Oral presentation | Turbulence simulation (DNS,LES,RANS)

Turbulence simulation(DNS,LES,RANS)-II

Wed. Jul 17, 2024 4:30 PM - 6:30 PM Room B

[9-B-02] Implicit U-Net Enhanced Fourier Neural Operator for Long-Term Dynamics Prediction in Turbulence

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Keywords: Large-eddy simulation, Data-driven, Fourier neural operator, Incompressible turbulence

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力学与航空航天工程系 DEPARTMENT OF MECHANICS AND AEROSPACE ENGINEERING

Implicit U-Net Enhanced Fourier Neural Operator for Long-term Dynamics Prediction in Turbulence

Zhijie Li, Wenhui Peng, Zelong Yuan and Jianchun Wang*

Speaker: Zhijie Li

Date: 17/07/2024

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Part 01

Research Background

Research Background

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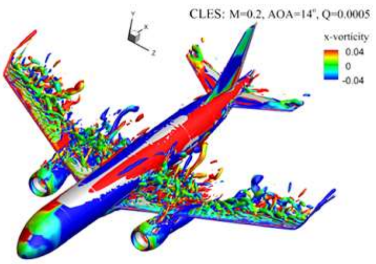
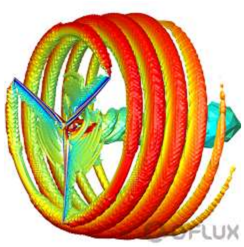
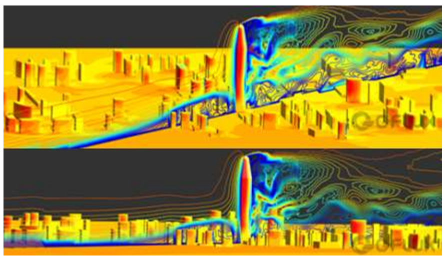
Turbulence is one of the core issues in fluid mechanics







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Research Background

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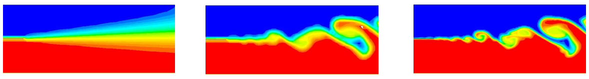
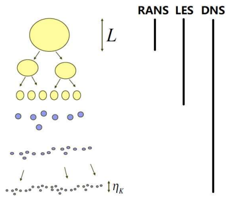
Numerical simulation

Reynolds-averaged Navier–Stokes simulation (RANS)	large-eddy simulation **(LES)**	direct numerical simulation (DNS)





Accuracy：RANS<LES<DNS

Efficiency：RANS>LES>DNS

GOVERNING EQUATIONS：

$$\tau_{ij} = \overline{u_i u_j} - \bar{u}_i \bar{u}_j$$

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0, \quad \frac{\partial \bar{u}_i}{\partial t} + \frac{\partial(\bar{u}_i \bar{u}_j)}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} - \frac{\partial \tau_{ij}}{\partial x_j} + v\frac{\partial^2 \bar{u}_i}{\partial x_j \partial x_j} + \overline{\mathcal{F}}_i.$$

SUBGRID SCALE MODEL

- Smagorinsky 模型： $\tau_{ij} = -2C_S^2 \Delta^2 |\bar{S}| \bar{S}_{ij} + \frac{\delta_{ij}}{3}\tau_{kk}$
- 梯度模型： $\tau_{ij}^G = \frac{\Delta^2}{12} \frac{\partial \bar{u}_i}{\partial x_k} \frac{\partial \bar{u}_j}{\partial x_k}$
- 相似模型： $\tau_{ij}^S = \widetilde{\bar{u}_l \bar{u}_j} - \tilde{\bar{u}}_i \tilde{\bar{u}}_j$
- 混合模型： $\tau_{ij}^{M1} = C_1 \tau_{ij}^{\mathrm{Smag}} + C_2 \tau_{ij}^S$
  $\tau_{ij}^{M2} = C_1 \tau_{ij}^{\mathrm{Smag}} + C_2 \tau_{ij}^G$

Neural Network Alternative Models?

