Fatigue Mitigation with Cobots: Investigating the Cobot Workspace

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Work-related musculoskeletal disorders (WMSDs) are among the most common work-related injuries affecting industrial workers. Over the recent years, industrial workspace has witnessed an increased integration of robots [1]. While many industrial robots work separated from human workers, there is an increasing effort to use collaborative robots (cobots) which work in direct interaction with humans. This, in parallel with the seriousness of the WMSD rates, has given rise to a research direction investigating using cobots to reduce WMSDs risk.

Repetitive motions, prevalent in repetitive industrial tasks, are a common cause of WMSDs [2] since they repeatedly load the same joints leading to localized joint fatigue. Thus, motor variability (varying motions during task execution) is recommended to reduce the risk of WMSDs [3]. To induce motor variability that could reduce joint fatigue in repetitive tasks, we propose using cobots to influence the human motion by changing the pose (or motion) of the cobot's end-effector which interacts with the human. Since we are dealing with repetitive tasks, the long term effect of a choice of the robot's end-effector (cobot's action) should be considered in each cycle through long-term planning. Also, the cobot's end-effector only partially constrains the human motion, due to human kinematics redundancy, which leads to planning under uncertainty. Finally, the human joint fatigue is not measurable and only partially observable through some motion measures which directly means dealing with partial observability. To account for the problem specifications we have, in a previous work, proposed a framework to plan cobot's end-effector pose using Partially Observable Markov Decision Process (POMDP) [4]. The proposed framework was validated on a simplified task example with two robot end-effector poses to select from in the planning phase. While the proposed approach showed promising results, one of its limitations was being tested using a hand-picked set of actions within the continuous robot workspace. Yet, other robot actions (not within the set) might lead to better fatigue minimization in the long run. However, it is not possible, in the POMDP planning phase, to consider the entire continuous action space nor sample a huge set of actions due to computational costs. Hence, in this work we address selecting a relevant set of actions for the problem's POMDP to plan from.

Our objective is finding an optimized set of actions which when used improves fatigue minimization compared to our previously hand-picked set and to a uniformly-sampled set of actions. Also, the action set should improve the planning outcome while respecting the limited-time constraint due to online action selection in each cycle. When dealing with continuous action space POMDPs, many discretize the action space online as with the Progressive Widening algorithms [5, 6]. Online approaches generate for each system state, or belief around the system state, a tailored discrete set of actions.

Ultimately, this can lead to more interesting choices compared to offline approaches constructing a global action set beforehand to use it later in planning. However, to refine these tailored sets and sample enough interesting actions per state, online approaches might need long computational times. Long computational times are hardly compatible with human-robot interaction applications in which the cobot needs to decide online its action for each cycle. Thus, we opt for an offline action space discretization which comes with no or limited time constraints. We investigate the characteristics of an action set that could potentially lead to improving joint fatigue minimization. For each joint j, if j is fatigued, the action set should contain actions allowing to reduce *j*'s fatigue over future cycles. Our approach focuses on the set of Pareto-front actions of the high-dimensional (one dimension per joint direction) fatigue evolution function. The Pareto-front action set contains for each joint j, and for any initial fatigue of j, and action that, when applied, would reduce to the best j's fatigue. To approximate the Pareto-front action set, we begin by uniformly sampling a large number of executable actions. Then, using a Digital Human Model Simulator [7], we dynamically simulate the human whole-body motion in reaction to a robot action, in order to compute the human joint torques associated with the motion. The associated torques are then fed to a state-of-the-art fatigue model to estimate the fatigue induced by an action at a joint i for any initial fatigue. We tested our approach on a specific use-case and approximated the Pareto-front action set starting from an initial set of 100 actions. The size of the Pareto-front set didn't exceed 10% of the initial set and we observed multiple joints whose fatigue evolution is idle to the action choice. In the future, we plan to test the performance of the POMDP using the Pareto-front action set. We also might test existing online approaches by sampling actions according to a reduced-dimension fatigue space excluding idle joints observed when finding the Pareto-front set.

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