Automatic selection of ergonomic indicators for the design of collaborative robots: a virtual-human in the loop approach

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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. Designing these robots requires to assess the ergonomic benefit they offer. However there is a lack of adapted assessment methods in the literature. Many biomechanical quantities can represent the physical solicitations to which the worker is exposed, but their relevance strongly depends on the considered task. This paper presents a method to automatically select relevant ergonomic indicators for a given task to be performed with a collaborative robot. A virtual human simulation is used to estimate thirty indicators for varying human and robot features. A variance-based analysis is then conducted to extract the most discriminating indicators. The method is validated on several different tasks. The relevance of the proposed approach is confirmed by the obtained results.**

I. INTRODUCTION

Work-related musculoskeletal disorders (MSD) represent a major health problem in developed countries. They account for the majority of reported occupational diseases and affect almost 50 % of workers [1]. Since MSD result from strenuous biomechanical solicitations [2], 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 and thereby provides a variety of benefits, such as strength amplification, inertia masking and guidance via virtual surfaces and paths [3].

In order to design a robot which decreases at best the risk of developing MSD, an ergonomic assessment of the robot-worker system must be performed throughout the design process. For cost and time reasons these evaluations can be carried out within a digital world where modifying the robot is simpler. Besides, the use of a virtual manikin enables easy access to many biomechanical quantities, which otherwise require heavy instrumentation of the worker.

To perform this kind of evaluation, several digital human software tools for ergonomic analysis are commercially available (e.g. Jack [4], Delmia, AnyBody [5]). However none of them provide an assessment method suitable for collaborative robots design [6]. Some return a sole criterion representing the global level of exposure, and are very rough or task-specific. Indeed the way the various MSD factors interact is not well-established, therefore it is hard to formulate a criterion both general and accurate. The others on the contrary return one measurement per joint and per kind of solicitation (e.g. joint position or force), and the high number of outputs makes it difficult for the user to interpret. Besides, in the context of optimal design for collaborative robots, these ergonomic criteria represent the objectives to minimize. So their number must be limited, yet the remaining criteria must sufficiently account for the global ergonomic level of the task.

It is therefore necessary to identify the most relevant criteria among all the available ones. Though the features of the considered task evidently affect the relevance of each criterion, establishing general selection guidelines based only on the task description (*a priori* selection) may be quite challenging and lead to inaccurate conclusion. This is especially true when a collaborative robot is used because it can deeply modify the physical stress experienced by the worker and change the nature of the task. Besides the general purpose is not to estimate the absolute level of MSD risk, but to find a proper way to compare different assistive devices. Therefore the most relevant criteria are the ones which differentiate the various ways of performing the task.

This paper presents a method to automatically select the most discriminating ergonomic indicators, for a given task but independently from the robot design because it is supposed to change during the optimization process. The chosen approach relies on a variance-based analysis of the indicators, *i.e.* how much they are affected by the way the task is performed. This requires to measure their values for various situations. Section II therefore presents the different elements needed to produce these data. Section III describes the ergonomic indicators and the selection method. The results are presented in section IV and discussed in section V.

II. SIMULATION SET-UP

The method presented in this paper is based on the study of a task execution in different situations, with and without the use of a collaborative robot. This requires to simulate the task jointly performed by a worker and a robot. Therefore the XDE dynamic simulation framework developed by CEA-LIST[1] is used, since it provides a digital human model which can be controlled and physically interact with a robot.

The only assistance considered in this work is strength amplification. The robot is therefore controlled so that its

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weight is compensated and the force it exerts on the environment is an amplified image of the force applied by the worker onto the robot. The control law is

$$\boldsymbol{\tau}_r = \alpha\, J_{ee,r}^T\, \mathbf{F_{vh}} + \mathbf{g_r}(\mathbf{q_r}) \quad (1)$$

where $\boldsymbol{\tau}_r$ is the robot joint torques, $\mathbf{q_r}$ the robot joint angles, $\mathbf{g_r}$ the vector of gravity forces, $J_{ee,r}^T$ the Jacobian matrix of the robot end effector, $\mathbf{F_{vh}}$ the force applied by the manikin onto the robot end effector, and α the amplification coefficient. As for the manikin control, it is described in section II-A.

