Jian-Xun Wang

List of Publications by Year
in descending order

47 papers	3,647 citations	304743 22 h-index	276875 41 g-index
48 all docs	48 docs citations	48 times ranked	1760 citing authors

#	Article	IF	Citations
1	Frame-independent vector-cloud neural network for nonlocal constitutive modeling on arbitrary grids. Computer Methods in Applied Mechanics and Engineering, 2022, 388, 114211.	6.6	12
2	Physics-informed graph neural Galerkin networks: A unified framework for solving PDE-governed forward and inverse problems. Computer Methods in Applied Mechanics and Engineering, 2022, 390, 114502.	6.6	67
3	PhyCRNet: Physics-informed convolutional-recurrent network for solving spatiotemporal PDEs. Computer Methods in Applied Mechanics and Engineering, 2022, 389, 114399.	6.6	55
4	AI-based Hybrid Model for Denoising Particle Trajectories Reconstructed from Magnetic Particle Tracking Method. , 2022, , .		0
5	Physics-informed deep learning for solving phonon Boltzmann transport equation with large temperature non-equilibrium. Npj Computational Materials, 2022, 8, .	8.7	23
6	A Deep-Learning Based Generalized Empirical Flow Model of Glottal Flow During Normal Phonation. Journal of Biomechanical Engineering, 2022, , .	1.3	0
7	Acoustic Inversion for Uncertainty Reduction in Reynolds-Averaged Navierâ€"Stokes-Based Jet Noise Prediction. AIAA Journal, 2022, 60, 2407-2422.	2.6	3
8	Machine Learning for Cardiovascular Biomechanics Modeling: Challenges and Beyond. Annals of Biomedical Engineering, 2022, 50, 615-627.	2.5	21
9	PhyGeoNet: Physics-informed geometry-adaptive convolutional neural networks for solving parameterized steady-state PDEs on irregular domain. Journal of Computational Physics, 2021, 428, 110079.	3.8	201
10	A Bi-fidelity ensemble kalman method for PDE-constrained inverse problems in computational mechanics. Computational Mechanics, 2021, 67, 1115-1131.	4.0	12
11	Assimilation of disparate data for enhanced reconstruction of turbulent mean flows. Computers and Fluids, 2021, 224, 104962.	2.5	17
12	Uncovering near-wall blood flow from sparse data with physics-informed neural networks. Physics of Fluids, 2021, 33, .	4.0	90
13	A semi-analytical solution and AI-based reconstruction algorithms for magnetic particle tracking. PLoS ONE, 2021, 16, e0254051.	2.5	4
14	Super-resolution and denoising of fluid flow using physics-informed convolutional neural networks without high-resolution labels. Physics of Fluids, 2021, 33, 073603.	4.0	82
15	Learning nonlocal constitutive models with neural networks. Computer Methods in Applied Mechanics and Engineering, 2021, 384, 113927.	6.6	20
16	Physics-informed Dyna-style model-based deep reinforcement learning for dynamic control. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2021, 477, .	2.1	10
17	Flows over periodic hills of parameterized geometries: A dataset for data-driven turbulence modeling from direct simulations. Computers and Fluids, 2020, 200, 104431.	2.5	67
18	Enforcing statistical constraints in generative adversarial networks for modeling chaotic dynamical systems. Journal of Computational Physics, 2020, 406, 109209.	3.8	77

