A digital human tool for guiding the ergonomic design of collaborative robots

Pauline Maurice, Vincent Padois, Yvan Measson, Philippe Bidaud

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P. MAURICE [a,*], V. PADOIS [a], Y. MEASSON [b], and P. BIDAUD [a,c]

[a] Sorbonne Universités, UPMC Univ Paris 06, CNRS, UMR 7222, Institut des Systèmes Intelligents et de Robotique (ISIR), F-75005, Paris, France

[b] CEA, LIST, Interactive Robotics Laboratory, Gif-sur-Yvette, F-91191, France

[c] ONERA, 91123 Palaiseau, France

Abstract

The growing number of musculoskeletal disorders in industry could be addressed by the use of collaborative robots, which allow the joint manipulation of objects by both a robot and a person. Efficiently designing these robots requires to assess the ergonomic benefit they offer. Despite the advances in human biomechanics and digital human model (DHM) simulation tools, the existing software for ergonomic analyses remain ill-adapted for collaborative robots design, because of both the DHM animation techniques and the biomechanic criteria that are measured. This paper presents a generic tool for performing detailed ergonomic assessments of activities including collaborative robots. The proposed method relies on an evaluation carried out within a digital world, using a DHM to simulate the worker. The evaluation of the robot-worker system can thus easily be performed throughout the whole design process. Multiple ergonomic indicators are defined in order to exhaustively estimate the different biomechanical demands which occur during manual activities. In order to simplify their interpretation, a sensitivity analysis is conducted to extract relevant indicators which best summarize the overall ergonomic performance of the considered activity, as well as identify the robot parameters which mainly affect this performance. In this purpose, multiple virtual human simulations of the activity - in which the DHM interacting with the collaborative robot is animated with an optimization-based whole-body controller - are run to measure all the ergonomic indicators for varying human and robot features. The relevant indicators resulting from this analysis can then be used to easily compare different robots, or to automatically optimize certain design parameters of a robot. The whole method is applied to the optimization of a robot morphology for assisting a drilling gesture. The sensitivity analysis is performed on 28 ergonomic indicators with 8 different human and robot parameters, resulting in a total of 8000 simulations. This analysis enables to reduce the number of ergonomic indicators to consider in the optimization from 28 to only 3, hence facilitating the convergence of the optimization: robots performing well on all 3 ergonomic objectives are produced with an evolutionary algorithm in about 150 generations. The comparison of the situations without assistance and with near-optimal robots shows some lack of transparency in the robots, but a comparatively significant improvements in the force-related ergonomic indicators. This result demonstrates the benefit of the optimized robots and thereby confirms the relevance of the proposed approach to provide robot designers with interesting preliminary designs to be further worked on.

Keywords: Ergonomics, Digital Human Model, Dynamic Motion Simulation, Collaborative Robotics, Sensitivity analysis.

1. Introduction

Work-related musculoskeletal disorders (MSDs) represent a major health problem in developed countries. They account for the majority of reported occupational diseases and affect almost 50 % of industrial workers (Schneider and Irastorza, 2010). Since MSDs mainly result from strenuous biomechanical solicitations (Luttmann et al., 2003), assisting workers with collaborative robots can be a solution when a task is physically demanding yet too complex to be fully automatized. A collaborative robot enables the joint manipulation of objects with the worker (co-manipulation) and thereby provides a variety of benefits, such as strength amplification, inertia masking and guidance via virtual surfaces and paths (Colgate et al., 2003).

The efficiency of a collaborative robot regarding the reduction of MSDs risks is highly task-dependent. So, in order to design an efficient robot, ergonomic assessments of the robot-worker system must be performed early in and throughout the whole design process. When it comes to workplace design, digital ergonomic evaluations - using a digital human model (DHM) to simulate the worker - are now often preferred to physical evaluations, since they decrease the overall development time and cost (Chaffin, 2007). DHMs enable easy access to many detailed biomechanical quantities, for different kinds of human morphologies, without requiring heavy instrumentation of multiple