Since the indicators selection must be independent from the robot design, many different robots must be considered in the analysis. In order to be as generic as possible, real designs are not used in the simulation, but rather a robot is modelled by its effects (positive and negative) on the worker. These effects are represented by a set of parameters, each combination of their values leading to a different situation. Parameters representing the diversity of workers are added, so as to ensure that the human features do not have a strong impact on the selection of the relevant indicators. Otherwise the robot should include some adjustable parts in order to adapt to each worker. However the computational cost of a simulation can be expensive, so the number of situations which are tested is limited and the values of the parameters must be carefully selected. This process is described in section II-B.

Eventually, the ergonomic indicators are measured in the simulation and then analyzed, in order to identify the relevant ones. The whole method is summarized in Fig 1.

In order to test this method and ensure that the task features do affect the selection of the ergonomic indicators, several case-study tasks of different kinds are considered:

- walking one or several steps, forward, backward or sideways;
- reaching various targets, with both hands;
- exerting various forces (direction and magnitude) with and without movement of the hand (e.g. pushing or carrying objects);
- following trajectories with the hand, with various accuracies and at various speeds;
- bending while leaning with one hand.

A. Manikin control

The XDE-manikin consists of 21 rigid bodies linked together by 20 joints with a total of 45 degrees of freedom, plus 6 DoFs for the free floating base. Each DoF is a hinge joint controlled by a sole actuator.

The motion of the manikin is determined by solving an optimization problem to compute the joint torques and contact forces which enable to follow some objectives at best (e.g. hand trajectory, center of mass acceleration, hand force), while respecting physical constraints. The LQP controller framework developed by Salini *et al.* [7] is used. The control

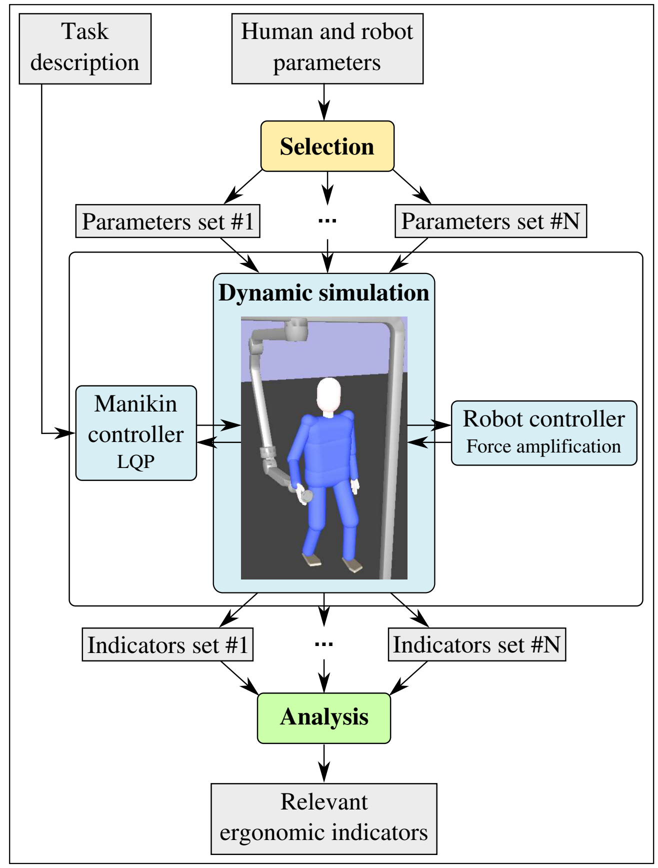


Fig. 1. Flow chart of the method presented in this paper to select relevant ergonomic indicators.

problem is formulated as follows

$$\begin{aligned} &\underset{\mathbb{X}}{\operatorname{argmin}} \quad \sum_i \omega_i T_i(\mathbb{X}) \\ &\text{s.t.} \begin{cases} M(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{g}(\mathbf{q}) = S\,\boldsymbol{\tau} - J_c^T(\mathbf{q})\mathbf{w_c} \\ G\mathbb{X} \preceq \mathbf{h} \end{cases} \end{aligned} \quad (2)$$

where $\boldsymbol{\tau}$ is the joint torques, $\mathbf{w_c}$ the contact forces, $\mathbf{q}$ the generalized coordinates of the system, with $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ its first and second derivatives, and $\mathbb{X} = (\boldsymbol{\tau}, \mathbf{w_c}, \ddot{\mathbf{q}})^T$. The first constraint is the equation of motion: M is the inertia matrix of the system, $\mathbf{C}$ the vector of centrifugal and Coriolis forces, $\mathbf{g}$ the vector of gravity forces, S the actuation selection matrix, and J_c^T the Jacobian of contacts. The second constraint includes the bounds on the joint positions, velocities and torques, and the contact existence conditions for each contact point.

