Reducing work-related physical fatigue with a collaborative robot: A decision-making approach

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***Index Terms*— Digital human simulation; Decision-making under uncertainty; Collaborative robotics; Ergonomics.**

I. INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) are one of the first cause of occupational diseases in many countries worldwide, representing a major health issue and an important cost for companies and society [1]. Force exertion, awkward postures, and repetitiveness of gestures are among the major biomechanical risk factors for WMSDs. By providing various types of physical assistance to address one or several of those factors, collaborative robotics has the potential to help reduce the prevalence of WMSDs [2]. For instance, weight compensation or strength enhancement are commonly envisioned. Recent studies also proposed to address the postural factor, by using collaborative robots to guide the user toward a task-dependent optimal posture [3], [4]. But those studies consider a single optimal posture, whereas researches in ergonomics suggest that motor variability in task execution –i.e., varying the motor strategy used to perform a task– might be beneficial to reduce the risk of developing WMSDs [5]. Along this line, Lorenzini *et al.* developed an adaptive controller that modifies the robot's pose depending on the current level of fatigue in the different human joints: the load is thereby redistributed to less fatigued joints, allowing recovery of fatigued joints [6].

While definitely a step forward, such purely reactive approach does not guarantee that the resulting behavior is optimal in the long term. It might, for instance, result in sudden changes in the robot's motion that surprise the user, possibly increasing the cognitive load and/or degrading productivity. In addition, most approaches targeting postural optimization consider that the user will adopt the optimal posture computed by the robot. Setting the robot's end-effector pose does, however, not fully constrain the human posture because of the kinematic redundancy of the human body. A same action of the robot might trigger different postural reactions from the user (associated with different levels of ergonomics risk), depending on the individual (user profile), as well as on the user's current state (e.g., fatigue, expertise) which often cannot be directly measured but only inferred [7], [8].

The present work aims at addressing the above-mentioned questions. Specifically, we propose a framework to plan a policy of a collaborative robot in order to reduce the user's physical fatigue in the long term, while taking into account the stochastic nature of the user's postural reaction.

II. METHODS

The problem addressed involves several sources of uncertainties since i) the postural reaction of the human is stochastic, and

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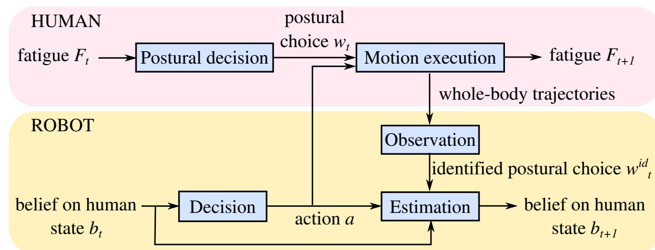

Fig. 1: Workflow of the human-robot interaction process during the execution phase, according to the proposed model. The robot decision follows the precomputed policy π.

ii) the fatigue of the human is a hidden variable (to measure an exact level of fatigue, one would need heavy instrumentation and/or a biophysical model with many user-specific parameters to identify). We therefore propose to use a framework for decision-making under uncertainty and under partial observability, namely the Partially Observable Markov Decision Process (POMDP) framework, to model the problem [9]. In this context, the problem is described by a tuple $\langle S, A, T, R, \Omega, O, b_0 \rangle$ where:

- S is the set of system states containing the human fatigue $\mathbf{f} = (f_1, \ldots, f_N)^T$ where f_i corresponds to the fatigue in the i-th joint or group of joints, and the previous human postural reaction;
- A is the set of robot actions, here the end-effector poses;
- $T : S \times A \to \mathbb{P}(S)$ is the transition function describing the probabilistic evolution of the system's state, which includes the probabilistic postural reaction of the human to the robot's action and the associated effect on the human fatigue;
- Ω is the space of observations formed by the set of possible human postural reactions;
- $O : S \times A \to \mathbb{P}(\Omega)$ is the observation function, i.e., a distribution over the postural reactions perceived by the robot, given the current state s (which includes the human's actual postural reaction) and the robot action a;
- $R : S \times A \times S \to \mathbb{R}$ is the reward function which depends on the human fatigue;
- $b_0 = P(S_0)$ is the initial belief about the the system's state, here the probability distribution over the initial fatigue of the human.

