# Prolonging Tool Life: A Structure-Mechanics-Guided Learning Framework for Acquiring Skillful Use of General-Purpose Tools

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Abstract (should be within 1st page)

In inaccessible environments, robots must rely on a limited set of tools to complete diverse tasks, causing a single tool to serve multiple purposes across different objects and requirements and effectively become a general-purpose tool. Such tools frequently experience non-optimal usage, where mismatched interactions generate unpredictable and damaging loads that accelerate fatigue, shorten lifespan, and reduce operational efficiency. Lowering motion intensity can slow damage but also reduces task performance efficiency, leaving existing strategies unable to resolve this efficiency trade-off. This dissertation develops a planning method for acquiring tool-use policies that extend tool lifespan without explicitly restricting motion intensity. The key philosophy is that structure mechanics can guide the selection of efficient tool-use strategies by identifying load conditions the tool can safely tolerate and showing how fatigue accumulates over repeated use, enabling a planner to search for motions that maximize lifespan while maintaining task performance. Two challenges arise from this objective: tool-use decisions must integrate high-dimensional mechanical responses and abstract lifespan information into a meaningful decision-making signal, and the learned motion must generalize across common object interactions, including free-moving and mechanically constrained cases, which involve fundamentally different load behaviors. To address these challenges, the proposed framework models mechanical responses using Finite Element Analysis and quantifies fatigue through Miner’s Rule to compute a Remaining Useful Life measure that is incorporated into the reinforcement learning reward to guide the agent toward lifespan-preserving behaviors without explicitly restricting motion intensity. Experiments show that the learned policies lower internal stress, select mechanically favorable load conditions, and substantially prolong tool lifespan in simulation, with successful transfer to real-robot experiments, demonstrating that a structure-mechanics–guided reinforcement learning framework enables efficient and sustainable use of general-purpose tools under varied conditions.