Musculoskeletal Load Analysis for the Design and Control of a Wearable Robot Bracing the Human Body While Crawling on a Floor

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ABSTRACT

Wearable robots, such as exoskeletons, can potentially reduce the load at targeted muscles of the human body during fatiguing tasks. It is common, however, that use of a wearable robot causes increased load at untargeted muscles, leading to minimal net improvement. Here, musculoskeletal impacts of a wearable robotic device are examined to establish a foundation for the design and control of a robot based on a musculoskeletal model and experimental data. The model predicts the effect of the device, called Supernumerary Robotic Limbs (SuperLimbs), on the wearer’s whole body muscular effort. SuperLimbs brace the upper body of a human while they work near floor-level. Its effectiveness varies depending on how it is attached to the human (harness design), how it is coupled to the floor (wrist and hand design), and how it is controlled (actuation policy). These behaviors and their interplay are analyzed and used to inform the design and control of the robot.

First, body movements are measured with a motion capture system while a human subject crawls on the floor. Their muscular activity and the floor reaction forces are then estimated based on a musculoskeletal model’s inverse dynamics optimization. The effect of the SuperLimbs is assessed by replacing both human arms in the model with robotic limbs. The analysis reveals that the human muscle load is minimized with a particular combination of SuperLimbs joint torques that can be used as feedforward commands to the SuperLimbs controller. Desirable harness and wrist properties are obtained by varying the parameters of the Human+Robot model, and tracking the effect of these changes on the distribution of muscles forces in the human’s back. It is found that a harness chest plate of the SuperLimbs attached at its anterior edge minimizes muscle activity in the back’s vulnerable lower lumbar region. The model is verified with ground reaction force experiments, and its validity is examined for every simulation experiment.

INDEX TERMS Biomechanics, Crawling, Exoskeletons, Musculoskeletal modeling, Supernumerary robotic limbs, Wearable robots

I. INTRODUCTION

EXOSKELETONS have been used for assisting workers in performing tasks that are ergonomically challenging [1], [2]. Working at an overhead area, for example, workers experience muscle fatigue and strain if they have to keep raising the arms for a long time. Exoskeletons, passive or active, can alleviate fatigue and muscle disorders to some extent. However, human subject tests have revealed that, although the exoskeletons are effective at reducing the load at targeted muscles, other parts of the muscle loads increase with the use of those exoskeletons. As a result, the overall effectiveness of exoskeletons is less significant than originally expected.

Theurel and coworkers [3] have shown that upper limb exoskeletons may reduce muscle activity in some muscles, including the shoulder flexor muscles, but have consequences in increased antagonist muscle activity, postural strains, cardiovascular demand, and modified kinematics. Work such as [4] and [5] discuss the need to analyze the effect of exoskeletons on the parts of a wearers body that are not directly augmented. Finally, [6] is some of the limited work that discusses the effect of exo-skeletons on un-targeted parts of a wearers body.

Lower limb exo-skeletons incur a metabolic penalty for their wearer during walking even if they reduce the work
done by a targeted set of muscles. This cost is due to factors such as changes in the operator’s natural kinematics, and an increase in their weight and inertia. This cost is also commonly larger than the reduction in the metabolic cost due to the action of the device. Work such as [7] and [8] demonstrate some of the earliest examples of a net reduction of the metabolic cost of walking below the un-assisted cost.

Working on or near a floor demands workers to take an ergonomically challenging posture. A human must brace his/her upper body on all fours, while performing a task on the floor. Installing flooring materials and carpets, planting and harvesting agricultural products, and welding steels laid on a floor are just a few examples of fatiguing tasks on or near a floor. Many work-related injuries at the back, shoulders, and the neck have been reported when workers have to crawl on their hands and knees for a long time. Simple bracing devices are occasionally used, but they are inflexible and not widely used [9]. Powered exoskeletons and other types of wearable robots have been developed for assisting crawling humans, but their effects on the wearer’s musculoskeletal state have been poorly understood.

Having hundreds of muscles that are coupled and overlapped, the human musculoskeletal structure is complex. A change to a load acting at one point, or changes to boundary conditions between the human body, a support device, and the environment, may influence other parts of the body. Particularly important is how the support devices are attached to the human and how they interact with the environment. The former pertains to the design of a harness and the latter pertains to the way in which the support device contacts the floor. It is also important to apply forces to the human through the support device in a way that minimizes their muscle strain.

Proper management of the influence of support devices necessitates a sound understanding of their musculoskeletal effect on the human body. The current work presents a cross-disciplinary study where musculoskeletal analysis informs the design and control of a wearable robot. Specifically, the musculoskeletal effects of a device for crawling support are analyzed based on bio-mechanics and motor-control modeling as well as human experiments, and guidelines for designing and controlling an effective robotic device that meets musculoskeletal requirements for crawling support are obtained.

II. SUPERNUMERARY ROBOTIC LIMBS FOR CRAWLING SUPPORT

Supernumerary Robotic Limbs, or SuperLims for short, are a type of wearable robot designed to aid humans. Unlike powered exoskeletons, which follow the human’s movements, SuperLims are separate from the human’s limbs and can take different postures simultaneously. This allows them to support the human in tasks where traditional exoskeletons are not effective.

There are numerous tasks that must be performed on or near a floor. The upper body of a human must be supported to perform tasks low to the floor. Merely increasing the joint torques of extremities with powered exoskeletons does not provide a necessary support. The SuperLims can brace the upper body so that the human does not have to use one hand to support the upper body. Fig. 1 shows a prototype of SuperLims for this class of floor tasks [10]. The wearer of the SuperLims can use both natural limbs for performing a given task.

Supporting the upper body with SuperLims, however, effects the stress distribution across the human body. It is necessary to examine how SuperLimb support influences the human musculoskeletal system.

The work in [11] is the first, that the authors are aware of, that analyzes the effect of a wearable robotic system on the load distribution of a crawling adult. It is shown that synchronizing the robot’s motion with the operator’s motion minimizes the mechanical work done by the operator’s back. The analysis justifies the proposed SuperLims crawling controller, which acts to synchronize the robot to the operator during crawling. The result is reported for a simple human model however, thus the validity of the result is unclear for more complex situations. In the current work the effect of the SuperLims on the human’s musculoskeletal system will be examined more rigorously using a whole body model and experimental and numerical validation. Furthermore, this model will be used to guide the design of the SuperLims in a way that prioritizes natural and healthy ergonomics. Finally, we demonstrate that ergonomic support can be quantified and used to facilitate a novel control algorithm.

Muscular skeletal disorders (MSDs) of the lower back are the most common type of injury reported [12], [13]. These injuries are commonly the result of back muscles exerting excessive force, leading to muscle and ligament sprains.
Increased work being done by the back (as predicted in [11]) implies that the back’s muscles are doing more work, however it is not necessarily the case that individual muscles are being over-exerted to the point that a person is at an increased risk of injury. The aim of this work is to model the effect of the SuperLimbs on the distribution of muscle forces in the human’s trunk during crawling, and to use this model to coordinate robot control and uncover design principles that favorably redistribute these forces. Only the design parameters that effect the interfaces between the SuperLimbs and the human, and the SuperLimbs and the ground are studied. Because of this, the presented results generalize to any kinematic structure of the SuperLimbs.