The objective function is a weighted sum of tasks T_i representing the squared error between a desired acceleration or wrench and the system acceleration/wrench (ω_i are the weighting coefficients). The following tasks are defined

- Operational space acceleration $\|J_i\ddot{\mathbf{q}} + \dot{J}_i\dot{\mathbf{q}} - \ddot{\mathbf{X}}_{\mathbf{i}}^*\|^2$
- Joint acceleration $\|\ddot{\mathbf{q}} - \ddot{\mathbf{q}}^*\|^2$
- Operational space wrench $\|\mathbf{w_i} - \mathbf{w_i^*}\|^2$
- Joint torque $\|\boldsymbol{\tau} - \boldsymbol{\tau}^*\|^2$

where $\ddot{\mathbf{X}}_{\mathbf{i}}$ is the Cartesian acceleration of body i, and $\mathbf{w_i}$ the wrench associated with body i. The superscript * refers to the desired acceleration/force, which are defined by a proportional derivative control. For instance, the desired acceleration is

$$\ddot{\mathbf{X}}^* = \ddot{\mathbf{X}}^{\mathbf{goal}} + K_v(\dot{\mathbf{X}}^{\mathbf{goal}} - \dot{\mathbf{X}}) + K_p(\mathbf{X}^{\mathbf{goal}} - \mathbf{X}) \quad (3)$$

where K_p and K_v are the proportional and derivative gains. The superscript ^{goal} indicates the position, velocity and acceleration wanted for the body or joint.

A ZMP preview control method [8] is used to compute the desired acceleration for the center of mass task, in order to ensure the balance of the manikin during both standing and walking phases. For the walking phases, the length and duration of a step are parameters of the controller and must be specified in advanced. The largest weight is associated with this balance task, since balancing is the first priority.

The hands operational position and force tasks are given the second most important weights, because they determine whether the job is correctly performed or not. At the same level, an orientation task is associated with the head so that the manikin looks at what it is doing.

Then low weight joint position tasks are added to make the manikin rest posture and motion more human-like. The default desired joint positions (reference posture) correspond to a standing posture, arms along the body. The weights of these tasks are not equal, but rather decrease when nearing the distal members (hands and feet), in order to favor their motion compared to the body parts closer to the torso.

Finally there is a joint torque task which aims at minimizing the joint torques to prevent useless effort. Its weight is very small since it must not hinder the other tasks.

B. Parameters definition

The input parameters represent the diversity of potential workers and collaborative robots. The worker is defined by his/her *height* and *body mass index* (bmi).

This work focuses on parallel comanipulation, *i.e.* the worker manipulates the robot only by its end effector. The robot is therefore simulated by a mass-spring-damper system attached to the manikin hand. To limit the number of parameters, only the *robot mass* varies whereas the stiffness and damping are currently kept constant. The *amplification coefficient* of the robot control law is also added to the parameters. Aside from these amplification and supplementary inertia effects, the robot can interfere with the worker because of its volume. This can be simulated without making hypotheses on the robot design, by limiting the movements of the worker (*joint limits*) and modifying his posture (*pelvis orientation* and *joint reference positions*). The robot is manipulated with the right hand, therefore the left part of the body is not affected by theses changes. Eventually, the *step length* and *weights of the arm joint position tasks* are added to the input parameters and represent either some preferences of the worker or some interferences with the robot.

