Graduate School of Science and Technology Master's Thesis Abstract

Laboratory name (Supervisor)	Robot Learning (Takamitsu Matsubara (Professor))		
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Thesis title	Deep Reinforcement Learning with FPNN-to-SNN Policy Distillation for Neurochip-Driven Robots		

Abstract

Neurochips have recently gained significant attention in robot control due to their use of brain-inspired Spiking Neural Networks (SNNs), which enable low power consumption and short calculation times. In robot control, Deep Reinforcement Learning (DRL) is employed to handle high-dimensional inputs, such as raw camera images, requiring Neural Networks (NNs) with high-approximation capabilities for complex function approximation. However, DRL using SNNs faces challenges, such as poor sample efficiency, because SNNs inherently utilize weights and activations with low accuracy. One approach to address this issue is to first train a high-accuracy Floating Point Neural Network (FPNN) and then convert it to an SNN through quantization techniques. However, this direct conversion often results in significant performance degradation due to quantization errors. To address this problem, we propose a novel DRL framework for acquiring SNN robot policies called Quantized Q-Distillation (QQD). In QQD, we also train an FPNN but, instead of direct conversion, we distill it into an SNN. This method allows the SNN to leverage the high accuracy of an FPNN through distillation, enabling the SNN to be updated as the FPNN and thus mitigating the severe performance degradation typically seen in SNNs. Evaluations on two simulation and one real-robot visual-servo tasks using a neurochip demonstrate that QQD can successfully achieve the tasks, while FPNN-to-SNN direct conversion cannot. QQD also showed at least a 32.9% improvement in sample efficiency compared to other recent works.