*Corresponding author. Email: p.maurice(at)neu.edu

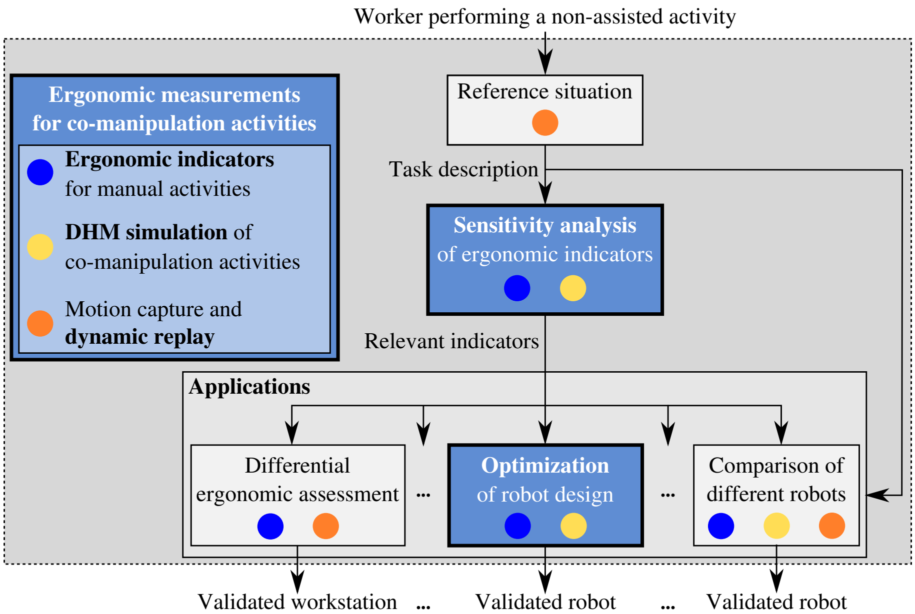


Figure 1: Overview of the methodology developed for performing ergonomic assessments of collaborative robots, and its possible applications. This paper presents the method and one application: the optimization of robot design.

subjects. Besides, a virtual - instead of a physical - mock-up of the workstation/robot is used, which is more easily modifiable.

Several commercially available DHM software for workplace design provide ergonomic analysis tools (*e.g.* Delmia, Jack, Ramsis, Sammie (Delleman et al., 2004)). These software include standard assessment methods, which estimate an absolute level of risk, depending on the main biomechanical MSDs factors (*e.g.* RULA, REBA and OWAS methods, OCRA index, NIOSH equation (David, 2005)). However, the provided ergonomic indicators are either quite rough (*e.g.* external loads consideration in RULA) and/or task-specific (*e.g.* NIOSH equation). So they do not cover all kinds of manual activities which may be addressed by collaborative robots. Besides, these assessment methods are static, meaning that dynamic phenomena are not taken into account. Yet fast motions do increase the risk of developing MSDs. Besides, collaborative robots may induce extra efforts from the worker in dynamic phases due to additional inertia. Beyond such standard ergonomic assessments methods associated with macroscopic human body models, other DHM software exist, which provide very accurate musculoskeletal models (*e.g.* OpenSim (Delp et al., 2007), AnyBody (Damsgaard et al., 2006), LifeMOD). These software enable access to quantities that more accurately account for the biomechanical demands on the human body, such as muscle force or tendon deformation, and often include dynamic effects. However the high number of outputs (one for each muscle/tendon/joint) is difficult to interpret without specific biomechanical knowledge, especially when the purpose is to summarize the global ergonomic level of an activity.

In addition, the existing DHM software present significant limitations regarding the animation of the DHM. The DHM motion is generated through forward or inverse kinematics, pre-defined postures and behaviors (*e.g.* walk towards, reach towards), or using motion capture data. Apart from motion capture, none of these animation techniques enables to come up with a dynamically consistent - even less with a truly realistic - motion (Lämkull et al., 2009). As for motion capture, it is highly time and resource consuming, since it requires that the human subject and the avatar experience a similar environment - including interaction forces - in order to obtain a realistic simulation. So the subject must either be provided with a physical mock-up or be equipped with heavy virtual reality instrumentation. Eventually, though most DHM software enable the simulation of the DHM within a static environment, they cannot simulate the motion of a collaborative robot which depends on its physical interaction with the manikin, both through its control law and through physical interferences.

