Robot Design Optimization for Human-Robot Collaborative Lifting Tasks

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I. INTRODUCTION

In recent years, there has been a drastic improvement in the robotic field concerning the development and control of humanoid robots to endow them with the ability to interact and collaborate with human beings for performing a large variety of tasks [1], [2], [3] and particular interest has been paid to the introduction of such platforms into the industry 4.0 [4]. In the aforementioned interaction, agents' safety and system efficiency are two of the main aspects to be ensured [5] leading to the *ergonomy* principle [6]. While several works have addressed the design of control architectures to achieve an *ergonomic* physical interaction [7], [8], the humanoid robot hardware design has been rarely considered as an element to be optimized for the specific collaborative action, and it is rather assumed as given. However, several works have proposed the usage of different algorithms to jointly consider hardware design and control requirements [9], [10]. The proposed co-optimization is achieved via classical optimization techniques such as block coordinate descendent methods [11]. Other works have exploited reinforcement learning techniques [12], [13], and evolutionary algorithm [14], [15], [16] to port the biological principle of *embodied cognition* [17] in the robotic field, showing evidence on how the environment and related tasks directly affect the complexity of the agent, thus underlining the importance of considering the environment in the design process of both the system morphology and the control strategy.

The aforementioned papers, despite the interesting work presented, apply the principles of embodied cognition to simple robotics platforms which are composed of a limited number of links and do not consider a possible interaction with a human being.

In this paper a novel strategy to design humanoid robots, to achieve ergonomic human-robot interaction is presented, extending the work done in [18], adding the robot hardware parameters in the loop to achieve an ergonomic interaction.

II. BACKGROUND

A humanoid robot is a multi-body mechanical system which is composed of $n+1$ rigid bodies, i.e. the *links*, which are connected by n *joints* with one degree of freedom (DoF) each. An element of the configuration space $q \in \mathbb{Q}$ is defined as the triplet $q = ({}^{\mathcal{I}}p_{\mathcal{B}}, {}^{\mathcal{I}}R_{\mathcal{B}}, s)$ where ${}^{\mathcal{I}}p_{\mathcal{B}} \in \mathbb{R}^3$ and ${}^{\mathcal{I}}R_{\mathcal{B}} \in SO(3)$ denote, respectively, the position and the orientation of the *base frame* expressed w.r.t. the inertial frame $\mathcal{I}$, and $s \in \mathbb{R}^n$ is the joints configuration representing the topology of the mechanical system. An element of the configuration velocity space $\nu \in \mathbb{V}$ is defined as $\nu = ({}^{\mathcal{I}}\mathrm{v}_{\mathcal{B}}, \dot{s})$ where ${}^{\mathcal{I}}\mathrm{v}_{\mathcal{B}} = ({}^{\mathcal{I}}\dot{p}_{\mathcal{B}}, {}^{\mathcal{I}}\omega_{\mathcal{B}}) \in \mathbb{R}^6$ denotes the linear and angular velocity of the *base frame*, and $\dot{s}$ denotes the joint velocities.

III. OPTIMUM HARDWARE DESIGN

Starting from the robot modelling of Section II, it is possible to parametrize each link of the robot kinematic chain w.r.t. hardware parameters, namely the density $\rho \in \mathbb{R}^+$, assumed to be constant for all the body points, and the geometry identified by a set of parameters $l \in \mathbb{R}^{n_l}$. By applying such a parametrization to each link of the robot kinematic chain and defining with π the set of hardware parameters defined considering all the links, one can apply the Euler-Poincarè formalism [19] and describe the robot dynamics with the following set of differential equations, with explicit dependency on the hardware parameters: $M(q,\pi)\dot{\nu} + h(q,\nu,\pi) = B\tau + J_c^T(q,\pi)f$ with $M \in \mathbb{R}^{n+6 \times n+6}$ the mass matrix, the term $h \in \mathbb{R}^{n+6}$ accounting for Coriolis and gravity forces, $B = (0_{n\times 6}, I_n)^T$ is a selector matrix, $\tau \in \mathbb{R}^n$ is a vector representing the robot's joint torques, $f \in \mathbb{R}^{6n_c}$ represents the wrenches acting on n_c contact links of the robot. To address the reference scenario, we need to consider the coupled human-robot-payload dynamics. Such dynamics can be described starting from the description of [20] making the dependency on the robot hardware parameters explicit, leading to the following dynamic

