Eliu Huerta

List of Publications by Year
in descending order

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

#	Article	IF	Citations
1	Enhanced sensitivity of the LIGO gravitational wave detector by using squeezed states of light. Nature Photonics, 2013, 7, 613-619.	31.4	825
2	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
3	The NANOGrav 11-year Data Set: High-precision Timing of 45 Millisecond Pulsars. Astrophysical Journal, Supplement Series, 2018, 235, 37.	7.7	448
4	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
5	Prospects for Observing and Localizing Gravitational-Wave Transients with Advanced LIGO and Advanced Virgo. Living Reviews in Relativity, 2016, 19, 1.	26.7	427
6	The NANOGrav 11 Year Data Set: Pulsar-timing Constraints on the Stochastic Gravitational-wave Background. Astrophysical Journal, 2018, 859, 47.	4.5	331
7	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
8	Characterization of transient noise in Advanced LIGO relevant to gravitational wave signal GW150914. Classical and Quantum Gravity, 2016, 33, 134001.	4.0	225
9	Deep neural networks to enable real-time multimessenger astrophysics. Physical Review D, 2018, 97, .	4.7	166
10	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
11	The NANOGrav 11 yr Data Set: Limits on Gravitational Waves from Individual Supermassive Black Hole Binaries. Astrophysical Journal, 2019, 880, 116.	4.5	102
12	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
13	Classification and unsupervised clustering of LIGO data with Deep Transfer Learning. Physical Review D, 2018, 97, .	4.7	100
14	Accurate and efficient waveforms for compact binaries on eccentric orbits. Physical Review D, 2014, 90, .	4.7	94
15	Complete waveform model for compact binaries on eccentric orbits. Physical Review D, 2017, 95, .	4.7	88
16	The basic physics of the binary black hole merger GW150914. Annalen Der Physik, 2017, 529, 1600209.	2.4	69
17	Effect of eccentricity on binary neutron star searches in advanced LIGO. Physical Review D, 2013, 87, .	4.7	68
18	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

#	Article	IF	Citations
19	Enabling real-time multi-messenger astrophysics discoveries with deep learning. Nature Reviews Physics, 2019, 1, 600-608.	26.6	53
20	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
21	Modeling the Uncertainties of Solar System Ephemerides for Robust Gravitational-wave Searches with Pulsar-timing Arrays. Astrophysical Journal, 2020, 893, 112.	4.5	49
22	Proposed search for the detection of gravitational waves from eccentric binary black holes. Physical Review D, 2016, 93, .	4.7	47
23	Influence of conservative corrections on parameter estimation for extreme-mass-ratio inspirals. Physical Review D, 2009, 79, .	4.7	45
24	Detection of eccentric supermassive black hole binaries with pulsar timing arrays: Signal-to-noise ratio calculations. Physical Review D, 2015, 92, .	4.7	42
25	DETECTING ECCENTRIC SUPERMASSIVE BLACK HOLE BINARIES WITH PULSAR TIMING ARRAYS: RESOLVABLE SOURCE STRATEGIES. Astrophysical Journal, 2016, 817, 70.	4.5	38
26	Deep transfer learning for star cluster classification: I. application to the PHANGSâ€“<i>HST</i> survey. Monthly Notices of the Royal Astronomical Society, 2020, 493, 3178-3193.	4.4	38
27	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
28	The NANOGrav 11 yr Data Set: Limits on Gravitational Wave Memory. Astrophysical Journal, 2020, 889, 38.	4.5	36
29	Accelerated, scalable and reproducible AI-driven gravitational wave detection. Nature Astronomy, 2021, 5, 1062-1068.	10.1	31
30	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
31	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
32	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
33	Intermediate-mass-ratio inspirals in the Einstein Telescope. I. Signal-to-noise ratio calculations. Physical Review D, 2011, 83, .	4.7	28
34	The NANOGrav 11 yr Data Set: Evolution of Gravitational-wave Background Statistics. Astrophysical Journal, 2020, 890, 108.	4.5	28
35	Star cluster classification in the PHANGSâ€“<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
36	Physics of eccentric binary black hole mergers: A numerical relativity perspective. Physical Review D, 2019, 100, .	4.7	26

#	Article	IF	Citations
37	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
38	Intermediate-mass-ratio inspirals in the Einstein Telescope. II. Parameter estimation errors. Physical Review D, 2011, 83, .	4.7	24
39	Convergence of artificial intelligence and high performance computing on NSF-supported cyberinfrastructure. Journal of Big Data, 2020, 7, .	11.0	22
40	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
41	Artificial neural network subgrid models of 2D compressible magnetohydrodynamic turbulence. Physical Review D, 2020, 101, .	4.7	18
42	Characterization of numerical relativity waveforms of eccentric binary black hole mergers. Physical Review D, 2019, 100, .	4.7	17
43	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
44	Deep Learning with Quantized Neural Networks for Gravitational-wave Forecasting of Eccentric Compact Binary Coalescence. Astrophysical Journal, 2021, 919, 82.	4.5	16
45	Deep Learning for Cardiologist-Level Myocardial Infarction Detection in Electrocardiograms. IFMBE Proceedings, 2021, , 341-355.	0.3	14
46	Statistically-informed deep learning for gravitational wave parameter estimation. Machine Learning: Science and Technology, 2022, 3, 015007.	5.0	14
47	Probing neutron star structure via <mml:math xmlns:mml="http://www.w3.org/1998/Math/MathML" display="inline"><mml:mi>f</mml:mi></mml:math> -mode oscillations and damping in dynamical spacetime models. Physical Review D, 2019, 99, .	4.7	12
48	A FAIR and AI-ready Higgs boson decay dataset. Scientific Data, 2022, 9, 31.	5.3	12
49	Gravitational Waves from Accreting Neutron Stars Undergoing Common-envelope Inspiral. Astrophysical Journal, 2018, 857, 38.	4.5	11
50	Observation of eccentric binary black hole mergers with second and third generation gravitational wave detector networks. Physical Review D, 2021, 103, .	4.7	11
51	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
52	Supporting High-Performance and High-Throughput Computing for Experimental Science. Computing and Software for Big Science, 2019, 3, 1.	2.9	9
53	Inference-Optimized AI and High Performance Computing for Gravitational Wave Detection at Scale. Frontiers in Artificial Intelligence, 2022, 5, 828672.	3.4	9
54	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

#	Article	IF	Citations
55	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
56	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
57	Interpretable AI forecasting for numerical relativity waveforms of quasicircular, spinning, nonprecessing binary black hole mergers. Physical Review D, 2022, 105, .	4.7	6
58	Advances in Machine and Deep Learning for Modeling and Real-Time Detection of Multi-messenger Sources. , 2021, , 1-27.		3
59	Initial data and eccentricity reduction toolkit for binary black hole numerical relativity waveforms. Classical and Quantum Gravity, 0, , .	4.0	2
60	Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA. , 2018, 21, 1.		2
61	Advances in Machine and Deep Learning for Modeling and Real-Time Detection of Multi-messenger Sources. , 2022, , 1793-1819.		0