Thus, despite many available tools for performing virtual ergonomic assessments, none of them is suitable for evaluating co-manipulation activities. This work therefore presents a novel approach for quantitatively comparing the ergonomic benefit provided by different collaborative robots when performing a given activity. The proposed tool consists of three components (Fig. 1):

1. A list of ergonomic indicators defined to accurately and exhaustively account for the different biomechanical demands which occur during manual activities, without requiring any a priori hypotheses on the activity assessed.

2. A framework enabling the dynamic simulation of a DHM interacting with a controlled collaborative robot, for indicators measurements. The DHM is animated through an optimization-

based whole-body controller, which can be used either with high level tasks descriptions (autonomous DHM) or with motion capture data (dynamic replay). Autonomous DHM simulations are used for the evaluation of robots under development, without the need for a human subject or physical mock-ups, whereas motion replay is used for acquiring a reference situation (non-assisted gesture) or evaluating existing robots.

3. A method for analyzing the relevance of each ergonomic indicator for a given activity, and its dependence with the robot parameters. This analysis enables to extract relevant indicators which best summarize the overall ergonomic performance of the considered activity, as well as identify the robot parameters which mainly affect this performance. The proposed approach relies on the aforementioned simulation framework to automatically simulate a variety of situations. A sensitivity analysis of the ergonomic indicators is thus easily conducted, without the need for much input data.

Thanks to the proposed tools, comparing and optimizing the ergonomic benefit provided by collaborative robots is facilitated, since the number and nature of the ergonomic indicators to consider are automatically adapted to the activity that is studied.
This paper presents a synthesis of our recent contributions in the domain of virtual ergonomics for the design of collaborative robots (Maurice et al., 2013),(Maurice et al., 2014a), (Maurice et al., 2014b), (Maurice et al., 2015), (Maurice, 2015). The paper is organized as follows. Section 2 describes the whole methodology (the three components). Section 3 presents an application of the proposed method, which purpose is the optimization of the morphology of a collaborative robot for a drilling gesture. The results are discussed in section 4.

2. Method

In this work, the human body is represented with rigid bodies, and does not include muscle actuation: the DHM is actuated by a single actuator at each joint. Compared to a musculoskeletal model, a rigid body model is easier to use (no muscle recruitment issue) and computationally more efficient. Moreover, even though muscle-related quantities cannot be estimated with such a model, numerous quantities can still be measured for representing the biomechanical demands that occur during whole-body activities (*e.g.* joint loads, joint dynamics, mechanical energy...).

2.1. Ergonomic indicators for collaborative robotics

Ergonomic indicators aim at quantifying exhaustively and concisely the physical demands to which a worker is exposed when executing various manual activities, with or without a collaborative robot. Contrarily to most ergonomic assessment methods, the different kinds of demands are not aggregated in one single score here, but considered in separate indicators, so that the formulation of the indicators is not task-dependent. Indeed, though the combination of several MSD factors does increase the risk, the way these various factors interact is not well-established in general (Li and Buckle, 1999).
The proposed ergonomic indicators are classified into two families: constraint oriented indicators, and goal oriented indicators (their mathematical formulations are detailed in (Maurice, 2015)). Constraint oriented indicators correspond to local joint measurements in terms of position, velocity, acceleration, torque and power (one indicator per quantity), and directly represent the relative level of joint demands. In order to limit the number of indicators, the squared contributions of every joint are summed up in one single indicator per body part (back, legs, right arm, left arm) The different quantities (position, velocity...) remain however considered in separate indicators. For quantities for which average physiological limit values are available (joint positions and torques), each joint demand is first normalized by its limit value to make the summing more meaningful.
Goal oriented indicators quantify the ability to comfortably perform certain actions. They have the advantage of being very compact, since one global measure accounts for the whole-body situation. The balance is estimated through two indicators: the sum of the square distances between the Center of Pressure (CoP) and the base of support boundaries (balance stability margin) (Xiang et al., 2010), and the time before the CoP reaches this boundary (dynamic balance), assuming its dynamics remains the same over a short time horizon. The first quantity represents the capacity to withstand external disturbances, whereas the second evaluates the dynamic quality of the balance. The capacity to produce force (resp. movement) in a given direction is evaluated with the dynamic force (resp. velocity) transmission ratio of the hand (Chiu, 1987; Yoshikawa, 1985). The rotational dexterity of the head (Yoshikawa, 1985) is used as a vision-related indicator, to estimate the ability to easily follow a visual target. The kinetic energy of the whole body is used as a global measure of human energetic performance.
All these indicators are instantaneous quantities and can be measured at each moment of the activity. In order to limit the number of indicators, the instantaneous values of each indicator are time-integrated. The whole activity is thus represented with only one scalar value per indicator. Note that the proposed quantities are relative indicators: they can be used to compare two situations, but they do not assess an absolute level of risk of developing MSDs.