$$\begin{aligned} &\mathbf{M}(\boldsymbol{q},\pi)\dot{\boldsymbol{\nu}} + \mathbf{h}(\boldsymbol{q},\boldsymbol{\nu},\pi) = \mathbf{B}\boldsymbol{\tau} + \mathbf{Q}^T(\boldsymbol{q},\pi)\mathbf{f}, \\ &\mathbf{Q}(\boldsymbol{q},\pi)\boldsymbol{\nu} = 0. \end{aligned} \tag{1}$$

Where the composite matrices are identified with $\mathbf{bold}$ and they collect the terms related to the human, the robot, and the payload. $\mathbf{Q}$ is a coupling matrix considering both the constraints of the contacts with the environment and those of the agent-payload contact points for each agent, namely the human and the robot, and $\mathbf{f}$ is a vector containing all the interaction wrenches (exchanged with the environment and between the agents and the payload) taking into account the action-reaction property for internal forces and reflecting the ordering in the constraints matrix $\mathbf{Q}$. Starting from Eq. (1), we want to identify a set of optimum robot hardware parameters able to ensure an ergonomic interaction with a human being. For this purpose, the metric considered was the expenditure of energy represented by the robot's and human's internal torques. Therefore the optimization problem

*The paper was supported by the Italian National Institute for Insurance against Accidents at Work (INAIL) ergoCub Project.

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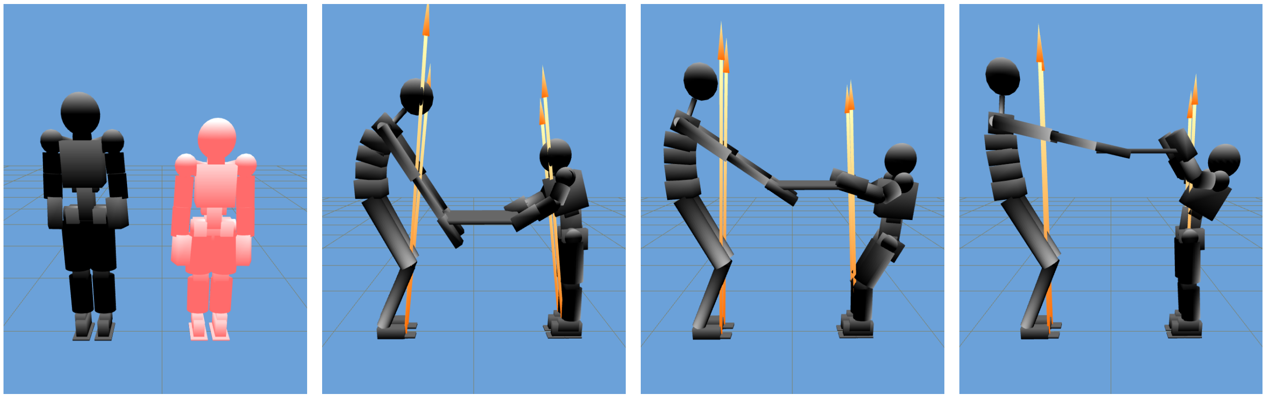

(a) (b) (c) (d)

Fig. 1: Multi-agent optimization output. In a) the optimized robot is compared to original model (depicted in red). (b), (c) and (d) show the optimum robot interacting with the human in the optimal configuration during collaborative lifting of a payload at height $0.8\ \mathrm{m}$ (b), height $1.0\ \mathrm{m}$ (c), height $1.2\ \mathrm{m}$ (d). In orange the wrenches exchanged with the ground are visualized.

of Eq. (2) has been defined, where n_k target payload heights are considered and the subscript 1,2,3, refer, respectively, to the robot, the human and the payload. The problem search variable is defined as follow: $\boldsymbol{y} = \begin{bmatrix} \tilde{\boldsymbol{q}} & \pi \end{bmatrix}^T$ where $\tilde{\boldsymbol{q}}$ is composed of robot, human and payload configurations, one per payload target height considered, and π are robot hardware parameters.