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Part 02

Research methods and ideas

研究内容及思路——FNO模型介绍

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Fourier neural operator[1] (FNO)

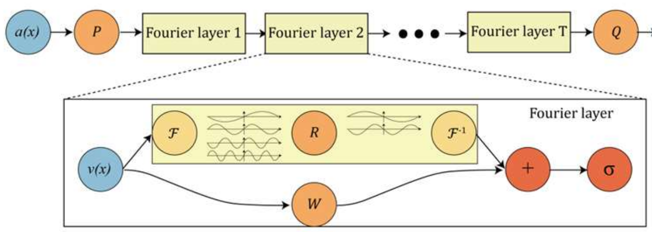

图 1. 傅里叶神经算子模型框架[1]

$$v_{t+1}(x) = \sigma\left(W v_t(x) + \left(\mathcal{K}(a;\phi)v_t\right)(x)\right)$$

$$\left(\mathcal{K}(\phi)v_t\right)(x) = \mathcal{F}^{-1}\left(R_\phi \cdot (\mathcal{F}v_t)\right)(x)$$

- Neural operators mainly learn mappings between function spaces.
- Learning coefficients in Fourier space, FFT improves computational efficiency

[1] Li, Zongyi, et al. "Fourier neural operator for parametric partial differential equations." arXiv preprint arXiv:2010.08895 (2020).

研究内容及思路——FNO相关研究现状

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表I. 不同神经网络模型在2-d Navier Stokes方程中的表现[1]

Config	Parameters	Time per epoch	$\nu = 1\mathrm{e}{-3}$ $T = 50$ $N = 1000$	$\nu = 1\mathrm{e}{-4}$ $T = 30$ $N = 1000$	$\nu = 1\mathrm{e}{-4}$ $T = 30$ $N = 10000$	$\nu = 1\mathrm{e}{-5}$ $T = 20$ $N = 1000$
FNO-3D	6,558,537	38.99s	**0.0086**	0.1918	**0.0820**	0.1893
FNO-2D	414,517	127.80s	0.0128	**0.1559**	0.0834	**0.1556**
U-Net	24,950,491	48.67s	0.0245	0.2051	0.1190	0.1982
TF-Net	7,451,724	47.21s	0.0225	0.2253	0.1168	0.2268
ResNet	266,641	78.47s	0.0701	0.2871	0.2311	0.2753

- The FNO model has the highest accuracy, surpassing the SOTA model

FFNO[2], AFNO[3], geo-FNO[4] improve innovation in two-dimensional flow

Can it be applied to complex three-dimensional turbulence?

[1] Li, Zongyi, et al. "Fourier neural operator for parametric partial differential equations." arXiv preprint arXiv:2010.08895 (2020).
[2] Tran, Alasdair, et al. "Factorized Fourier Neural Operators." arXiv preprint arXiv:2111.13802 (2021).
[3] J. Guibas, M. Mardani, Z. Li, A. Tao, A. Anandkumar, and B. Catanzaro, "Adaptive fourier neural operators: Effcient token mixers for transformers," arXiv preprint arXiv:2111.13587 (2021).
[4] Z. Li, D. Z. Huang, B. Liu, and A. Anandkumar, "Fourier neural operator with learned deformations for pdes on general geometries," arXiv preprint arXiv:2207.05209 (2022).

