Recently, deep learning [2] has received considerable attention in the field of fluids. Therefore, some researchers are committed to predicting airfoil flow fields. Afshar et al. [3] proposed an approximation model based on convolution neural networks (CNN) to predict the velocity and pressure field for new geometries under new flow conditions. Sekar et al. [4] used CNN to parameterize the airfoil image with some useful parameters.

In this research, we propose an airfoil flow field prediction model that uses deep learning technology instead of CFD simulation. Among the various deep learning models, pix2pix method [5] for image-to-image transformation has been selected.

2. Methods

This section describes the deep learning techniques used to predict the airfoil flow field and the data used to train the deep learning.

2.1 Generative adversarial network (GAN)

A GAN [6] is one of the generative models and one of the most actively research topics in deep learning. The GAN architecture consists of a generator and discriminator, which generate data through adversarial training. The generator produces fake data from random vector noise and the discriminator distinguishes between real and fake data. The generator is trained to generate data that discriminator cannot distinguish from real data, and discriminator is trained to accurately distinguish fake data from real data. The architecture of GAN is shown in Fig. 1(a).

2.2 Conditional Generative Adversarial Networks (cGAN)

cGAN [7] is a variant of GAN and has been proposed to conditionally generate data. These cGAN conditions can be input in various forms such as noise vectors, images, and class labels. The architecture of the cGAN is shown in in Fig.1(b)., where the input Z and condition C are combined and provided to the generator, and the input to the discriminator is also provided combined with condition C.

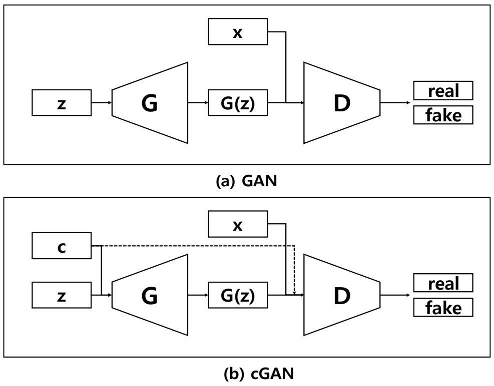

Fig. 1. architecture of GAN and cGAN.

2.3 Image-to-Image Translation with Conditional Adversarial Net (pix2pix)

pix2pix is a universal solution to the image-to-image translation problem utilizing cGANs. The generator of pix2pix is a U-net architecture that is universally used in the image-to-image translation. U-net is a structure that directly connects the encoder layer and the decoder layer through 'skip connection'. Through skip connection, more stable learning than a simple encoder-decoder architecture is possible. The discriminator employs a convolutional PatchGAN classifier. PatchGAN classifies images by patches of a specific size, rather than the entire area. This trains the generator to produce more realistic images. The architecture of the pix2pix is shown in Fig. 2.

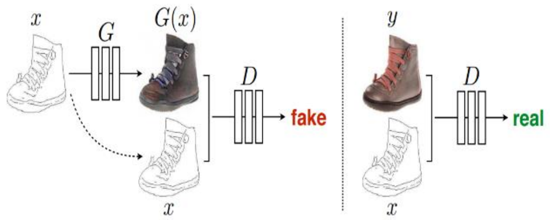

Fig. 2. Structure of pix2pix [3]

2.3 Airfoil Flow Field Prediction with pix2pix

In this study, pix2pix is used to predict the airfoil flow field. It uses a 19-coordinate image of the airfoil as input and the image of the airfoil flow field as the target. Additionally, the angle of attack of the airfoil is displayed as a graph and the Reynolds number is displayed as text. The flow chart of pix2pix for airfoil flow field prediction is shown in Figure 3.

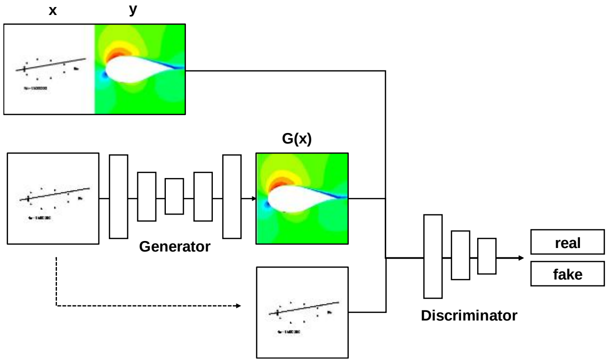

Fig. 3. The flow chart of pix2pix for airfoil flow field prediction

The objective function for training is as Equation (1). L_{cGAN} is a loss function of cGAN, which is optimized towards minimizing the parameter for generator and maximizing the parameter for discriminator. The L_{cGAN} loss function is the same as Equation (2). L_{L1} is optimized towards minimizing difference between actual value (y) and predicted value G(x). L_{L1} is the same as Equation (3). λ is the hyper-parameter that balances the L_{cGAN} and L_{L1}.

$$G^* = argminmaxL_{cGAN}(G,D) + \lambda L_{L1}(G) \quad (1)$$

$$L_{cGAN}(G,D) = \mathbb{E}_{x,y}[logD(x,y)] + \mathbb{E}_{x,z}[1 - D(x, G(x,z))] \quad (2)$$

$$L_{L1}(G) = \mathbb{E}_{x,y,z}[\| y - G(x,y) \|_1] \quad (3)$$

2.5 Dataset

In order to train pix2pix, a dataset was obtained using CFD in-house code with genetic algorithm [1]. By applying a genetic algorithm, up to 400 airfoil flow fields of various shape were obtained for each calculation condition. Simulations are performed over the DU 00-W2-401, DU 00-W2-350, DU 97-W-300, DU 91-W2-250 and DU 93-W-210 airfoils. Simulations are performed at Reynolds numbers of 0.5×10^6, 1.5×10^6 and 3.0×10^6 and with an angle of attack of 0° to 18°.

