Identifying the dynamics of a human-exoskeleton system

Katherine L. Poggensee, Koushil Sreenath and Steven H. Collins
Carnegie Mellon University, Pittsburgh, USA
ktpognc@cmu.edu, koushils@cmu.edu, stevecollins@cmu.edu

1 Introduction

A primary goal of robotic rehabilitation is to provide repeatable, cost-effective therapy that is comparable to or better than conventional therapy. Lower-limb rehabilitation robots can be separated into robot-dominant devices, where the robot drives the motion of the human, and cooperative devices, where the robot and the human share control. Robot-dominant approaches have been shown to be less effective, as the human is less actively engaged [1]. Cooperative rehabilitation robots are typically force-controlled, employing techniques such as assist-as-needed, error augmentation, or proportional electromyography. While upper-limb rehabilitation robots have outperformed conventional therapy [2], conventional lower-limb therapy is still the most effective option.

Some rehabilitation robot techniques implicitly assume a relationship between robot actions and human neuromuscular response. If these models are wrong for a particular subject, the therapy will be less effective. A control strategy which incorporates model identification could overcome this problem.

We propose a new strategy for robotic gait rehabilitation, in which the dynamics of the human-robot system are identified and used to design a controller that guides the patient to a desirable gait pattern. In this study, we will use linear models to approximate system dynamics, which have low computational cost and have been effective in previous studies of robot and human dynamics [3]. We will consider different state definitions and control inputs, to find parameterizations with high predictive validity and applicability to rehabilitation.

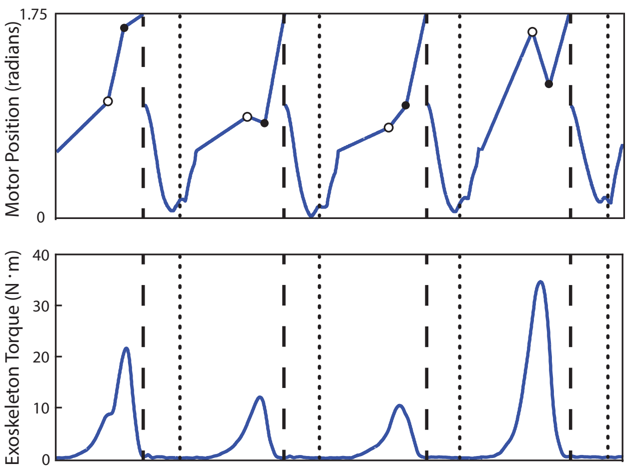

Figure 1: Exoskeleton data from four representative walking strides. The top plot shows the desired motor position (radians). θ_0, θ_3 were fixed and correspond to normal ankle angles at heel strike and toe-off. θ_1, θ_2, represented by white and black dots, respectively, were randomly generated for each step. The bottom plot shows the corresponding torque generated by the exoskeleton (N·m). The dashed line indicates toe-off, and the dotted line indicates mid-stance of the contralateral foot.

2 Methods

2.1 Walking experiment

One subject (male, 22 years old) walked on a split-belt treadmill for four minutes at 1.25 m/s, resulting in 221 steps. The subject wore a unilateral tethered one degree-of-freedom ankle foot orthosis [4]. The torque at the ankle was governed by series spring displacement and an off-board motor.

During stance, the motor tracked the position of four predetermined angles (Fig. 1). The initial (θ_0) and final (θ_3) angles are at instances of zero exoskeleton torque and correspond to the ankle angles seen in normal walking. The two intermediate angles (θ_1, θ_2) occurred at the same point in the gait cycle for each step. The magnitudes, between 0 and 1.75 radians, were randomly generated at heel strike. The desired motor position trajectory resulted in exoskeleton torque (Fig. 1).

2.2 System definitions

We attempt to find a linear model

$$y_i = Cx_i + Du_i \tag{1}$$

where x_i represents the states at right toe-off, u_i the inputs at right toe-off, and y_i states at two corresponding Poincaré sections, in particular, toe-off on the exoskeleton side and the following contralateral mid-stance.

