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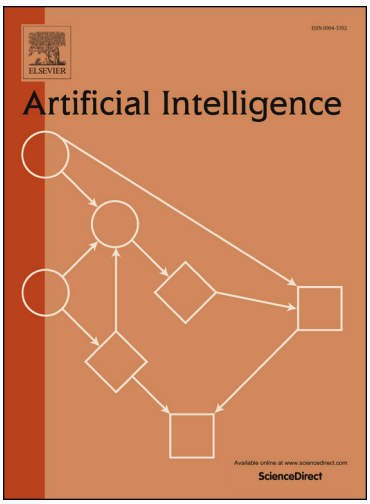

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Decentralized Reinforcement Learning of Robot Behaviors

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Abstract

A multi-agent methodology is proposed for Decentralized Reinforcement Learning (DRL) of individual behaviors in problems where multi-dimensional action spaces are involved. When using this methodology, sub-tasks are learned in parallel by individual agents working toward a common goal. In addition to proposing this methodology, three specific multi agent DRL approaches are considered: DRL-Independent, DRL Cooperative-Adaptive (CA), and DRL-Lenient. These approaches are validated and analyzed with an extensive empirical study using four different problems: 3D Mountain Car, SCARA Real-Time Trajectory Generation, Ball-Dribbling in humanoid soccer robotics, and Ball-Pushing using differential drive robots. The experimental validation provides evidence that DRL implementations show better performances and faster learning times than their centralized counterparts, while using less computational resources. DRL-Lenient and DRL-CA algorithms achieve the best final performances for the four tested problems, outperforming their DRL-Independent counterparts. Furthermore, the benefits of the DRL-Lenient and DRL-CA are more noticeable when the problem complexity increases and the centralized scheme becomes intractable given the available computational resources and training time.

Keywords: Reinforcement Learning, multi-agent systems, decentralized control, autonomous robots, distributed artificial intelligence.

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