All these parameters take continuous values, but the number of simulations is limited by their computational cost, so

Parameter	Minimum	Maximum
manikin height (m)	1.65	1.80
manikin bmi ($kg.m^{-2}$)	21.0	27.0
arm tasks weights	1, 0.1, 0.01	1, 1, 1
step length (m)	0.2	0.4
upper body joint limits	0.3	1.0
upper body reference positions ($°$)	0, 0, 0, 45	15, 45, 45, 135
pelvis orientation ($°$)	0	30
robot mass (kg)	2	10
amplification coefficient	1	3

Fig. 2. Parameters minimum and maximum values. The weights of the arm joint position tasks are specified as ratio of the largest one of these weights, and they are given in the following order: scapula, shoulder, forearm (elbow and wrist). The upper body joint limits are specified as ratio of the regular joint limits, and applied on each joint of the back and right arm. The reference positions of the upper body joint tasks are only modified for the following joints: back flexion, shoulder flexion, shoulder abduction, elbow flexion. They are given in this order and relative to the regular reference posture (upright, arms along the body). The root orientation is given relative to facing the work area.

the exploration of the parameters space must be optimized. The values of the parameters sets are therefore chosen according to the exploration method used for the Fourier amplitude sensitivity testing (FAST) [9]. This is a good trade-off between the number of trials, which is a lot smaller than with Monte-Carlo methods, and the comprehensiveness of the space exploration. The sample size is $n = 2000$ for each parameter, which results in a total of 18000 simulations, with one simulation taking approximately 2 minutes. The numerical upper and lower bounds of the input parameters considered in this work are given in Fig. 2.

III. ERGONOMIC INDICATORS

This section details the ergonomic indicators that are considered, and the method used to identify the relevant ones.

A. Indicators definition

The ergonomic indicators quantify the effects of the physical solicitations on the worker. Most ergonomic assessment methods exclude dynamic phenomena though they also generate MSD. Here on the contrary, the following biomechanical quantities are measured thanks to the dynamic simulation framework: *joint position (A)*, *velocity (B)*, *acceleration (C)*, *power (D)* and *torque (E)*. Similarly to what is done for robot manipulators [10], each one of these quantities is then summed up on all the joints of a given body part, in order to form more synthetic performance criteria. The mathematical form of a criterion is

$$\frac{1}{p}\sum_{i=1}^{p}(s_i)^2 \quad (4)$$

where s_i is the biomechanical quantity (position, velocity, ...) of joints i, and p the number of joints in the considered body part: torso *(a)*, right arm *(b)*, left arm *(c)*, or legs *(d)*. When physiological limit values are available, s_i is normalized by its limit value s_i^{max} before the summing [6]. However these limits are strongly person-dependent, and maximum values are often not well-documented in the literature (e.g. joint velocities or accelerations), making the normalization impossible.

In addition to these local indicators, global quantities which represent the ability of the manikin to comfortably perform certain actions are considered. Its balance is estimated through two indicators: the *sum of the square distances between the ZMP and the base of support boundaries (F)* [11], and the *time before the ZMP reaches this boundary (G)*, assuming its dynamic remains the same. 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 *force (H)* (resp. *velocity (J)*) *transmission ratio of the right hand* proposed by Chiu [12], except that the dynamic manipulability [13] is used instead of the kinematic one. Eventually the *kinetic energy (K)* of the whole body is added to the indicators list.

B. Selection method

The general purpose of this work is to limit the number of ergonomic indicators needed to compare different collaborative robots. Therefore it is necessary to identify, among the aforementioned indicators, the ones that best explain the disparity of the results when the task is performed in various ways. Thus the main ergonomic differences between several situations (e.g. several collaborative robots designs) can be summarized with only a few criteria.

Reducing the number of ergonomic indicators to keep only the most informative ones is a problem of dimensionality reduction. However most dimensionality reduction methods form composite variables (*i.e.* combinations of the initial variables), whereas here the resulting variables must remain the ergonomic indicators. Indeed meaningful ergonomic criteria cannot be formed by aggregating various indicators, because the latter potentially have very different physical meanings. So standard dimensionality reduction methods, such as principal components analysis (PCA) cannot be used here.

The importance of each ergonomic indicator is therefore represented directly by its variance. A Scree test (or "elbow" rule) is then performed on the values of these variances, to identify the discriminating indicators. This criterion is usually used to select the number of dimensions in a PCA.

However before performing this analysis, the ergonomic indicators must be scaled because they have non-homogeneous units (therefore not the same order of magnitude), so they cannot be compared as such. In standard dimensionality reduction methods, this is often done with the variables standard deviation, but then the scaled variables all have a unit variance. Since the variance is precisely what represents the indicators global sensitivity to the task parameters, this scaling would result in the loss of relevant information. Therefore another option is to use the indicators physiological limit values for this scaling. Though this is ergonomically very meaningful, some indicators do not have well-defined limits (e.g. kinetic energy), and even the existing ones are often hard to find as stated in section III-A. Instead, the order of magnitude of an indicator is estimated here with its average value on all the case-study tasks. Indeed tasks of many different kinds are considered and performed in many different ways, therefore it can be assumed that the range of values of each indicator is covered quite exhaustively.

