ABSTRACT
This study presents a deep learning-based framework to reconstruct high-resolution turbulent velocity fields from extremely low-resolution data at various Reynolds numbers using the concept of generative adversarial networks (GANs). A multiscale enhanced super resolution generative adversarial network (MS-ESRGAN) is applied as a model to reconstruct the high-resolution velocity fields, and direct numerical simulation (DNS) data of turbulent channel flow with large longitudinal ribs at various Reynolds numbers are used to evaluate the performance of the model. The model is found to have the capacity to accurately reproduce high-resolution velocity fields from data at two different low-resolution levels in terms of the quantities of velocity fields and turbulent statistics. The results further reveal that the model is able to reconstruct velocity fields at Reynolds numbers that are not used in the training process.

KEY WORDS
DNS, High-resolution reconstruct, Deep learning

1. INTRODUCTION
Reconstruction of high-resolution (HR) images from low-resolution (LR) images has been an active area of research in the field of computer science. Meanwhile one of the major pursuits in both experimental and computational fluid dynamics is the need for high-resolution flow data[1]. The resolution reconstruction of images from their low-resolution data is called as resolution analysis. Bicubic interpolation is a traditional image processing method using cubic convolution algorithm[2]. Besides, using convolutional neural network (CNN) and the hybrid down-sampled skip-connection/multi-scale (DSC/MS) model to do super-resolution analysis is a more efficient method[3]. However, above models do not perform well enough in the reconstruction of super low resolution. In this study, we will utilize more advancing deep learning network named enhanced super-resolution generative adversarial networks (ESRGAN) to reconstruct HR channel flow data from SR data[3]. And, based on this model, we also did some improvements. As for data, all the training and testing data with various Reynolds Number (Re) is generated by DNS.

2. Methodology
2.1 Training data
Re turbulent flow data with variant Re is obtained from direct numerical simulation (DNS). The simulation model is 3D channel flow with large longitudinal ribs[4], but in this project we only use 2D slices snapshots collected from 3D data, as show in Fig. 1. We totally choose 3 Re flow data that is Re=292, Re=550, Re=850. Every Re flow data includes 8000 snapshots of training data as well as 2000 snapshots of testing data, respectively. Different Re training data is mixed together and make those data random, then, input them to ESRGAN to do training work. As for low resolution flow data, we use Maxpooling and Upsampling to get LR data. We choose 3 different LR data, medium LR, low LR and super low LR, which represents doing 3 times, 4 times and 5 times Maxpooling and Upsampling, respectively. 2.2 Deep learning network
Usually, the normal GAN is constituted by two parts, namely, generator and discriminator as show in Fig. 2. Compared with normal GAN, the main improvements of ESRGAN are two things. For one thing, it is using Residual-in-Residual Dense Block (RRDB) in generator. For another, we use relativistic discriminator to get a new-defined loss. What is more, we also use perceptual loss in generator that is the compression of the output from VGG after we input ground truth (GT) and generated HR to pretrained VGG network[5].

Fig.1: Channel flow contour of velocity u with 292 Re.
3. Conclusion

Expectant result is that medium and low resolution LR is reconstructed well from LR to HR with a less than 0.003 mean square error (mse) compared to ground truth images. But the super low LR data may not be reconstructed well enough without some detailed features compared to ground truth images.

There are still many ways to improve the ESRGAN, such as using 3 different layers of VGG to output image features before calculating perceptual loss or using Multi-scale CNN in generator network.

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