In bio-mechanics literature, muscular-skeletal models are commonly used to analyze human movement by estimating muscle and ground reaction forces during walking and running [14], [15]. These tools are also used to design prosthetic devices that aid people as they walk and run, [16]. This work presents a novel use of muscular-skeletal modeling to design a tool that aids in crawling.

Section III describes the method used to build and analyze the dynamic model of our experimental subject. Section IV presents a validation experiment that illustrates the accuracy of the human model’s force prediction. Section V demonstrates the benefit of computing real-time SuperLimbs control effort based on the human model. Section VI describes the analyses used to estimate the human’s muscle activation as a function of varied SuperLimbs design parameters. These insights are collected into a set of design guidelines. Finally, Section VII summarizes the contributions of this work.

III. MUSCULOSKELETAL MODELING METHODS

This section summarizes existing modeling methods required for constructing a musculoskeletal model of human crawling that is used to predict the human’s muscle forces and ground reaction forces. This prediction is made based on the human’s measured crawling kinematics. Fig. 2 shows the task flow of data collection and analysis, consisting of 1) human measurement, 2) kinematic modeling and analysis, and 3) estimation of muscle recruitment and ground reaction forces based on dynamic musculoskeletal modeling and optimization.

The human crawling motion is replicated on a musculoskeletal model with matched kinematic and inertial properties. Because the human musculoskeletal system is highly redundant with multiple muscles acting on the same joint, a technique called muscle recruitment optimization is employed together with an inverse dynamics analysis to estimate the force that each muscle exerts during the measured motion. This analysis method is based on a wealth of biomechanics and neuromotor control literature, as summarized below.

A. INVERSE KINEMATICS ANALYSIS

The human model used in this analysis consists of \( n_r = 175 \) generalized coordinates (GCs): 169 joint displacements plus the position and orientation of the pelvis viewed from inertial reference frame. These GCs, denoted \( q \in R^{175} \), are determined from experimental data. As detailed in the experiment section, markers numbered 1 through \( n \) are placed on a human body, and the coordinates of the markers \( x_i^{exp} \in R^{3}, (1 \leq i \leq n) \) are measured. The GCs are fitted to the experimental data by minimizing the following squared error with regularization terms.

\[
 \hat{q} = \arg \min_q \sum_{i=1}^{n} w_{m,i} ||x_i^{exp} - x_i(q)||^2 + \sum_{j \in N_{reg}} w_{r,j} (q_j^{reg} - q_j)^2. \tag{1}
\]

where \( \hat{q} \) is the generalized coordinates of the estimated human posture, \( x_i(q) \) is the predicted position of the \( i \)-th marker, \( w_{m,i} \in R^2 \) are weights on individual markers, and the second term is for regularization. In crawling, a group of joints \( q_j \in R \) where \( j \in N_{reg} \) are likely to take certain values, or follow prescribed time functions, \( q_j^{reg} \). For example, the GCs of the spinal column should take a posture near to that of a neutral spine to yield a computed range of motion that is consistent with the spine’s physiological limits [17]. With weights \( w_{r,j} \), deviation of the corresponding GCs from the prescribed \( q_j^{reg} \) is penalized, so that the solution is regularized around the physiologically meaningful values.

B. EQUATIONS OF MOTION AND INVERSE DYNAMICS

The subject’s dynamic model, evaluated with their measured kinematic motion, is used to predict the forces exerted by their muscles. The governing equations of motion (EoM) can be given as a multi-rigid body system, following standard robotics textbooks, such as [18],

\[
 H(\dot{q}) \ddot{q} + C(\dot{q}, \dot{q}) + G(q) = Q_T^T \tau + Q_2^T (\ddot{q}) W \tag{2}
\]
where $H$, $C$, and $G$ are, respectively, inertial, Coriolis, and gravitational terms of the model’s EoM, $\tau \in \mathbb{R}^{155}$ is the vector of torques exerted by the muscles on the model’s muscle powered joints, $Q^T$ is a configuration matrix that converts the joint torques into generalized forces, $W$ is the ground reaction forces and moments (GRFM) or wrenches, and $Q^T$ is the configuration matrix converting GRFM to generalized forces.

Multiple muscles contribute to each joint torque. The $k$-th joint torque can be written as,

$$ \tau_k = \sum_{m=1}^{n_m} F_m r_{m,k}. \quad \text{(3)} $$

where $F_m$ is the force of $m$-th muscle, $n_m$ is the total number of muscles, and $r_{m,k}$ is the moment arm of muscle $m$ on joint $k$ [19].

### C. MUSCLE RECRUITMENT

Given $\ddot{q}, \dot{q}, \dot{\dot{q}}$ in eq.(2), joint torques $\tau$ and GRFM can be determined as an inverse dynamics problem. However, there is no unique solution to this inverse dynamics problem for determining the individual muscle forces $F_m$. Thus, we formulate an optimization problem that minimizes a cost functional that has been proven to be physiologically meaningful. This muscle recruitment problem has been addressed by many authors. The work presented in [20] is among early work that discusses principles for solving the muscle recruitment problem. Kralj [21] proposed to use the sum of a body’s muscle forces as an objective function to find a unique solution to the muscle recruitment problem. A variety of alternative cost functions have since been proposed [22]-[20]. In [28], the Sum of Squares (SoS) of normalized muscle forces $a_m$ is used for the optimization cost functional. The same cost functional is employed here. Variable $a_m$ is also referred to as the muscle activation level.

$$ J_4 = \sum_{m=1}^{n_m} a_m^2 \quad \text{(4)} $$

$$ a_m = \frac{F_m}{F_{max,m}}. \quad \text{(5)} $$

where $F_m$ is the force applied by muscle $m$ and $F_{max,m}$ is the maximum force that can be produced by muscle $m$. The muscle activation levels $a_m$’s are determined by minimizing the cost functional $J_4$ subject to constraints.

Muscle force is modeled as the sum of a passive force $F_{passive}$ and active force $F_{active}$ [31]. The active contribution is the portion that a human is able to control. We use the following muscle model [31] for each muscle force $F_m$. For brevity, subscript $m$ is omitted below.

$$ 0 \leq F_{active} \leq f_{AL}(l_{CE}) f_v(l_{CE}) \quad \text{(6)} $$

$$ F_{passive} = f_{PE}(l_{CE}) \quad \text{(7)} $$

$$ F = F_{ISO}(F_{active} + F_{passive}) \cos(\phi(q)). \quad \text{(8)} $$

Variable $F_{ISO}$ is the maximum isometric force that the muscle can apply, $l_{CE}$ is a muscle’s length and $\phi$ is its pennation angle. Both $l_{CE}$ and $\phi$ are functions of the joint displacements and are evaluated at their estimates $\hat{q}$. Function $f_{AL}$ is the active force - length curve, $f_v$ is the force - velocity curve, and $f_{PE}$ is the passive force - length curve. The above eq.(5) is based on the muscle model developed for an in-extensible tendon. We assume in-extensible tendons because there is no report stating that significant amounts of elastic-energy are stored at the tendons during crawling [32]. Furthermore, crawling is a mild motion similar to walking, and walking is accurately modeled without elastic energy storage [33]. With this muscle model, variables $a_m$ of eq.(4) are determined by minimizing $F$.