研究内容及思路——FNO模型训练框架

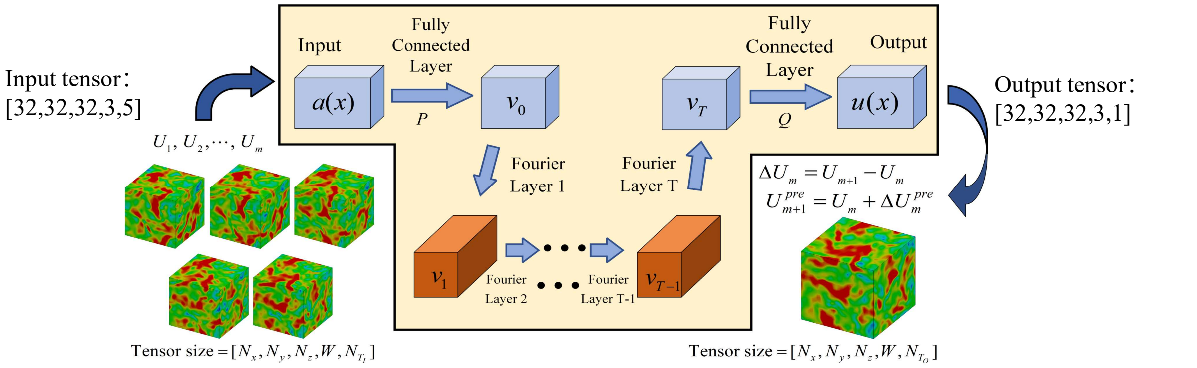


图 2. FNO模型用于三维湍流大涡模拟预测

Model training：(fDNS data)

Input： velocity field at the first five moments $(T_1, T_2, T_3, T_4, T_5)$

Output： velocity error field between the 6th and the 5th $(T_6 - T_5)$

Predict：

In： $(T_1, T_2, T_3, T_4, T_5)$

Out： $(T_6^{pre} - T_5)$

$(T_2, T_3, T_4, T_5, T_6^{pre}) \Rightarrow T_7^{pre}$

$(T_3, T_4, T_5, T_6^{pre}, T_7^{pre}) \Rightarrow T_8^{pre}$

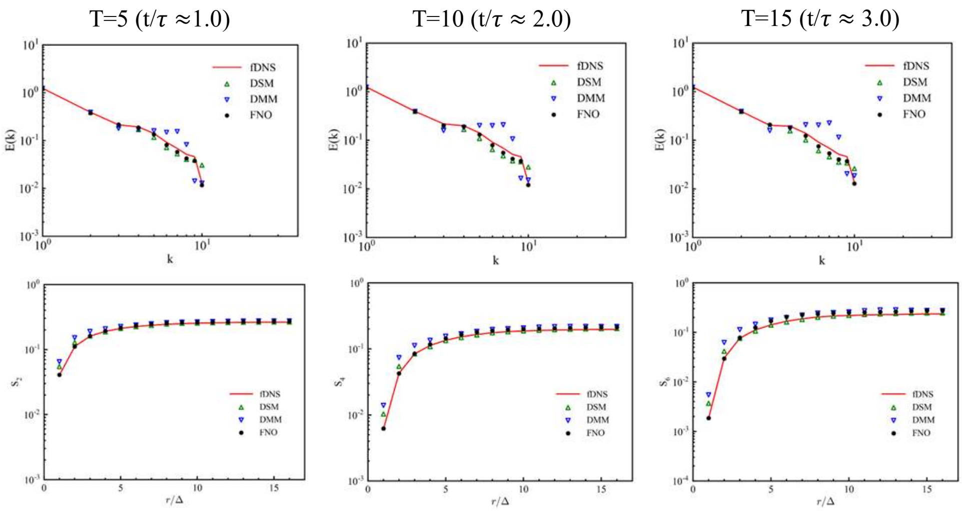
⋮

FNO模型——统计量对比

Velocity spectrum：

Structural Function：

$$S_n(r) = \left\langle \left| \frac{\delta_r \bar{u}}{\bar{u}^{rms}} \right|^n \right\rangle$$