The ergonomic indicators presented in section III-A are measured for each time step of the simulation. However, the selection method described here requires that each indicator (for each situation) is represented by a single value. Therefore the time-integral value of the indicator (on the whole duration of the considered task) is used.

IV. RESULTS

Fig. 3 summarizes the ergonomic indicators that are identified as relevant for each task according to the selection method detailed in section III-B. From 29 indicators in the global list, between 3 and 9 indicators are selected for each task. This selection results in the loss of less than 30 % of the total information about the variance.

A. General remarks

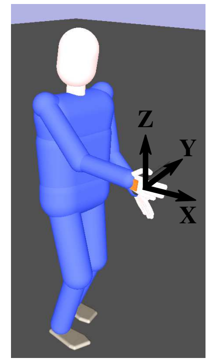
Many of the selected indicators are in accordance with what could be expected given the features of the corresponding task. This is especially true for the tasks where force exertion is associated with slow dynamic (e.g. tasks 12, 15 and 17). The biggest MSD risk factor therefore comes from the significant efforts. Indeed the torque indicators of the upper body parts (right arm, back and left arm in phase 17) are among the most discriminating indicators.

In most of the walking and reaching tasks, the kinetic energy is selected as a relevant indicator, whereas it is not selected in other tasks. This is consistent with the fact that walking and reaching generally involve whole-body motion, but no significant effort. Even if the aim of this paper is not to provide general guidelines for indicators selection, the kinetic energy seems to be a good indicator to summarize the global ergonomy of reaching and walking tasks, independently from their detailed features.

Besides, the situations for which the selected indicators take extreme values are physically consistent. Fig. 4 displays the parameter values for which the most discriminating indicator takes extreme values, in four typical tasks. These tasks have been chosen because the most discriminating indicator can be clearly identified (*i.e.* its variance is distinctly superior to the others). The lower and upper extreme values of an indicator are defined by its 5th and 95th percentiles values. For each task, only one parameter appears in this table, because the values of the other parameters are quite equally distributed for these extreme cases. The results are discussed below.

Walking sideways: In task 2, the kinetic energy increases with the step length. The duration of one step is imposed, so the bigger the step length, the faster the leg trajectory. Besides, a faster step is more disturbing for the balance. Therefore it leads to more motion of the whole body, which also increases the kinetic energy.

		1 Walk forward 20cm	2 Walk sideways 30cm	3 Step forward	4 Step backward	5 Walk forward 50cm	6 Reach RH 1	7 Reach RH 2	8 Reach RH 3	9 Reach RH 4	10 Reach RH 5	11 Reach LH	12 Trajectory 1 RH[1]	13 Trajectory 2 RH[2]	14 Trajectory 3 RH[3]	15 Push RH[4]	16 Bend forward[5]	17 Carry RH[6]
Kinetic energy	K ●	0.28	0.91	0.20	0.15	0.18	0.75	0.08	0.34		0.25							
VTR RH Z	Jz ●																	
VTR RH Y	Jy ●																	
VTR RH X	Jx ●																	
FTR RH Z	Hz ●												0.02					
FTR RH Y	Hy ●																	
FTR RH X	Hx ●	0.39								0.07	0.23	0.38				0.8		
Dynamic balance	G ●										0.22		0.09		0.43			
Balance robustness	F ●							0.09	0.22	0.14			0.11		0.15			
Legs torque	Ed ●	0.44	0.24	0.64	0.15	0.33												
Legs power	Dd ●		0.23	0.28	0.33	0.08												
Legs acceleration	Cd ●	0.32	0.27	0.49														
Legs velocity	Bd ●	0.17	0.45	1.25	0.74	0.09												
Legs position	Ad ●											0.14	0.02					0.32
LA torque	Ec ●																4.6	4.8
LA power	Dc ●																2.1	0.40
LA acceleration	Cc ●	2.59	0.43	0.91		0.16						0.57		8.9			1.4	
LA velocity	Bc ●	0.27		0.22	0.59							0.07	0.02				0.99	
LA position	Ac ●																	
RA torque	Eb ●							0.05		0.11			0.11		0.06	0.73		0.61
RA power	Db ●						0.40		0.13									
RA acceleration	Cb ●								0.21					16.7				
RA velocity	Bb ●						3.54	0.10	0.32	0.18	0.98						0.96	
RA position	Ab ●									0.15	0.20		0.05		0.07	0.15		1.1
Back torque	Ea ●					0.15		0.08			0.12	0.65	0.07		0.07	0.44		1.3
Back power	Da ●		0.05			0.14	0.30	0.13	0.14	0.08	0.16	0.58					0.84	
Back acceleration	Ca ●						0.27		0.20			0.12		6.9			2.5	
Back velocity	Ba ●						0.49	0.15	0.17			0.14					2.2	
Back position	Aa ●							0.05		0.19	0.10	0.17	0.05		0.18	0.10		
% of total variance		77	81	82	79	70	83	72	80	75	80	77	81	86	83	81	80	82