2.2. Simulation of co-manipulation activities

In order to numerically evaluate the ergonomic indicators defined above, the execution of the considered activity must be simulated with an autonomous dynamic DHM, interacting with a controlled collaborative-robot. The simulation is run in a dynamic simulation framework based on a physics engine, so that the

physical consistency of the motion is guaranteed.
The motion of the manikin is computed by solving an optimization problem to determine the actuation variables (joint torques and ground contact forces) which enable to follow some objectives at best (*e.g.* hand trajectory, center of mass acceleration), while respecting physical constraints. Optimization techniques enable to solve the human kinematic redundancy, while considering both equality and inequality constraints: the dynamic and the biomechanical (*e.g.* joint limits) consistency of the motion is thus ensured. In this work, the linear quadratic programming (LQP) controller framework developed by Salini *et al.* (Salini et al., 2011) is used. The equations of the controller for the DHM animation are detailed in (Maurice, 2015). The objective function of the optimization is a weighted sum of the different tasks that need to be performed, where the weights depend on the relative importance of the corresponding tasks. Tasks are defined as the error between a desired acceleration or wrench and the system acceleration/wrench, either in Cartesian space or in joint space (Fig 2).

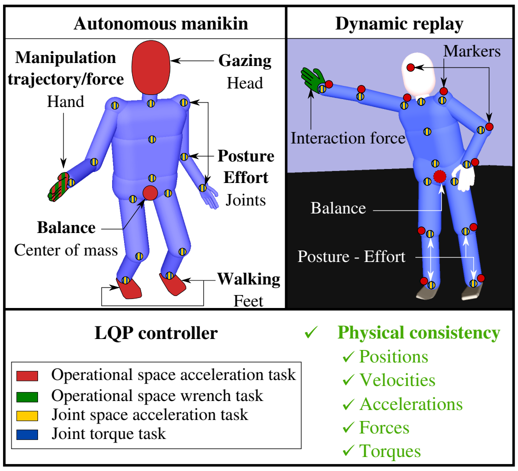


Figure 2: Tasks used in the LQP controller for simulating manual activities with the autonomous DHM (left) or for dynamically replaying human motion (right).

The LQP controller is generic and can be used either with motion capture data, or with high level tasks descriptions[1] (*e.g.* target to reach, place to go). In both cases, the balance of the DHM is managed with a high weight center of mass acceleration task, which reference is computed using a Zero Moment Point preview control method (Kajita et al., 2003). Low weight joint position tasks (postural task) and joint torque tasks are used to define a natural reference posture (standing, arms along the body), and to prevent useless effort. In autonomous mode, only the body parts that are directly needed to perform the activity - generally one or both hands and the head - are explicitly controlled with an operational acceleration and/or force task. On the contrary, in replay mode, an operational acceleration task is created for each marker positioned on the body of the human subject, and the reference trajectory corresponds to the recorded marker trajectory.

As for the robot, this work focuses on collaborative robots which provide strength amplification, and are manipulated by the end-effector only[2] (parallel co-manipulation). Strength amplification consists in controlling the robot (*i.e.* computing the joint torques) so that the force it exerts on the manipulated tool (or environment) is an amplified image of the force applied by the worker onto the robot. The gravity and viscous friction are also compensated.