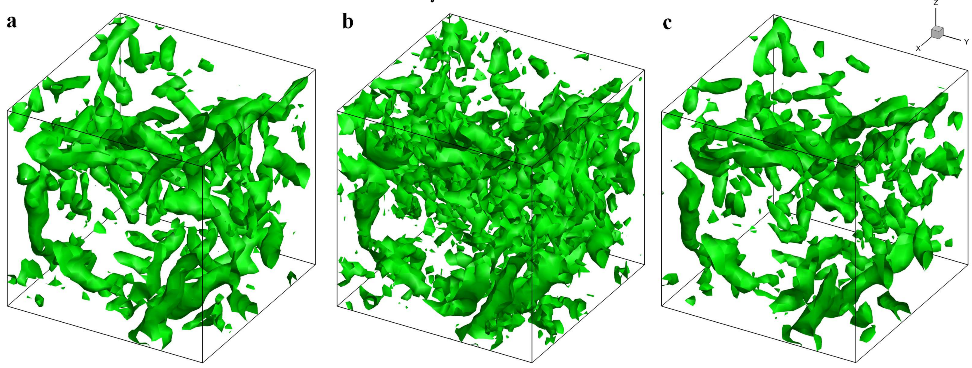


- The velocity spectrum and structure function predicted by the FNO model are more accurate than those of the traditional subgrid model DSM and DMM, and are in good agreement with the filtered DNS.

FNO模型——涡量等值面图

Vorticity 3D isosurface: qualitatively reflects the model's ability to reconstruct the coherent structure of the flow field

$\bar{\omega}/\bar{\omega}^{rms}_{fDNS} = 1.5$



- The FNO model has a more accurate ability to reconstruct the instantaneous flow field than the traditional sub-grid model DSM, and can well restore the flow field state of the filtered DNS.

第三部分

Part 03

基于FNO的改进模型

IU-FNO模型

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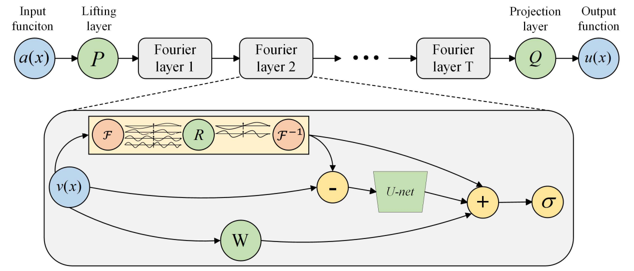

图 6. U-net enhanced Fourier neural operator (U-FNO)模型框架

U-FNO模型

$$v_{t+1}(x) := \sigma\left(W v_t(x) + \mathcal{F}^{-1}(R_\phi \cdot (\mathcal{F} v_t))(x) + \mathcal{U}^* s_t(x)\right), \quad \forall x \in D$$

$$s_t(x) := v_t(x) - \mathcal{F}^{-1}(R_\phi \cdot (\mathcal{F} v_t))(x), \quad \forall x \in D$$

提高精度

[1] Wen G, Li Z, Azizzadenesheli K, et al. U-FNO—An enhanced Fourier neural operator-based deep-learning model for multiphase flow[J]. Advances in Water Resources, 2022, 163: 104180.

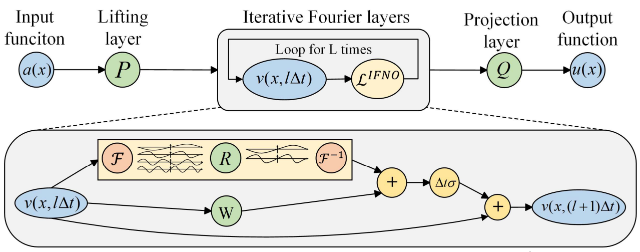

图 7. Implicit Fourier neural operator (IFNO) 模型框架

IFNO模型

$$v(x,(l+1)\Delta t) = \mathcal{L}^{IFNO}[v(x,l\Delta t)]$$
$$:= v(x,l\Delta t) + \Delta t\sigma\left(W v(x,l\Delta t) + \mathcal{F}^{-1}(R_\phi \cdot (\mathcal{F} v(x,l\Delta t)))(x)\right)$$

加深网络

[2] Li, Zongyi, et al. "Fourier neural operator for parametric partial differential equations." arXiv preprint arXiv:2010.08895 (2020).