[1] Follow straight line roughly
0.1m/s average velocity - 36N force down

[2] Follow straight line roughly
0.5m/s average velocity - 5N force down

[3] Follow square path accurately
0.065m/s average velocity - No force

[4] Push 100N RH along X axis - No RH movement

[5] Bend whole body forward - Lean on table LH

[6] Pick up 3kg object RH - Move it 60cm
Lean on table LH

FTR: force transmission ratio
VTR: velocity transmission ratio

RH: right hand
LH: left hand
RA: right arm
LA: left arm

Fig. 3. Ergonomic indicators identified as relevant based on their variance, for each phase of the task (presented in chronological order). An indicator is relevant for a given phase when the corresponding square is colored. The number in the square is the value of the variance, computed on the scaled indicator. The number at the bottom of each column corresponds to the total percentage of variance explained by the selected indicators. The red-green-blue colors do not have a particular meaning, they are used only to help the reading of the table.

	Discriminating indicator		Significant parameter
Phase 2 Walk sideways	*Kinetic energy*		*Step length*
	min	0.7	0.2 m
	max	3.4	0.4 m
Phase 13 Fast trajectory tracking	*RA acceleration*		*Robot mass*
	min	18	2 kg
	max	39	10 kg
Phase 15 Push 100N	*RA torque*		*Amplification*
	min	1	3
	max	9	1
Phases 16-19 Bend forward with support	*LA torque*		*Manikin height*
	min	4	1.65 m
	max	12	1.80 m

Fig. 4. Parameter associated with the extreme values of the most discriminating ergonomic indicator, in four typical phases. The indicators minimum and maximum values are displayed, with the corresponding parameters values. The indicators values are the normalized ones (see section III-B), therefore there is no unit. RA (resp. LA) stands for right (resp. left) arm.

Fast trajectory tracking: In task 13, the right arm acceleration increases with the robot mass. This is due to the robot inertia driving the manikin arm when the direction of motion changes.

Pushing: In task 15, the right arm torque indicator is minimum when the force amplification coefficient is maximum (and vice versa). Indeed, the bigger the amplification provided by the robot, the smaller the force left to the manikin to exert.

Bending: In tasks 16-17, the left arm torque indicator increases with the manikin height. While bending, the manikin leans on a table with its left arm to help keep its balance. But the table height remains unchanged, so the taller the manikin, the more it has to bend to reach the table. This results in a more horizontal posture of its trunk, and therefore in more weight to support on its leaning arm.

B. Analysis of specific phenomena

As stated in the previous section, most of the results are consistent with what could be expected. However Fig. 3 also displays some less straightforward results which require further explanation. They are detailed thereafter.

Force/Velocity transmission ratio (FTR/VTR): The FTR represents the ease to exert a force in a given direction. Therefore when a contact force is exerted in this direction, the FTR is a qualitative image of the joint torques (e.g. task 15). However it has no meaning when no contact force is exerted with the corresponding body part, *i.e.* the right hand in tasks 1, 9, 10 and 11. The same remark applies to the velocity transmission ratio (VTR): if no motion is required in the studied direction, the VTR cannot represent the current ergonomic situation. Therefore, the initial list of indicators must be adapted before the selection process: the global indicators with no physical meaning for the considered task should be removed. This can also explain why the VTR indicators are never selected as relevant: most of the time, the hand motion is not solely along one of the 3 main directions (X,Y,Z). Actually it would be more meaningful to compute the VTR along the hand direction of motion, and the FTR too since the right hand drags the robot. However, the corresponding data are very noisy and therefore cannot be used in this work.

