

DATA-DRIVEN DEEP LEARNING OF HUMAN BIOLOGY ENABLES PERSONALIZED GENERALIZATION OF CONTROL FOR WEARABLE ROBOTICS

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Introduction: One of the major barriers that prevents wearable lower limb robotic systems, such as powered prostheses and exoskeletons, from being adopted ubiquitously is the lack of control systems that handle real-world multi-task locomotion activities. Studies show mobility is strongly linked to quality of life, participation and depression, and these technologies have significant ability to enhance human ambulation, reduce fall risk, and improve overall quality of life [1]. However, current state-of-the-art systems tend to struggle to be useful in more than 1 or 2 tasks due to the difficulty of hand engineering systems to perform well across both heterogeneous human populations as well as highly varied real-world use in numerous tasks such as multi-speed walking, stairs, ramps, sit-to-stand and start/stops. The advent of end-to-end deep learning offers a new solution to this problem but requires massive datasets to be effective. We have engineered a new class of training datasets for exoskeleton users focused on physiological state estimation, such as biological joint moment, which enables user-independent and task agnostic control capability [2].

In this study, we test the hypothesis that a deep learning-based control system trained to human biological moment can unify control across a variety of locomotion modes to reduce metabolic cost and joint work compared to not using an exoskeleton [3].

Methods: We first collected a series of training data (N=24) which consisted of exoskeleton users walking in a custom powered hip exoskeleton weighing 4.5 kg and providing up to 18 Nm peak torque (Fig 1A) [4]. Users completed trials consisting of standing, level walking at different speeds, transitions, ramps at different inclines, and stairs at different heights. Motion capture and force plate data were collected for all these tasks and standard inverse dynamics was run to compute net joint torques. We trained a temporal convolutional network (TCN) to estimate joint torques in real time and scale assistant to 20% biological moment [2]. We performed tests in a new cohort (N=10) to test the accuracy of the unified deep learning system in real-time. We also performed outcomes testing which included metabolic cost and joint work to localize energy changes to joints. For metabolic testing, we also compared to gold standard human-in-the-loop (HIL) optimized spline based control in which the controller had previously been optimized on a task specific basis, which in theory represented the ceiling of what could be achieved. We also compared to a zero impedance condition.

Results & Discussion: The unified control system enabled by deep learning human physiological state provided reliable and accurate assistance both within and across task transitions. Average R^2 values for estimating biological hip moment across level walking, ramps and stairs was above 0.8 (representative tracking curves shown in Fig. 1B), which enabled a highly controllable system for all testing subjects during real-time operation. Human outcomes matched our hypothesis with the unified controller significantly ($p<0.01$) reducing metabolic cost by over 5% level walking and over 10% in ramp ascent compared to the no exoskeleton condition. The unified controller also matched HIL optimized spline control in level walking and surprisingly exceeded it's performance by 5% ($p<0.01$) in ramp ascent.

Total positive joint work (compared to no exoskeleton) was reduced with unified control in level walking by 17.5%. Unsurprisingly, this was primarily due to the human users reducing their hip-level joint efforts (by 29.2%), but smaller reductions were observed at both the knee (9.7% reduction) and ankle (7.7%), indicating some level of redistribution of effort occurred across lower limb joints.

Significance: We demonstrate, for the first time, a novel unified control system based on deep learning of human physiological state capable of real-time estimation and control for exoskeleton applications [3]. Key significance is that we can now enable reliable and useful control without the need for estimating tasks explicitly (typically achieved through either a state machine or mode classifier) or the need to estimate gait phase for control. In addition, all deployments were user-independent (no training data from the test subject) and absolutely no hand tuning or user-specific configurations were allowed in this study. This new style of control has the potential to enable exoskeleton technology to be deployed in real-world and community ambulatory environments.

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References: [1] Metz (2000), *Transport policy* 7(2); [2] Molinaro et al., (2022). *IEEE TMRB* 4(1); [3] Molinaro et al. (2024), *Science Robotics* (in press); [4] Kang et al. (2021) *Robotics and Automation Letters* 6(2).

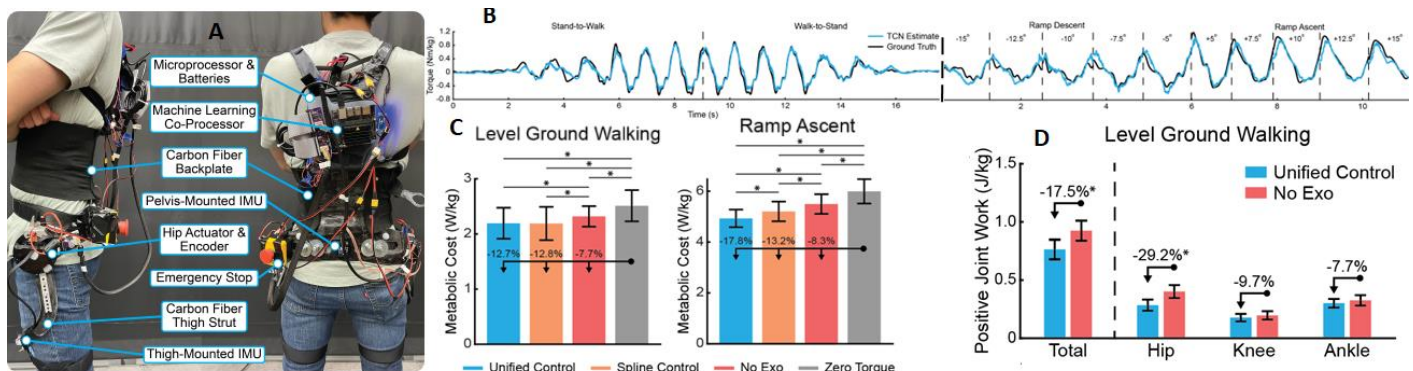


Figure 1: This N=34 study was conducted with an autonomous robotic hip exoskeleton designed at Georgia Tech (A). Representative tracking of the deep learning system (B) showed an average R^2 of 0.84 across walking, ramps and stairs compared to ground truth inverse dynamics. Our unified control system reduced both metabolic cost (C) and joint work (D) significantly compared to the no exoskeleton baseline.