IU-FNO模型

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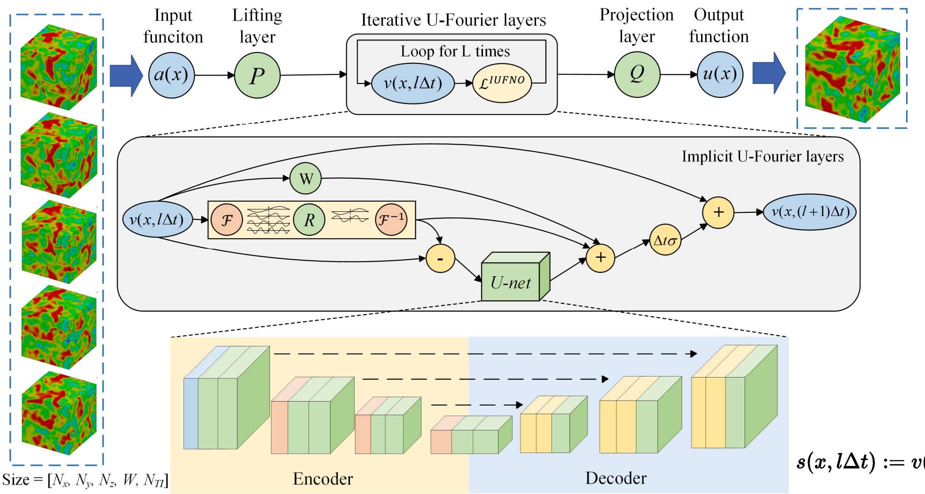

$$(T_1, T_2, T_3, T_4, T_5) \Rightarrow T_6^{pre}$$

$$(T_2, T_3, T_4, T_5, T_6^{pre}) \Rightarrow T_7^{pre}$$

$$\vdots$$

$$s(x,l\Delta t) := v(x,l\Delta t) - \mathcal{F}^{-1}(R_\phi \cdot (\mathcal{F} v(x,l\Delta t)))(x)$$

图 8. Implicit U-Net enhanced Fourier neural operator (IU-FNO) 模型

$$c(x,l\Delta t) := W v(x,l\Delta t) + \mathcal{F}^{-1}(R_\phi \cdot (\mathcal{F} v(x,l\Delta t)))(x) + \mathcal{U}^* s(x,l\Delta t)$$

$$v(x,(l+1)\Delta t) := v(x,l\Delta t) + \Delta t\sigma(c(x,l\Delta t))$$

IU-FNO模型

表 II. 网络参数对比结果.

Model	$L=4(T=4)$	$L=10$	$L=20$	$L=40$
FNO	331.80M	N/A	N/A	N/A
U-FNO	332.01M	N/A	N/A	N/A
IFNO	82.97M	82.97M	82.97M	82.97M
IU-FNO	83.02M	83.02M	83.02M	83.02M

- IU-FNO模型参数量不随层数而增加，相比于原始FNO模型参数量降低约75%

表 III. 最小loss误差结果对比

	(Training Loss, Testing Loss)			
Model	$L=4(T=4)$	$L=10$	$L=20$	$L=40$
FNO	(0.2250, 0.2548)	N/A	N/A	N/A
U-FNO	(0.1741, 0.1982)	N/A	N/A	N/A
IFNO	(0.2442, 0.2607)	(0.2163, 0.2281)	(0.1987, 0.2139)	(0.1850, 0.2010)
IU-FNO	(0.1916, 0.2108)	(0.1711, 0.1898)	(0.1395, 0.1631)	**(0.1433, 0.1547)**