### D. GROUND REACTION FORCES AND MOMENTS

It is difficult to directly measure the Ground Reaction Forces and Moments (GRFM) in eq. (2) in a reliable manner. It is particularly difficult to simultaneously measure 6 axes of force and moment at the four contact points, two hands and two knees, in crawling. In the biped locomotion literature, methods have been developed for estimating GRFMs from kinematic and dynamic data. GRFMs are treated as forces and moments generated by a set of “virtual muscles”, and their activation levels are incorporated into the cost functional of the real muscles. GRFMs are then determined through the minimization of the extended cost functional. Following the methods in [14] and [15], the GRFMs are expressed as

$$ F_c = \begin{bmatrix} a_{c,x} f_{c,x} \cr a_{c,y} f_{c,y} \cr a_{c,z} f_{c,z} \end{bmatrix} \in \mathbb{R}^3 \quad \text{(9)} $$

$$ \tau_c = \begin{bmatrix} a_{c,\tau x} \tau_{c,x} \\ a_{c,\tau y} \tau_{c,y} \\ a_{c,\tau z} \tau_{c,z} \end{bmatrix} \in \mathbb{R}^3 \quad \text{(10)} $$

$$ W = \begin{bmatrix} F_1 \\ \vdots \\ \tau_4 \end{bmatrix} \in \mathbb{R}^{24} \quad \text{(11)} $$

where index $c = 1, \ldots, 4$ corresponds to the left and right hands, and left and right knees respectively. Vectors $a_{c,F} = [a_{c,x}, a_{c,y}, a_{c,z}]$ and $a_{c,\tau} = [a_{c,\tau x}, a_{c,\tau y}, a_{c,\tau z}]$ are the decision variables corresponding to each component of GRFM, respectively. Vectors $F_c = [F_{c,x}, F_{c,y}, F_{c,z}]$ and $\tau_c = [\tau_{c,x}, \tau_{c,y}, \tau_{c,z}]$ are contact weights for the components of force and torque applied at each contact point $c$. Both vary with time, between zero and maximum values ($0 \leq F_c \leq F_{c,max}$ and $0 \leq \tau_c \leq \tau_{c,max}$), based on the contact condition of the human’s limbs, as described below.

### E. ESTIMATION OF MUSCLE FORCES AND GRFM

In the above formulation, muscle forces and GRFM must satisfy the equations of motion, eq.(2), where the left hand side is evaluated with the measured kinematic data. Considering
the modeling imperfections, the estimated kinematic trajectories and their time derivatives \( \dot{q}, \ddot{q}, \dddot{q} \) may not perfectly satisfy the EoM. This entails a residual force vector \( R \in \mathbb{R}^{175} \) in the EoM.

\[
H(\dot{q})\dddot{q} + C(\dot{q}, \ddot{q})\ddot{q} + G(q) = Q_1^T \tau + Q_2^T (\dddot{q}) W + R
\] (12)

The magnitude of \( R \) approaches zero as modeling errors become small, thus it is used as a measure of modeling fidelity.

Inclusion of the residual forces \( R \) is also required for alleviating numerical instability in estimating the muscle activities [34]. With the residual forces, the inverse dynamic optimization is performed where the muscle forces and GRFM are minimized together with the residual forces. As such, the residual forces are normalized in a manner similar to the muscle forces and GRFM.

\[
R_j = a_{j,r} R_{j,gc}.
\] (13)

Parameter \( R_{j,gc} \) is the weight for each GCs’ residual force \( j \). This weight is constant over time, and is chosen by the designer to be small. This penalizes large residual forces by requiring large values for the decision variable \( a_{j,r} \), which is minimized in (15).

The \( a \)-variables are collectively represented as a vector \( \hat{a} \),

\[
\hat{a} = [a_1, \ldots, a_{n_m}, a_{1,f}, \ldots, a_{4,f}, a_{1,r}, \ldots, a_{4,r}, a_{1,r}, \ldots, a_{n_r,r}]^T.
\] (14)

The muscle recruitment and GRFMs are simultaneously determined by minimizing the cost functional

\[
J = \hat{a}^T K \hat{a}.
\] (15)

According to,

\[
K^o = \arg \min_{\hat{a}} J.
\] (16)

In addition to the aforementioned constraints, the muscle recruitment optimization also enforces

\[
a_{c,fz} \geq 0.
\] (17)

This ensures that the model does not pull up on the ground, by only allowing for a positive \( z \)-component to the GRFM.

It is important to note that the above estimation of muscle forces and GRFM is a convex optimization problem. A unique solution is guaranteed, if the problem is convex. An optimization is convex if all of the constraints are convex functions, any boundaries on the decision variables form a convex set, and the objective is a convex function. A function \( f \) is convex if [35],

\[
f(tx + (1-t)y) \leq tf(x) + (1-t)f(y),
\]

\[\forall x, y \text{ and } \forall 0 < t < 1.\] (18)

This implies that affine functions are convex. The constraint functions are all affine with respect to the decision variables (eqn. (14)), thus they are convex. The cost (eqn. (15)) is quadratic, thus it satisfies eqn. (18). Finally, the boundaries on \( a \) are a simple convex set. Thus, this optimization is convex and the solution is unique.

IV. CRAWLING EXPERIMENTS AND MODEL VALIDATION

Experiments of human crawling were conducted for tuning the parameters involved in the musculoskeletal model described above as well as for validating the model with the experimental data. The experimental study (ID: 2108000452) was approved by the Institutional Review Board of the Massachusetts Institute of Technology, and informed consent was obtained for the subject prior to testing.

A. COLLECTION OF KINEMATIC CRAWLING MOTION DATA

A 3D motion capture system (MoCap, Optitrack Flex 3) is used for measuring a human crawling on a flat floor, see Fig. 3. Tracking markers, \( x_{\text{landmark}}^{\text{exp}} \in \mathbb{R}^3 \), are placed on \( n_l \) bony landmarks on the human subject (landmark-markers). Virtual landmark-markers, \( x_{\text{landmark}}^{\text{vir}} \in \mathbb{R}^3 \), are then placed at the same positions on the human model. The human model developed by Burkhardt et. al. for [36] is used in this study. The markers are placed on the model by matching the landmarks manually, for instance one may visually locate the Acromion’s bulge on the subject and on the model. The position of these landmark-markers are used to scale the skeleton model to match the subject’s true proportions.

