Methods to Improve System Identification in 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

Robotic assistive devices have been proposed as a cost-effective, repeatable alternative to conventional physical therapy. Recent successes in rehabilitative robotics for post-stroke gait therapy [1] are due to a focus on the patient's active engagement in the therapy. One quantitative measure of active engagement, muscle activity, is a highly non-linear signal that varies greatly between subjects. Therefore, devices which target that measure would benefit from a personalized, adaptive strategy, which does not rely on assumptions of how the patient population interacts with that device.

We are investigating a model-free approach to robotic gait therapy, in which the patient's response to a device is identified and used to design controllers to guide the patient to some desired therapy target. Previous attempts at system identification for a human-exoskeleton system have been presented at Dynamic Walking [2]. Random disturbances were applied with an ankle exoskeleton to able-bodied subjects during normal walking. The human-exoskeleton system was identified offline as a discrete-time linearized Poincaré map. The experimental results indicated that some portion ($R^2 = 0.34$) of muscle activity could be modeled in this way, but very little could be predicted using this identified model ($R^2 = 0.12$).

We employed system identification techniques used in human systems [3]. These techniques were able to describe over twice as much variation in human dynamics than we observed in our experiment. There is thus a fundamental difference between how the human responds to a robotic device and how the human responds to the natural variations seen during unperturbed walking. To improve our system identification technique for this system, we sought to address the underlying cause for the poor predictive power in the experiment.

System identification of a simulation of a hopping ankle joint with an exoskeleton was done to recreate the potential problems in the experimental results. In particular, we simulated

- noise in the sensors,
- time-varying human dynamics,
- greater distance between the Poincaré sections, and
- differing contributions of the input on the output.

Noise in the sensors and human dynamics are inherent to the human-exoskeleton system, so methods to mitigate these effects may be necessary to improve the identification. Changing the distance between the Poincaré sections and the type of exoskeleton control to vary the input-output relationship can be easy to implement if they are also shown to reduce the quality of the identification. These adjustments to the simulation are explained in more detail in Section 2. In Section 3, the results from the simulation are given, and Section 4 outlines ways to mitigate the effects of these factors, which will be implemented in future experiments.

2 Methods

A simulated hopping ankle joint was used to test the hypotheses listed in the previous section. The ankle joint was controlled by a Hill-type plantarflexor muscle and an ankle exoskeleton. For the majority of the simulations, the motor of the exoskeleton tracked a position trajectory, as in the experiment. The difference in position of the motor and position of the ankle joint gave rise to the torque applied by the exoskeleton. The desired motor position trajectory was piecewise-linear, with the magnitude of the peak desired torque randomly varied at each hop.

A discrete-time linearized Poincaré mapping was used to identify the system, as in the experiment. The Poincaré map was taken from the bottom of the center-of-mass position trajectory to the end of stance. The map was linearized about the fixed point, which was approximated by a low-pass filter on the data taken at each section. The model variables were chosen to be comparable to the experiment: states were center-of-mass height, activation of the muscle and its integral from the beginning of stance to the first Poincaré section; the output was the integral of activation from the bottom of the position trajectory to take-off; and the input was the peak desired motor position. From this set of states, linearly dependent states were removed to produce the final system model.

The simulation was altered to test the hypotheses to explain why the predictive power of the system identification in the experiment was low. Gaussian noise was added to simulate noise in the sensors used in the experiment. The amplitude of the added noise was a scalar multiple of the range of values measured at the Poincaré section. Time-varying human dynamics were simulated as a randomly-varying gain in the stretch reflex control of the muscle and as descending neural input added as a weighted sum to the stimulation calculated from the stretch reflex control. The distance between the Poincaré sections was increased by moving the first section further back. The exoskeleton control was then changed to be a commanded torque, which was a non-linear function of the input.

Regressions were calculated on the first fifty hops. The adjusted R^2-value was used to determine the quality of the fit. The identified model was then used to predict the next fifty hops. The predicted values were then compared to the observed values, and the corresponding adjusted R^2-value was used to quantify the predictive ability of the fit.