- IU-FNO训练和测试的L_2误差更低

第四部分

Part 04

IU-FNO模型结果分析

- 均匀各向同性湍流(HIT)
- 自由剪切湍流
- 衰减湍流

1. 均匀各向同性湍流——稳定性对比

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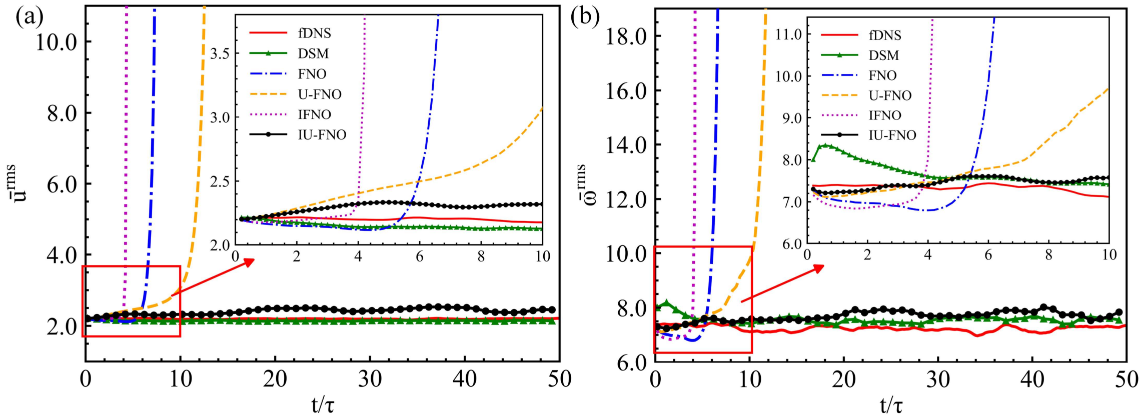

图 9. 速度RMS和涡量RMS随时间的演化结果

- 相比于其他FNO改进模型，IU-FNO模型能保持长时间预测的稳定性。

1. 均匀各向同性湍流——统计量对比

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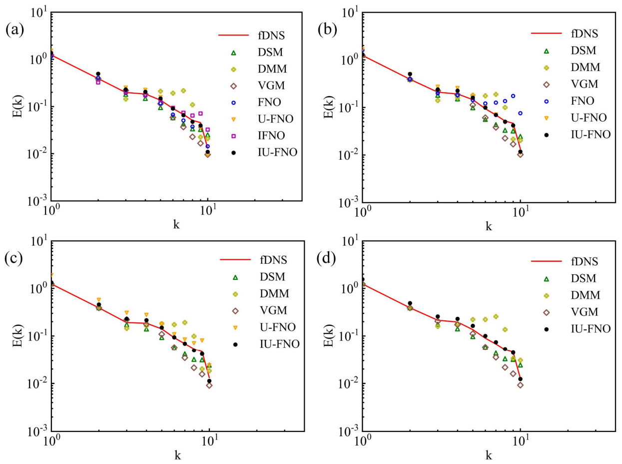

图 10. 不同模型预测的能谱对比: (a) $t/\tau \approx 4.0$; (b) $t/\tau \approx 6.0$; (c) $t/\tau \approx 8.0$; (d) $t/\tau \approx 50.0$

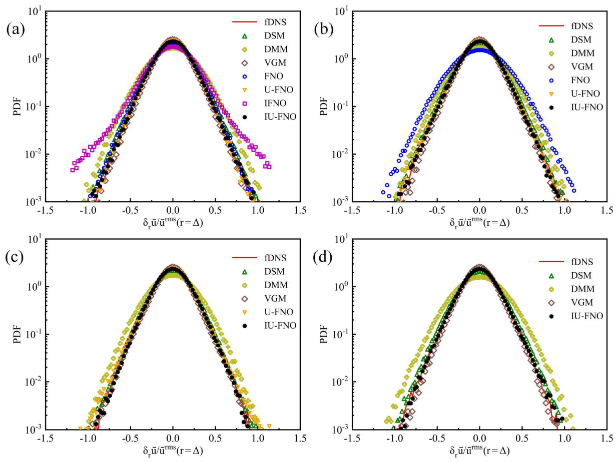

图 11. 不同模型预测的速度增量PDF对比: (a)$t/\tau \approx 4.0$; (b)$t/\tau \approx 6.0$; (c)$t/\tau \approx 16.0$; (d)$t/\tau \approx 50.0$

