Experimental comparison of torque control methods on an ankle exoskeleton during human walking

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Abstract—Few comparisons have been performed across torque controllers for exoskeletons, and differences among devices have made interpretation difficult. In this study, we designed, developed and compared the torque-tracking performance of nine control methods, including variations on classical feedback control, model-based control, adaptive control and iterative learning. Each was tested with four high-level controllers that determined desired torque based on time, joint angle, a neuromuscular model, or electromyography. Controllers were implemented on a tethered ankle exoskeleton with series elastic actuation. Measurements were taken while one human subject walked on a treadmill at 1.25 m s−1 for one hundred steady-state steps. The combination of proportional control with damping injection and iterative learning resulted in the lowest errors for all high-level controllers. With time-based desired torque, root-mean-squared errors were 0.6 N m (1.3% of peak desired torque) step by step, and 0.1 N m (0.2%) on average. These results indicate that model-free, integration-free feedback control is suited to the uncertain dynamics of the human-robot system, while iterative learning is effective in the cyclic task of walking.

Index Terms—Rehabilitation Robotics, Ankle Exoskeleton, Torque Control, Human-Robot Interaction

I. INTRODUCTION

Exoskeletons have been used for performance restoration [1] and enhancement [2]. Recently, the importance of the natural dynamics of the human body [3], energy input [4] and comfort of human-robot interactions [5, 6] have been given increased attention in exoskeleton applications. In these approaches to exoskeleton assistance torque control is crucial. In such systems, series-elastic actuators [7] are commonly used to provide lower error torque tracking in the presence of unknown and changing human dynamics.

It has been a common interest for the lower-limb exoskeleton community to improve locomotion performance. The ankle joint has drawn attention for effort reduction in walking [8] since it produces more mechanical work than other joints [9]. Better ankle joint torque tracking would therefore benefit experimental studies. Such techniques are also expected to extend to knee and hip exoskeletons, for which the control problem is similar.

Control of exoskeletons is normally hierarchical, with high-level controllers determining behavior-related desired torques and torque control lying at a lower level. Therefore, in this study we refer to torque controllers as low-level controllers and desired torque generators as high-level controllers.

Many low-level control methods have been employed for torque or position tracking in exoskeletons, including classical feedback control [6], model-based control [5], adaptive control [10] and iterative learning control [11]. However, it remains unclear which method has the best performance, or how performance may vary with high-level controllers. High-level controllers based on time [4], joint angle [12], neuromuscular models [6], and electromyographic measurements [8] have been used to assist human walking. Each may be advantageous in some assistance paradigms, and each generates desired torques with different dynamics.

The topic of exoskeleton torque control has not drawn as much attention as high-level control and biomechanics outcomes. In cases where torque control has been addressed directly, it has typically been investigated under unrealistic conditions, i.e., during benchtop tests rather than human-robot interactions [13], and results have often not been reported quantitatively [14]. Moreover, little has been reported on the relative performance of different torque controllers on the same platform, making differentiation among candidate methods difficult. This study aims to compare the torque-tracking performance of prominent torque controllers, under realistic experimental conditions, with multiple high-level controllers, in a single exoskeleton platform. These results are expected to help guide the selection and tuning of exoskeleton torque controllers, particularly in lower-limb exoskeletons for locomotion assistance.

II. METHODS

Nine torque controllers, including variations and combinations of classical feedback control, model-based control, adaptive control and iterative learning, were experimentally compared in this study. Each was tested separately with four high-level controllers that determined desired torque based on time, ankle angle, a neuromuscular model, or electromyography. Controllers were implemented on a tethered ankle exoskeleton with series-elastic actuation and tuned to minimize error. Under each high- and low-level controller combination, the exoskeleton was tested with one subject who walked one hundred steady-state steps on a treadmill. The root mean squared torque errors were calculated for each step and for an averaged step.
A. Exoskeleton Testbed

The ankle exoskeleton testbed used in experiments consisted of an off-board geared electric motor with real-time driver, a flexible Bowden cable transmission with series compliance, and an exoskeleton that interfaced with the human body (Fig. 1).

A dedicated real-time control system sampled sensor data at 5000 Hz, which were then filtered at 200 Hz. The desired motor velocity commands were generated at 500 Hz. The motor unit was composed of a low-inertia 1.6 kW AC servo motor and a 5:1 planetary gear. Motor input voltage was regulated by a motor driver running in velocity control mode, which provides smoother torque tracking in series elastic actuators [15]. A digital optical encoder was used to measure motor position.