Arm indicators in walking phases: The results of most walking/stepping tasks are at first counter-intuitive. The left arm dynamic indicators are often very discriminating (large variance), sometimes more than the legs indicators. This actually highlights a balance problem. The stability of the stepping is strongly affected by the input parameters. So for some combination of their values, the manikin is very unstable and performs bracing motions to help regain balance. Since the feet positions and trajectories are imposed, the arm motions which are not constrained are in comparison much more diverse. The left arm is more affected because the robot inertia on the right arm slows the arm motions down. The balance-related indicators are not necessarily strongly affected by this phenomena, because the arms bracing can be sufficient to keep the ZMP trajectory quite unchanged between different situations. Therefore they do not appear in the discriminating indicators. However, though these results are physically meaningful, the balance loss might result more from a control problem (humanoid balance for dynamic movements), than from a truly unstable situation for a human being.

V. Discussion

The physically consistent results validate the method proposed in this paper. 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.

A. Automatic segmentation of the task

The analysis proposed in this paper requires that, for a given situation, each ergonomic indicator is represented by a unique value (its time-integral, see section III-B). This hypothesis makes sense here, because only elementary tasks are considered. On the contrary industrial tasks that could be addressed with collaborative robots are generally complex. They should not be regarded as one and only task, but rather as a succession of elementary tasks. The value of an ergonomic indicator may vary significantly from one elementary task to another, so summarizing an indicator with its time-integral on the whole task would result in a considerable loss of information. Therefore a complex task needs to be segmented in several elementary phases, in order to select discriminating indicators separately for each phase.

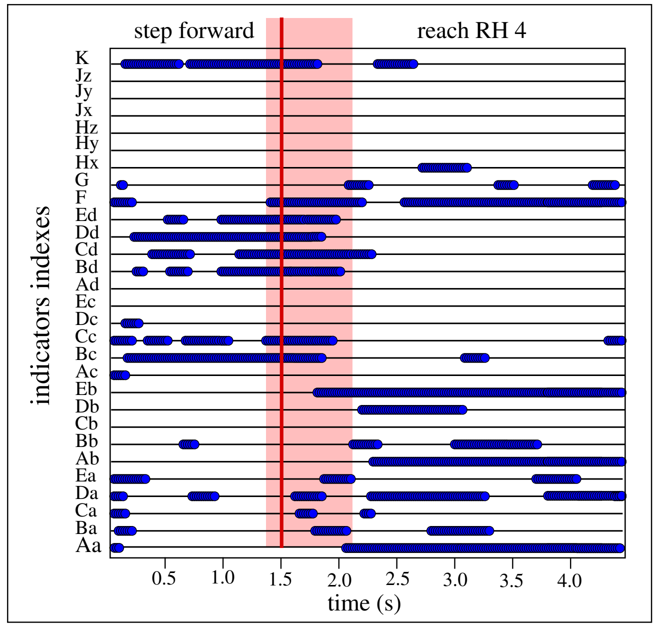


Fig. 5. Ergonomic indicators identified as discriminating for each time step of tasks 3 and 9 played as a unique complex task. Each indicator is represented by its corresponding letter defined in section III-A. A blue dot on an indicator line means that this indicator is relevant for the corresponding time step The red line is the limit between the phases used in this work. The pink zone represents the transition phase in which the selected indicators remain quite the same.

If the identification of the main phases can be done manually by the user, defining the limit between two phases is more difficult. Indeed the first phase often affects the following one, therefore defining the limit between both phases when the second motion starts may not be optimal regarding the selected indicators. This is especially true for post-walking phases. The end of the walking represents a strong change in the global dynamic of the body. This change, which happens at the end of the walking phase, can disturb the balance and therefore have consequences in the next phase because regaining balance is not immediate. To illustrate this phenomenon, tasks 3 (step forward) and 9 (reach 4) of Fig. 3 are concatenated and simulated as one single task. Fig. 5 displays the ergonomic indicators that are identified as discriminating for each time step of this two phases. The limit between both phases is chosen here as the time when the objectives in the manikin controller change. No modification in terms of the selected indicators happens at the pre-defined limit (red line on Fig. 5). On the contrary, the fact that the same indicators are selected around the transition (pink zone in Fig. 5) suggests that the biomechanical solicitations during the transition are specific. Therefore the transition should be considered as a distinct phase. But the duration of the transition phase strongly depends on the features of the first phase and cannot be known beforehand. Therefore the segmentation of the task in phases should rather be automatic and based on the evolution of the indicators relevance. Besides, some elementary tasks themselves segmented in several distinct phases could probably be assessed more accurately.