- IU-FNO模型对速度能谱和速度增量的PDFs在短时和长时的预测效果都比传统亚格子模型DSM，和FNO其他改进模型更准确，且与滤波后的DNS吻合得很好。

1. 均匀各向同性湍流——统计量对比

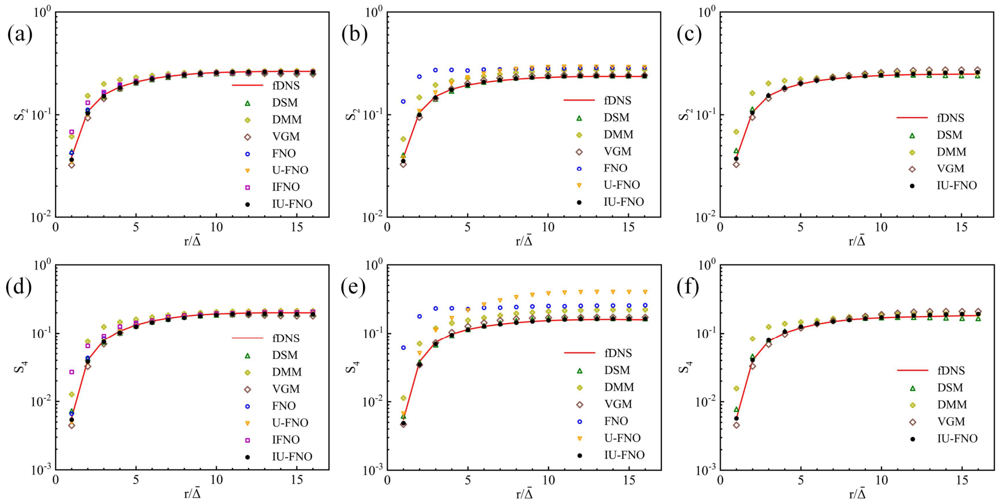

图 12. 不同模型预测的二阶及四阶结构函数

- IU-FNO模型预测得到的高阶统计量(二阶和四阶)相比于传统亚格子模型DSM更准确，且与滤波后的DNS吻合得很好。

2. 自由剪切湍流——统计量对比

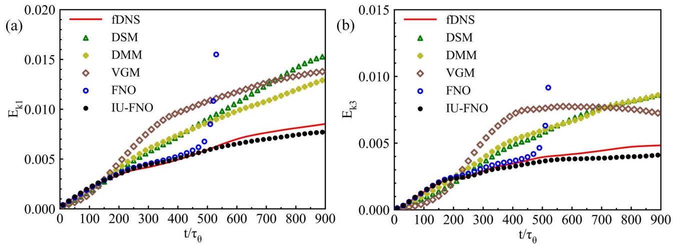

图 17. 流向湍动能E_{k1} 和展向湍动能 E_{k3} 随时间的演化

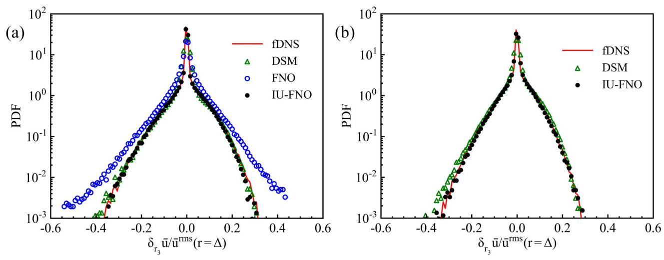

图 18. 不同模型预测的展向速度增量的PDF: (a)$t/\tau_\theta \approx 500$ (b)$t/\tau_\theta \approx 900$.