The flexible Bowden cable that transmitted forces was composed of a coiled-steel outer conduit and a 0.003 m diameter Vectran® inner rope, and was 2 m in length. A coil spring with an effective stiffness of 190 N-m-rad⁻¹ was attached at the end of the rope to provide increased compliance.

The exoskeleton frame generated a plantarflexion torque which was measured using strain gauges on the heel lever with 1000 Hz signal conditioning. Joint angle was measured using a digital optical encoder. Muscle activity was measured using a wired electromyography system for one high-level controller.

The components of the system interacted as in Fig. 2. The high-level controller used time, \(t\), exoskeleton joint angle, \(\theta_a\), or electromyography (EMG) to determine the desired torque, \(\tau_{\text{des}}\). The low-level controller tracked torque by changing the desired motor velocity, \(\dot{\theta}_{m,\text{des}}\), determined by desired torque, measured torque, \(\tau\), motor angle, \(\theta_m\), and/or exoskeleton angle. A motor driver regulated motor velocity. Motor motion was transmitted through the Bowden cable to one end of a series spring and generated exoskeleton torque together with exoskeleton motion. Both the human and the series spring exerted torques on the exoskeleton frame and led to exoskeleton rotation.

B. Controllers

Nine prominent low-level torque control methods were compared in this study in combination with four high-level assistance controllers. High-level controllers generated desired torque, which low-level controllers tracked.

1) Low-Level Torque Controllers: Desired motor velocity was commanded to a dedicated hardware motor controller for all torque controllers investigated:

\[
\dot{\theta}_{m,\text{des}} = \Delta \theta_{m,\text{des}} T^{-1} = (\theta_{m,\text{des}} - \theta_m) T^{-1}
\]

where \(\dot{\theta}_{m,\text{des}}\) is the commanded motor velocity; \(T\) is a constant related to motor position rise time; \(\Delta \theta_{m,\text{des}}\) is the desired motor displacement; \(\theta_{m,\text{des}}\) is the desired motor position; \(\theta_m\) is the measured motor position.

\(L_1\): Proportional Control with Damping Injection (PD)

This controller was a variant of the classical proportional-derivative control of torque, with the derivative term replaced by damping injection [16]:

\[\Delta \theta_{m,\text{des}} = -K_p e_{\tau} - K_d \dot{\theta}_m\]

where \(K_p\) is proportional gain, \(e_{\tau} = \tau - \tau_{\text{des}}\) is torque error, \(\tau\) is measured exoskeleton torque, \(\tau_{\text{des}}\) is desired exoskeleton torque, \(K_d\) is damping gain, and \(\dot{\theta}_m\) is measured motor velocity. Lower noise was obtained with damping injection than with the derivative of torque error because motor position was measured by a digital encoder while torque was measured by analog strain gauges subject to electromagnetic interference.

\(L_2\): Proportional Control with Damping Injection and Error-Dependent Gains (PD+EDG)

This controller was the same as \(L_1\), except that the proportional gain was error-dependent [17, 18]:

\[\Delta \theta_{m,\text{des}} = -K_p e_{\tau} - K_d \dot{\theta}_m \]

where operation ‘ceil’ rounds the element to the next smallest integer, \(K_p\) is the error-dependent proportional gain, \(h_{\tau}\) and \(h_k\) are torque error and proportional gain step sizes, and \(K_{\text{max}}\) is the maximum allowable gain. This controller was intended to limit overshoot and oscillations during torque tracking.

\(L_3\): Proportional Control with Damping Injection and Previous-Error Compensation (PD+PEC)

This controller was the same as \(L_1\), except that desired torque was altered based on torque error from the previous time step [as done in 19]:

\[\tau'_{\text{des}} = \tau_{\text{des}} - \epsilon_{\tau,\text{prev}}\]

\[\Delta \theta_{m,\text{des}} = -K_{\text{pec}} (\tau - \tau'_{\text{des}}) - K_d \dot{\theta}_m\]

where \(\tau'_{\text{des}}\) is the compensated desired torque and \(\epsilon_{\tau,\text{prev}}\) is the torque error from the previous time step. This was intended to increase control response for large errors.
4: Proportional-Integral Control with Damping Injection (PID)
This controller was a variant of the classical proportional-integral-derivative control, with the derivative term replaced by damping injection:

\[ \Delta \theta_{m,des} = -K_p e_t - K_d \hat{\theta}_m + (\theta_{mdl} - \theta_m) \]

where \( K_i \) is the gain on the integral of torque error, and \( t_0 \) is the time at which the stance phase of current step begins.