Additional markers are also placed on the subject’s body to aid in the inverse kinematics computation. These \( n_s \) additional markers, called support-markers, \( x_{\text{support}}^{\text{exp}} \in \mathbb{R}^3 \), are placed arbitrarily on the subject’s body. Then, after the model has been scaled, a careful inverse kinematics optimization is run to compute the pose of the subject based on the landmark-markers. This allows one to record the position of the support-markers relative to the landmark-markers, and then to place support-markers on the model, \( x_{\text{support}}^{\text{vir}} \in \mathbb{R}^3 \). All the landmark markers are numbered \( 1 \) through \( n_l \), and the support markers are numbered \( n_l + 1 \) through \( n = n_l + n_s \). Both markers are used for the inverse kinematics computation in eq. (1) where \( x_i, 1 \leq i \leq n \) are markers of the model and \( x_i^{\text{exp}}, 1 \leq i \leq n \) are experimental data of the markers.

The measured marker trajectories inevitably contain gaps due to occlusion. These gaps are filled and smoothed with a 4th order, 12 Hz, Butterworth filter. OpenSim 4.2 is then used for marker placement, model scaling, and inverse kinematics computation, as described in (Sec III-A). A 4th order, 6hz, Butterworth filter is then applied to \( \dddot{q} \) before computing the inverse dynamics and ground contact conditions. This is followed by the estimation muscle activation levels and GRFM.

B. GROUND REACTION FORCE MEASUREMENT

Measured ground reaction forces are used to tune the parameters in the model and validate it.
A human subject was asked to crawl in a straight line, at a comfortable speed, on a platform that is instrumented with a bio-mechanics force-plate (Kistler 9260AA Force-plate, 5691A DAQ). Three-axis ground reaction forces are obtained for the subject’s left arm as well as the left knee. Because the subject crawls in a straight line for this study, we assume symmetrical loading for their unmeasured limbs. Twenty consecutive passes were measured for the subject’s hand contact, and another twenty consecutive passes were measured for the subject’s knee contact.

C. PARAMETER TUNING AND MODEL VALIDATION

Experimeental studies of human walking have used measured GRFM for determining parameters associated to ground contacts and validating the model as in [14] and [15]. In contrast, studies of human crawling are very few and none of them have published experimental data from crawling trials. The comparison in Fig. 4 is encouraging. Even though a crawling human forms a closed kinematic chain with no unique solution for the GRFM, the estimated ground reaction forces match many features of the experimental data as well as it’s approximate magnitude. This assures us that our model parameters are accurate enough for a comparative study of the effect of the SuperLimb.

V. ANALYSIS FOR CONTROL

A. MUSCULOSKELETAL MODEL-BASED CONTROL

Using the musculoskeletal model obtained for human crawling, this section derives a model-based control algorithm for SuperLimb and evaluates its effectiveness. To this end, the human arms of the model are replaced with SuperLimb for the remainder of the analysis. This hybrid human-SuperLimbs model uses pure torque actuators, $\tau_{SL} \in R^{14}$, for the arms instead of muscles. The equations of motion (EoM) of this model are,

$$ H(\dot{q})\ddot{q} + C(\dot{q}, \dot{q})\dot{q} + G(\dot{q}) = Q_T^T \tau_{hmn} + Q_2^T (q)W + Q_3^T \tau_{SL} + Q_4 R, $$

where $\tau_{hmn} \in R^{155}$ is the vector of torques exerted by the muscles on the model’s muscle powered joints, $Q_T^T$ converts the SuperLimb torques to a full generalized force vector, $R$ are the residual forces conjugate to each generalized coordinate that is not controlled by the SuperLimbs, and $Q_4$ converts $R$ into a full vector of generalized coordinates. These terms on the right hand side of the above equation are mapped to specific subspaces in the generalized coordinate space. Fig. 5 visualizes the relationship among these terms. The matrix $Q_T^T$ maps muscle joint torques $\tau_{hmn}$ onto the subspace associated to the first 155 GCS, which are directly activated with the muscles. The next 14 GCS are for the SuperLimb: $Q_3^T \tau_{SL}$. The ground reaction forces and moments $W$ is distributed over the entire space by $Q_2^T$. While the muscle torques and the SuperLimb torques are in separate subspaces, they are coupled to each other through the GRFM. This manifests that the joint torques generated by the SuperLimbs influence the human muscles.

The model of SuperLimbs is to support the human upper body in a manner that minimizes the human effort. In the musculoskeletal model, the human effort has been quantified all of the trials. The results shown in Fig. 4 are overlaid with the human model’s estimated ground reaction forces.

### TABLE 1: The characteristic weights for the component of force and torque applied at each ground contact point. The wrist can apply torque about all axis. The forces weights are normalized by the mass of the subject.

| Max Value (N/kg) | Max Value (Nm) |
|-----------------|----------------|
| $F_{1,x} = F_{2,x} = 0.5$ | $\tau_{c,x} = 11.9$, for $c = 1, 2$ |
| $F_{1,y} = F_{2,y} = 0.33$ | $\tau_{c,y} = 11.9$, for $c = 1, 2$ |
| $F_{3,x} = F_{4,x} = 1.02$ | $\tau_{c,z} = 11.9$, for $c = 1, 2$ |
| $F_{3,y} = F_{4,y} = 0.39$ | $\tau_{c} = 0$, for $c = 3, 4$ |

FIGURE 3: Tracking markers are placed on a volunteer (based on [37]). Their motion is recorded as they crawl over flat ground.
as muscle activation levels $\dot{A}$ in eq. (14) for general human crawling. Now that both human arms are replaced with SuperLimbs, the activation vector $\dot{A}$ must be modified in accordance with the new EoM (19). Namely, the modified activation vector excludes the muscles of the shoulders, elbows and hands. We can also exclude those muscles at the ankles and other lower legs that are irrelevant to our optimization problem. The variables to be optimized are now fourfold. The relevant muscle activation levels, the GRFMs, and the residuals are both optimized and minimized through $\dot{A}$’s minimization. Finally, the SuperLimbs torques $\tau_{SL}$, which are optimized though not minimized. The updated cost functional and decision variables replace eqs. (15) and (16),

$$ (A_{rel}^o, \tau_{SL}^o) = \arg \min_{\dot{A}_{rel}, \tau_{SL}} |\dot{A}_{rel}|^2. $$

where $\dot{A}_{rel}$ is an activation vector updated to only include relevant muscle activations. This optimization is subject to the dynamics constraint eq. (19) and inequality constraints eq. (17).

Note that by solving this optimization problem we can obtain an optimal control law for controlling the SuperLimbs. Namely, the human effort can be minimized when the SuperLimbs support the human with the torque $\tau_{SL}^o$. This particular combination of the SuperLimbs’ joint torques $\tau_{SL}^o$ allows the human to crawl with the minimum effort in terms of the activation levels of the relevant muscles.

This optimization computation consists of three major steps. First, the kinematic variables of the human body in the generalized coordinate system must be obtained. Second, the left-hand side of the EoM (19) must be evaluated:

$$ L(\ddot{q}, \dot{q}, \ddot{q}) = H(\ddot{q}) + C(\dot{q}, \ddot{q}) + G(\ddot{q}). $$

Third, the optimization of the activation levels at the relevant muscles must be made. Finding joint torques based on kinematic and dynamic computations is a standard procedure in robotics. However, the current work is unique and challenging due to the complexity of the musculoskeletal model of the human.
As described in the experiment section, the posture of a human crawling on a floor can be determined from measurements of the body using a motion capture system. If we combine other sensor modality, in particular, Inertial Measurement Units (IMUs) placed at multiple points on the body, more accurate kinematic and dynamics measurements will be possible. In the current work, we assume that these kinematic and dynamic measurements are available and that the generalized coordinates of the human body can be obtained by solving the inverse kinematics problem, eq. (1).