The flow fields are obtained by solving the Reynolds Averaged Navier-Stokes (RANS) equations utilizing the finite volume method, for which the *k-w* turbulence model is employed. The obtained flow field structure was processed into 256×256 velocity field images using Tecplot.

3. result

3.1 Implementation Details

We constructed two datasets based on the dataset described in subsection 2.5. In Dataset 1, airfoil flow field datasets of various shapes were constructed by applying a constant angle of attack and Reynolds number to 0◦and 1.5×10^6. In dataset2, five angles of attack and three Reynolds numbers were applied to construct airfoil flow field data of various shapes. Detailed data set information is shown in Table 2. The dataset was divided into training data, validation data, and test data by dividing the data set in a ratio of 4:1:1.

We train the model with the ADAM optimizer by setting $\beta_1 = 0.5$, $\beta_2 = 0.999$ and $\varepsilon = 10^{-8}$. The initial learning rate is initialized to 0.0002

Table 1. Computational grid system of 8-pitch heat pipe

	Condition	value
Dataset1	Airfoil	DU 00-W2-401
		DU 00-W2-350
		DU 97-W-300
		DU 91-W2-250
		DU 93-W-210
	Re	1.5×10^6
	AOA	10◦
	number of total data : 606	
Dataset2	Airfoil	DU 00-W2-401
		DU 00-W2-350
		DU 97-W-300
		DU 91-W2-250
		DU 93-W-210
	Re	0.5×10^6, 1.5×10^6, 3.0×10^6
	AOA	$0^\circ, 5^\circ, 10^\circ, 15^\circ, 18^\circ$
	number of total data : 12405	

3.2 Shape variation (dataset 1)

Dataset 1 was trained on a batch sizes of 2. After training process of 250 epochs, the MAEs of training and validation datasets were 0.06602 and 0.1162, respectively. The total learning time is 2 hours 22 minutes. The MAE of the test data set was 0.1369. The test result is shown in Figure 4.

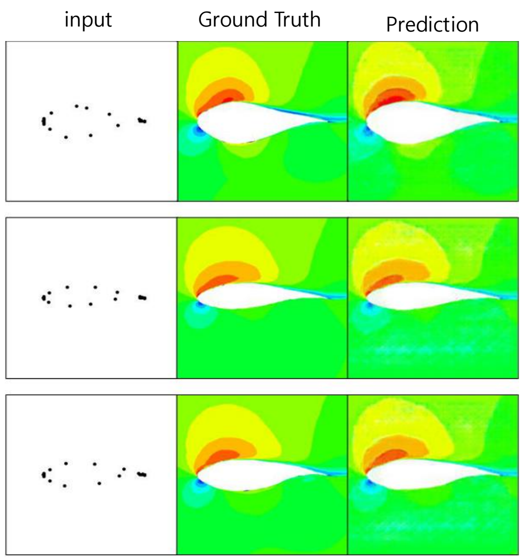

Fig. 4. The flow chart of pix2pix for airfoil flow field

3.3 Shape, angle of attack, and Reynolds number variation (dataset 2)

Dataset 2 was trained on a batch sizes of 10. After training process of 50 epochs, the MAEs of training and validation datasets were 0.06425 and 0.06245, respectively. The total learning time is 7 hours 10 minutes. The MAE of the test data set was 0.0764. The test result is shown in Figure 5.

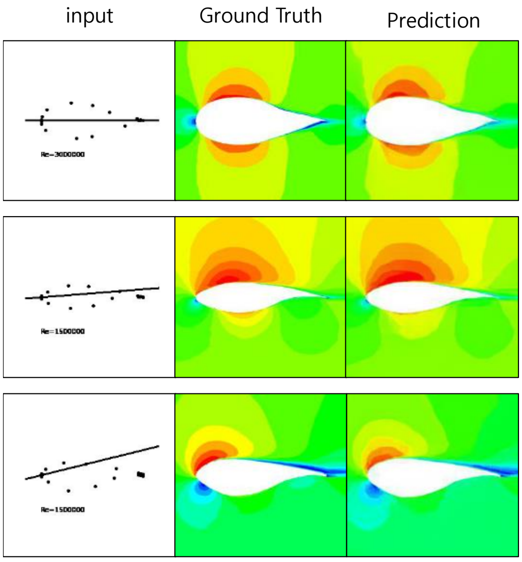

Fig. 5. The flow chart of pix2pix for airfoil flow field

4. Conclusion

The pix2pix method is implemented to predict the airfoil flow field using thick airfoil shapes with various Reynolds numbers and angle of attack. CNN has been successfully implemented using fully implicit high resolution scheme based compressible CFD code with a genetic algorithm to train pix2pix. As a result of the deep learning, vortical flow fields can be predicted well through pix2pix method. In the future, the pix2pix method will be further advanced and used as a design tool.

The pix2pix method is a universal solution to the image-to-image translation problem. Therefore, various applications are possible depending on a dataset used for training. In the nuclear field, we will obtain a temperature and pressure field datasets of the Bayonet Heat Exchanger of the Micro Reactor. In addition, by training the constructed datasets with the pix2pix method, Convolutional Neural Networks that predict the temperature and pressure fields of the Bayonet Heat Exchanger will be implemented and used as a shape optimization design tool.

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