5: Proportional Control with Damping Injection and Model-based Compensation (PD+M)
This controller combined the feedback controller of 1.1 and a model-based feed-forward term, which was intended to anticipate changes in desired motor position due to either exoskeleton joint displacements or changes in desired joint torque:

\[ \Delta \theta_{m,des} = -K_p e_t - s + Y_d(\tau, \tau_t, \tau_a) \hat{\Gamma} \]

where \( \theta_{mdl} \) is model-based motor position compensation, \( \theta_m \) is measured motor position, \( \theta_a \) is measured exoskeleton ankle joint angle, \( \hat{R} \) is estimated total gear ratio from motor to exoskeleton joint, and \( \hat{K}_c \) is estimated total stiffness of the transmission with respect to the motor displacement.

6: Passivity-based Adaptive Control (PAS)
This provably stable adaptive controller was based on a dynamic model of the motor, transmission and exoskeleton. It is described as

\[ \Delta \theta_{m,des} = -K_p e_t - K_s s + Y_d(\tau, \tau_t, \tau_a, \hat{\theta}_a) \hat{\Gamma} \]

where \( K_s \) is the sliding control gain and \( s \) is a sliding vector:

\[ s = \tau - \tau_{des} + \lambda e_t = \tau - \tau_t \]

where \( \lambda \) is a positive scalar and \( \tau_t \) is a virtual reference torque.

\( Y_d \) is a regressor defined as

\[ Y_d(\tau, \tau_t, \tau_a, \hat{\theta}_a) = [\tau, \tau_t, \tau_a, \hat{\theta}_a] \]

which expresses the dynamics as a linear combination of system parameters. \( \hat{\Gamma} \) is the system parameter vector. Its estimate \( \hat{\Gamma} \) was updated by the law

\[ \hat{\Gamma} = -LY_d^T s, \]

where \( L \) is a positive definite parameter adaptation gain matrix.

This controller was intended to reduce model uncertainties by parameter adaptation and address unknown human-robot interactions.

7: Iterative Learning of Desired Motor Position (LRN)
This controller updates a desired motor position trajectory for the next step using torque errors of the current step [11, 20]:

\[ \theta_{m,des}(i, n+1) = \beta \theta_{m,des}(i, n) - K_L e_{flt}(i, n) \]

\[ \Delta \theta_{m,des}(i, n) = \theta_{m,des}(i+D, n) - \theta_m(i, n) \]

where \( i \) is the time index on the next step, while commanded motor velocity at this time index is based on a preview of desired motor position later in the same step.

\( \beta \in [0, 1] \) is a weighting term on the learned trajectory to add “forgetting” into learning. \( e_{flt} \) is the filtered torque error trajectory, initially an array of zeros, expressed as

\[ e_{flt}(i, n) = (1 - \mu) e_{flt}(i, n-1) + \mu e_c(i, n) \]

where \( \mu \in [0, 1] \) is a weighting term on the learned error.

This controller exploits the cyclic nature of the task to accommodate complex dynamics without an explicit model.

8: Iterative Learning of Desired Motor Position + Proportional-Damping Compensation (LRN+PD)
This controller combined iterative learning (7) with proportional-damping control (1) compensation [11, 21]. Motor commands arose primarily from the learned feed-forward trajectory, while feedback control compensated for step-by-step variations in desired torque:

\[ \theta_{m,des}(i, n+1) = \beta \theta_{m,des}(i, n) - K_L e_{flt}(i, n) \]

\[ \theta_{m,des}(i, n) = \theta_{m,des}(i+D, n) - K_p e_t(i, n) - K_d \hat{\theta}_m(i, n) \]

\[ \Delta \theta_{m,des}(i, n) = \theta_{m,des}(i, n) - \theta_m(i, n) \]

