Multi-objective Trajectory Optimization to Improve Ergonomics in Human Work Activities

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***Abstract*—This paper proposes a framework to optimize human wholebody motions w.r.t. one or more ergonomics scores. We show that optimal motions for a score might degrade other scores. Then, we use multi-objective optimization (MOO) to select motions from a set of trade-off solutions.**

***Index Terms*—Ergonomics, Digital Human Simulation, Wholebody Motion Optimization, Multi-Objective Optimization**

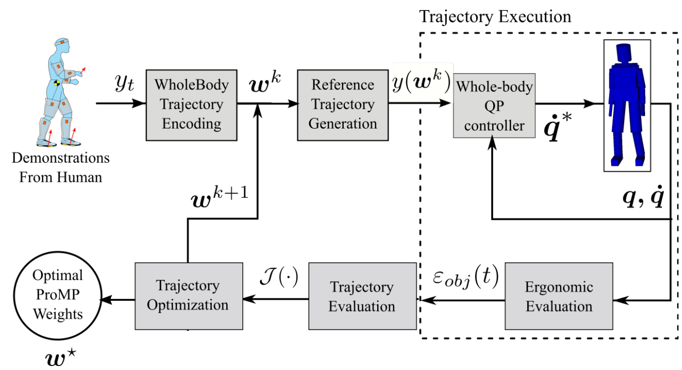

Fig. 1. Ergonomics human motion optimization framework. The entire motion is encoded into motion primitives that can be readily optimized with respect to multiple ergonomics scores.

I. Introduction

Work-related musculoskeletal disorders (WMSDs) represent a major health issue worldwide, with important costs for companies and society [1]. One of its major risk factors is represented by awkward body postures that cause biomechanical demands that exceed the workers' physical capacities [2]. In many situations, workers are able to choose among a variety of postural strategies to execute a task. Yet, their natural choice does not always match the best strategy concerning long-term health. Recommending ergonomic postures for the specific task that workers have to perform is, therefore, a promising avenue to reduce the prevalence of WMSDs.

Posture recommendation requires prior identification of the best postural strategies for a given individual under a given activity's constraints [3], [4]. This question is also pushed forward by the growing interest in collaborative robotic assistance. Collaborative robots can be used to guide workers toward a more ergonomic posture via the positioning of their end-effector [5]–[7], but such assistance also requires the knowledge of the user's optimal posture.

Here, we propose a framework to optimize entire wholebody trajectories with respect to one or more ergonomics scores related to WMSDs, while under several constraints related to the human movement and the work activity itself (Fig. 1). Moreover, the framework is utilized to analyze how optimal wholebody trajectories are affected by work activities and several ergonomics scores.

II. Methods

A 43 DoFs digital human model (DHM) is simulated in a physics engine and controlled by a multi-task quadratic programming (QP) solver [8]. The QP controller takes Cartesian reference trajectories as input, and outputs desired joint velocities for the DHM. Some work activities may require fixed reference trajectories, as with feet in double support, or policies, as in a manipulation activity that requires a fixed hand orientation regardless of the hand position. Therefore, in our framework, not all reference trajectories need to be optimized. Additionally, the user may also deliberately choose to optimize only a few references and, due to the QP formulation, the trajectories of the other links will also be indirectly modulated.

The optimizable reference trajectories are parameterized by probabilistic movement primitives (ProMPs) [9]. Each trajectory of a given task coordinate is encoded as a weighted sum of basis functions, with a weight vector, $\boldsymbol{w}_{task}$. For a compact representation of all ProMP task trajectories all weights can be stacked into a single vector: $\boldsymbol{w} = [\boldsymbol{w}_1 \dots \boldsymbol{w}_{n_{tasks}}]$.

The DHM movement is evaluated w.r.t. the RMS value of a diverse set of ergonomics scores, ε_{obj}, (table I) at each time step. Given an episode k in the optimization loop (Fig. 1), a point $\boldsymbol{w}^k$ is considered feasible if, and only if, the wholebody trajectories $\boldsymbol{y}(\boldsymbol{w}^k)$ are always within the DHM workspace, the DHM does not fall, and the activity is successfully executed. Therefore, this trajectory optimization is a derivative-free problem with black-box non-linear constraints.

Given the restrictive constraints of the problem, we bootstrap the optimization process with initial feasible solutions taken from human motion demonstrations. First, the motion is optimized w.r.t. each one of the ergonomics scores in Tab. I individually using a single-objective optimizer, COBYLA. Then, the motion is optimized w.r.t. a set of antagonistic scores at the same time using a multi-objective optimizer, NSGA-II.

Work Activities: The human demonstrations are taken from 2 different work activities (A and B). Activity A is a reaching movement, in which the human demonstrator pick-and-places

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TABLE I
INSTANT ERGONOMICS EVALUATION SCORES

Description	**Score**	$\varepsilon_{\text{obj}}(t)$
RULA-C	Linear regression of RULA	ε_{rc}
Normalized Wholebody Effort	$\frac{1}{n_{joints}} \sum_{i \in joints} \left(\frac{\tau_t^i}{\tau_{max}^i} \right)^2$	ε_{nwe}
Torques Shoulder	$\left\| \tau^{shoulder} \right\|$	ε_{tsh}
Torques Lumbar	$\left\| \tau_{lumbar} \right\|$	ε_{tlb}
Back Flexion	$\left\| \theta_{L5S1}^{Y} \right\|$	$\varepsilon_{\text{back}}$

an object from a shelf at the shoulder level. And activity B is a lifting movement, in which the demonstrator lifts a box from the ground up to the subject's waist level.

III. Results and Discussion

The single-objective optimizations w.r.t. each ergonomics score lead to solutions with improved respective initial ergonomics score for each work activity, as depicted by Fig. 2. The back flexion score improved 99.37 % (A), and 93.42% (B); the RULA-C score improved 4.52% (A), and 30.02% (B); the normalized wholebody effort score improved 12.92% (A), and 87.67% (B); the torques shoulder score improved 60.36% (A), and 64.97% (B); and the torques lumbar score improved 77.24% (A), and 67.32% (B). Fig. 2 also indicates that optimal solutions for a given score could degrade other scores in comparison to the initial demonstration set. In activity A, minimizing the torque shoulder score also increases the wholebody effort, and back flexion, while in activity B minimizing back flexion increases the torque shoulder score.

The multi-objective optimization (MOO) handles these antagonistic scores simultaneously, yielding a set of motions with ergonomics scores trade-offs, a Pareto-optimal front. In the simulation experiments, we observed a large variety of motions and ergonomics scores in the Pareto front, which could be used as a guide to decide on which Pareto optimal motion to select. *E.g.*, in activity B, a user could prefer motions that require more effort from the shoulder rather than from the back.

IV. Conclusions

Our framework optimizes wholebody motion through motion parameterization, and a DHM in a physics engine. We have shown that certain ergonomics scores can be conflicting, therefore, single-score optimization may not be sufficient to guarantee motions that reduce the overall risks of WMSDs. The proposed MOO is useful to select movements that are simultaneously ergonomic for several scores. One could use our framework to pick trajectories from a Pareto front, and input them as a reference to a human-robot interaction controller.

Fig. 2. Effect of single-objective optimization on different ergonomic scores for Activity A and Activity B. The costs are normalized by the maximum observed value for each score.

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