The optimization of muscle activation levels in eq. (20) provide the SuperLims with a type of feedforward compensation, as shown in the block diagram in Fig. 6. This open-loop joint torque control can be supplemented with closed loop control in order to regulate the SuperLimbs’ joint angles $\hat{q}_{SL}$ around the joint angles $q_{SL}$. Various control methods can be applied to this feedback control, including the joint level impedance control described in Appendix VIII. The focus of this section is to evaluate the effectiveness of the feedforward compensation that minimizes the human effort in terms of relevant muscle activation, which will be discussed next.

B. COMPARATIVE ANALYSIS

It must be noted that the musculoskeletal model has inevitable errors in estimating muscle activation/recruitment. The absolute values of these estimated quantities depend on weights and parameter values. However, their relative values, or the differences between two cases, provides us with meaningful information, since the weights and parameter values used for estimation are kept the same. Our objective in this work is to assess the effects of control optimization as well as design changes made to the crawling support. We thus present a comparative analysis. Furthermore, the fidelity of the computation is verified by monitoring the magnitude of residue $R$, scaled by the human’s body weight for residual forces and their peak hip torque for residual moments.

Aside from the optimal $\tau_{SL}^o$ that are computed based on the human musculoskeletal model, there are numerous ways to control the SuperLimbs. We conduct simulation experiments to compare optimally computed SuperLimb torques to those computed by a naive policy, for a stationary posture with a non-moving human. The naive policy acts to have zero wrist torque and zero shear force at the SuperLimbs. This is equivalent to friction-less wheels placed at the tip of both SuperLimbs; the ground reaction force is only a normal force with no torque transmitted. In contrast, the optimal policy is allowed to utilize wrist torque and does not attempt to minimize the SuperLimb shear force.

The result illustrates the difference in the distribution of muscle forces in the human’s trunk due to the difference of the SuperLimb’s control policy. The musculoskeletal model used for the simulation experiments has 620 muscles, which are divided into the 16 groups described by Fig. 7 to facilitate interpretation of the results. These modeled muscles exclude those that are irrelevant to or insignificant for our analysis.

Fig. 8 shows the comparison of activation levels of each muscle group for the two different controllers. The optimal SuperLimb torque $\tau_{SL}^o$ significantly reduces the muscle activation levels in nearly all groups of relevant muscles. Notably, the forces drop significantly for the Psoas Major, Latissimus Dorsi, Serratus Anterior, and Transversus Spinalis muscle groups, when the optimal joint torque $\tau_{SL}^o$ is used. There appears to be a favorable reduction of muscle loads particularly at the trunk of the body.

Fidelity: The fidelity of the above simulation experiments must be examined. As addressed in [40], the fidelity of a model can be evaluated by the magnitude of the normalized residuals. This is done in Table 2 for the floating body coordinates. The residual moments are normalized by the maximum hip extension torque, and the residual forces are normalized by the weight of the subject. The maximum hip extension torque of the human subject is expected to be $226\,Nm$, based on the work in [41], since the subject weighs $79kg$ at $1.8m$ tall. The residues are found to be small enough to confirm the fidelity of the simulation experiments.
The challenges in implementing the optimal feedforward control presented above is the computational complexity. The computation of $\tau_{SL}^o$ entails inverse kinematics, inverse dynamics, and optimization. To streamline these steps of computation, here we construct a surrogate model that can predict the ground-truth optimal torque in real time through simplified computation in response to actual sensor measurements. As described previously, various sensor systems, including a motion capture system and IMUs attached to the body, can be used for monitoring the body movement. These measures are collectively represented as vector $y$. We construct a surrogate that minimizes the following:

$$\min_\theta \sum_{i=1}^N (|\tau_{SL}^0_{Sur}(i) - \tau_{SL}^o(i)|^2)$$

where $\tau_{SL}^0_{Sur}(i)$ is the output of a surrogate model in response to measurement $y(i)$, and $\theta$ is a parameter vector involved in the surrogate model.

C. REAL-TIME COMPUTATION USING A SURROGATE

There are multiple methods for constructing this surrogate. A neural network is a convenient method for generating a nonlinear model for mapping input $y(i)$ to output $\tau_{SL}^0_{Sur}$. The parameter vector $\theta$ is the collection of the weights involved in all the neural units. Effective tools have been developed and widely used for training neural networks [42].

Alternatively, a low-order physical model can be used as a surrogate for predicting $\tau_{SL}^0_{Sur}$. Fig. 9 shows an example of Reduced order Model (RoM) consisting of 12 links represented with 24 generalized coordinates. A similar model has been used for designing a controller for synchronizing SuperLimbs with the human leg motion [11]. The parameters in this case are involved in the inverse kinematics, inverse dynamics, and optimization of the reduced-order model. Neither the black-box neural net method nor the RoM physical modeling method provides accurate human muscle activation, which is available only with use of the full musculoskeletal model. However, they can be trained to produce the SuperLimbs joint torque. The point is that once the data of the ground-truth optimal SuperLimbs joint torque $\tau_{SL}^o$ is created using the full musculoskeletal model, the data can be used for generating a surrogate model in the form of neural network or physical RoM.

VI. ANALYSIS FOR DESIGN

The human model can be used to make design guidelines for the SuperLimbs, in addition to being used for control. The goal of the SuperLimbs is to let a worker release his/her hands from bracing their upper body without increasing muscular loads at vulnerable parts of their body. The region of the back surrounding the lumbar spine is a particularly critical area, since this is the site that is most commonly plagued by MSDs. Using the musculoskeletal model and human crawling data, now we assess the effects of using SuperLimbs as a crawling aid. Compared to the bracing with natural arms, SuperLimbs differ at two interfaces. One is the interface between SuperLimbs and the environment, i.e. the floor, and the other is the interface between SuperLimbs and

![Image 1](https://via.placeholder.com/150)

FIGURE 9: Example of Reduced-order Model with fewer rigid links and joints [11].
the human body to which the robot is attached. These two may cause significant changes to the human musculoskeletal system, which must be reflected to the design and control of SuperLimbs. The human interface pertains to the design of the harness that attaches the SuperLimbs to the human’s trunk. The ground interface pertains to the design of the palm and wrist of the robotic limbs as well as the location of the hands placed on the ground relative to the human body.

A. THE EFFECT OF SUPERLIMBS WRIST TORQUE ON LOAD REDISTRIBUTION

Human hands apply both force and moment to the contacting ground. Generating this moment with the SuperLimbs would require actuators for the wrist, which would make the robot’s design more complex, bulky, and costly. We investigate the effect of eliminating wrist torque on the musculoskeletal system in order to determine if the actuators are necessary.