9: Proportional Control with Damping Injection + Iterative Learning Compensation (PD+LRN)
This controller combined proportional-damping control (1) with iterative learning (7) compensation [11, 21]. Motor commands arose primarily from feedback control, with learned feed-forward compensation for consistent tracking errors:

\[ \theta_{m,des}(i, n+1) = \beta \Delta \theta_{m,des}(i, n) - K_L e_{flt}(i, n) \]

\[ \Delta \theta_{m,des}(i, n) = -K_p e_t(i, n) - K_d \hat{\theta}_m(i, n) + \Delta \theta_{LRN}(i+D, n) \]

2) High-Level Assistance Controllers: During the stance phase, desired torque \( \tau_{des} \) was determined by high-level controllers \( h_1-h_4 \) detailed below. During the swing phase, motor position control was employed to allow free human ankle movement while maintaining minimal cable slack:

\[ \Delta \theta_{m,des} = \theta_a \hat{R} - \theta_m \]

where \( \hat{R} \) is the estimated gear ratio from motor to exoskeleton.

h1: Time Based Desired Torque Trajectory (TIME)

This high-level controller set desired torque as a function of time. We used a curve (Fig. 3) that resembled a scaled-down

Fig. 3. High-level control based on a fixed trajectory in time.
version of the human ankle moment during unassisted walking [9] with a stance period of 0.66 s.

\( H_2: \) Joint Angle Based Desired Torque (ANGLE)

This high-level controller set desired torque as a function of ankle angle and phase of the gait cycle [12]. We used a piece-wise linear curve that resembled a scaled-down version of the human ankle moment during unassisted walking (Fig. 4), calculated as \( \tau_{des} = \frac{\theta_i - \theta_{i-1}}{\theta_i - \theta_{i+1}} (\theta_i - \theta_{i-1}) \), in which \( (\theta_i, \tau_i) \) defines a node in torque-angle space. The node \( (\theta_{i-2}, \tau_2) \) marked the transition from the Dorsiflexion phase, in which ankle velocity was negative, to the Plantarflexion phase, in which ankle velocity was positive. Since the exact transition point varied on each step, the angle and torque at the moment of transition, \( (\theta'_{i+2}, \tau') \) replaced \( (\theta_{i-2}, \tau_2) \) for calculating desired torque in the first portion of Plantarflexion, i.e., when \( i = 3 \).

\( H_3: \) Neuromuscular Model Based Desired Torque (NMM)

This high-level controller set desired torque using a virtual muscle and neural system model. The virtual muscle took human ankle position and velocity as inputs and generated a virtual joint torque which was conditioned and used as desired torque. The virtual torque was also fed into the virtual neural system where it was delayed and linearly scaled to generate the stimulation signal of the virtual muscle. This virtual reflex mechanism realized a form of positive feedback in the model. A complete description of the reflex-based muscle model was available in [6].

\( H_4: \) Electromyography Based Desired Torque (EMG)

This high-level controller set desired torque in proportion to EMG measurements [8] from the subject’s gastrocnemius muscle. Electrical activity was measured using surface electrodes, high-pass filtered at 20 Hz, rectified, low-pass filtered at 6 Hz, offset by a small value of -0.008, and amplified by a gain of 283 to obtain the desired torque.

C. Experimental Methods

Experiments were conducted with one healthy subject (30 yrs, 56 kg, 1.65 m tall, female), who walked on a treadmill at 1.25 m s\(^{-1}\) with a self-paced step period of 1.08 ± 0.06 s while wearing the exoskeleton on one leg.

Before collecting data, we tuned parameters for each combination of high- and low-level controller as the subject walked while wearing the exoskeleton on one leg.

III. Results

The best torque tracking performance was observed with the combination of feedback control and iterative learning, i.e., PD+LRN or LRN+PD, for all high-level controllers, both in real-time and for the average step. Between the two, PD+LRN showed lower errors before convergence. Depending on high-level conditions, the real-time torque errors with PD+LRN were 38%-84% lower than with PD (t-test, \( p < 1.9 \cdot 10^{-34} \)), and average-step torque errors were 91%-97% lower. Other additions to feedback control showed minor performance effects, except that model-based compensation increased torque error. While providing low errors for average tracking, pure iterative learning resulted in high real-time errors. For the EMG-based controller, torque tracking errors and variability were generally higher for all torque controllers.