2.3. Sensitivity analysis of the ergonomic performance

All the ergonomic indicators defined in section 2.1. can be measured with the DHM simulation framework. However, these measurements cannot be used as such to guide the design of collaborative robots. Firstly, comparing the overall ergonomic performance of different robots based on all the ergonomic indicators is not straightforward, because each indicator has a different biomechanical meaning, so different indicators may lead to different conclusions. Secondly, the raw measurements do not provide any hint about how to improve the robot design, *i.e.* which parameters should mainly be modified in order to enhance the overall ergonomic performance. In order to answer these questions, the most informative indicators must be identified, as well as how much they are influenced by each parameter of the robot. Since no straightforward analytical relation between robot parameters and ergonomic indicators can generally be established, a statistical sensitivity analysis (SA) - which rely on the numerical evaluation of the ergonomic indicators for many values of the input parameters - must be conducted (Saltelli et al., 2000). The whole process can be summarized as follows (Fig. 3):

1. Define the robot parameters which can be altered and select, among all the possible combinations, the values that should be tested.

2. Simulate the execution of the activity with the autonomous DHM, for each selected combination of parameters values, in order to measure the ergonomic indicators.

3. Compute sensitivity measures for the ergonomic indicators, based on their values in all the tested cases.

At the early stages of the design process, the number of possible robot designs is infinite, and there is *a priori* no reason to choose one over another. Therefore, in order to be very generic, real robot designs are not used for the SA. Instead a robot is simulated with a parametrizable 6D mass-spring-damper system (robot abstraction) attached to the DHM hand, and on which external forces can be applied to simulate the robot actuation. This system represents the positive

[1] See (Maurice, 2015) and (Maurice et al., 2015) for a detailed description of the tasks included in the controller in autonomous and in replay modes.

[2] Simulating grasping is beyond the scope of this work, so the human grasp is represented by a 6D spring-damper system between the manikin hand and the robot handle.

(strength amplification) and negative (equivalent dynamic of the robot at the end-effector) effects on the worker. The possible geometric interferences between the robot and the worker are simulated by limiting the DHM movements (joints range of motion) and modifying its posture (feet positions, joint reference position...). Parameters representing the diversity of workers are added, to ensure that human features do not have a strong impact on the ergonomic situation. The experimental design of the extended FAST (Fourier amplitude sensitivity testing) method (Saltelli et al., 1999) is used for choosing the appropriate parameters values to test for the SA. Indeed, the exploration method used in FAST is a good compromise between the comprehensiveness of the space exploration and the number of trials.

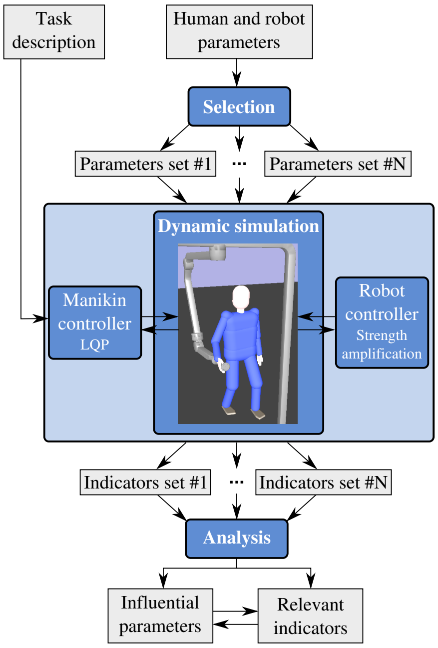


Figure 3: Flow chart of the method for identifying informative ergonomic indicators and influential parameters.

Once the simulations are run for all the selected combinations of parameters values, the SA is performed to identify the most relevant ergonomic indicators. The purpose of this work is not to assess the absolute level of MSDs risks, but to compare different collaborative robots. In this context, the relevance of an indicator is not related to its value, but to its variations when the activity is performed with different robots: the most informative indicators are the ones with the highest variance. The indicators have non-homogeneous units and do not have the same order of magnitude, so they need to be scaled before their variances can be compared. An average value of the order of magnitude of each indicator is roughly estimated by measuring the indicator in many different situations (through DHM simulations), and is used for the scaling (Maurice et al., 2014b). Once the indicators are ranked according to their variance, the number of indicators that are kept to sufficiently summarize the overall ergonomic situation is chosen according to the Scree test (criterion used in PCA).