We conduct two simulation experiments. Case one is without wrist torque; SuperLimbs can apply only point loads to the ground. Case two is with wrist torque, applying both force and moment to the ground.

For these simulation experiments, the SuperLimbs are installed at the wearer’s shoulder joints, coincident with their natural limbs. The SuperLimbs’ hands track the trajectories of the human’s hands.

1) Stationary Case

Fig. 10 shows the comparison of activation levels of each muscle group with and without wrist torque, when the human is stationary: no crawling along a floor. The load distribution changes significantly. Notably, the Sacro Spinalis muscle group, which includes the injury-prone muscles of the lumbar spine, is significantly lowered with wrist torque on. On the other hand, Latissimus Dorsi, Ribcage and External Obliques significantly increase. There appears to be a favorable redistribution of muscle loads away from the vulnerable lower-back to the upper-back and core, which are less commonly the sites of MSDs. These effects must be taken into account when designing and controlling SuperLimbs.

2) Moving Case

When crawling along a floor, muscle groups are dynamically activated. Fig. 11 shows the average activation of each muscle group as a function of time, for one period of a crawl obtained for the case of wrist torque off. A similar plot is obtained for the case of wrist torque on. Fig. 12 shows the root mean square of each muscle group averaged over one cycle of crawling for both with and without wrist torque. Comparing to the stationary case, the activation level is almost uniformly higher. This is expected, as the muscles must support inertial loads in addition to the gravitational loads of the stationary posture.

3) Fidelity

The fidelity is verified through the normalized residual forces that are reported in Table 3. They are small enough to confirm the fidelity of the simulation experiments.

4) Existence of a Bounded Optimal Wrist Torque

In Section III-D we explain that we bound the wrist torque to \( \tau_{c,\text{max}} \). This is to prevent a situation where an impractically large wrist torque is required for the SuperLimb wrist. Here, an abbreviated study of the effect of the wrist torques’ amplitude on the optimal cost and muscle activation of a static posture is done to investigate whether the optimal wrist torque is finite or not.
FIGURE 12: The root-mean-square of each muscle’s activation during the crawling period is taken, then these values are averaged for each of the major muscle groups under consideration. The groups with significant load redistribution are circled.

TABLE 3: The average, normalized residual forces and moments that are conjugate to the floating body coordinates.

| Muscles       | Wrist Off (Static) | Upper Chest (Static) | Wrist Off (Moving) | Upper Chest (Moving) |
|--------------|-------------------|----------------------|-------------------|----------------------|
| $R_{F,x}$    | -1.5e-7           | -2.3e-7              | -2.2e-7           | -1.0e-6              |
| $R_{F,y}$    | 4.1e-8            | 1.1e-7               | 5.6e-8            | 5.3e-7               |
| $R_{F,z}$    | -7.2e-8           | -1.1e-7              | 5.9e-7            | 2.2e-6               |
| $R_{r,x}$    | 3.4e-7            | -2.3e-6              | -9.3e-7           | -2.2e-6              |
| $R_{r,y}$    | -3.5e-6           | -1.8e-6              | -4.8e-6           | -1.8e-5              |
| $R_{r,z}$    | 2.2e-8            | 4.4e-7               | 2.6e-6            | 6.0e-6               |

For this study, the sagittal plane wrist torques $\tau_{wrist,y}$ for both wrists are constrained to be equal and varied as shown in Fig. 13. The muscle activations are collected in vector $\kappa_{major}$, which is a subset of $\kappa$. The sum-of-squares of the muscle activations, $J_{major} = \kappa_{major} \cdot \kappa_{major}$, are plotted against $\tau_{wrist,y}$ in addition to the optimal cost $J^*$. Fig. 13 shows that there is an optimal value for $\tau_{wrist,y}$ that locally minimizes $J$. This means that the optimal wrist torque is bounded at least for the natural postures observed in the crawling experiment.

Fig. 13 also shows that the value for $\tau_{wrist,y}$ that minimizes $J_{major}$ is different than the value that minimizes $J$. Knowing that the human is generally more susceptible to muscular-skeletal injury from a high $J_{major}$, a designer can predict the human’s muscle kinetics using $J$ for the cost functional, and then interpret the results using $J_{major}$ in order to specify guidelines for selecting actuators for the wrists.

B. HARNESSE Effect ASSESSMENT

The SuperLimbs transmit force to the human through a chest harness, instead of being directly affixed to their shoulder joints as in the previous simulation experiment. With a harness attached to the shoulders and chest of a wearer, the load will be distributed over the harness and affect a broad area of the musculoskeletal system.

FIGURE 13: The optimal cost $J^*$ (includes ground reaction forces and moments, as well as residual forces) as well as the sum-of-squares of the muscles’ optimal activations, $J^*_{major}$, are plotted against the wrist torque $\tau_{wrist,y}$. The wrist torque is normalized by $\tau_{c,max}$, defined in Table 1 (Inset) $\tau_{wrist,y}$ is the wrist torque in the sagittal plane for both of the wrists. A positive torque is sketched, from the floor to the wrist.

TABLE 4: The average, normalized residual forces and moments that are conjugate to the floating body coordinates.

| Muscles       | Wrist Off (Static) | Wrist On (Static) | Wrist Off (Moving) | Wrist On (Moving) |
|--------------|-------------------|-------------------|-------------------|-------------------|
| $R_{F,x}$    | -1.6e-4           | -5.7e-3           | -8.8e-2           | -4.4e-2           |
| $R_{F,y}$    | -2.8e-5           | 1.5e-3            | -1.2e-2           | -5.3e-3           |
| $R_{F,z}$    | -6.4e-5           | -1.9e-3           | 5.6e-2            | 5.0e-2            |
| $R_{r,x}$    | 3.3e-5            | 9.6e-4            | -1.1e-2           | -1.2e-3           |
| $R_{r,y}$    | 7.3e-4            | 1.3e-3            | 6.8e-1            | 2.4e-1            |
| $R_{r,z}$    | -2.3e-4           | -2.2e-3           | 1e-1              | 3.3e-2            |

1) The Effect of a Rigid Harness on Load Distribution

First, we consider the case where the harness is rigid. The pressure between a harness and the contacting chest and shoulders must be estimated in order to assess the effect of the harness. However, it is infeasible to obtain the pressure distribution directly from physical conditions alone. Instead, we estimate the pressure distribution by extending the method for estimating ground reaction forces and moments. Namely, we consider virtual muscles generating the contacting forces between the harness and the chest and shoulders, and formulate another optimization problem to find a distribution of contact forces that minimize the effort of the virtual muscles. The harness is modeled as having distributed point contact along the front and rear of human’s rib-cage (7 contact points each), and at the center of their shoulders, as shown in Fig. 14. The mid-shoulder force points represent the portion of the harness that wraps around the human’s shoulders, such as shoulder straps. Each point $r_{j,h} = [r_{j,h,x}, r_{j,h,y}, r_{j,h,z}]^T$ can transmit force $F_{j,h} = \tau_{c,max}$. A positive torque is sketched, from the floor to the wrist.