Some interactions between high- and low-level torque controllers were observed. Pure feedback control outperformed pure iterative learning control for Angle and EMG based high-level conditions, while an opposite trend was seen in Time and NMM conditions. For the the Time-based controller, poor tracking at the onset of desired torque, including a delay and overshoot, was observed for all controllers without a learning component. Adding iterative learning to PD resulted in the greatest improvement in performance for the Time based condition. A minor improvement in performance over pure PD was seen with an additional integral term (PID) for Time and Angle based conditions. With Time-based high-level control, passivity (PAS) and previous-error compensation (PD+PEC) also showed a small benefit.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>( K_p )</td>
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<tr>
<td>( K_d )</td>
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<tr>
<td>( K_{max} )</td>
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<tr>
<td>( K_{pec} )</td>
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<tr>
<td>( K_i )</td>
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<tr>
<td>( h_T )</td>
<td>11.3 N·m</td>
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<tr>
<td>( R )</td>
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<tr>
<td>( K_c )</td>
<td>195 N·m·rad(^{-1})</td>
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<td>( D )</td>
<td>0.022 s</td>
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Means and standard deviations of step-wise root-mean-squared torque error (RMS-E) and average-step root-mean-squared error (RMS-E AVG) are shown in Fig. 5. Error values for PD+LRN and their percentage of the peak desired torque, \( \tau_{\text{max}} \), for the average step are given in Table II. Overlapped desired and measured torque trajectories for one hundred steps with PD+LRN are shown in Fig. 6. The high variations of torques for Angle- NMM- and EMG-based high level controllers are the result of step-to-step gait variation of the subject. PD+LRN with Angle-based desired torque also showed consistent performance for higher torque on two different devices (peak torques of 80–86 N·m) with a taller male subject in later experiments [22].

**IV. DISCUSSION**

We evaluated the performance of nine prominent torque controllers by experiments on a tethered ankle exoskeleton, with series-elastic actuation, during human walking, with four high-level controllers. Model-free proportional control with damping injection, compensated by iterative learning, resulted in the lowest torque errors for all high-level controllers, both in real-time and for the average step. This approach is analogous to the classical proportional-integral-derivative control; the proportional term provides basic tracking, iterative learning eliminates steady-state cyclic errors, and damping injection provides stability. We thus label the method as proportional-learning-damping control.

Few studies have compared the torque tracking performance of various controllers in practical conditions for exoskeletons and active orthoses. Few quantitative reports on torque control of lower-limb exoskeletons are available, and these mostly concern benchtop tests. These tests usually do not reflect the unknown, complex and time-varying dynamics of human-robot interactions, which define the biggest challenge in exoskeleton torque control. Little data and analysis have been provided.
which makes interpretation of the results difficult. From the information available, proportional-learning-damping compensation (PD+PEC), or passivity-based adaptation (PAS), torque tracking was slightly improved for the Time-based condition, which suggested that the model-free continuous-time integration elements in torque controllers may be beneficial when the desired torque is consistent in time. Error-dependent gains (PD+EDG) did not provide benefits and may be more suited for motion based control in rehabilitation.

While showing promise in simulation and theory, model-based control elements generally worsened or had no effect on control performance in our experiments. Sensitivity to modeling accuracy seems to be a fundamental issue. The partially model-based PAS controller showed a slight benefit in some conditions due to its adaptive nature, but the effect was not consistent.

Comparisons across high-level controllers were difficult to make for the same low-level control due to un-normalized tracking difficulty. Multiple values for high-level parameters were not tested in this study, which is an area for future work. Changes in the profiles of desired torque and joint kinematics across low-level controllers for the same high-level condition reveal an interaction effect. For example, more variability in desired torque was observed with NMM-based than Angle-based control elements generally worsened or had no effect on control performance in our experiments. Sensitivity to modeling accuracy seems to be a fundamental issue. The partially model-based PAS controller showed a slight benefit in some conditions due to its adaptive nature, but the effect was not consistent.

Hardware, series elasticity in particular, also interacted with torque control performance. The interactions between series elasticity, torque control gains and high-level control objectives should be investigated in the future.

V. CONCLUSIONS

A systematic comparison of exoskeleton torque controllers under walking conditions was conducted, demonstrating that proportional control with damping injection compensated by iterative learning had better torque tracking performance than any other methods tested or previously demonstrated. Implementation of this proportional-learning-damping controller was straightforward, requiring sequential tuning of only four parameters. Our results suggest that this approach can be applied to multiple torque-controlled lower-limb exoskeletons used in cyclic processes like locomotion. There remains a rich area for future research on complex interactions between exoskeleton hardware, torque control, assistance control, task goals and human behavior.

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