Eventually, the most influential parameters (*i.e.* the parameters that have the strongest effects on the relevant indicators) are identified through the computation of Sobol indices (Sobol, 1993), with the FAST method. Indeed, Sobol indices allow a precise ranking of the influence of the different parameters: each index measures the percentage of variance of an indicator that is explained by the corresponding parameter.

3. Application

The whole method for guiding the design of a collaborative robot is applied to a real activity. The motion of a human subject performing the activity is recorded and replayed, in order to acquire the technical gesture to execute. This gesture is used as an input for the SA. Based on the SA results, the robot parameters which should mainly be worked on in order to enhance the ergonomic performance are selected. An evolutionary algorithm optimization (Goldberg, 1989) is then used to determine optimal values of these parameters - with respect to the identified relevant indicators.

3.1. Acquisition of the initial situation

The task considered here consists in drilling six holes consecutively in a vertical slab of autoclaved aerated concrete, with a portable electric drill. The subject's motions are recorded with a CodaMotion system, and a 6 axes ATI force sensor is embedded in the drill handle, for measuring the drilling forces (Fig. 4). The recorded motion is replayed with a DHM[3] in the XDE dynamic simulation framework (Merlhiot et al., 2012), according to the dynamic replay method described in section 2.2..

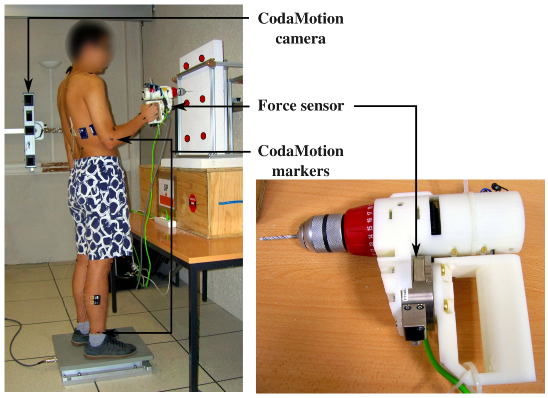


Figure 4: Motion capture instrumentation for the drilling. A commercial drill has been modified to embed a force sensor. The red circles on the slab represent the drilling points.

3.2. Sensitivity analysis

Once the technical gesture is known (hand trajectory and drilling force profile recorded on the human subject), the drilling activity is simulated in XDE with the

[3] See video here: http://pages.isir.upmc.fr/~padois/website/fichiers/videos/maurice_drilling_dyn_replay.mp4

Table 1: Sobol indices for all five ergonomic indicators identified as relevant, for the drilling activity. The ergonomic indicators are presented in decreasing order of importance (decreasing variance) from left to right: the percentages below their names correspond to the percentage of the total variance they explain. FTR stands for force transmission ratio. Numbers are colored from blue (minimum) to red (maximum), to facilitate the reading.

		Relevant ergonomic indicators				
		Legs position	Right Arm torque	Back torque	FTR drilling direction	Right Arm position
		31 %	19 %	14 %	10 %	7 %
Parameters	Manikin height	$\mathbf{10^{-3}}$	**0.13**	**0.19**	**0.42**	**0.07**
	Manikin bmi	$\mathbf{10^{-3}}$	**0.05**	**0.02**	**0.21**	$\mathbf{10^{-5}}$
	Pelvis orientation	$\mathbf{10^{-4}}$	**0.10**	**0.01**	**0.15**	**0.15**
	Pelvis distance	$\mathbf{10^{-3}}$	$\mathbf{10^{-4}}$	**0.01**	**0.02**	**0.03**
	Upper body ref. position	**0.60**	**0.20**	**0.56**	**0.08**	**0.23**
	Upper body joint limits	**0.26**	**0.01**	**0.06**	$\mathbf{10^{-3}}$	**0.28**
	Robot mass	$\mathbf{10^{-4}}$	$\mathbf{10^{-6}}$	$\mathbf{10^{-5}}$	$\mathbf{10^{-6}}$	$\mathbf{10^{-5}}$
	Amplification coefficient	$\mathbf{10^{-4}}$	**0.46**	$\mathbf{10^{-5}}$	$\mathbf{10^{-4}}$	$\mathbf{10^{-5}}$

autonomous DHM, in all the conditions that need to be tested for the SA. The input parameters representing the diversity of potential workers and robots that are used in the present experiment, are listed in table 1 (the DHM upper-body joint limits and reference positions, and pelvis distance/orientation with respect to the stab represent the robot-worker geometric interference). The choice of the parameters values according to the FAST analysis results in a total of 8000 trials.