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[\begin{align*}
F_{j,h,x}, F_{j,h,y}, F_{j,h,z} \end{align*}]
only for \( j = 1, \ldots, 16 \)
as shown in Fig. 16, with no torque transmitted.

\[ F_{j,h} \text{ is computed as,} \]
\[ a_{j,h} = \begin{bmatrix}
a_{j,h,x} \\
a_{j,h,y} \\
a_{j,h,z}
\end{bmatrix}. \]

where \( a_{j,h} \) is a vector of decision variables for each component of the harness force, and \( F_h \) is a characteristic interaction force. Vector \( a_{j,h} \) is included in the cost eq. (20), thus is minimized in the same way as the estimation of GRFM and others.

Two constraint conditions must be added to this optimization. First, the contact at the chest can only apply positive normal force \( (a_{j,h,z} > 0 \ \forall j \in 1, \ldots, 7) \) and the contact at the back \( (a_{j,h,z} < 0 \ \forall j \in 8, \ldots, 14) \) can only apply negative normal force. Second, force and moment balance conditions must be satisfied for the SuperLims, in order to solve for feasible harness interaction forces,

\[ 0 = \sum_{j=1}^{9} F_{j,h} + \sum_{c=1}^{2} F_c + \sum_{j=1}^{9} r_{j,h} \times F_{j,h} + \sum_{c=1}^{2} p_c \times F_c + \tau_c. \]

The SuperLimb is able to apply wrist torque, \( \tau_c \).

In designing a harness, two questions are addressed. One is where on a chest the harness should be attached. The other is the size of a harness; how widely the harness should cover the chest. The effect of these design parameters upon the musculoskeletal load distribution is examined.

Three cases are studied, one with a harness that spans the front of the rib-cage from the shoulder joint to the middle ribs, the 7th thoracic vertebrae (\( l_{\text{harness}} \) in Fig. 14), a second is the lower half of the rib-cage, from the 8th thoracic vertebrae to the 12th thoracic vertebrae, and finally a third is with a harness that spans the whole front of the rib-cage from the shoulder joints to the ribs attached to the 12th thoracic vertebrae. This spans the feasible range of harness sizes, bounding the design parameter space. The portion of the harness in contact with the human’s back stays at a fixed size, spanning the shoulder joints and the ribs attached to the 12th thoracic vertebrae.

**a: Stationary Case**

Figure 15 shows the comparison of activation levels of each muscle group for full and partial chest harnesses, when the human is stationary. The lower rib-cage harness is most advantageous, compared to the full and upper rib-cage harnesses. While this is interesting, a lower ribcage harness would likely interfere with the wearer’s breathing pattern. This makes such a design impractical. The harness covering the whole chest is better than the upper rib-cage harness, thus it is the most practical choice.

**b: Moving Case**

The z-component of the harness interface force \( F_{j,h} \) is given for the full-sized harness, as a function of time, in Fig. 16. Fig. 17 shows the root mean square of each muscle group averaged over one cycle of crawling for both a full and upper chest harness. The full chest harness reduces loading for a majority of muscle groups. It is interesting to note that there
FIGURE 16: The z-component of the harness force for the outer four contact points of a full chest harness are plotted. (Inset Top) The times that the left and right knees contact the ground are illustrated. (Inset Right) The contact points that are plotted are labeled H1-H4.

FIGURE 17: The root-mean-square of each muscle’s activation during the crawling period is taken, then these values are averaged for each of the major muscle groups under consideration.

is a less pronounced redistribution of loads away from the Sacro Spinalis than there was for the crawling study with wrist torque though.

c: Fidelity
The fidelity is verified through the normalized residual forces that are reported in Table 3 for the full and upper chest harnesses. They are small enough to confirm the fidelity of the simulation experiments, the lower chest harness residual forces are similarly low.

2) The Effect of a Compliant Harness on Load Distribution
Next, we consider a compliant harness. In general, a compliant harness is more comfortable to wear. The human’s torso naturally flexes and deforms during crawling. A compliant harness would better conform to the body, and allow it to retain a more natural range of motion for the trunk. A highly compliant harness, however, does not transmit the load from SuperLimbs to a broad area of the harness, but it concentrates it to a local area, as indicated in red in Fig. 18.

It is difficult to analyze the interaction between a compliant harness and the contacting soft tissue of the human chest. Our objective, however, is to analyze the effect of a load acting at a specific local area of the chest upon the musculoskeletal system. The effect of the concentrated load can be assessed by introducing a set of constraints to the previous optimization problem.

Let \( r_{CoP} \) be the Center of Pressure (CoP) on a compliant harness. The location of CoP can be expressed as the center of pressure across a harness. For the sample points shown in Fig. 14 for example, the CoP projected on the ground plane is given by

\[
\begin{align*}
    r_{CoP} &= \frac{\sum_{j=1}^{9} r_{j,h,x} F_{j,h,z}}{\sum_{j=1}^{9} F_{j,h,z}} \\
    &\quad \frac{\sum_{j=1}^{9} r_{j,h,y} F_{j,h,z}}{\sum_{j=1}^{9} F_{j,h,z}}
\end{align*}
\]  

(27)

The effect of having the chest CoP at a particular location can be examined by solving the optimization problem subject to eq. (27), which is treated as constraints with a specified value of \( r_{CoP} \). The optimization solution provides the estimated muscle activation levels where the CoP is at the specified location. Three CoP regions are evaluated at the posterior, medial, and anterior thirds of the harness. See Fig. 20. This spans the feasible range of CoP positions, bounding the design parameter space. The SuperLimb is able to apply a wrist torque for this simulation experiment.

a: Stationary Case
The CoP’s region does not have a strong influence on load distribution for static postures.
TABLE 5: The average, normalized residual forces and moments that are conjugate to the floating body coordinates.

| CoP Posterior (Static) | CoP Medial (Static) | CoP Anterior (Static) | CoP Posterior (Moving) | CoP Medial (Moving) | CoP Anterior (Moving) |
|------------------------|---------------------|-----------------------|------------------------|---------------------|-----------------------|
| $\bar{R}_{F,x}$ | -1.2e-7 | -2.0e-7 | -7.4e-7 | -9.8e-8 | -8.2e-7 | -2.0e-7 |
| $\bar{R}_{F,y}$ | -2.2e-7 | 9.5e-8 | -3.5e-7 | 9.1e-8 | 5.2e-7 | 3.8e-8 |
| $\bar{R}_{F,z}$ | -8.3e-8 | -1.5e-6 | -4.4e-7 | 4.6e-7 | 2.1e-6 | 4.0e-7 |
| $\bar{R}_{\tau,x}$ | 7.2e-6 | -1.3e-6 | -2.8e-6 | 1.2e-7 | -3.8e-6 | 1.5e-6 |
| $\bar{R}_{\tau,y}$ | -4.9e-6 | -6.1e-7 | -2.7e-6 | -4.3e-6 | -1.8e-5 | -4.7e-6 |
| $\bar{R}_{\tau,z}$ | -2.9e-6 | 4.8e-7 | -1.0e-6 | 2.8e-7 | 5.7e-6 | 1.1e-6 |

TABLE 6: The average pressure in each region of the model’s chest, compared to the constrained position of the center of pressure.

| Location | Mean Anterior Pressure | Mean Medial Pressure | Mean Posterior Pressure |
|----------|------------------------|----------------------|-----------------------|
| Anterior CoP | .08 | .09 | .07 |
| Medial CoP | .01 | .01 | 0.0 |
| Posterior CoP | .01 | .03 | .03 |

b: Moving Case

Fig. 20 shows the root mean square of each muscle group averaged over one cycle of crawling for each CoP region. The notable trend is that the medial CoP region has the maximum muscle activation for most muscle groups. This implies that attaching SuperLimbs to the medial area of the chest with a compliant harness is not recommended.

c: Fidelity

The normalized standard deviation of the residual forces are given in Table 5. They are small enough to validate the accuracy of the results. Table 6 shows average pressure in each region of the human model’s chest, see the schematic in Fig. 19 for reference.

