Tom Tetzlaff

List of Publications by Year in descending order

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TOM TETZLAFE

#	Article	IF	CITATIONS
1	Sequence learning, prediction, and replay in networks of spiking neurons. PLoS Computational Biology, 2022, 18, e1010233.	3.2	8
2	Dynamical Characteristics of Recurrent Neuronal Networks Are Robust Against Low Synaptic Weight Resolution. Frontiers in Neuroscience, 2021, 15, 757790.	2.8	4
3	Firing rate homeostasis counteracts changes in stability of recurrent neural networks caused by synapse loss in Alzheimer's disease. PLoS Computational Biology, 2020, 16, e1007790.	3.2	10
4	Conditions for wave trains in spiking neural networks. Physical Review Research, 2020, 2, .	3.6	15
5	The speed of sequence processing in biological neuronal networks. , 2020, , .		0
6	Deterministic networks for probabilistic computing. Scientific Reports, 2019, 9, 18303.	3.3	10
7	A Model of Spatial Reach in LFP Recordings. Springer Series in Computational Neuroscience, 2018, , 509-533.	0.3	0
8	Firing-rate models for neurons with a broad repertoire of spiking behaviors. Journal of Computational Neuroscience, 2018, 45, 103-132.	1.0	13
9	Homologous Basal Ganglia Network Models in Physiological and Parkinsonian Conditions. Frontiers in Computational Neuroscience, 2017, 11, 79.	2.1	14
10	Hybrid Scheme for Modeling Local Field Potentials from Point-Neuron Networks. Cerebral Cortex, 2016, 26, 4461-4496.	2.9	89
11	Effect of Heterogeneity on Decorrelation Mechanisms in Spiking Neural Networks: A Neuromorphic-Hardware Study. Physical Review X, 2016, 6, .	8.9	15
12	Hybrid scheme for modeling local field potentials from point-neuron networks. BMC Neuroscience, 2015, 16, .	1.9	7
13	Deterministic neural networks as sources of uncorrelated noise for probabilistic computations. BMC Neuroscience, 2015, 16, .	1.9	2
14	Dynamics of self-sustained asynchronous-irregular activity in random networks of spiking neurons with strong synapses. Frontiers in Computational Neuroscience, 2014, 8, 136.	2.1	38
15	Power Laws from Linear Neuronal Cable Theory: Power Spectral Densities of the Soma Potential, Soma Membrane Current and Single-Neuron Contribution to the EEG. PLoS Computational Biology, 2014, 10, e1003928.	3.2	38
16	The Correlation Structure of Local Neuronal Networks Intrinsically Results from Recurrent Dynamics. PLoS Computational Biology, 2014, 10, e1003428.	3.2	91
17	The variability of tidewater-glacier calving: Origin of event-size and interval distributions. Journal of Glaciology, 2014, 60, 622-634.	2.2	27
18	Firing-rate models for neurons with a broad repertoire of spiking behaviors. BMC Neuroscience, 2013, 14, .	1.9	1

Tom Tetzlaff

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19	Recurrence and external sources differentially shape network correlations. BMC Neuroscience, 2013, 14, .	1.9	0
20	Hybrid scheme for modeling LFPs from spiking cortical network models. BMC Neuroscience, 2013, 14, .	1.9	0
21	Firing-rate models capture essential response dynamics of LGN relay cells. Journal of Computational Neuroscience, 2013, 35, 359-375.	1.0	16
22	Effect of localized input on bump solutions in a two-population neural-field model. Nonlinear Analysis: Real World Applications, 2013, 14, 997-1025.	1.7	4
23	Invariance of covariances arises out of noise. , 2013, , .		5
24	Echoes in correlated neural systems. New Journal of Physics, 2013, 15, 023002.	2.9	42
25	Frequency Dependence of Signal Power and Spatial Reach of the Local Field Potential. PLoS Computational Biology, 2013, 9, e1003137.	3.2	133
26	A unified view on weakly correlated recurrent networks. Frontiers in Computational Neuroscience, 2013, 7, 131.	2.1	61
27	Simplified model of the frequency dependence of the LFPâ \in Ms spatial reach. BMC Neuroscience, 2012, 13, .	1.9	0
28	Decorrelation of Neural-Network Activity by Inhibitory Feedback. PLoS Computational Biology, 2012, 8, e1002596.	3.2	159
29	Modeling the Spatial Reach of the LFP. Neuron, 2011, 72, 859-872.	8.1	393
30	Stability of bumps in a two-population neural-field model with quasi-power temporal kernels. Nonlinear Analysis: Real World Applications, 2011, 12, 3073-3094.	1.7	4
31	Dynamics of self-sustained activity in random networks with strong synapses. BMC Neuroscience, 2011, 12, .	1.9	0
32	Rate dynamics of the retina-LGN connection. BMC Neuroscience, 2011, 12, .	1.9	0
33	Decorrelation of low-frequency neural activity by inhibitory feedback. BMC Neuroscience, 2010, 11, .	1.9	4
34	Neurons hear their echo. BMC Neuroscience, 2010, 11, .	1.9	2
35	Rate dynamics of leaky integrate-and-fire neurons with strong synapses. Frontiers in Computational Neuroscience, 2010, 4, 149.	2.1	20
36	Dependence of Spike-Count Correlations on Spike-Train Statistics and Observation TimeÂScale. , 2010, , 103-127.		1

Tom Tetzlaff

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#	Article	IF	CITATIONS
37	Self-feedback shapes correlation functions. Neuroscience Research, 2010, 68, e106.	1.9	0
38	Estimating the spatial scale of local field potentials in a cortical population model. Neuroscience Research, 2010, 68, e212-e213.	1.9	0
39	Dynamical Response Properties of Neocortical Neuron Ensembles: Multiplicative versus Additive Noise. Journal of Neuroscience, 2009, 29, 1006-1010.	3.6	56
40	Synchronization and rate dynamics in embedded synfire chains: effect of network heterogeneity and feedback. BMC Neuroscience, 2009, 10, .	1.9	4
41	Dependence of Neuronal Correlations on Filter Characteristics and Marginal Spike Train Statistics. Neural Computation, 2008, 20, 2133-2184.	2.2	69
42	Correlations and Population Dynamics in Cortical Networks. Neural Computation, 2008, 20, 2185-2226.	2.2	99
43	Consequences of realistic network size on the stability of embedded synfire chains. Neurocomputing, 2004, 58-60, 117-121.	5.9	11
44	The spread of rate and correlation in stationary cortical networks. Neurocomputing, 2003, 52-54, 949-954.	5.9	24
45	The ground state of cortical feed-forward networks. Neurocomputing, 2002, 44-46, 673-678.	5.9	21

46 Sequence learning in a memristive crossbar array. , 0, , .