Choosing a meaningful criterion to automatically identify different phases in a task is not straightforward. As depicted in Fig. 5, a segmentation based only on a change in the set of discriminating indicators is not possible, because it leads to far too many phases. However, this problem needs to be worked on because it would improve the relevance of the final ergonomic assessment.

B. Realism of the manikin behavior

Since the discriminating ergonomic indicators are identified based on a virtual human simulation, the ergonomic relevance of the resulting selection strongly depends on the realism of the manikin movements and forces. Though the results presented in section IV show some physical consistency, it is not sufficient to prove the human-like behavior of the manikin.

First it should be noted that the realism of most common DHM software tools for ergonomic assessment can be quite limited. As highlighted in [14] and [15], biomechanical quantities computed through virtual human simulation do not always match their equivalent measured directly on a human-being, which leads to wrong assessment of the risk. Indeed, within most of these tools, the manikin is animated either through motion capture data or directly by the user through direct or inverse kinematics. In the first case, recording the data require heavy instrumentation of the worker and also a physical mock-up of the workstation so that the motion are realistic, which is very time consuming. In the case where direct kinematics is used, the manikin motions and postures are entirely decided by the user. They are therefore hardly ever realistic, especially when the user does not have particular skills about human motion. Inverse kinematics leads to better motions, however they still lack realism partly because dynamics is not considered. Even when some semi-automatic controls are provided (e.g. reaching, grasping, gazing, walking) the motion sometimes looks unnatural. Besides in all these tools, the interaction forces with the environment are rarely considered to compute the motion, except in Jack [4] where static posture can be predicted based on hand force exertions. Also balance is almost always ignored.

In this paper however, the manikin is animated with an optimization technique which takes into account the dynamics of the human body, the external force exertion and the balance problem (see section II-A). The hands forces required to perform a given task (e.g. push) are still specified by the user, but the hands and feet contact forces necessary to maintain balance result from the optimization. Therefore, though there is still much to improve, this is a first step towards a more human-like behavior of the manikin.

Actually simulating highly realistic human motions requires to understand the psychophysical principles that voluntary movements obey. Many studies have already been conducted in order to establish mathematical formulae of these principles, especially for reaching motions (Fitt's law, minimum jerk principle,...). De Magistris *et al.* [16] have successfully implemented some of them within the XDE framework. However these improvements are currently limited to reaching motions since these driving principles are not yet known for all kinds of motions. For instance, the problem of feet positioning is of a very different kind, and is a current research topic, both for walking [17] and for manipulation tasks with significant interaction forces [18].

Nevertheless it should be noted that if the results of the method proposed in this paper (*i.e.* which ergonomic indicators are selected) strongly depends on the realism of the manikin behavior, the method in itself is independent from the manikin control. Thus in the near future an improved control law could be used to animate the manikin, while the indicators analysis method remains the same.

VI. CONCLUSIONS

A method to automatically identify relevant ergonomic indicators for a given task performed with a collaborative robot has been proposed. It is based on a virtual human simulation to estimate the indicators values, for varying human and robot features. A variance-based analysis was then used to extract the most discriminating indicators. The method has been validated on a complex task formed by several different phases, analyzed separately. Between 3 and 9 indicators were selected in each phase, out of a list of 30 indicators. The selected indicators were for the most part in accordance with intuitive ergonomic considerations. Results also highlighted some less straightforward phenomena. The chosen segmentation of the task in phases was questioned. As a consequence, future work will be directed towards the automatic segmentation of a task in different phases, so that the segmentation is optimal with respect to the relevance of the ergonomic indicators. A sensitivity analysis of the ergonomic indicators will also be conducted in order to evaluate the ergonomic effects of the various human and robot parameters.

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