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19	Surrogate modeling for fluid flows based on physics-constrained deep learning without simulation data. Computer Methods in Applied Mechanics and Engineering, 2020, 361, 112732.	6.6	408
20	SSR-VFD: Spatial Super-Resolution for Vector Field Data Analysis and Visualization. , 2020, , .		38
21	Physics-constrained bayesian neural network for fluid flow reconstruction with sparse and noisy data. Theoretical and Applied Mechanics Letters, 2020, 10, 161-169.	2.8	93
22	Non-intrusive model reduction of large-scale, nonlinear dynamical systems using deep learning. Physica D: Nonlinear Phenomena, 2020, 412, 132614.	2.8	26
23	A bi-fidelity surrogate modeling approach for uncertainty propagation in three-dimensional hemodynamic simulations. Computer Methods in Applied Mechanics and Engineering, 2020, 366, 113047.	6.6	14
24	Quantification of model uncertainty in RANS simulations: A review. Progress in Aerospace Sciences, 2019, 108, 1-31.	12.1	228
25	Adding Constraints to Bayesian Inverse Problems. Proceedings of the AAAI Conference on Artificial Intelligence, 2019, 33, 1666-1673.	4.9	6
26	Recent progress in augmenting turbulence models with physics-informed machine learning. Journal of Hydrodynamics, 2019, 31, 1153-1158.	3.2	23
27	Turbulence Modeling in the Age of Data. Annual Review of Fluid Mechanics, 2019, 51, 357-377.	25.0	755
28	Data-Augmented Modeling of Intracranial Pressure. Annals of Biomedical Engineering, 2019, 47, 714-730.	2.5	22
29	Prediction of Reynolds stresses in high-Mach-number turbulent boundary layers using physics-informed machine learning. Theoretical and Computational Fluid Dynamics, 2019, 33, 1-19.	2.2	33
30	Inferring tsunami flow depth and flow speed from sediment deposits based on Ensemble Kalman Filtering. Geophysical Journal International, 2018, 212, 646-658.	2.4	5
31	TSUFLIND-EnKF: Inversion of tsunami flow depth and flow speed from deposits with quantified uncertainties. Marine Geology, 2018, 396, 16-25.	2.1	13
32	Physics-informed machine learning approach for augmenting turbulence models: A comprehensive framework. Physical Review Fluids, 2018, 3, .	2.5	309
33	An Implicitly Consistent Formulation of a Dual-Mesh Hybrid LES/RANS Method. Communications in Computational Physics, 2017, 21, 570-599.	1.7	11
34	A Priori Assessment of Prediction Confidence for Data-Driven Turbulence Modeling. Flow, Turbulence and Combustion, 2017, 99, 25-46.	2.6	51
35	A random matrix approach for quantifying model-form uncertainties in turbulence modeling. Computer Methods in Applied Mechanics and Engineering, 2017, 313, 941-965.	6.6	29
36	Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data. Physical Review Fluids, 2017, 2, .	2.5	403

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37	Data-driven CFD modeling of turbulent flows through complex structures. International Journal of Heat and Fluid Flow, 2016, 62, 138-149.	2.4	25
38	Quantification of uncertainties in turbulence modeling: A comparison of physics-based and random matrix theoretic approaches. International Journal of Heat and Fluid Flow, 2016, 62, 577-592.	2.4	10
39	Quantifying and reducing model-form uncertainties in Reynolds-averaged Navierâ€"Stokes simulations: A data-driven, physics-informed Bayesian approach. Journal of Computational Physics, 2016, 324, 115-136.	3.8	209
40	A Bayesian Calibrationâ€"Prediction Method for Reducing Model-Form Uncertainties with Application in RANS Simulations. Flow, Turbulence and Combustion, 2016, 97, 761-786.	2.6	42
41	INCORPORATING PRIOR KNOWLEDGE FOR QUANTIFYING AND REDUCING MODEL-FORM UNCERTAINTY IN RANS SIMULATIONS. , 2016, 6, 109-126.		9
42	Dynamic Evaluation of Mesh Resolution and Its Application in Hybrid LES/RANS Methods. Flow, Turbulence and Combustion, 2014, 93, 141-170.	2.6	9
43	Mechanics condition of thin-walled tubular component with rib hydroforming. Transactions of Nonferrous Metals Society of China, 2012, 22, s280-s286.	4.2	5
44	Beam transport modeling of PPM focused THz sheet beam TWT circuit. , 2011, , .		12
45	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part II: Numerical simulation. Marine Geology, 2010, 269, 119-131.	2.1	46
46	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part I: Experimental study. Marine Geology, 2010, 269, 107-118.	2.1	50
47	Assessment of Regularized Ensemble Kalman Method for Inversion of Turbulence Quantity Fields. AIAA Journal, 0, , 1-11.	2.6	1