3 Results

The system identification for the original simulation was identified. Both the model fit and the prediction were very good ($R^2 > 0.99$ for both). Adding large quantities of noise reduced the quality of the model fit to 0.48 and the prediction to 0.18. The time-varying conditions reduced the quality of the fits when the time-varying dynamics were applied only during plantarflexion, i.e., between the two Poincaré sections. For the randomly-varying muscle gain, the quality of the model fit was 0.62 and the prediction was 0.39. When randomly-varying descending neural input was added as 25% of the total stimulation, the quality of the model fit and the prediction were reduced to 0.56 and 0.18, respectively. Increasing the distance between the Poincaré sections without adding the current input information reduced the quality of the fits to 0.15 and 0.14, respectively. The input-output relationship for the motor-position controller was linear ($R^2 = 0.78$), while applying torque as a non-linear function of the input decreased the quality of the model and prediction fits to 0.17 and 0.28, respectively.

4 Discussion

The findings from the experiment and prior knowledge of the elements of the system guided the choice of the conditions for the simulation. For example, noise exists in the sensors, and unknown human dynamics, e.g., neural signals, play a large role in the muscle activity seen during walking. Decreasing the distance between the Poincaré sections by half nearly doubled the quality of the fits in the experiment ($R^2 = 0.34$ vs. $R^2 = 0.75$). The inputs were also non-linearly related to the output, so the contribution of the input was much smaller in the calculation of the model fit. These simulation results indicate that factors which are likely to exist in the real system would cause the current method of identification to fail for our system. We will address each factor and propose future work to counteract its effect on the system identification.

Noise in the sensors was simulated as a normally-distributed random variable within the range of the actual measurements; this means that up to half of the value used in the system identification could be random noise. These values are not unrealistic for the experimental system given the small range of values measured at the specified Poincaré sections. Theoretically, linear regression analysis should account for some degree of random noise to find the underlying relationships in the data. Despite the poor quality of the prediction when comparing the predicted data to the noisy output data, the quality of the prediction is much more closely aligned with the true data ($R^2 = 0.56$), which suggests that noise in the data may not play as large of a role in the experimental discrepancies. To mitigate the effects of noise, we will consider using basis functions to approximate the value at the Poincaré section rather than the value itself. This may reduce the effect of noise by defining a point as a vector of coefficients rather than a scalar value.

Time-varying human dynamics reduced the quality of the identification when the dynamics changed between the Poincaré sections. This is equivalent to the human changing their dynamics in an unforeseeable way during the window of interest. Neural signals take on the order of 100 milliseconds to reach the muscle, so we would be able to space the Poincaré sections such that this effect of unknown, rapidly changing dynamics can be mitigated.

The **greater distance between the Poincaré sections** in the experiment was constrained by the exoskeleton controller. The inputs which generated the random disturbances were chosen at heel strike, and we wanted to capture the dynamics of as much of stance as we could, so the Poincaré sections were chosen to be heel strike to toe-off on the exoskeleton-side foot. When the distance between the sections were reduced (i.e., mid-stance to toe-off), the quality of the identification increased. Future experiments will implement a torque-tracking controller rather than a motor position-tracking controller, which allows for more choices in both the positions and the number of Poincaré sections.

This change in the controller will also address the **differing contributions of the input on the output**. The input-output relationship was not clear in the experiment, while it had a very large linear contribution to the system identifications in the simulation. We will continue to investigate exoskeleton control strategies that improve the relative importance of the input on the human dynamics. Our next experiment will incorporate these results to improve the system identification of this human-exoskeleton system.

References

[1] S. Srivastava, P. C. Kao, S. H. Kim, P. Stegall, D. Zanotto, J. S. Higginson, S. K. Agrawal, and J. P. Scholz, "Assist-as-Needed Robot-Aided Gait Training Improves Walking Function in Individuals Following Stroke," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 6, pp. 956–963, 2015.

[2] K. L. Poggensee, K. Sreenath, and S. H. Collins, "Identifying the dynamics of a human-exoskeleton system," in *Dynamic Walking*, 2015.

[3] Y. Wang and M. Srinivasan, "Stepping in the direction of the fall: the next foot placement can be predicted from current upper body state in steady-state walking," *Biology Letters*, vol. 10, no. 9, 2014.