Table 1 summarizes the ergonomic indicators that are identified as relevant according to the proposed analysis, as well as Sobol indices for these indicators. Five ergonomic indicators are identified as relevant, out of 26 indicators in the initial list (see section 2.1.). These five indicators together represent 80 % of the total variance information, therefore only little information is lost by not considering the other indicators. The selection of the upper-body torque and position indicators is not surprising, given that the activity requires the exertion of a non-negligible force with the right hand, while covering a quite extended area. The absence of any velocity or acceleration indicators seems consistent with the fact that the drilling activity does not require fast motions. However, the presence of the legs joint position indicator as the most discriminating indicator is less expected and could hardly have been guessed. Similarly, some parameter-indicator relations are strongly expected, and confirm the consistency of the proposed analysis (*e.g.* right arm torque *vs.* amplification coefficient), while others highlight some less straightforward effects (*e.g.* upper-body geometric parameters strongly affect the legs position indicator).

Overall, the SA highlights two important trends for the design of a robot for the drilling activity: the mass of the robot does not seem to be a critical parameter (from an ergonomic point of view), whereas the morphology of the robot is (significant effect of the parameters representing the robot-worker interference).

3.3. Optimization of a robot morphology

Once the crucial design parameters have been identified (robot morphology here), they need to be optimized with respect to the relevant ergonomic indicators. In the present application, a generic 7 DoFs robot architecture is considered, in which the lengths of the first five segments are variable (Fig. 5). The optimization aims at finding optimal values for the segments lengths, as well as for the position and orientation of the robot base. As the purpose here is to make a proof of concept, only one average worker morphology is considered for the optimization.

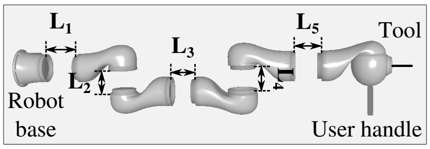
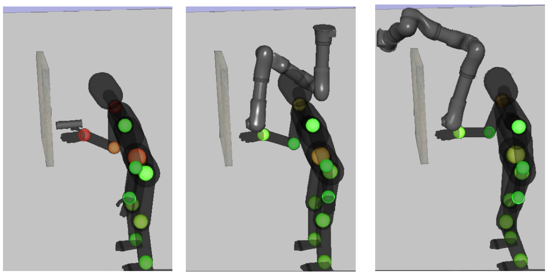


Figure 5: 7 DoFs Kuka LWR-like robot.

The optimization is performed thanks to a coupling between the evolutionary algorithm software Sferes$_{v2}$ (Mouret et al., 2010) and the XDE simulation framework. Sferes$_{v2}$ provides robot candidates to evaluate, and, for each candidate, its performances are measured through an autonomous DHM simulation.

In order to limit the number of objectives (optimization criteria) in the optimization (which otherwise never converges), only the ergonomic indicators identified as relevant are considered. Furthermore, given the parameters that are optimized here and the parameter-indicator relations (Table 1), the right hand FTR is removed (not affected) and the right arm and the back torque indicators are gathered into one single indicator (affected in similar ways). Consequently, a total of three ergonomic objectives are included in the optimization. The position error of the drill extremity during the drilling phases is added to the objectives, to evaluate the quality of the task execution.

The optimization converges after about 150 generations. Over generations, the mean value of each objective in the whole population decreases, showing that the overall performance (*i.e.* the four objectives) of the robots in the population do improve. However, the situation with the robot is never compared with the non-assisted situation, so there is no certainty that the use of a robot - even an optimized one - is indeed beneficial. The ergonomic indicators that are relevant for the current activity (Table 1) are therefore measured in the reference situation (no robot) and with the assistance of two near-optimal robots, chosen to represent a certain diversity of solutions (Fig. 6). The results are displayed in Table 2.