C. DISCUSSION

Based on the above analyses using the musculoskeletal model, a few practical design issues can be discussed.

1) Eliminating Wrist Joints by Re-positioning SuperLimb Hands

From a practical engineering design viewpoint, it is desirable if active wrist joints can be eliminated, so that the SuperLimbs are more compact, lightweight, and less energy-consuming. In Section VI-A1, we found that SuperLimb wrist torque tends to reduce the muscle activation of the Sacro Spinalis when the SuperLimb’s hand is placed at the human’s natural ground-contact position. We hypothesize that this same effect can be generated with zero wrist torque by instead placing the SuperLimb hands at alternative locations on the ground. This means that instead of implementing a 3-axis wrist torque on the SuperLimbs it is just as beneficial to instead modify the hand placement on the ground. This reduces the complexity of the robotic system.

Further analysis has revealed the following [43]:

- For a static case where the human stays at a stationary location, there exists a hand location that generates the same effect as active wrist joints. Although the hand location differs from the natural human crawl, the net effect upon the musculoskeletal system remains the same.
- While a similar result holds true for a dynamic crawling human, the effect of a zero-wrist torque hand position is limited, because the wrist torque varies during the hand’s contact phase.

2) Optimal Attachment Location

Finding an optimal location to attach SuperLimbs is a critical design problem. In the above musculoskeletal analysis, an anterior CoP minimizes muscle activation when compared to other two tested regions (section VI-B2). However, we can not find a globally optimal CoP location from these three evaluated CoP regions, because the cost is not quadratic with respect to the CoP location. It is possible that an untested CoP region further improves the load distribution. Furthermore,
the most critical in the analysis is the load on the back, in particular, Sacro Spinalis. It is desirable to gain more insight as to the relationship between the SuperLimbs attachment location and the load on the back. Further analysis has revealed the following [43]:

- The optimal location for attaching SuperLimbs is at the human shoulder sockets. This implies that the human body has a musculoskeletal structure that minimizes the muscle effort when bearing a load at the shoulders.
- The rigid and compliant chest plate harnesses have similar load re-distributions when properly attached, see Fig. 21. Due to comfort and wearability, a compliant, full-chest harness should be used where the center of pressure is around the shoulder sockets.

VII. CONCLUSION

There are numerous tasks that must be performed on or near a floor, where workers must take an ergonomically challenging posture for long periods of time, leading to injuries at the back, shoulders, and elsewhere. SuperLimbs have been proposed to assist workers to brace the upper body and allow them to use both hands not to brace the body but to perform a given task. SuperLimbs are expected to relieve workers from fatiguing postures and increase productivity. However, the impact of the use of SuperLimbs on the human body is complex; the load may be distributed across the myriad of muscles and skeletal structure. While reducing a load at targeted muscles, it may increase at un-targeted muscles.

This paper presented a musculoskeletal model for analyzing the load distribution at the trunk of a human crawling on a floor being assisted with SuperLimbs. While published data on human crawling are limited, a musculoskeletal model was constructed based on relevant biomechanics literature, human measurements and publicly accessible software. The model was verified using a ground reaction force plate, and the validity of the model was checked for each simulation experiment based on the magnitude of residual terms.

Using the musculoskeletal model an optimal combination of SuperLimbs joint torques that minimizes the human muscular effort was obtained. With the optimal joint torques, the SuperLimbs can best assist the human in terms of the muscular effort. The effectiveness is evaluated in terms of the overall muscle activation levels and a comparison was made between the optimal case and a naive case. The optimal joint torques significantly reduce the activation level at nearly all the muscle groups.

The computation of the optimal joint torques is too heavy to perform in real time. To alleviate the computational load, a surrogate model for predicting the optimal joint torques in response to the measurements of the body motion was proposed. This can be treated as a machine learning problem using a neural network, or a reduced-order modeling problem, where the optimal joint torques obtained from the full musculoskeletal model are used for tuning the surrogate.

The musculoskeletal analyses also informed the design of SuperLimbs. Two specific design issues were addressed. One is the interface between SuperLimbs and the ground, i.e., the robot end-effector or the wrist. It was found that the torque at a wrist contacting a ground effectively redistributes the load so that the overall muscular effort significantly reduces. However, it is practically difficult to attach powerful actuators to the tips of SuperLimbs. Furthermore, large robotic wrists and hands may interfere with the human hands and limit the work space. The desired load redistribution can instead be achieved by optimizing the placement location of the SuperLimbs’ hands. Selecting an optimal location for placing a hand, comparable effects can be obtained without use of active wrists. The other critical is the interface between SuperLimbs and the human body, i.e. the attachment design. It was found that a compliant harness attaching SuperLimbs at the sockets of the human shoulders provides the best result. To avoid interference with the human shoulders, however, a creative design solution is necessary that virtually transmits the load from a floor to the shoulder socket position, while the SuperLimb base mechanism is outside the human shoulders. A pantograph mechanism, for example, can meet this requirement.

Based on these design guidelines and control algorithm derived from the musculoskeletal model, practical techniques must be developed for building a functional SuperLimbs prototype. Such a SuperLimbs prototype will be significantly different from naive designs based on robotics and engineering design perspectives. Because SuperLimbs are attached to a human body, their impact on the full, complex musculoskeletal network must be considered. As an effort to promote cross-disciplinary studies, this paper attempted to establish a biomechanical foundation for machine design, robotics, and control.
The controller discussed in Section V is supplemented with a joint level impedance controller to account for any errors in the model that may otherwise lead to motion that does not match that predicted by the optimization.

\[ \tau_{imp} = K_d(\dot{q}_{SL} - \dot{q}_L) + K_p(\ddot{q}_{SL} - \ddot{q}_L) \]  
\[ \tau_{SL} = \tau_{imp} + \tau_{SL} \]  

The closed loop joint torques \( \tau_{imp} \) remain small when an accurate human model is used, thus the human’s muscle force distribution should remain close to the predicted optimal distribution. \( \tau_{SL} \) is commanded on the SuperLimbS to yield the desired motion.

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