Eliu Huerta

List of Publications by Year in descending order

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172457 144013 5,704 61 29 57 citations h-index g-index papers 64 64 64 5898 citing authors all docs docs citations times ranked

#	Article	IF	CITATIONS
1	Statistically-informed deep learning for gravitational wave parameter estimation. Machine Learning: Science and Technology, 2022, 3, 015007.	5.0	14
2	Interpretable AI forecasting for numerical relativity waveforms of quasicircular, spinning, nonprecessing binary black hole mergers. Physical Review D, 2022, 105, .	4.7	6
3	A FAIR and Al-ready Higgs boson decay dataset. Scientific Data, 2022, 9, 31.	5.3	12
4	Inference-Optimized AI and High Performance Computing for Gravitational Wave Detection at Scale. Frontiers in Artificial Intelligence, 2022, 5, 828672.	3.4	9
5	Advances in Machine and Deep Learning for Modeling and Real-Time Detection of Multi-messenger Sources. , 2022, , 1793-1819.		O
6	Star cluster classification in the PHANGS– <i>HST</i> survey: Comparison between human and machine learning approaches. Monthly Notices of the Royal Astronomical Society, 2021, 506, 5294-5317.	4.4	28
7	Deep learning ensemble for real-time gravitational wave detection of spinning binary black hole mergers. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2021, 812, 136029.	4.1	29
8	Advances in Machine and Deep Learning for Modeling and Real-Time Detection of Multi-messenger Sources., 2021,, 1-27.		3
9	A Gravitational-wave Measurement of the Hubble Constant Following the Second Observing Run of Advanced LIGO and Virgo. Astrophysical Journal, 2021, 909, 218.	4.5	144
10	Observation of eccentric binary black hole mergers with second and third generation gravitational wave detector networks. Physical Review D, 2021, 103, .	4.7	11
11	Deep learning for gravitational wave forecasting of neutron star mergers. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2021, 816, 136185.	4.1	29
12	Accelerated, scalable and reproducible Al-driven gravitational wave detection. Nature Astronomy, 2021, 5, 1062-1068.	10.1	31
13	Deep Learning with Quantized Neural Networks for Gravitational-wave Forecasting of Eccentric Compact Binary Coalescence. Astrophysical Journal, 2021, 919, 82.	4.5	16
14	Deep Learning for Cardiologist-Level Myocardial Infarction Detection in Electrocardiograms. IFMBE Proceedings, 2021, , 341-355.	0.3	14
15	Gravitational wave denoising of binary black hole mergers with deep learning. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2020, 800, 135081.	4.1	61
16	Physics-inspired deep learning to characterize the signal manifold of quasi-circular, spinning, non-precessing binary black hole mergers. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2020, 808, 135628.	4.1	18
17	Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA. Living Reviews in Relativity, 2020, 23, 3.	26.7	447
18	Artificial neural network subgrid models of 2D compressible magnetohydrodynamic turbulence. Physical Review D, 2020, 101, .	4.7	18

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19	Deep transfer learning for star cluster classification: I. application to the PHANGS–⟨i⟩HST⟨ i⟩ survey. Monthly Notices of the Royal Astronomical Society, 2020, 493, 3178-3193.	4.4	38
20	The NANOGrav 11 yr Data Set: Evolution of Gravitational-wave Background Statistics. Astrophysical Journal, 2020, 890, 108.	4.5	28
21	The NANOGrav 11 yr Data Set: Limits on Gravitational Wave Memory. Astrophysical Journal, 2020, 889, 38.	4.5	36
22	Modeling the Uncertainties of Solar System Ephemerides for Robust Gravitational-wave Searches with Pulsar-timing Arrays. Astrophysical Journal, 2020, 893, 112.	4.5	49
23	Convergence of artificial intelligence and high performance computing on NSF-supported cyberinfrastructure. Journal of Big Data, 2020, 7, .	11.0	22
24	The NANOGrav 11 yr Data Set: Limits on Gravitational Waves from Individual Supermassive Black Hole Binaries. Astrophysical Journal, 2019, 880, 116.	4.5	102
25	Fusing numerical relativity and deep learning to detect higher-order multipole waveforms from eccentric binary black hole mergers. Physical Review D, 2019, 100, .	4.7	25
26	Characterization of numerical relativity waveforms of eccentric binary black hole mergers. Physical Review D, 2019, 100, .	4.7	17
27	Enabling real-time multi-messenger astrophysics discoveries with deep learning. Nature Reviews Physics, 2019, 1, 600-608.	26.6	53
28	Deep learning at scale for the construction of galaxy catalogs in the Dark Energy Survey. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2019, 795, 248-258.	4.1	37
29	Probing neutron star structure via <mml:math display="inline" xmlns:mml="http://www.w3.org/1998/Math/MathML"><mml:mi>f</mml:mi></mml:math> -mode oscillations and damping in dynamical spacetime models. Physical Review D, 2019, 99, .	4.7	12
30	Supporting High-Performance and High-Throughput Computing for Experimental Science. Computing and Software for Big Science, 2019, 3, 1.	2.9	9
31	Physics of eccentric binary black hole mergers: A numerical relativity perspective. Physical Review D, 2019, 100, .	4.7	26
32	P ython O pen source W aveform E xtracto R (POWER): an open source, Python package to monitor and post-process numerical relativity simulations. Classical and Quantum Gravity, 2018, 35, 027002.	4.0	8
33	Deep neural networks to enable real-time multimessenger astrophysics. Physical Review D, 2018, 97, .	4.7	166
34	The NANOGrav 11-year Data Set: High-precision Timing of 45 Millisecond Pulsars. Astrophysical Journal, Supplement Series, 2018, 235, 37.	7.7	448
35	Gravitational Waves from Accreting Neutron Stars Undergoing Common-envelope Inspiral. Astrophysical Journal, 2018, 857, 38.	4.5	11
36	Eccentric, nonspinning, inspiral, Gaussian-process merger approximant for the detection and characterization of eccentric binary black hole mergers. Physical Review D, 2018, 97, .	4.7	100