$$
\begin{aligned}
\mathbf{y}^* = \underset{\mathbf{y}}{\operatorname{argmin}} & \left(K_\tau \sum_k \|\boldsymbol{\tau}(\mathbf{y})_k\|_2^2 + K_c \left\| \frac{1}{{}^{\mathcal{I}}p_{z0,com}} \right\|_2^2 + \right. \\
& \left. + K_f \sum_k \|\boldsymbol{f}(\mathbf{y})_k - \boldsymbol{f}_k^*\|_2^2 \right) \\
s.t. \quad & \\
& e_z^T \cdot z_{3,\mathcal{B},k} = 1, \forall k \in [1, n_k], \\
& e_z^T \cdot z_{i,j,k} = 1, \forall i \in [1, n_c], \forall j \in [1,2], \forall k \in [1, n_k], \\
& {}^{\mathcal{I}}p_{i,j,k} = 0, \forall i \in [1, n_c], \forall j \in [1,2], \forall k \in [1, n_k], \quad \text{(2a)} \\
& {}^{\mathcal{I}}p_{3k} = h_k^*, \forall k \in [1, n_k]. \quad \text{(2b)}
\end{aligned}
$$

The functions $\boldsymbol{\tau}(\mathbf{y})$ and $\boldsymbol{f}(\mathbf{y})$ are computed by projecting the dynamic of Eq. (1) into the constraint at static configuration. The reference wrench $\boldsymbol{f}^*$ is computed such that the static friction cones are satisfied for all the contacts. The product $e_z^T \cdot z_{i,j,k}$ represents the misalignment in between the gravity direction e_z and the z versor $z_{i,j,k}$ of the frame j of the agent i for the target height k. The quantity ${}^{\mathcal{I}}p_{z,\mathcal{A}}$ represents the z-component of the position of the frame $\mathcal{A}$, thus the Eq. (2a) ensures the feet to be on the ground, meanwhile Eq. (2b) ensure the hands of both the human and the robot, to be at the object target heights h_k^* with $k \in [1, n_k]$. The cost $\left\| \frac{1}{{}^{\mathcal{I}}p_{z0,com}} \right\|_2^2$ minimizes the center of mass height, computed at the robot null configuration.

IV. VALIDATION

The proposed hardware parametrization and design optimization process have been tested starting from the humanoid robotic platform iCub [21] which has been modelled with simple shapes i.e. *sphere*, *cylinder* and *box*, resulting in the model showed in Fig. 1a. The optimization problem of Eq. (2) has been applied to identify an optimum robot design for performing collaborative lifting tasks of a payload, placed at different heights, in collaboration with a human. For such an optimization, the set of considered hardware parameters was composed of the length multipliers, that scales the shape geometry along the direction in which the robot kinematic chain grows, for the torso, arms and legs links, i.e. $\pi = [l_{m_1}, ..., l_{m_{n_l}}]$, the optimization problem has been defined using CasADi [22], and the interior point method [23] has been used to solve the non-linear problem defined. The human being has been modeled as a 48 DoF multi body system 1.82 m tall [24] and the payload has been considered as a box of dimensions $0.5\ \mathrm{m} \times 0.5\ \mathrm{m} \times 0.025\ \mathrm{m}$ and of $5\ \mathrm{kg}$ weight. The optimization output, together with the wrenches exchanged by the agent to the ground, are depicted in Fig. 1. The payload target heights considered are $0.8\ \mathrm{m}$ (Fig. 1b), $1.0\ \mathrm{m}$ (Fig. 1c), and $1.2\ \mathrm{m}$ (Fig. 1d).

V. CONLCUSIONS

This paper presents a methodology to identify humanoid robot hardware optimized for specific task execution, namely collaborative payload lifting. The proposed strategy allows to consider kinematics and dynamics constraints and results in an improved interaction with the human by optimizing robot hardware parameters via ergonomic metrics such as the internal stress expenditure.

In future work, we plan to extend the proposed approach to consider also the time evolution of the system and to introduce a more complete model for the contacts, i.e. the interaction both with the environment and with the payload. In addition, we plan to move towards evolutionary algorithms to design optimum humanoid robots for ergonomic human-robot interaction to overcome the limits of classical optimization methods w.r.t. local minima.

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