Let $b \in B$ be the belief state, i.e., the probability distribution over the true state of the system, given the past actions $a_{1:t}$ and past observations $o_{1:t}$, such that $b(s) = P(S_t = s | a_{1:t}, o_{1:t})$. Solving this problem consists in computing an optimal policy $\pi : B \to A$ associating to each belief state $b \in B$ the action a to perform in order to maximize the average discounted cumulated reward $E[\sum \gamma^t r_t]$ during execution (r_t and γ being respectively the reward of step t and the discount factor). Fig. 1 depicts an example step

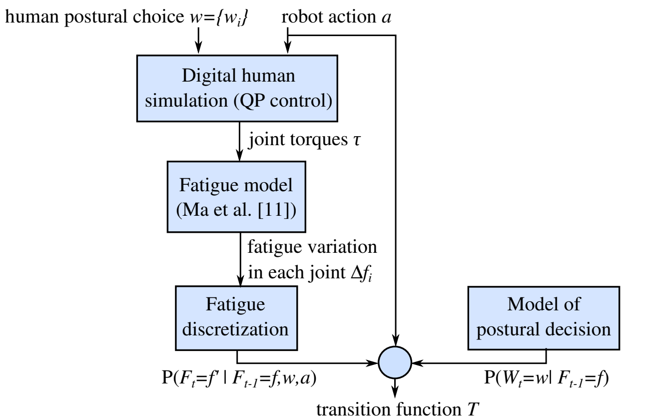

Fig. 2: Workflow of the process used to compute the transition function T of the POMDP model, that describes the probabilistic evolution of the human postural reaction and associated discrete fatigue.

of the proposed model.

In order to assign numerical values to the different functions of the model, we rely on a digital human simulation in a physics engine to simulate the postural reactions of the human and evaluate the associated fatigue. The human is modeled as a tree-like kinematic chain, and its whole-body motion is computed by solving a quadratic programming (QP) problem which main objective is to bring the human hand to the robot's end-effector pose [10]. A diversity of postural reactions is simulated by changing the relative weights of lower-priority postural objectives in the QP controller, thereby penalizing more or less the motion of certain joints. Each reaction is thus represented by a vector $\mathbf{w} = (w_1, \ldots, w_N)$ where w_i is the weight of the postural objective associated with the i-th joint (or group of joints).

The digital human simulation enables to compute the time-series of human joint torques for each pair of robot action and human postural reaction. We then use the fatigue/recovery model proposed by Ma *et al.* to compute the evolution of fatigue in each joint [11]. The resulting fatigue is however a continuous variable, which cannot be handled by the POMDP formalism because it would lead to an infinite set of states. We therefore discretize the fatigue in each joint. For each pair of robot action and human reaction, the probability $P(F_t = f | F_{t-1} = f')$ –where f and f' are discrete fatigue states– is computed as the projection of each fatigue interval at time t in each fatigue interval at time $t+1$, by running a large number of simulations with randomly selected (continuous) values as fatigue start state. The corresponding workflow is described in Fig. 2.

III. EXPERIMENTS

In order to demonstrate our framework, we consider a toy example in which the robot brings a piece to the user who works on it with a hand-held tool. The robot's set of actions corresponds to a set of possible poses for the manipulated piece, which are selected *a priori* within the robot's workspace to elicit significantly different motions from the human. For each action of the robot, two postural reactions are considered for the human: performing the task with the right hand or with the left hand. The human is modeled as aware of his/her fatigue, such that the probability of selecting a weight w_i for the postural objective of joint i depends on the real fatigue level in the joint (handedness is not considered in this work). We use the SARSOP solver to compute the optimal policy [12]. The computation and analysis of the results are work in progress.

IV. CONCLUSION

In this work, we proposed to use a decision-making under uncertainty framework to compute the policy of a collaborative robot that minimizes the fatigue of the user, while taking into account the fact that the human can adopt different postural reactions depending on his/her fatigue state which is hidden for the robot. In a future work, we will benchmark our framework on more complex situations where the human can adopt a larger variety of postural reactions, and validate the computed policy experimentally. Importantly, we centered this work on fatigue, but the proposed framework enables to account for many more variables that would allow to compute even more user-specific policies. For instance, the fatigue time constant of the model by Ma *et al.* could be individualized to account for people that fatigue faster. Expertise with respect to fatigue perception and management could also be included and affect the choice of postural reaction. Finally, the reward function could include additional costs, linked for instance to the quality and/or rapidity of task execution, or to the cognitive load caused by a change in the robot behavior between two consecutive cycles. Such additions, however, require to deal with heterogeneous cost functions.

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