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37	Deep Learning for real-time gravitational wave detection and parameter estimation: Results with Advanced LIGO data. Physics Letters, Section B: Nuclear, Elementary Particle and High-Energy Physics, 2018, 778, 64-70.	4.1	230
38	Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA. Living Reviews in Relativity, 2018, 21, 3.	26.7	808
39	The NANOGrav 11 Year Data Set: Pulsar-timing Constraints on the Stochastic Gravitational-wave Background. Astrophysical Journal, 2018, 859, 47.	4. 5	331
40	Classification and unsupervised clustering of LIGO data with Deep Transfer Learning. Physical Review D, 2018, 97, .	4.7	100
41	Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA. , 2018, 21, 1.		2
42	The basic physics of the binary black hole merger GW150914. Annalen Der Physik, 2017, 529, 1600209.	2.4	69
43	Search for Gravitational Waves Associated with Gamma-Ray Bursts during the First Advanced LIGO Observing Run and Implications for the Origin of GRB 150906B. Astrophysical Journal, 2017, 841, 89.	4.5	52
44	Complete waveform model for compact binaries on eccentric orbits. Physical Review D, 2017, 95, .	4.7	88
45	BOSS-LDG: A Novel Computational Framework That Brings Together Blue Waters, Open Science Grid, Shifter and the LIGO Data Grid to Accelerate Gravitational Wave Discovery. , 2017, , .		6
46	Characterization of transient noise in Advanced LIGO relevant to gravitational wave signal GW150914. Classical and Quantum Gravity, 2016, 33, 134001.	4.0	225
47	Prospects for Observing and Localizing Gravitational-Wave Transients with Advanced LIGO and Advanced Virgo. Living Reviews in Relativity, 2016, 19, 1.	26.7	427
48	DETECTING ECCENTRIC SUPERMASSIVE BLACK HOLE BINARIES WITH PULSAR TIMING ARRAYS: RESOLVABLE SOURCE STRATEGIES. Astrophysical Journal, 2016, 817, 70.	4.5	38
49	Proposed search for the detection of gravitational waves from eccentric binary black holes. Physical Review D, 2016, 93, .	4.7	47
50	Detection of eccentric supermassive black hole binaries with pulsar timing arrays: Signal-to-noise ratio calculations. Physical Review D, 2015, 92, .	4.7	42
51	Accurate and efficient waveforms for compact binaries on eccentric orbits. Physical Review D, 2014, 90, .	4.7	94
52	Self-forced evolutions of an implicit rotating source: A natural framework to model comparable and intermediate mass-ratio systems from inspiral through ringdown. Physical Review D, 2014, 90, .	4.7	6
53	Effect of eccentricity on binary neutron star searches in advanced LIGO. Physical Review D, 2013, 87, .	4.7	68
54	Enhanced sensitivity of the LIGO gravitational wave detector by using squeezed states of light. Nature Photonics, 2013, 7, 613-619.	31.4	825

Eliu Huerta

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55	Accurate modeling of intermediate-mass-ratio inspirals: Exploring the form of the self-force in the intermediate-mass-ratio regime. Physical Review D, 2012, 86, .	4.7	10
56	Importance of including small body spin effects in the modelling of intermediate mass-ratio inspirals. II. Accurate parameter extraction of strong sources using higher-order spin effects. Physical Review D, 2012, 85, .	4.7	16
57	Importance of including small body spin effects in the modelling of extreme and intermediate mass-ratio inspirals. Physical Review D, 2011, 84, .	4.7	29
58	Intermediate-mass-ratio inspirals in the Einstein Telescope. I. Signal-to-noise ratio calculations. Physical Review D, 2011, 83, .	4.7	28
59	Intermediate-mass-ratio inspirals in the Einstein Telescope. II. Parameter estimation errors. Physical Review D, $2011,83,\ldots$	4.7	24
60	Influence of conservative corrections on parameter estimation for extreme-mass-ratio inspirals. Physical Review D, 2009, 79, .	4.7	45
61	Initial data and eccentricity reduction toolkit for binary black hole numerical relativity waveforms. Classical and Quantum Gravity, 0, , .	4.0	2