Given the state $x_i \in \mathbb{R}^n$ and input $u_i \in \mathbb{R}^m$ at the toe-off of the i-th step, define

$$z_i := \begin{bmatrix} x_i \\ u_i \end{bmatrix} \tag{2}$$

For a given step i and z_i, the states and inputs at toe-off, we wish to predict outputs y_i at the following contralateral mid-stance. In particular, we seek a linear relationship between the deviation from the mean states/inputs at toe-off and the deviation from the mean states at the following mid-stance,

$$\Delta y_i = J\Delta z_i \tag{3}$$

where $\Delta y_i = y_i - \bar{y}$ and $\Delta z_i = z_i - \bar{z}$, with $\bar{y}, \bar{z}$ the mean outputs and states/inputs, respectively, across all steps. J is the Jacobian, which we estimate by least squares method: for ΔZ and ΔY where the i-th column represents all of the deviations of the states/inputs and states for the i-th step,

$$J^T = \left((\Delta Z)^T\right)^{\dagger} (\Delta Y)^T \tag{4}$$

where † refers to the Moore-Penrose Pseudoinverse.

We can then extract the C and D matrices for the linear model. J is a block matrix such that

$$J = \begin{bmatrix} C & D \end{bmatrix} \tag{5}$$

Exploratory analysis is still in progress to determine the predictive power of the inputs and states as defined in our pilot data collection. Variables include kinematics, kinetics and electromyography (EMG) data of major muscle groups for both legs, and torque parameters from the device. Poincaré sections were taken at toe-off on the exoskeleton side and the following mid-stance. The sections were chosen to capture the case where exoskeleton activity on the unaffected limb is used to alter paretic limb activity on the subsequent step. For future work, we plan to test this approach among individuals with chronic hemiparesis following stroke.

After J was calculated, we multiplied each column by the mean absolute state/input deviation to see the mean effect of each state and input. We then normalized each row to determine the relative contribution of each state and input to the output state.

3 Results

We were able to determine a linear model mapping the set of center-of-mass velocity (lateral and forward); knee and ankle flexion angles and joint velocities for both legs; and exoskeleton inputs, defined as θ_1, θ_2, and the integral of exoskeleton torque over the step, to the set of muscle activity (defined as integral of EMG signals) for the biceps femoris, vastus medialis, soleus, medial and lateral gastrocnemius, and tibialis anterior in the unassisted leg; hip, knee, and ankle flexion angles for both legs; and knee and ankle joint velocities for both legs. The output states were up to 69% explained by the linear model (mean $R^2 = 0.4$, all $p < 0.05$).

4 Discussion

Exploratory analyses will continue to determine a set of inputs and outputs that are relevant to rehabilitation and can explain relevant human dynamics. For this set of inputs and outputs, a linear model was found which explains almost half of the deviation of the output states. The ultimate goal of this project is to guide the human to a desired state, which will be achieved through the model definition described above and adaptive control techniques. With the present control inputs and states, the controllability matrix has poor conditioning, which may be resolved by alternate parameterizations.

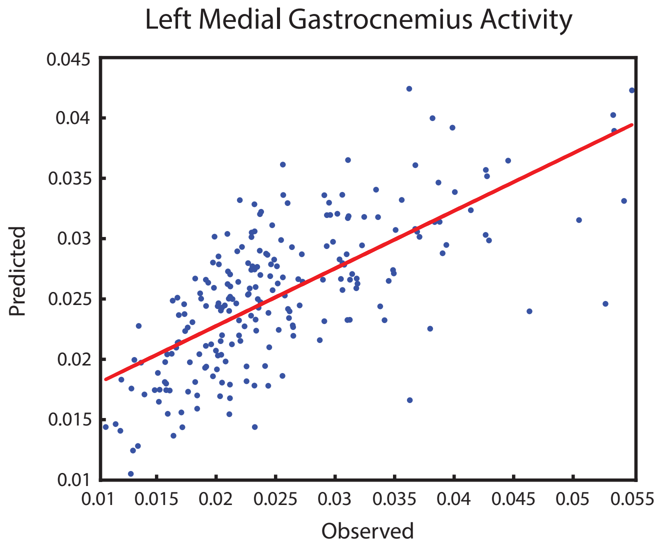

Figure 2: A representative plot of experimental Δy_i data vs. predicted $J\Delta z_i$ data for medial gastrocnemius activity. The observed data were taken at mid-stance of the unassisted leg, and the predicted data were the prediction of mid-stance states from exoskeleton-side toe-off. (Slope of the best fit line = 0.48, $R^2 = 0.5$, $p = 1 \times 10^{-32}$).

One result was that of the four inputs, the integral of torque and θ_1 were the largest absolute factors in predicting the outputs, but with opposite effects. For example, applying more torque on one leg during early stance led to increased lateral gastrocnemius activity in the other leg during early stance. We will continue to explore the relationships between the human-exoskeleton states in the coming months.

5 Acknowledgments

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References

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