(a) No robot (b) Robot R_1 (c) Robot R_2

Figure 6: Snapshot of the autonomous DHM performing the drilling activity, without any assistance and with the assistance of two different near-optimal robots. The colored spheres represent the instantaneous level of joint effort.

Table 2: Values of the relevant ergonomic indicators measured without assistance (*No robot*), and with the assistance of two near-optimal robots (R_1 and R_2). For each indicator, the value displayed is the percentage of the indicator reference value (used for the scaling), so that the comparison is more understandable (the reference value gives an insight into the average order of magnitude of the indicator, however it does not provide any indication on the absolute level of risk). The indicators in red are worsened by the robot, whereas those in green are improved.

	No robot	R_1	R_2
Right arm position	90	105	125
Legs position	15	25	18
Right arm torque	125	38	47
Back torque	75	43	38
FTR drilling	130	105	112

The right arm position indicator is actually degraded by the use of the collaborative robots. This is due to the lack of transparency of the robot: the robot geometric volume hinders the manikin gesture. On the contrary, the torque indicators (right arm and back) are significantly improved by the use of the robots. This is expected since the robot provides strength amplification. In the end, though some indicators are degraded, the comparatively significant improvements in the torque indicators demonstrate the benefit of the robots. Nevertheless, the performances of both robots are not equivalent, and it is hard to say which robot is overall the best. The choice between the different near-optimal robots is then left to the designer or ergonomist, according to his/her main concerns. The optimization remains nevertheless useful, since it performs a pre-selection of the best performing robots. Moreover, the purpose of the optimization is not to replace the designer, but to provide him/her with interesting preliminary designs to be worked on, for further improving the robot performances.

4. Discussion

The physically consistent results, and the improvement of the robots performances obtained through the optimization, demonstrate the usefulness of the proposed method. However its application within the design process of collaborative robots for industrial tasks should be considered carefully because of some current limitations, which are discussed thereafter.

In the proposed ergonomic indicators, the repetitiveness factor is not taken into account at all, though it is an important MSDs risk factors. Therefore, only robots which do not significantly affect the work rate can be compared, which restricts the range of possible applications of the proposed assessment method. Besides, the duration factor is only roughly taken into account through the time integral value of each ergonomic indicator, thus neglecting its temporal variations. Taking into account the time-frequency aspect of the gesture in the evaluation would definitely enable a more accurate assessment. However, it requires to understand how these time factors affect the human physical capacities, which is closely related to the open problem of fatigue modeling.

The realism of the autonomous DHM behavior is also a crucial issue, since it affects the biomechanical reliability of the results. Compared to kinematic animation techniques, the optimization based controller used here is a first step in the right direction, but there is still a long way to go. For instance, the DHM currently lacks autonomy regarding feet placement, which can lead to awkward postures especially if the robot hinders the DHM gestures. However, simulating highly realistic human motions requires to understand the psychophysical principles that voluntary movements obey. Nevertheless, though the results of the SA and optimization presented in this paper are affected by these autonomous DHM limitations, the method in itself is independent from the DHM control. Thus in the near future an improved control law could be used to animate the autonomous DHM, while the analysis methods remain the same.

5. Conclusion

This paper presents a generic tool for performing detailed ergonomic comparisons of collaborative robots, and its application to the ergonomic design of such robots. The whole tool is based on dynamic DHM simulations, and therefore requires only very little input data. For each new activity, relevant ergonomic indicators are automatically selected among a list of about 30 indicators, thanks to a sensitivity analysis, and critical design parameters of the robot are identified. The whole method is applied to the optimization of a robot morphology for assisting a drilling gesture. The results of the sensitivity analysis are for the most part in accordance with intuitive ergonomic considerations, but they also highlight and quantify some less straightforward phenomena. In the end, the output of the evolutionary optimization demonstrates the interest of the proposed approach for easily providing well-performing preliminary robot designs. Eventually, if the framework presented in this work addresses specifically the collaborative robots providing strength amplification, it could easily be adapted for other kinds of collaborative robots, assistive devices, or more generally workstations

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