氏　　　　　名	LEE Hosun
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論 文 題 目	An Explainable Deep Reinforcement Learning Framework for Patrol Speed Control and Sim-to-Real Deployment of Rail-Guided Robot System
論文審査委員	CHONG Nak Young　JAIST　Professor
	LIM Yuto　JAIST　Professor
	INOUE Naoya　JAIST　Assoc. Prof.
	LEE Jaeryoung　Chubu University　Assoc. Prof.
	ELIBOL Armagan　Al Ain University　Assoc. Prof.

論文の内容の要旨

Intelligent facility monitoring increasingly relies on autonomous robotic systems, yet the deployment of learning-based control policies in real environments remains challenging due to their black-box nature and the discrepancy between simulation and real-world conditions. Rail-guided patrol robots, while mechanically stable and suitable for large indoor facilities, commonly operate with fixed-speed or rule-based controllers that do not adapt to variations in visual scene complexity. This dissertation presents a deep reinforcement learning–based framework for adaptive patrol speed control of a rail-guided robot system. Patrol speed control is formulated as a continuous decision-making problem in which the robot observes forward-facing RGB images and outputs a continuous velocity command. The Deep Deterministic Policy Gradient (DDPG) algorithm is employed to learn context-dependent speed modulation along a predefined rail trajectory. To encourage adaptation to visual conditions, an entropy-driven reward function is adopted. Image entropy is used as a proxy for visual information density, allowing the learned

policy to adjust patrol speed in response to changes in visual scene complexity without relying on manually designed heuristics. This formulation enables perception-driven patrol behavior to emerge from visual statistics. To facilitate analysis of the learned policy, gradient-based visual interpretation is incorporated into the framework. Grad-CAM is applied to the actor network to generate action-specific attention maps that highlight image regions associated with speed decisions. These visualizations provide interpretable evidence of how visual inputs are reflected in control outputs and support qualitative inspection of internal policy behavior. For deployment, the visual discrepancy between simulation and real environments is addressed using CycleGAN-based unpaired image-to-image translation. Real camera images are translated into simulation-style representations, enabling zero-shot execution of the trained policy. The consistency of visual attention patterns before and after translation is examined through Grad-CAM-based analysis. Beyond algorithmic development, a complete rail-guided patrol robot system is implemented and deployed in an agricultural wholesale market on a ceiling-mounted rail loop of approximately 220 meters to verify system-level integration and operational feasibility. Experiments conducted in simulation and controlled testbeds involve the quantitative analysis of patrol behavior and visual attention patterns, and are used to examine behavioral consistency across environments, rather than to provide full validation of real-world performance.

This dissertation contributes to deep reinforcement learning and robotic perception by addressing adaptive patrol speed control under visually heterogeneous environments with a particular focus on policy interpretability. While prior work on learning-based control primarily emphasizes performance, it often provides limited insight into how perceptual information influences continuous control decisions. This research instead emphasizes interpretability as a means of analyzing and understanding learned behavior. A central contribution of this work is the formulation of patrol speed control as a perception-driven continuous control problem, in which visual scene complexity directly influences the learned policy. Image entropy is employed as a reward signal to reflect variations in visual information density, providing a practical mechanism for linking perception and control without relying on task-specific heuristics. Another key contribution is the application of Grad-CAM to the actor network of a continuous-action deep reinforcement learning policy. By producing action-specific attention maps, the proposed framework provides interpretable visual evidence of image regions associated with speed decisions. These visualizations are treated as correlational indicators rather than causal explanations, and their limitations are explicitly acknowledged. The integration of interpretability with sim-to-real transfer further strengthens the contribution of this research. Instead of evaluating domain adaptation solely through control performance, this dissertation examines whether interpretable visual cues remain consistent after visual domain translation. The analysis of Grad-CAM attention before and after CycleGAN-based translation provides empirical insight into the stability of interpretability across simulated and real environments. Overall, this dissertation does not claim the introduction of new learning algorithms or theoretical models. Its contribution lies in the structured integration of adaptive deep reinforcement learning, visual interpretability,

and sim-to-real deployment within a unified patrol framework, offering methodological insights applicable to a broad range of robotic monitoring and inspection systems.

Keywords: Rail-guided patrol robot, Adaptive speed control, Deep reinforcement learning (DRL), DDPG-based robot control, Simulation-to-real transfer, CycleGAN-based domain adaptation, Explainable artificial intelligence (XAI), Grad-CAM visualization, Facility monitoring automation

論文審査の結果の要旨

This dissertation aimed to present a deep reinforcement learning-based framework for adaptive patrol speed control of a rail-guided robot system under visually heterogeneous environments with a particular focus on policy interpretability. Unlike most prior work on learning-based control that provided limited insight into how perceptual information influences continuous control decisions, this research emphasized interpretability as a means of analyzing and understanding learned behavior. To enable context-aware decision making, the Deep Deterministic Policy Gradient (DDPG) algorithm was employed for adaptive control of the robot's patrol speed. Specifically, the continuous control capability of DDPG allowed the robot to fine-tune its movement speed in response to varying environmental complexity. In addition to adaptive behavior, explainability was addressed, integrating a Grad-CAM-based explainable AI (XAI) module into the control system.

The contribution of this dissertation lies in the following aspects. Firstly, this work highlighted the synergy between deep reinforcement learning and explainable AI for robot control. Patrol speed control was formulated as a perception-driven continuous control problem, in which scene complexity directly influenced the learned policy. In detail, image entropy was employed as a reward signal to reflect variations in visual information density, providing a practical mechanism for linking perception and control without relying on task-specific heuristics. Secondly, the use of XAI supported user trust, facilitated model debugging, and improved system transparency. The combined DDPG and Grad-CAM framework enabled both effective control and explainable decision-making. By producing action-specific attention maps, the proposed framework provided interpretable evidence of image regions associated with speed decisions. These visualizations were treated as correlational indicators rather than causal explanations. Thirdly, the framework's modular design allows for future extension to include anomaly detection, obstacle avoidance, and additional robotic behaviors. Finally, the proposed system was validated through simulation and on-site deployment in an agricultural market setting. Overall, the proposed system offers a scalable and trustworthy solution for long-term autonomous facility management. It streamlined the structured integration of adaptive deep reinforcement learning, visual interpretability, and sim-to-real deployment within a unified patrol framework, offering methodological insights applicable to a broad range of robotic monitoring and inspection systems.

This is an excellent dissertation, and we approve awarding a doctoral degree to Mr. LEE Hosun.