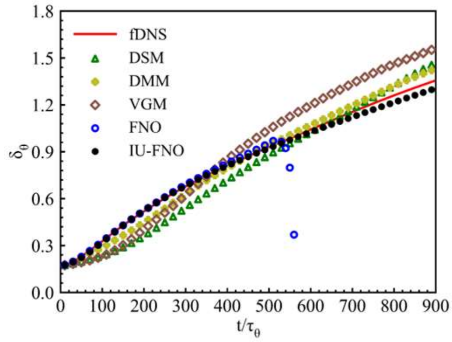

图 19. 动量层厚度δ_θ 随时间的演化

- IU-FNO模型预测得到的流向湍动能、展向湍动能、速度增量PDF和动量层厚度变化相比于传统亚格子模型DSM和原始FNO更准确，且与滤波后的DNS吻合得很好。

2. 自由剪切湍流—— Q判据

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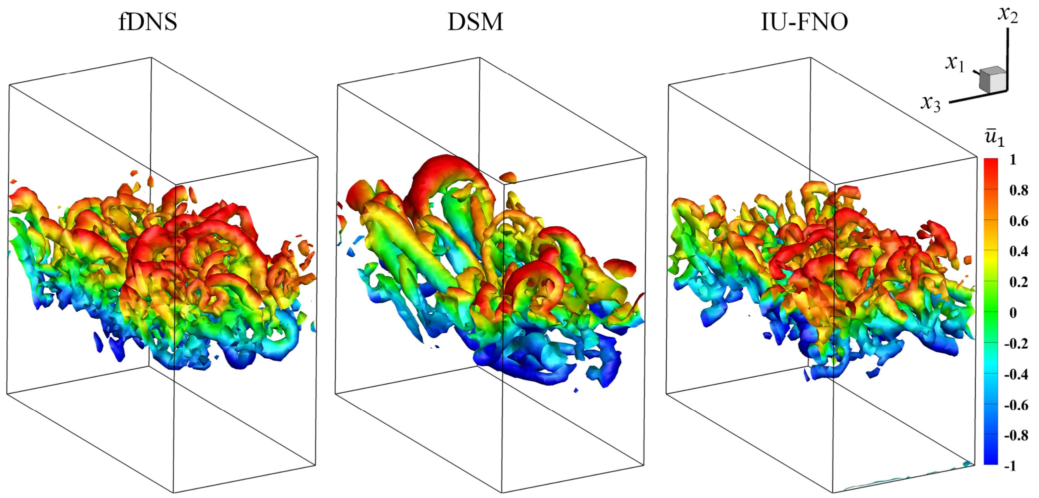

图 20. Q判据的等值面云图, 流向速度染色($Q = 0.2$, $t/\tau_\theta \approx 900$)

$$Q = \frac{1}{2}(\bar{\Omega}_{ij}\bar{\Omega}_{ij} - \bar{S}_{ij}\bar{S}_{ij})$$

- IU-FNO模型对涡的空间结构的重构能力比传统亚格子DSM模型更好。

总结与展望

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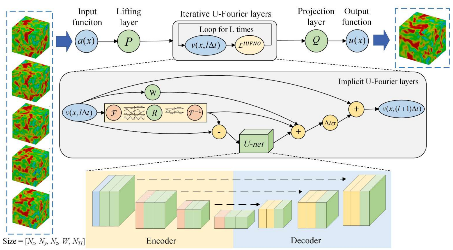

总结：

IU-FNO是通过输入前几个时刻的三维速度场, 以预测下一时刻速度场的变化。从数据中习得流场演化规律。

创新点：

- 相比于原始FNO模型，参数量减少约75%，能让网络不断加深。
- IU-FNO具有长时间稳定预测的能力。
- 更快, 更准的预测能力, 相比于传统亚格子DSM模型和FNO等模型，IU-FNO模型对速度谱、涡量PFD等统计量以及瞬时空间流动结构都具有更精确的预测能力，且能上百倍的提升计算速度。
- 较强的泛化能力，用低泰勒雷诺数湍流训练好的模型可以直接推广用于高泰勒雷诺数的湍流预测。

展望：

- 结合geo-FNO的优点，拓展处理非均匀网格和非周期边界条件的能力，以便应用于更复杂的工程流动中。
- 发展并行大规模计算。

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Thank You For Your Attention

欢迎批评指正

Zhijie Li, Wenhui Peng, Zelong Yuan and Jianchun Wang*