

BIOMECHANICAL ANALYSIS OF THE SHOULDER UNDERGOING INDUSTRY RELEVANT TASKS

Carlo Canezo^{1*}, Dustin Crouch², Greg Sawicki¹,

¹Physiology of Wearable Robots Lab, School of Mechanical Engineering, Georgia Tech, Atlanta, Georgia

²Upper Limb Assist Lab, University of Tennessee, Knoxville, Tennessee

*Corresponding author's email: ccanezo3@gatech.edu

Introduction: Upper-body wearable devices such as exoskeletons have the potential to reduce injuries for industry workers completing highly repetitive or high load tasks. The challenge lies in developing effective control schemes over a set of diverse tasks while accounting for the physical interaction between the human and the device [1]. Unlike lower-body wearable devices where a design developmental framework has been established based on lower body biomechanics for common cyclic tasks such as walking or running [2], the upper body regime lacks a formal “roadmap” tailored to guide device designs. This is principally because upper-body tasks are high DOF, unstructured and non-cyclical. – all features that pose challenges for computing inverse dynamics. Our research aims to fill this gap by compiling data from real-world upper body tasks in a highly instrumented lab setting to drive computational models and calculate upper body joint-level outcome measures that can be used to identify injury “hotspots”. In this study, we test the following hypothesis with a focus on the shoulder joint: a) increased interaction loads will lead to an increase in joint level biomechanical demand* that is exacerbated by b) increased proximity to the workspace extremes where demand* is measured via joint moments, powers, work, and impulse.

Methods: Our setup involved replicating a shelf stacking task across the upper body workspace for one arm. This was done by a 2x three level shelf setup (Fig.1). The participant (N=1) performed a static holding task at a specified workspace region by moving a weighted object to and from a specified home position.. Three interaction loads were used: Low (0.2kg), Medium (1.82kg), and High (3.75kg). Three task locations were chosen that involved moving the load closer to the “extreme” parts of the workspace, defined as needing greater than 90 degrees of the shoulder elevation angle, for a single arm. These were location A (close sagittal), location B (extreme sagittal), and location C (extreme sagittal + frontal). Motion capture data were used to compute inverse kinematics and inverse dynamics in OpenSim while accounting for the added mass of the interaction loads with a specific focus on the shoulder joint [4]. We calculated shoulder elevator joint moment, joint power, and joint impulse and joint work to assess task demand and compare them across load and workspace region.

Results & Discussion:

As expected, within a given workspace location (A, B, or C), when interaction load increased (blue, green, red), the joint moment, net joint work and net joint impulse also increased (Fig. 2). Joint power output was more variable, and increased with load only for tasks at the workspace extremes. Within a given interaction load, joint moment, joint power, and net joint work all increased as the movement task approached the workspace extreme (A to B to C), while net joint impulse remained invariant across the workspace. Interestingly, adding asymmetry by layering sagittal + frontal ROM demands had little effect on mechanical demand. Overall, in line with biomechanical intuition, our data set identified key ‘hotspots’ in the acceleration and braking phases of the motion (dynamic phases) that were more pronounced with higher interaction loads (Fig 2 – dark shaded).

Significance: Key significance of this study is the application of computational biomechanics to understand upper-body joint-level mechanical demands across a range of industry relevant tasks. Data can now be analyzed to determine shoulder elevator joint torque vs angle curves than can be directly translated to upper body wearable device actuator design specifications. These data can also be used as ‘ground truth’ to train data-driven machine learning models that may be deployed for exoskeleton control [4].

Acknowledgments: This work is supported by NSF under Grant Award Number 2202862.

References: [1] Crouch et al. (2020), *J. App Biomech.* 36(2); [2] Nuckols et al. (2020), *PLOS ONE* 15(8); [3] Saul et al (2015), *Comp. Methods in Biomech & BioEng* 18(13) [4] Molinaro et al. (2024) *Nature* 635(8038).

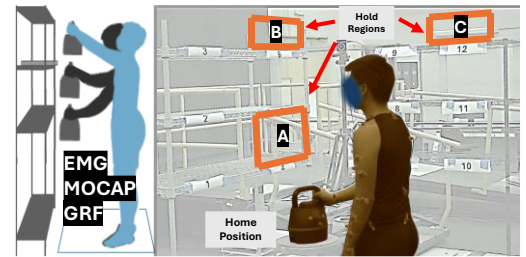


Figure 1: Experimental Workspace Setup for Upper body Tasks. Three locations are shown: A: Non-extreme Workspace, B: Extreme Workspace Sagittal Plane, C: Extreme Workspace Frontal Plane

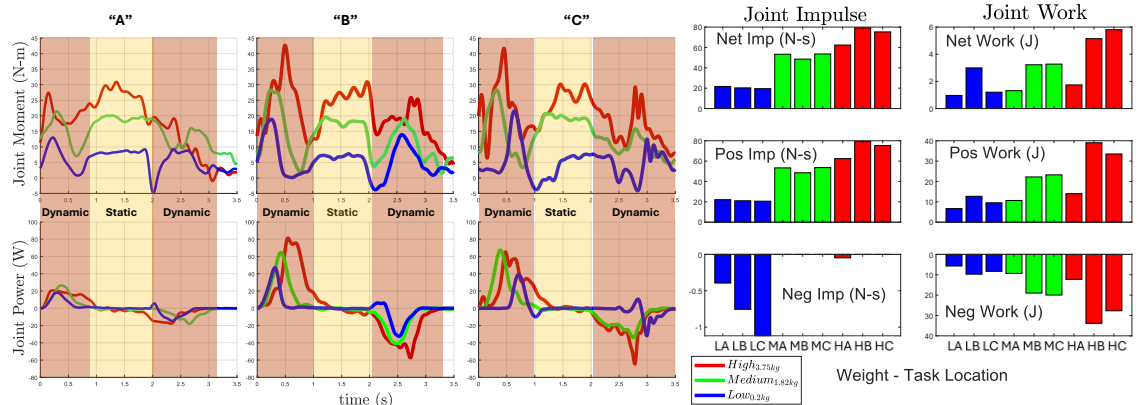


Figure 2: Shoulder mechanical demand for various weights and workspace locations. Dark shaded regions indicate dynamic motion, and light shaded region indicates when the interaction load is held statically.