# Leveraging Human Behavioral Characteristics for Enriching Imitation Learning

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Abstract

Humans demonstrate a variety of interesting behaviors which enhancing task performance, for instance, moderating actions to mitigate sensed risks. However, Imitation Learning (IL), which attempts to teach robots to perform these same tasks from observations of human demonstrations, often fails to capture such behavior. Specifically, common IL algorithms rely solely on the mapping between states and actions of a human demonstrator, overlooking the underlying characteristics that drive such behaviors (e.g., risk-sensitive behavior), limiting robot generalizability and applicability. To address this, we present a novel mechanism for designing IL algorithms based on findings in behavioral psychology, thereby embodying principles to capture and leverage a human behavioral characteristic for enriching IL. Our first human behavioral characteristic is risk-sensitivity revealed from the *speed-accuracy trade-off*, in which humans in risky situations slow down their movement speed to enhance accuracy. Our mechanism is verified through two distinct IL frameworks that leverage the human speed-accuracy trade-off to enrich risk-sensitivity as follows: 1) we introduce the risk estimator derived from human risk-sensitivity to improve safety under the on-policy IL setup, as a robot agent executes a task with its unmatured policy and iteratively optimized through human corrections in risky areas, and 2) we introduce the risk-sensitive disturbance model to ensure demonstration feasibility under a disturbance-injected IL setup, as disturbances are injected into human action commands during demonstrations to robustify the robot's policy while regulating its level small in risky areas. The effectiveness of our methods is verified through risk-sensitive simulations and real-robot experiments for various assembly tasks. Results show that, through improved risk-sensitivity, the task execution performance of policy, training safety as well as demonstration feasibility, are significantly better than comparison methods.