Eiji Uchibe

List of Publications by Year in descending order

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FULLCHIRE

#	Article	IF	CITATIONS
1	Deep learning, reinforcement learning, and world models. Neural Networks, 2022, 152, 267-275.	5.9	110
2	Randomized-to-Canonical Model Predictive Control for Real-World Visual Robotic Manipulation. IEEE Robotics and Automation Letters, 2022, 7, 8964-8971.	5.1	2
3	Modular deep reinforcement learning from reward and punishment for robot navigation. Neural Networks, 2021, 135, 115-126.	5.9	27
4	Generative Imitation Learning using Forward and Inverse Reinforcement Learning. Journal of the Robotics Society of Japan, 2021, 39, 617-620.	0.1	0
5	Forward and inverse reinforcement learning sharing network weights and hyperparameters. Neural Networks, 2021, 144, 138-153.	5.9	13
6	Parallel and hierarchical neural mechanisms for adaptive and predictive behavioral control. Neural Networks, 2021, 144, 507-521.	5.9	13
7	Constrained Deep Q-Learning Gradually Approaching Ordinary Q-Learning. Frontiers in Neurorobotics, 2019, 13, 103.	2.8	35
8	Deep reinforcement learning with smooth policy update: Application to robotic cloth manipulation. Robotics and Autonomous Systems, 2019, 112, 72-83.	5.1	114
9	Sigmoid-weighted linear units for neural network function approximation in reinforcement learning. Neural Networks, 2018, 107, 3-11.	5.9	603
10	Model-Free Deep Inverse Reinforcement Learning by Logistic Regression. Neural Processing Letters, 2018, 47, 891-905.	3.2	29
11	Robustness of linearly solvable Markov games employing inaccurate dynamics model. Artificial Life and Robotics, 2018, 23, 1-9.	1.2	5
12	Online meta-learning by parallel algorithm competition. , 2018, , .		9
13	Cooperative and Competitive Reinforcement and Imitation Learning for a Mixture of Heterogeneous Learning Modules. Frontiers in Neurorobotics, 2018, 12, 61.	2.8	5
14	Efficient sample reuse in policy search by multiple importance sampling. , 2018, , .		1
15	Adaptive Baseline Enhances EM-Based Policy Search: Validation in a View-Based Positioning Task of a Smartphone Balancer. Frontiers in Neurorobotics, 2017, 11, 1.	2.8	42
16	Deterministic Policy Search Method for Real Robot Control. The Brain & Neural Networks, 2017, 24, 195-203.	0.1	0
17	Deep Inverse Reinforcement Learning by Logistic Regression. Lecture Notes in Computer Science, 2016, , 23-31.	1.3	2
18	From free energy to expected energy: Improving energy-based value function approximation in reinforcement learning. Neural Networks, 2016, 84, 17-27.	5.9	16

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#	Article	IF	CITATIONS
19	EM-based policy hyper parameter exploration: application to standing and balancing of a two-wheeled smartphone robot. Artificial Life and Robotics, 2016, 21, 125-131.	1.2	6
20	Forward and Inverse Reinforcement Learning Based on Linearly Solvable Markov Decision Processes. The Brain & Neural Networks, 2016, 23, 2-13.	0.1	0
21	Inverse reinforcement learning using Dynamic Policy Programming. , 2014, , .		7
22	Combining learned controllers to achieve new goals based on linearly solvable MDPs. , 2014, , .		9
23	Evaluation of linearly solvable Markov decision process with dynamic model learning in a mobile robot navigation task. Frontiers in Neurorobotics, 2013, 7, 7.	2.8	16
24	Scaled free-energy based reinforcement learning for robust and efficient learning in high-dimensional state spaces. Frontiers in Neurorobotics, 2013, 7, 3.	2.8	8
25	Derivatives of Logarithmic Stationary Distributions for Policy Gradient Reinforcement Learning. Neural Computation, 2010, 22, 342-376.	2.2	7
26	NeuroEvolution Based on Reusable and Hierarchical Modular Representation. Lecture Notes in Computer Science, 2009, , 22-31.	1.3	1
27	Emergence of Different Mating Strategies in Artificial Embodied Evolution. Lecture Notes in Computer Science, 2009, , 638-647.	1.3	0
28	Co-evolution of Rewards and Meta-parameters in Embodied Evolution. Lecture Notes in Computer Science, 2009, , 278-302.	1.3	2
29	Learning how, what, and whether to communicate: emergence of protocommunication in reinforcement learning agents. Artificial Life and Robotics, 2008, 12, 70-74.	1.2	7
30	Natural actor-critic with baseline adjustment for variance reduction. Artificial Life and Robotics, 2008, 13, 275-279.	1.2	3
31	Finding intrinsic rewards by embodied evolution and constrained reinforcement learning. Neural Networks, 2008, 21, 1447-1455.	5.9	17
32	Co-evolution of Shaping Rewards and Meta-Parameters in Reinforcement Learning. Adaptive Behavior, 2008, 16, 400-412.	1.9	20
33	A New Natural Policy Gradient by Stationary Distribution Metric. Lecture Notes in Computer Science, 2008, , 82-97.	1.3	6
34	Evolutionary Development of Hierarchical Learning Structures. IEEE Transactions on Evolutionary Computation, 2007, 11, 249-264.	10.0	34
35	Constrained reinforcement learning from intrinsic and extrinsic rewards. , 2007, , .		20
36	ã,µã,₿fãf¼ãfãf¼ãf‡ãf³ãf^ãf—ãfã,,ã,§ã,⁻ãf^. The Brain & Neural Networks, 2007, 14, 293-304.	0.1	0

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#	Article	IF	CITATIONS
37	Finding Exploratory Rewards by Embodied Evolution and Constrained Reinforcement Learning in the Cyber Rodents. Lecture Notes in Computer Science, 2007, , 167-176.	1.3	0
38	Incremental Coevolution With Competitive and Cooperative Tasks in a Multirobot Environment. Proceedings of the IEEE, 2006, 94, 1412-1424.	21.3	25
39	The Cyber Rodent Project: Exploration of Adaptive Mechanisms for Self-Preservation and Self-Reproduction. Adaptive Behavior, 2005, 13, 149-160.	1.9	58
40	An Evolutionary Approach to Automatic Construction of the Structure in Hierarchical Reinforcement Learning. Lecture Notes in Computer Science, 2003, , 507-509.	1.3	4
41	Behavior generation for a mobile robot based on the adaptive fitness function. Robotics and Autonomous Systems, 2002, 40, 69-77.	5.1	12
42	State Space Construction for Cooperative Behavior Acquisition in the Environments Including Multiple Learning Robots Journal of the Robotics Society of Japan, 2002, 20, 281-289.	0.1	5
43	Multiagent learning towards RoboCup. New Generation Computing, 2001, 19, 103-120.	3.3	0
44	Cooperative behavior acquisition for mobile robots in dynamically changing real worlds via vision-based reinforcement learning and development. Artificial Intelligence, 1999, 110, 275-292.	5.8	120
45	An Application of Vision-Based Learning in RoboCup for a Real Robot with an Omnidirectional Vision System and the Team Description of Osaka University "Trackies― Lecture Notes in Computer Science, 1999, , 316-325.	1.3	5
46	Vision Based State Space Construction for Learning Mobile Robots in Multi Agent Environments. Lecture Notes in Computer Science, 1998, , 62-78.	1.3	5
47	Evolution of rewards and learning mechanisms in Cyber Rodents. , 0, , 109-128.		0